Assignment Tasks:

Task 1: Exploratory Data Analysis (EDA) and Business Insights

1. Perform EDA on the provided dataset. ¶

2. Derive at least 5 business insights from the EDA.

○ Write these insights in short point-wise sentences (maximum 100 words per insight).

Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import time
import os
```

In [2]:
```
print(os.listdir(r'C:\Users\HP\OneDrive\Documents\Python_Program\Data Science Assignment e
```

```
['.ipynb_checkpoints', 'Customers.csv', 'Products.csv', 'Transactions.csv', 'Untitled.ipynb']
```

Exploratory Data Analysis

In [3]:
```
ls Datasets
```

```
 Volume in drive C is OS
 Volume Serial Number is B09C-EF2A

 Directory of C:\Users\HP\OneDrive\Documents\Python_Program\Data Science Assignment eCommerce
\Datasets

26-01-2025  21:46    <DIR>          .
28-01-2025  00:38    <DIR>          ..
26-01-2025  21:46    <DIR>          .ipynb_checkpoints
25-01-2025  11:59             8,542 Customers.csv
25-01-2025  12:00             4,247 Products.csv
25-01-2025  12:01            54,748 Transactions.csv
26-01-2025  21:46                72 Untitled.ipynb
               4 File(s)         67,609 bytes
               3 Dir(s)  46,252,654,592 bytes free
```

In [4]:
```
1
2 customer_df = pd.read_csv("Datasets/Customers.csv")
3 product_df = pd.read_csv("Datasets/Products.csv")
4 transaction_df = pd.read_csv("Datasets/Transactions.csv")
5
```

In [5]:
```
1 customer_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   CustomerID    200 non-null    object
 1   CustomerName  200 non-null    object
 2   Region        200 non-null    object
 3   SignupDate    200 non-null    object
dtypes: object(4)
memory usage: 6.4+ KB
```

In [6]:
```
1 product_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 4 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   ProductID    100 non-null    object 
 1   ProductName  100 non-null    object 
 2   Category     100 non-null    object 
 3   Price        100 non-null    float64
dtypes: float64(1), object(3)
memory usage: 3.3+ KB
```

In [7]:
```
1 transaction_df.head()
```

Out[7]:

	TransactionID	CustomerID	ProductID	TransactionDate	Quantity	TotalValue	Price
0	T00001	C0199	P067	2024-08-25 12:38:23	1	300.68	300.68
1	T00112	C0146	P067	2024-05-27 22:23:54	1	300.68	300.68
2	T00166	C0127	P067	2024-04-25 07:38:55	1	300.68	300.68
3	T00272	C0087	P067	2024-03-26 22:55:37	2	601.36	300.68
4	T00363	C0070	P067	2024-03-21 15:10:10	3	902.04	300.68

In [8]:
```
1 customer_df[customer_df["CustomerID"] == "C0199"]
```

Out[8]:

	CustomerID	CustomerName	Region	SignupDate
198	C0199	Andrea Jenkins	Europe	2022-12-03

In [9]:
```
1 product_df[product_df["ProductID"] == "P067"]["Category"].values[0]
```

Out[9]: 'Electronics'

In [10]:
```
category = []
product_name = []
customer_region = []
signupdate=[]

for customer_id, product_id in zip(transaction_df["CustomerID"].tolist(), transaction_df["
    category_ = product_df[product_df["ProductID"] == product_id]["Category"].values[0]
    product_name_ = product_df[product_df["ProductID"] == product_id]["ProductName"].value
    region_ = customer_df[customer_df["CustomerID"] == customer_id]["Region"].values[0]
    signupdate_=customer_df[customer_df["CustomerID"]==customer_id]["SignupDate"].values[0
    category.append(category_)
    product_name.append(product_name_)
    customer_region.append(region_)
    signupdate.append(signupdate_)

```

In [11]:
```
transaction_df["Category"] = category
transaction_df["ProductName"] = product_name
transaction_df["Region"] = customer_region
transaction_df["SignupDate"]=signupdate
```

In [12]:
```
transaction_df.sample(5)
```

Out[12]:

	TransactionID	CustomerID	ProductID	TransactionDate	Quantity	TotalValue	Price	Category	ProductName
791	T00278	C0077	P097	2024-09-26 16:10:17	1	319.34	319.34	Books	BookWorld Cookbook
550	T00467	C0045	P096	2024-03-16 04:08:29	3	922.41	307.47	Electronics	SoundWave Headphones
604	T00353	C0012	P063	2024-10-22 21:55:48	1	33.59	33.59	Books	TechPro Novel
3	T00272	C0087	P067	2024-03-26 22:55:37	2	601.36	300.68	Electronics	ComfortLiving Bluetooth Speaker
258	T00607	C0175	P051	2024-10-04 01:18:02	4	260.64	65.16	Home Decor	ComfortLiving Desk Lamp

In [13]:
```
transaction_df.to_csv("transaction_data.csv", index=False)
```

In [14]:
```
transaction_df.shape
```

Out[14]:
```
(1000, 11)
```

In [15]:
```
customer_df["Region"].value_counts()
```

Out[15]:
```
Region
South America    59
Europe           50
North America    46
Asia             45
Name: count, dtype: int64
```

In [16]:
```
1 transaction_df.isnull().sum()
```

Out[16]:
```
TransactionID      0
CustomerID         0
ProductID          0
TransactionDate    0
Quantity           0
TotalValue         0
Price              0
Category           0
ProductName        0
Region             0
SignupDate         0
dtype: int64
```

In [17]:
```
1 transaction_df.duplicated().sum()
```

Out[17]:
```
0
```

In [18]:
```
1 transaction_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   TransactionID    1000 non-null   object 
 1   CustomerID       1000 non-null   object 
 2   ProductID        1000 non-null   object 
 3   TransactionDate  1000 non-null   object 
 4   Quantity         1000 non-null   int64  
 5   TotalValue       1000 non-null   float64
 6   Price            1000 non-null   float64
 7   Category         1000 non-null   object 
 8   ProductName      1000 non-null   object 
 9   Region           1000 non-null   object 
 10  SignupDate       1000 non-null   object 
dtypes: float64(2), int64(1), object(8)
memory usage: 86.1+ KB
```

In [19]:
```
1 transaction_df.describe()
```

Out[19]:

	Quantity	TotalValue	Price
count	1000.000000	1000.000000	1000.00000
mean	2.537000	689.995560	272.55407
std	1.117981	493.144478	140.73639
min	1.000000	16.080000	16.08000
25%	2.000000	295.295000	147.95000
50%	3.000000	588.880000	299.93000
75%	4.000000	1011.660000	404.40000
max	4.000000	1991.040000	497.76000

In [20]:
```
1 transaction_df.columns
```

Out[20]:
```
Index(['TransactionID', 'CustomerID', 'ProductID', 'TransactionDate',
       'Quantity', 'TotalValue', 'Price', 'Category', 'ProductName', 'Region',
       'SignupDate'],
      dtype='object')
```

In [21]:
```
1 transaction_df["ProductName"].unique().tolist()
```

Out[21]:
```
['ComfortLiving Bluetooth Speaker',
 'HomeSense T-Shirt',
 'ActiveWear Smartphone',
 'TechPro Textbook',
 'TechPro Running Shoes',
 'TechPro Rug',
 'ActiveWear Cookware Set',
 'BookWorld Biography',
 'BookWorld Cookware Set',
 'HomeSense Novel',
 'ComfortLiving Smartphone',
 'SoundWave Cookbook',
 'ComfortLiving Smartwatch',
 'SoundWave Mystery Book',
 'TechPro Vase',
 'HomeSense Desk Lamp',
 'ActiveWear Wall Art',
 'ComfortLiving Biography',
 'ComfortLiving Desk Lamp',
 'SoundWave Novel',
 'ComfortLiving Cookware Set',
 'TechPro Novel',
 'BookWorld Running Shoes',
 'ActiveWear Jeans',
 'BookWorld Jacket',
 'BookWorld Smartwatch',
 'ActiveWear Textbook',
 'ActiveWear Smartwatch',
 'ActiveWear Cookbook',
 'SoundWave Headphones',
 'HomeSense Rug',
 'HomeSense Sweater',
 'TechPro Smartwatch',
 'ActiveWear Running Shoes',
 'HomeSense Wall Art',
 'SoundWave Rug',
 'ActiveWear Headphones',
 'SoundWave Jeans',
 'SoundWave Desk Lamp',
 'BookWorld Cookbook',
 'BookWorld Wall Art',
 'TechPro Cookbook',
 'SoundWave Jacket',
 'BookWorld Sweater',
 'HomeSense Bluetooth Speaker',
 'SoundWave Textbook',
 'HomeSense Headphones',
 'ActiveWear Biography',
 'ComfortLiving Laptop',
 'ActiveWear Rug',
 'HomeSense Running Shoes',
 'ComfortLiving Mystery Book',
 'ActiveWear T-Shirt',
 'TechPro T-Shirt',
 'ActiveWear Jacket',
 'BookWorld Rug',
 'TechPro Headphones',
 'ComfortLiving Sweater',
 'SoundWave Smartwatch',
 'ComfortLiving Rug',
 'ComfortLiving Headphones',
 'HomeSense Cookware Set',
 'BookWorld Bluetooth Speaker',
 'SoundWave Laptop',
```

```
 'SoundWave Bluetooth Speaker',
 'SoundWave T-Shirt']
```

In [22]:
```
1 transaction_df.dtypes
```

Out[22]:
```
TransactionID       object
CustomerID          object
ProductID           object
TransactionDate     object
Quantity             int64
TotalValue         float64
Price              float64
Category            object
ProductName         object
Region              object
SignupDate          object
dtype: object
```

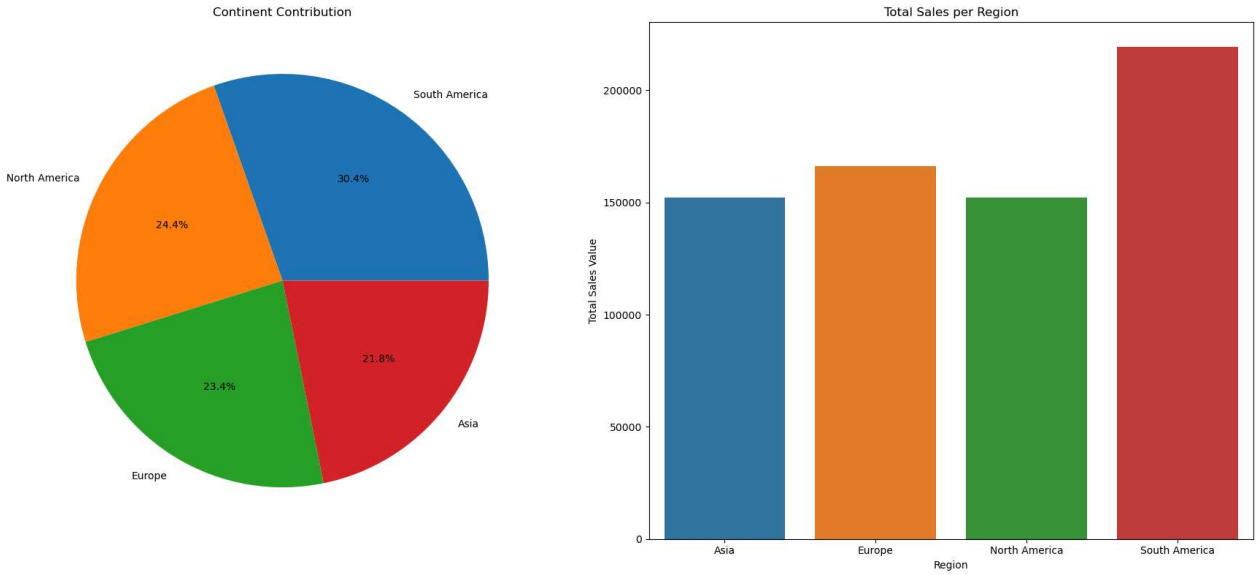
In [23]:
```
1 transaction_df.nunique()
```

Out[23]:
```
TransactionID      1000
CustomerID          199
ProductID           100
TransactionDate    1000
Quantity              4
TotalValue          369
Price               100
Category              4
ProductName          66
Region                4
SignupDate          178
dtype: int64
```

Business Insights Through EDA and Visualizations

Total Sales per Region

In [24]:
```
f,ax=plt.subplots(1,2,figsize=(18,8))
transaction_df['Region'].value_counts().plot.pie(autopct='%1.1f%%', ax=ax[0])
ax[0].set_title('Continent Contribution')
ax[0].set_ylabel('')
region_sales = transaction_df.groupby('Region').agg({'TotalValue': 'sum'}).reset_index()
sns.barplot(x='Region', y='TotalValue', data=region_sales, estimator=sum, ax=ax[1])
plt.title('Total Sales per Region')
plt.xlabel('Region')
plt.ylabel('Total Sales Value')
plt.tight_layout()
plt.show()


```



Insights:-

1> The pie chart displays the relative share of each region’s purchase count as a percentage of the total.

Here, South America contributes the most and Asia contributes the least to the total number of transactions.

2> The count plot visually represents the absolute number of transactions for e ach region

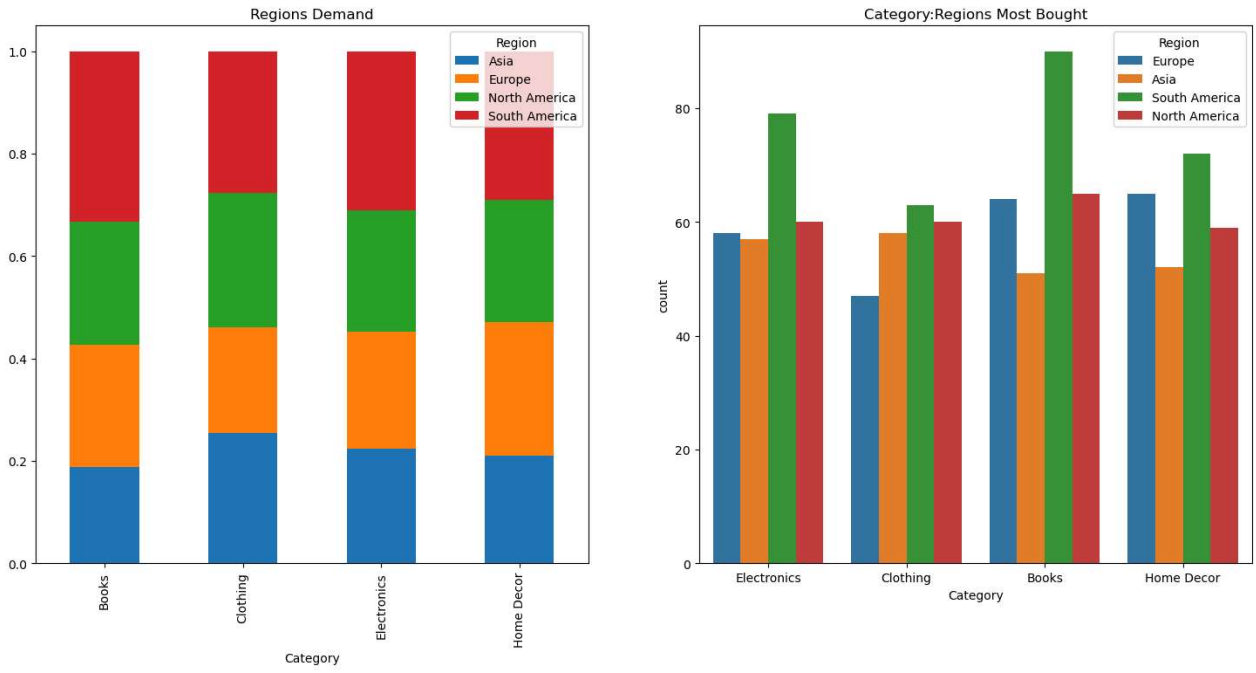
Here, Asia contributes total sacles of around 150000

Product preference In each Region

In [25]:
```
1 transaction_df.groupby(['Category','Region'])['Region'].count()
```

Out[25]:
```
Category     Region
Books        Asia             51
             Europe           64
             North America    65
             South America    90
Clothing     Asia             58
             Europe           47
             North America    60
             South America    63
Electronics  Asia             57
             Europe           58
             North America    60
             South America    79
Home Decor   Asia             52
             Europe           65
             North America    59
             South America    72
Name: Region, dtype: int64
```

In [26]:
```
1
2 f,ax=plt.subplots(1,2, figsize=(18,8))
3 region_distribution = transaction_df.groupby(['Category'])['Region'].value_counts(normaliz
4 region_distribution.plot.bar(ax=ax[0], stacked=True) #percentage value
5 ax[0].set_title('Regions Demand')
6 sns.countplot(x='Category',hue='Region',data=transaction_df,ax=ax[1])  #absolute value
7 ax[1].set_title('Category:Regions Most Bought')
8 plt.show()
```



Insights:-

The distribution of regions (e.g., North, South, East, West) as a proportion of total demand for each category.

By stacking, the relative contribution of each region within a category.

Regional preferences: How different regions compare in their interest/demand for various product categories.

For example, you might see that the South region contributes 60% of the demand for a particular category

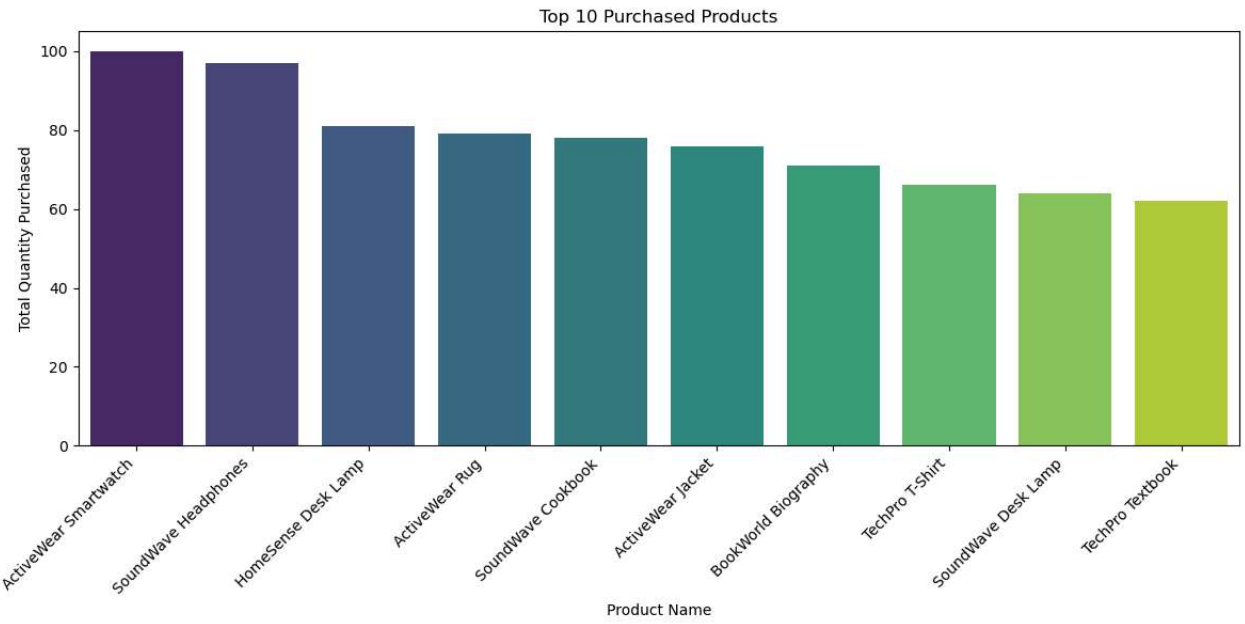
while other regions are less engaged

Here, Books are mostly preferred by South America, followed by North America and Europe

Through stacked bar graphs we can visualize the contribution of each regoin in different categories of sales

Top 10 Products sold in the company

In [27]:
```
top_products = transaction_df.groupby('ProductName')['Quantity'].sum().reset_index()
top_products = top_products.sort_values(by='Quantity', ascending=False).head(10)

#visualize
plt.figure(figsize=(12, 6))
sns.barplot(data=top_products, x='ProductName', y='Quantity', palette='viridis')
plt.title('Top 10 Purchased Products')
plt.xlabel('Product Name')
plt.ylabel('Total Quantity Purchased')
plt.xticks(rotation=45, ha='right')  # Rotate product names for better readability
plt.tight_layout()

# Show the plot
plt.show()
```



Insights:-

Here ActiveWear Smartwatches are the most sold product in the company

Product Sales Distribution VS Region

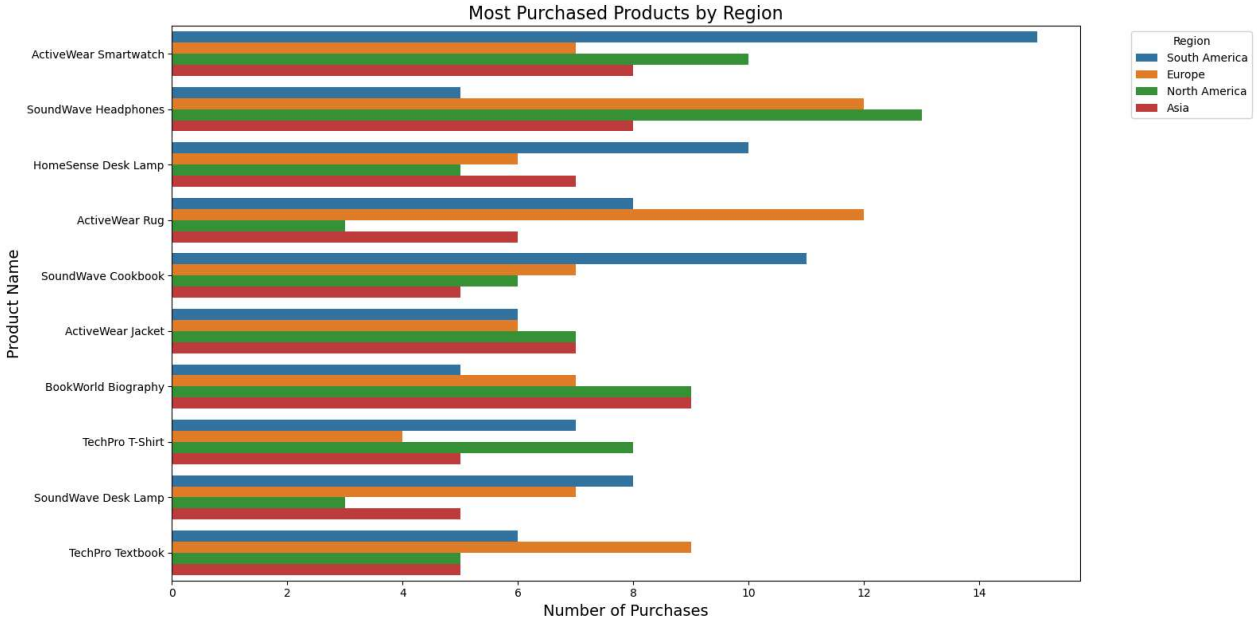
In [28]:
```
filtered_df = transaction_df[transaction_df['ProductName'].isin(top_products['ProductName'
filtered_df
```

Out[28]:

	TransactionID	CustomerID	ProductID	TransactionDate	Quantity	TotalValue	Price	Category	ProductName
37	T00004	C0004	P049	2024-07-19 10:56:13	4	591.80	147.95	Books	TechPro Textbook
38	T00105	C0087	P049	2024-02-12 08:14:34	3	443.85	147.95	Books	TechPro Textbook
39	T00136	C0010	P049	2024-02-22 18:44:05	2	295.90	147.95	Books	TechPro Textbook
40	T00237	C0065	P049	2024-02-27 22:16:22	2	295.90	147.95	Books	TechPro Textbook
41	T00239	C0132	P049	2024-12-06 19:03:54	2	295.90	147.95	Books	TechPro Textbook
...	...	...	...	...	...	...	...	...	...
988	T00418	C0184	P077	2024-01-03 02:43:36	2	531.02	265.51	Electronics	ActiveWear Smartwatch
989	T00549	C0093	P077	2024-09-16 02:11:37	2	531.02	265.51	Electronics	ActiveWear Smartwatch
990	T00624	C0105	P077	2024-08-03 23:04:47	4	1062.04	265.51	Electronics	ActiveWear Smartwatch
991	T00778	C0175	P077	2024-07-18 11:21:41	4	1062.04	265.51	Electronics	ActiveWear Smartwatch
992	T00920	C0090	P077	2024-04-26 11:22:42	1	265.51	265.51	Electronics	ActiveWear Smartwatch

292 rows × 11 columns

In [29]:
```
plt.figure(figsize=(16, 8))
sns.countplot(
    y='ProductName', hue='Region', data=filtered_df, order=top_products['ProductName']
)
plt.title('Most Purchased Products by Region', fontsize=16)
plt.xlabel('Number of Purchases', fontsize=14)
plt.ylabel('Product Name', fontsize=14)
plt.legend(title='Region', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



Insights:-

Here, SoundWave Headphones are mostly buyed in North America whereas TechPro Textbook is most popular in Europe

Customer's MAX vs Min Sales

In [34]:
```
max_purchase_row = transaction_df.loc[transaction_df['TotalValue'].idxmax()]
customer_id = max_purchase_row['CustomerID']
max_purchase_value = max_purchase_row['TotalValue']
min_purchase_row = transaction_df.loc[transaction_df['TotalValue'].idxmin()]
customer_id = min_purchase_row['CustomerID']
min_purchase_value = min_purchase_row['TotalValue']
```

In [36]:
```

print(f'The Customer with customer ID {customer_id} max purchase {max_purchase_value}')
print(f'The Customer with customer ID {customer_id} min purchase {min_purchase_value}')
```

```
The Customer with customer ID C0112 max purchase 1991.04
The Customer with customer ID C0112 min purchase 16.08
```

Insights:-

Here maximum and minimum customer transaction/ purchase can be found and based on that sales and discounts and offers can be given

Sales Trends Over Time

In [37]:
```
transaction_df['TransactionDate'] = pd.to_datetime(transaction_df['TransactionDate'])
sales_over_time = transaction_df.groupby(transaction_df['TransactionDate'].dt.date)['Total
sales_over_time
```

Out[37]:

	TransactionDate	TotalValue
0	2023-12-30	313.92
1	2023-12-31	3455.60
2	2024-01-01	1468.94
3	2024-01-02	1818.03
4	2024-01-03	2224.41
...	...	...
332	2024-12-24	2589.58
333	2024-12-25	1343.90
334	2024-12-26	5108.25
335	2024-12-27	752.56
336	2024-12-28	476.79

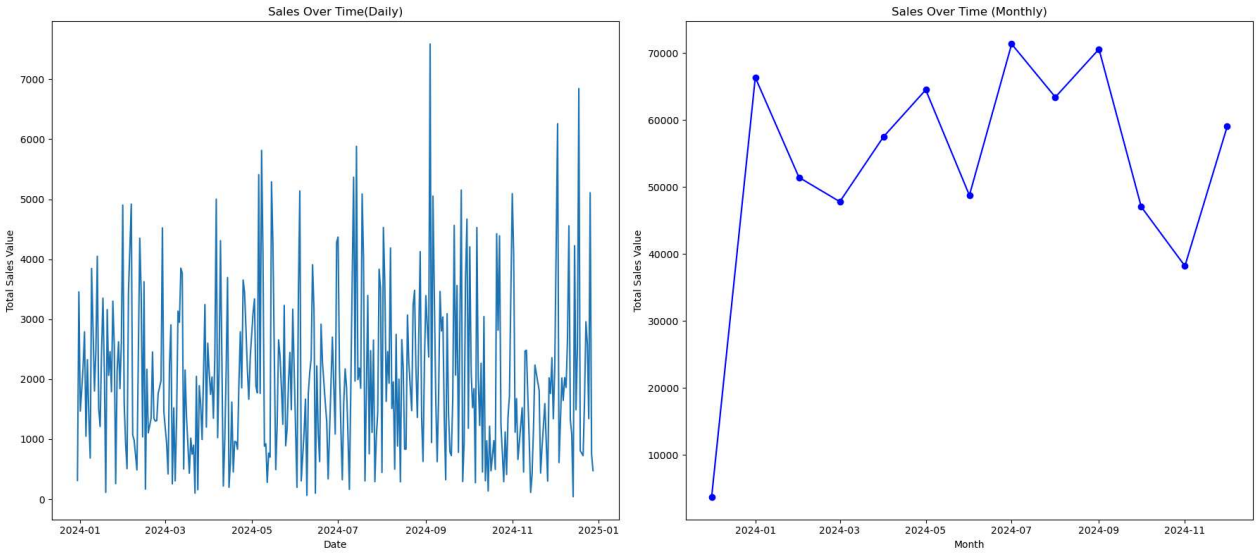
337 rows × 2 columns

In [38]:
```
transaction_df['TransactionDate'] = pd.to_datetime(transaction_df['TransactionDate'])
sales_over_time_monthly = transaction_df.groupby(transaction_df['TransactionDate'].dt.to_p
sales_over_time_monthly
```

Out[38]:

	TransactionDate	TotalValue
0	2023-12	3769.52
1	2024-01	66376.39
2	2024-02	51459.27
3	2024-03	47828.73
4	2024-04	57519.06
5	2024-05	64527.74
6	2024-06	48771.18
7	2024-07	71366.39
8	2024-08	63436.74
9	2024-09	70603.75
10	2024-10	47063.22
11	2024-11	38224.37
12	2024-12	59049.20

In [39]:
```
f,ax=plt.subplots(1,2, figsize=(18,8))
sns.lineplot(x='TransactionDate', y='TotalValue', data=sales_over_time, ax=ax[0])
ax[0].set_title('Sales Over Time(Daily)')
ax[0].set_xlabel('Date')
ax[0].set_ylabel('Total Sales Value')

# Convert 'TransactionDate' from Period to Timestamp by applying .dt.to_timestamp()
sales_over_time_monthly['TransactionDate'] = sales_over_time_monthly['TransactionDate'].dt

# Create the line plot

ax[1].plot(sales_over_time_monthly['TransactionDate'], sales_over_time_monthly['TotalValue

# Adding titles and labels
ax[1].set_title('Sales Over Time (Monthly)')
ax[1].set_xlabel('Month')
ax[1].set_ylabel('Total Sales Value')

# Display the plot
plt.tight_layout()
plt.show()
```



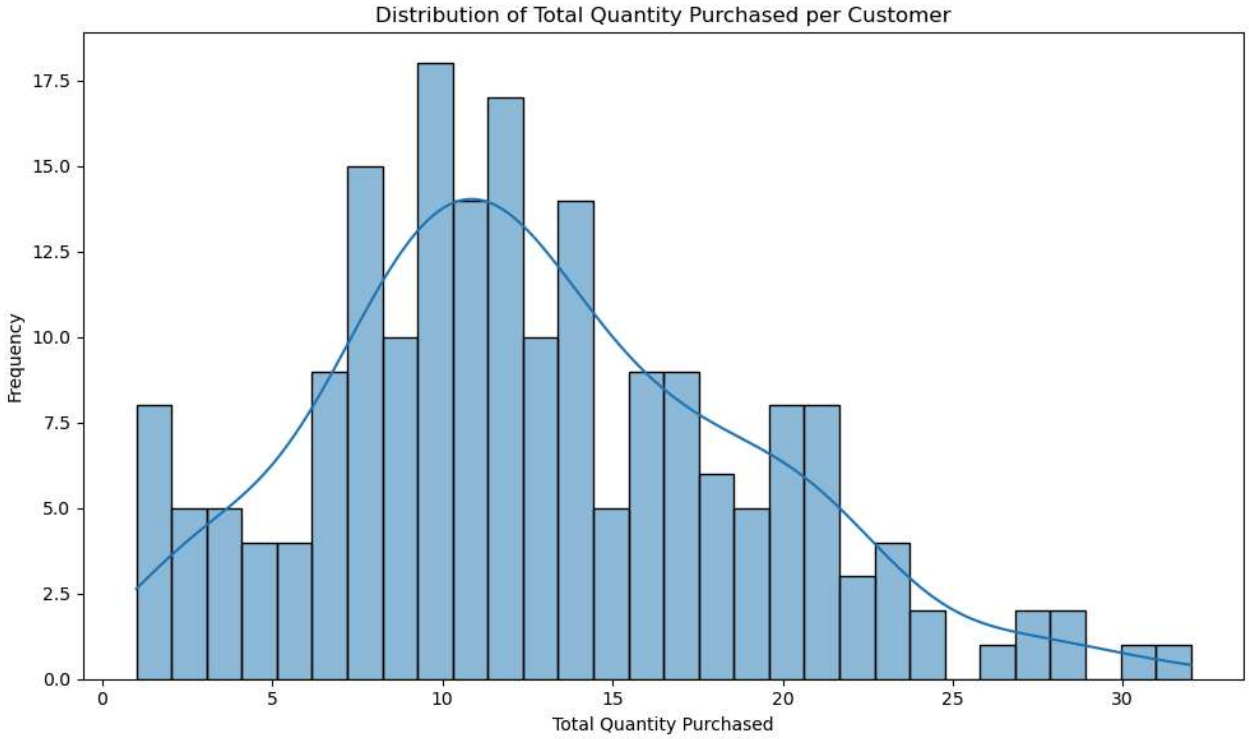
Insights :-

By analyzing time-based trends, we can determine certain seasons, months, or weeks with higher sales.

Here, sales in the month of Febuary seems to have certain spike followed by the month of September-October
which is the festive season.

Customer Buying Behavior

In [40]:
```
customer_purchase = transaction_df.groupby('CustomerID')['Quantity'].sum().reset_index()
plt.figure(figsize=(10, 6))
sns.histplot(customer_purchase['Quantity'], kde=True, bins=30)

plt.title('Distribution of Total Quantity Purchased per Customer')
plt.xlabel('Total Quantity Purchased')
plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```

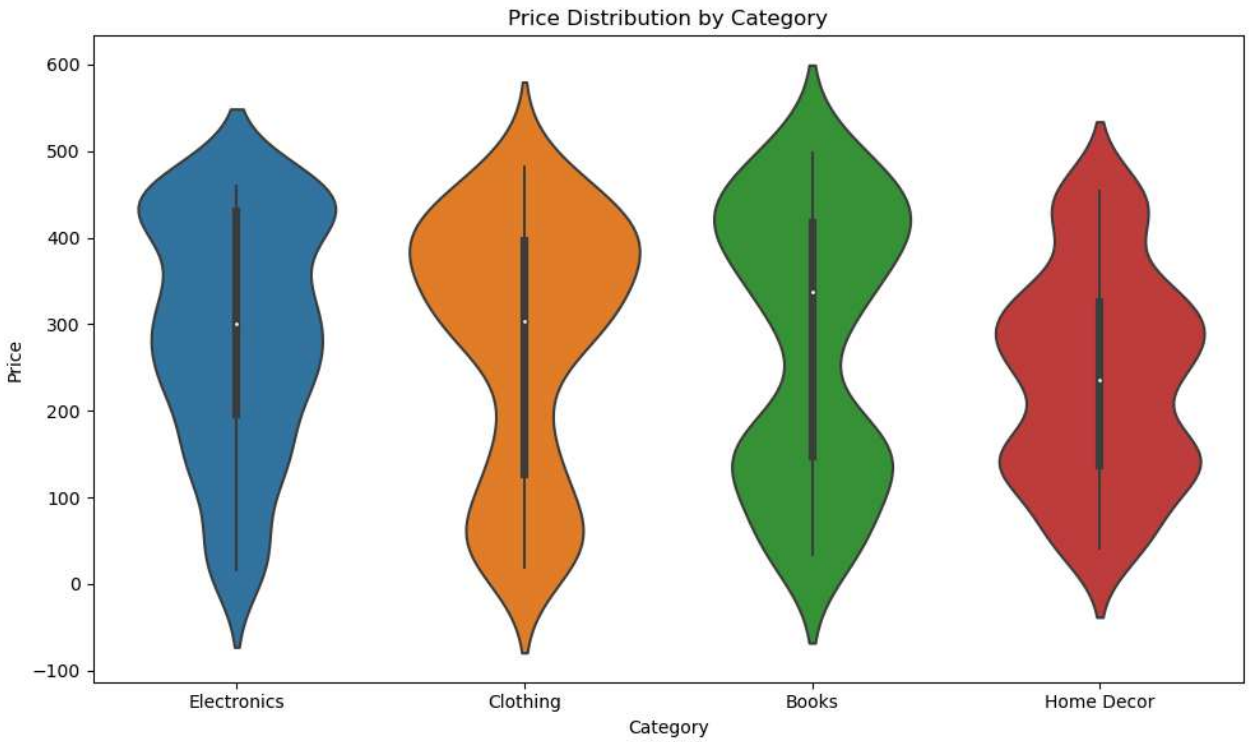


Insights:-

Certain customers tend to buy more frequently or purchase higher quantities. This can help with segmentation or customer profiling

Price Distribution of Products

In [41]:
```
# Violin plot to compare price distribution across categories
plt.figure(figsize=(10, 6))
sns.violinplot(x='Category', y='Price', data=transaction_df)

# Adding title and labels
plt.title('Price Distribution by Category')
plt.xlabel('Category')
plt.ylabel('Price')

# Show the plot
plt.tight_layout()
plt.show()
```



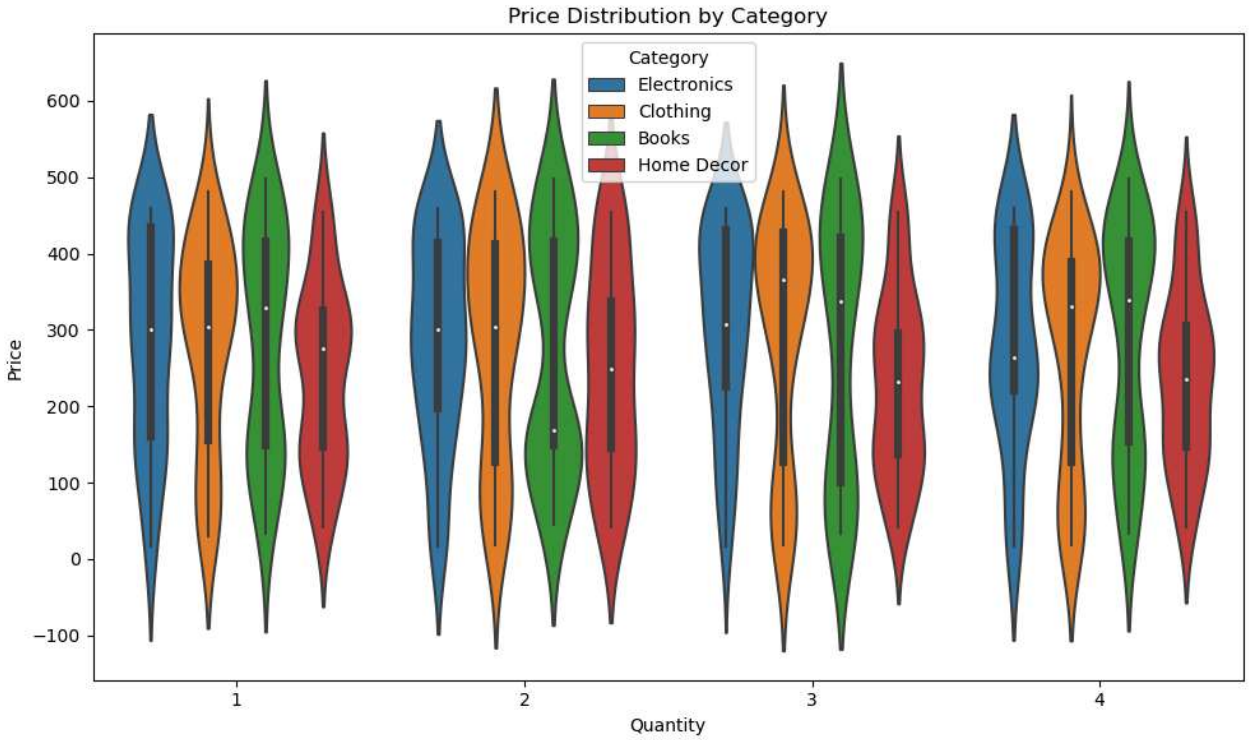
Insights :-

It determines the distribution of product prices, identify outliers, or see price trends for different product categories.

Here, price of Clothing are mostly around 450 while in case of Home Decor the price range varies from 100- 250

Price Distribution by Category across Region

In [42]:
```
# Violin plot to compare price distribution across categories
plt.figure(figsize=(10, 6))
sns.violinplot(x='Quantity', y='Price', hue ='Category', data=transaction_df)

# Adding title and labels
plt.title('Price Distribution by Category')
plt.xlabel('Quantity')
plt.ylabel('Price')

# Show the plot
plt.tight_layout()
plt.show()
```

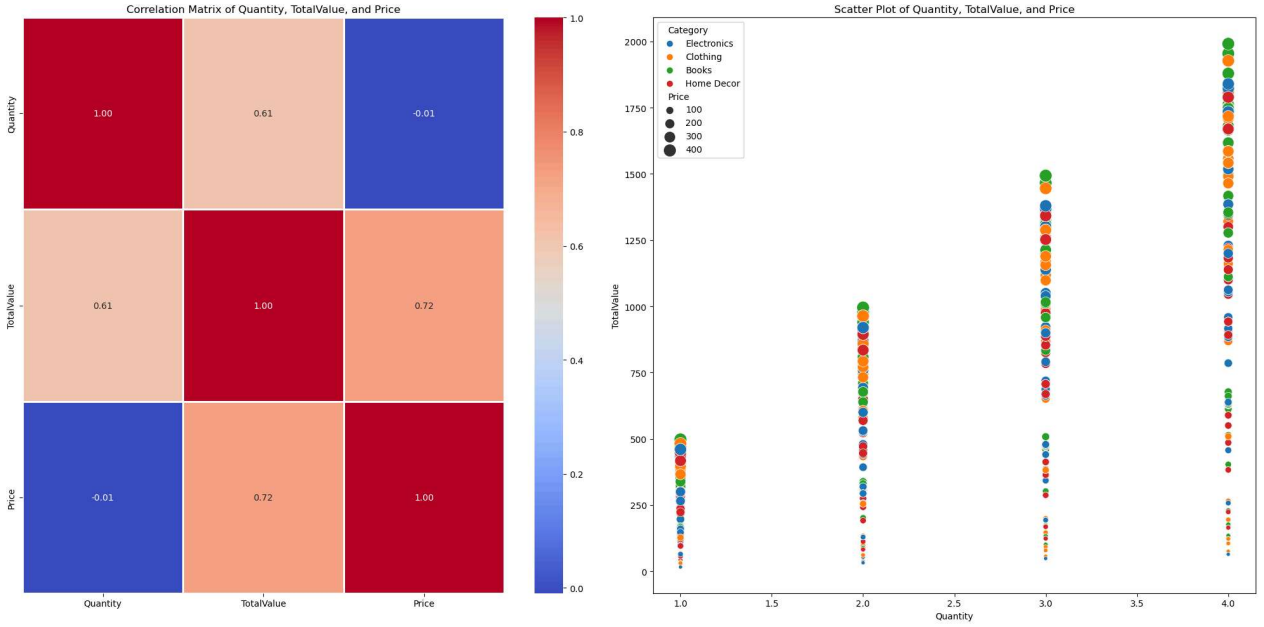


Insight:

Identifies how the price and categories of products varies and how they are distributed across region.

Correlation Matrix and Scatter Plot

In [46]:
```
f,ax=plt.subplots(1,2, figsize=(20,10))
correlation_matrix = transaction_df[['Quantity', 'TotalValue', 'Price']].corr()

# Plot the heatmap for the correlation matrix

sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=1, ax=a
ax[0].set_title('Correlation Matrix of Quantity, TotalValue, and Price')
#
sns.scatterplot(x='Quantity', y='TotalValue', data=transaction_df, hue='Category', size='P
ax[1].set_title('Scatter Plot of Quantity, TotalValue, and Price')
plt.tight_layout()
plt.show()

```



Insight:-

Show how the total value of a product correlates with its quantity sold. This can give insights into whether high-value products are being bought in large quantities or not.

In [47]:
```
transaction_df["Transaction_Date"] = transaction_df["TransactionDate"].dt.date
transaction_df["Transaction_Time"] = transaction_df["TransactionDate"].dt.time
transaction_df = transaction_df.drop(columns=["TransactionDate"])
```

In [48]:
```
transaction_df["Transaction_Time"] = transaction_df["Transaction_Time"].astype(str)
transaction_df["hour"] = transaction_df["Transaction_Time"].apply(lambda x: int(x[:2]))

```

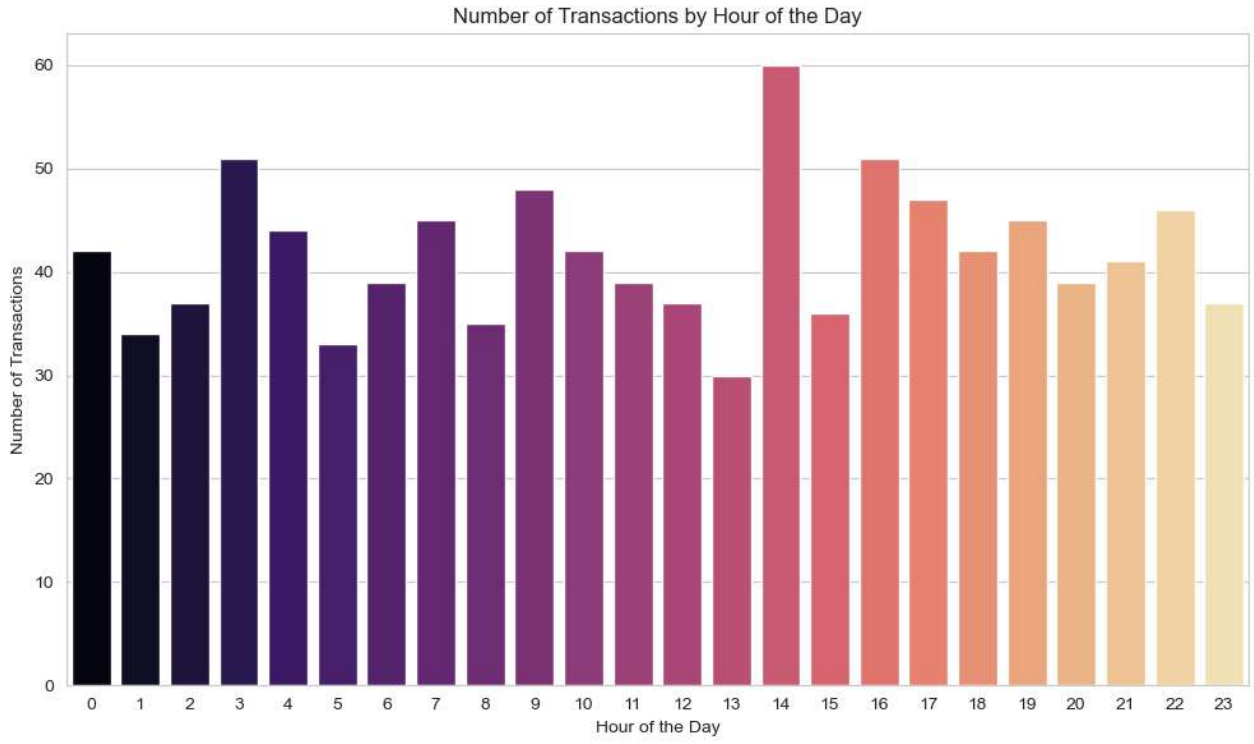
In [50]:
```
transaction_df.sample(3)
```

Out[50]:

	TransactionID	CustomerID	ProductID	Quantity	TotalValue	Price	Category	ProductName	Region	SignupDa
766	T00419	C0030	P004	3	287.07	95.69	Home Decor	BookWorld Rug	North America	2024-01-
489	T00861	C0141	P042	4	1517.76	379.44	Electronics	ActiveWear Headphones	Europe	2023-02-
72	T00952	C0139	P053	1	274.94	274.94	Home Decor	TechPro Rug	North America	2022-03-

Transactions Per Hour

In [53]:
```
transactions_by_hour = transaction_df.groupby('hour')['TransactionID'].count().reset_index

# Visualization
plt.figure(figsize=(10, 6))

# Create the bar plot
sns.barplot(x='hour', y='TransactionID', data=transactions_by_hour, palette='magma')

# Add titles and labels
plt.title('Number of Transactions by Hour of the Day')
plt.xlabel('Hour of the Day')
plt.ylabel('Number of Transactions')

# Show the plot
plt.tight_layout()
plt.show()
```



Insight:-

1> Peak Sales Hours:The total sales by hour plot will show at what time of day most revenue is generated.

If certain hours of the day consistently show higher sales values, it indicates that customers tend to make higher-value purchases during those hours.

2> Optimal Timing for Promotions:promotions, specific shopping behaviors, or just more customers buying during peak times.

Here, most active timing for shopping is 13hr of the day