IMPORTING REQUIRED LIBRARIES

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
```

READING THE CSV FILE AND LOADING IT'S CONTENTS INTO A PANDAS DATAFRAME

```
df=pd.read_csv(r"D:\Python\Project\ecommerce_customer_data_large.csv")
```

TOP 5 ENTERIES

```
df.head()

   Customer ID      Purchase Date Product Category  Quantity  \
0        43799  13-09-2023 18:42         Clothing         2
1        37031  13-09-2023 18:37            Books         3
2         7982  13-09-2023 18:33             Home         4
3        25927  12-09-2023 13:54      Electronics         5
4        28694  13-09-2023 18:02             Home         2

   Total Purchase Amount Payment Method  Customer Age  Returned
Returns  \
0                   2076         PayPal            66       0.0
No
1                   3998    Credit Card            25       0.0
No
2                   4634         PayPal            68       0.0
No
3                  25465         PayPal            38       1.0
No
4                   4492    Credit Card            25       1.0
No

      Customer Name  Age  Gender  Churn  Purchase Month  Purchase Year

0     Jessica Jones   66  Female      0               9           2023

1    Julia Campbell   25  Female      0               9           2023

2     Jessica Clark   68  Female      0               9           2023

3   Michael Johnson   38    Male      0               9           2023

4  Jennifer Nichols   25  Female      0               9           2023
```

LAST 5 ENTERIES

```
df.tail()
```

```
        Customer ID     Purchase Date Product Category  Quantity  \
249995         6380  01-01-2020 00:28             Home         5
249996        25222  01-01-2020 00:24         Clothing         1
249997           51  07-01-2020 00:28         Clothing         2
249998        38053  13-03-2020 02:18         Clothing         3
249999        43906  05-10-2020 07:47         Clothing         3

        Total Purchase Amount Payment Method  Customer Age  Returned
Returns  \
249995                   5150         PayPal            54       0.0
No
249996                   4197           Cash            34       1.0
Yes
249997                    103           Cash            18       NaN
NaN
249998                    102    Credit Card            18       0.0
No
249999                    100    Credit Card            18       NaN
NaN

         Customer Name  Age  Gender  Churn  Purchase Month  Purchase
Year
249995  Ashlee Johnson   54  Female      1               1
2020
249996    John Delgado   34  Female      0               1
2020
249997    Colleen Pace   18    Male      0               1
2020
249998         Lori Yu   18    Male      0               3
2020
249999     Ashley Hall   18    Male      0              10
2020
```

DIMENTIONS OF DATAFRAME

```
df.shape
```

```
(250000, 15)
```

SUMMARY OF DATAFRAME STURUCTURE

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250000 entries, 0 to 249999
Data columns (total 15 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
```

```
 0   Customer ID            250000 non-null  int64
 1   Purchase Date          250000 non-null  object
 2   Product Category       250000 non-null  object
 3   Quantity               250000 non-null  int64
 4   Total Purchase Amount  250000 non-null  int64
 5   Payment Method         250000 non-null  object
 6   Customer Age           250000 non-null  int64
 7   Returned               202618 non-null  float64
 8   Returns                202618 non-null  object
 9   Customer Name          250000 non-null  object
 10  Age                    250000 non-null  int64
 11  Gender                 250000 non-null  object
 12  Churn                  250000 non-null  int64
 13  Purchase Month         250000 non-null  int64
 14  Purchase Year          250000 non-null  int64
dtypes: float64(1), int64(8), object(6)
memory usage: 28.6+ MB
```

CHECKING FOR DUPLICATES

```
df.duplicated().sum()

0
```

CHECKING FOR MISSING OR NULL VALUES IN COLUMNS

```
df.isnull().sum()

Customer ID                  0
Purchase Date                0
Product Category             0
Quantity                     0
Total Purchase Amount        0
Payment Method               0
Customer Age                 0
Returned                 47382
Returns                  47382
Customer Name                0
Age                          0
Gender                       0
Churn                        0
Purchase Month               0
Purchase Year                0
dtype: int64
```

- Dropping 'Returned' column since 'Returns' column contains the same information

```
df.drop('Returned',axis=1,inplace=True)
```

DEALING WITH NULL VALUES

```
df['Returns']=df['Returns'].fillna(df['Returns'].mode()[0])
```

```
df.isnull().sum()
```

```
Customer ID              0
Purchase Date            0
Product Category         0
Quantity                 0
Total Purchase Amount    0
Payment Method           0
Customer Age             0
Returns                  0
Customer Name            0
Age                      0
Gender                   0
Churn                    0
Purchase Month           0
Purchase Year            0
dtype: int64
```

GENERATING SUMMARY STATISTICS FOR NUMERICAL COLUMNS IN THE DATAFRAME

```
df.describe()
```

```
         Customer ID       Quantity  Total Purchase Amount   Customer
Age  \
count  250000.000000  250000.000000          250000.000000
250000.000000
mean    25017.632092       3.004936            2727.053920
43.798276
std     14412.515718       1.414737            1450.886867
15.364915
min         1.000000       1.000000             100.000000
18.000000
25%     12590.000000       2.000000            1477.000000
30.000000
50%     25011.000000       3.000000            2726.000000
44.000000
75%     37441.250000       4.000000            3975.000000
57.000000
max     50000.000000       5.000000           25465.000000
70.000000

                 Age         Churn  Purchase Month  Purchase Year
count  250000.000000  250000.00000   250000.000000  250000.000000
mean       43.798276       0.20052        6.190376    2021.377136
std        15.364915       0.40039        3.353238       1.074712
min        18.000000       0.00000        1.000000    2020.000000
25%        30.000000       0.00000        3.000000    2020.000000
```

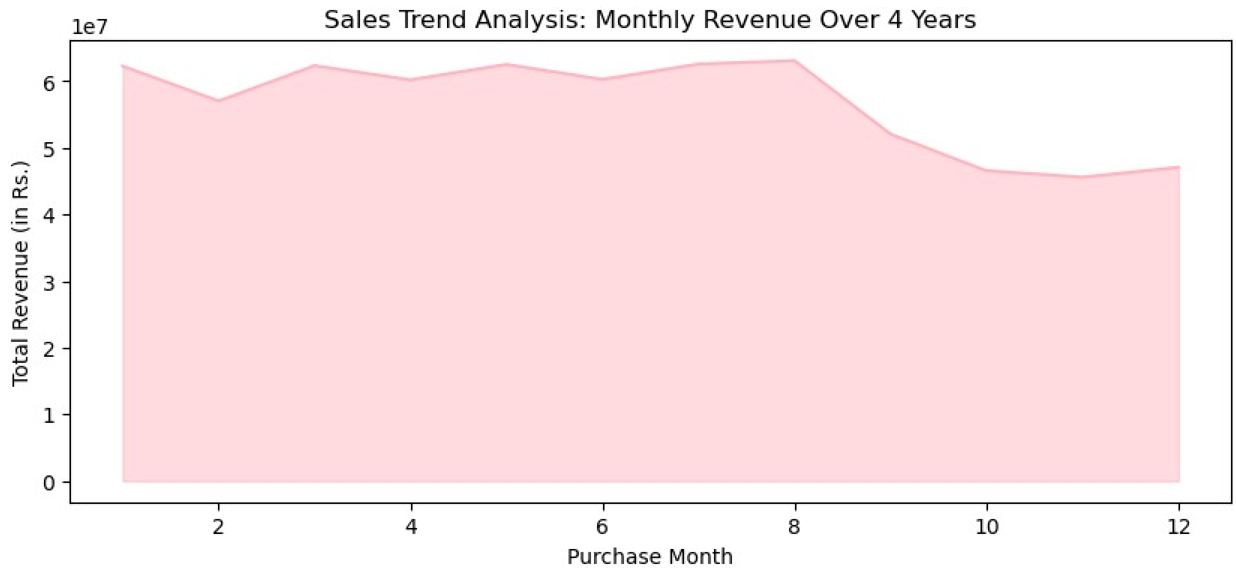
```
50%          44.000000        0.00000         6.000000    2021.000000
75%          57.000000        0.00000         9.000000    2022.000000
max          70.000000        1.00000        12.000000    2023.000000
```

EXPLORATORY DATA ANALYSIS

```
print("Total Revenue(in Rs.) : ",df["Total Purchase Amount"].sum())

Total Revenue(in Rs.) :  681763480
```

Sales Performance Overview

```
temp1=df.groupby("Purchase Month")["Total Purchase
Amount"].sum().reset_index()
temp1

    Purchase Month  Total Purchase Amount
0                1               62283958
1                2               57050354
2                3               62355745
3                4               60217450
4                5               62533980
5                6               60286066
6                7               62587751
7                8               63093912
8                9               52068193
9               10               46595245
10              11               45604668
11              12               47086158

plt.figure(figsize=(10,4))
sns.lineplot(x=temp1['Purchase Month'],y=temp1['Total Purchase
Amount'],color='lightpink')
plt.fill_between(temp1['Purchase Month'], temp1['Total Purchase
Amount'], color='lightpink', alpha=0.5)
plt.xlabel('Purchase Month')
plt.ylabel('Total Revenue (in Rs.)')
plt.title('Sales Trend Analysis: Monthly Revenue Over 4 Years')
plt.show()
```

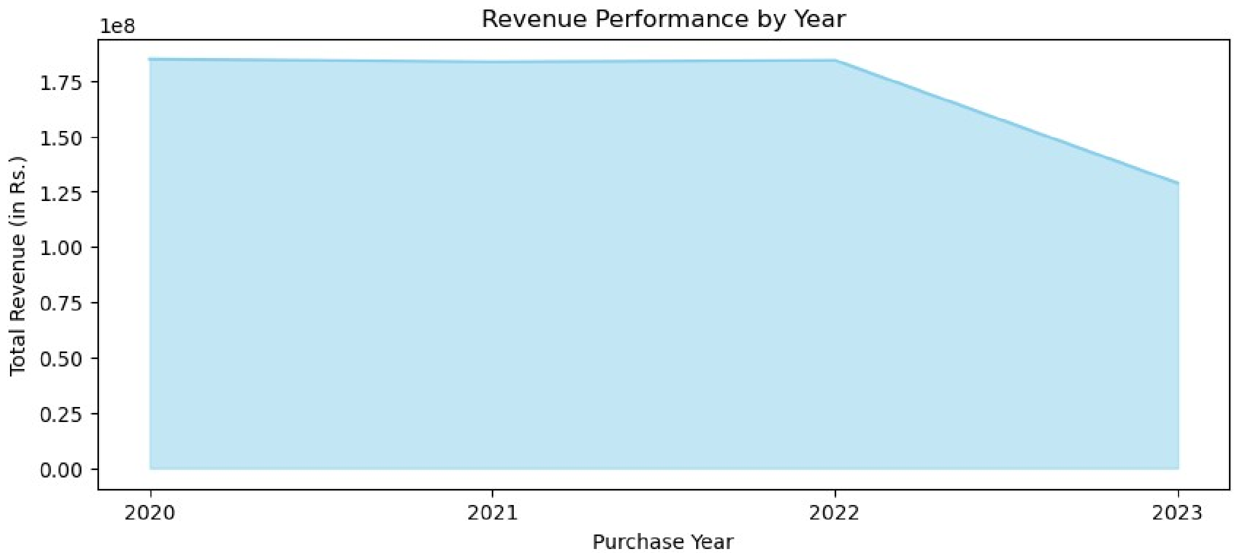



- Monthly revenue over four years reveals a peak around mid-year followed by a consistent decline. The chart highlights fluctuating sales trends with a clear upward movement in the first half and a downward trend in the second half of the year.

```
temp2=df.groupby('Purchase Year')['Total Purchase
Amount'].sum().reset_index()
temp2
```

| | Purchase Year | Total Purchase Amount |
|---|---|---|
| 0 | 2020 | 184959504 |
| 1 | 2021 | 183672481 |
| 2 | 2022 | 184344727 |
| 3 | 2023 | 128786768 |

```
plt.figure(figsize=(10,4))
sns.lineplot(temp2,x='Purchase Year',y='Total Purchase
Amount',color='skyblue')
plt.fill_between(temp2['Purchase Year'],temp2['Total Purchase
Amount'],color='skyblue', alpha=0.5)
plt.xticks([2020, 2021, 2022, 2023])
plt.xlabel('Purchase Year')
plt.ylabel('Total Revenue (in Rs.)')
plt.title('Revenue Performance by Year')
plt.show()
```



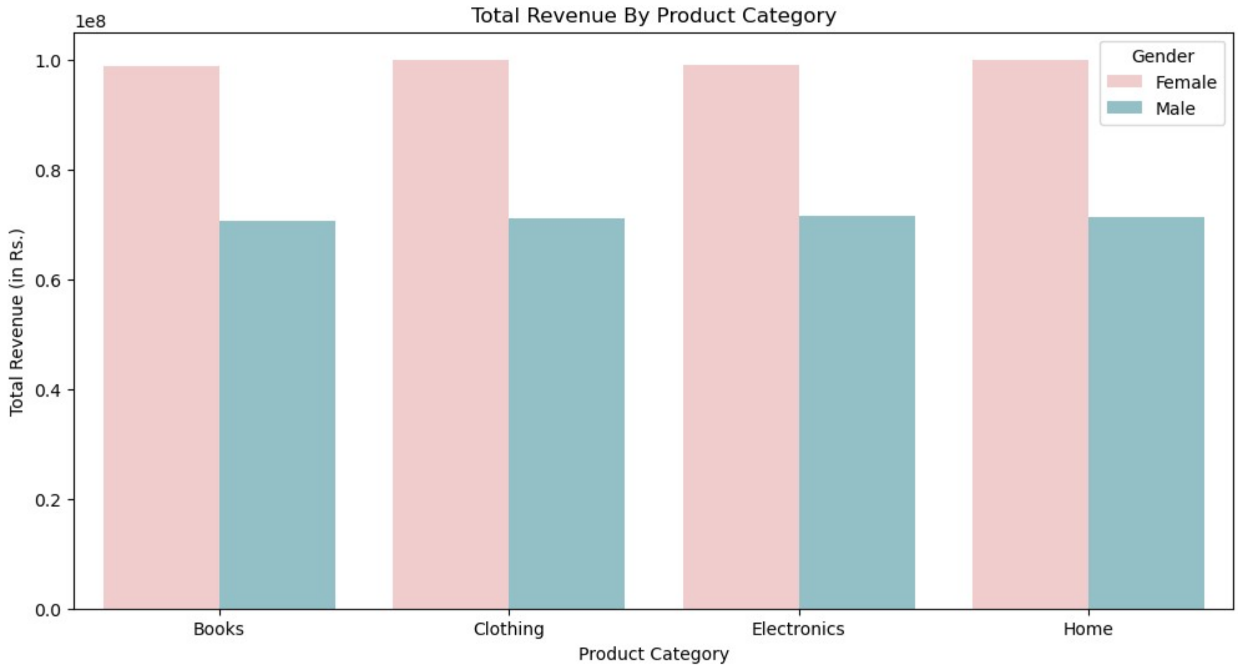

- The area chart illustrates the trend of total revenue over a four-year period. While revenue remained relatively stable from 2020 to 2022, a significant decline is observed in 2023, suggesting potential factors impacting revenue generation that year.

Revenue Trends Across Categories

```
temp3=df.groupby(['Product Category','Gender'])['Total Purchase
Amount'].sum().reset_index()
temp3
```

| | Product Category | Gender | Total Purchase Amount |
|---|---|---|---|
| 0 | Books | Female | 98756562 |
| 1 | Books | Male | 70588674 |
| 2 | Clothing | Female | 99830815 |
| 3 | Clothing | Male | 70954307 |
| 4 | Electronics | Female | 99068344 |
| 5 | Electronics | Male | 71425862 |
| 6 | Home | Female | 99963070 |
| 7 | Home | Male | 71175846 |

```
plt.figure(figsize=(12,6))
custom_palette = ["#F7C6C7", "#8AC6D0"]
sns.barplot(temp3,x='Product Category',y='Total Purchase
Amount',palette=sns.color_palette(custom_palette),hue='Gender')
plt.xlabel('Product Category')
plt.ylabel('Total Revenue (in Rs.)')
plt.title('Total Revenue By Product Category')
plt.show()
```



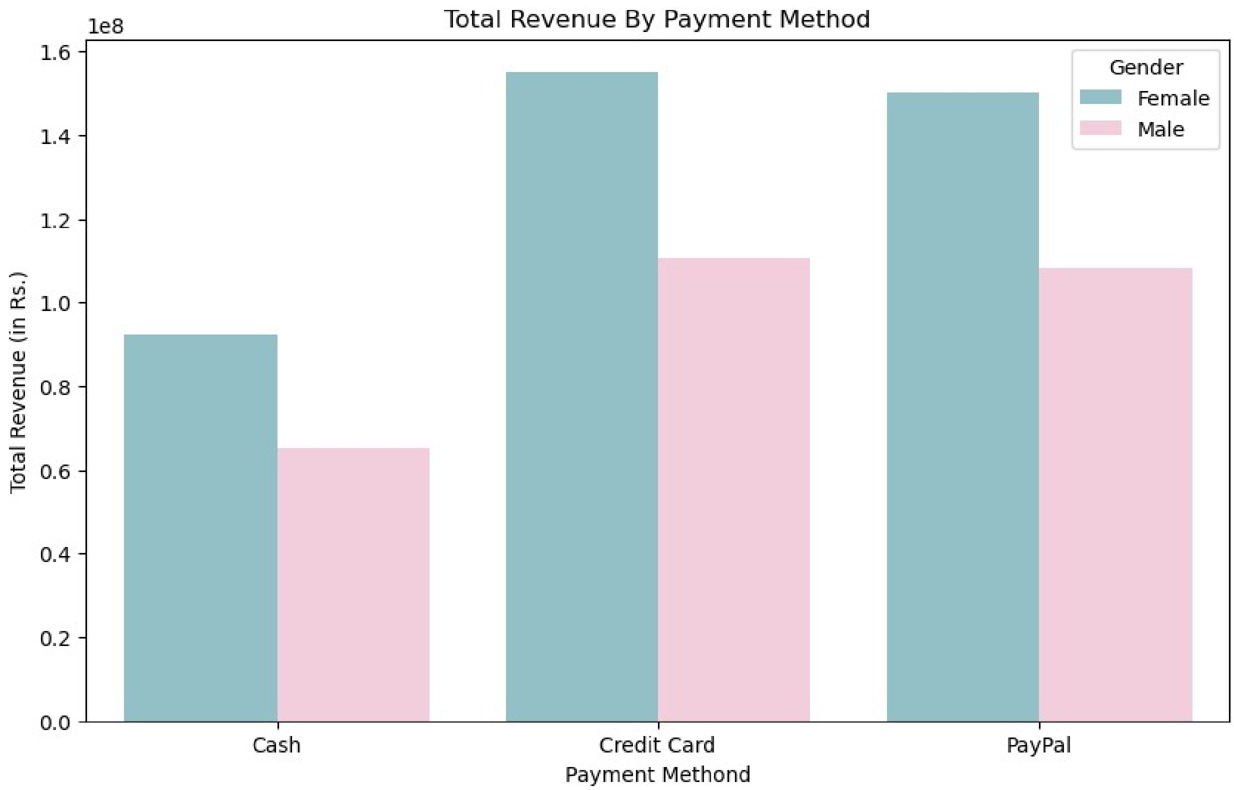

- Females generate higher revenue across all product categories compared to males.
- Books, Clothing, Electronics, and Home categories show a consistent trend, with female revenue significantly exceeding male revenue.
- Males contribute less revenue in every category, indicating either lower purchase frequency or spending.
- The revenue gap is evident in all categories, suggesting female customers are the primary buyers in these product segments.

Revenue By Payment Method

```
temp4=df.groupby(['Payment Method','Gender'])["Total Purchase Amount"].sum().reset_index()
temp4
```

| | Payment Method | Gender | Total Purchase Amount |
|---|---|---|---|
| 0 | Cash | Female | 92212251 |
| 1 | Cash | Male | 65160100 |
| 2 | Credit Card | Female | 155243421 |
| 3 | Credit Card | Male | 110656115 |
| 4 | PayPal | Female | 150163119 |
| 5 | PayPal | Male | 108328474 |

```
plt.figure(figsize=(10,6))
custom_palette = ["#8AC6D0","#F8C8DC"]
sns.barplot(temp4,x='Payment Method',y='Total Purchase Amount',hue='Gender',palette=sns.color_palette(custom_palette))
plt.xlabel('Payment Menthod')
plt.ylabel('Total Revenue (in Rs.)')
plt.title('Total Revenue By Payment Method')
plt.show()
```



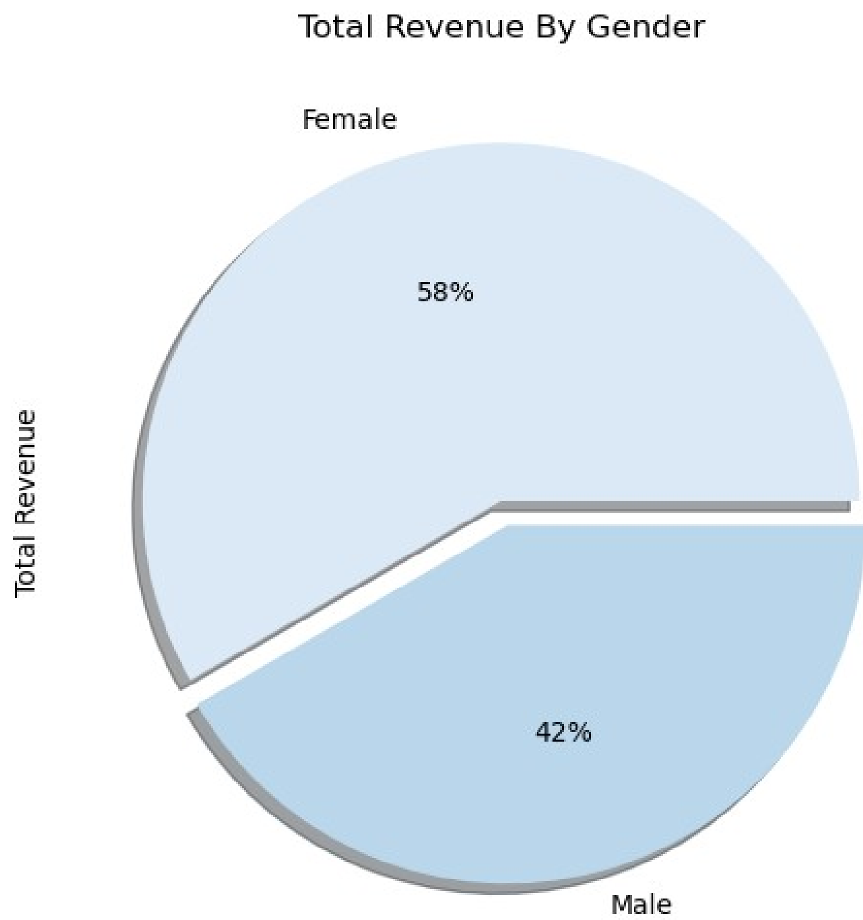

- Credit Card and PayPal generate the highest revenue, with females contributing more than males in both.
- Cash payments have the lowest revenue, with a smaller gap between male and female customers.
- Females prefer digital payments (Credit Card & PayPal) over cash, indicating a shift towards online transactions.
- Males generate less revenue across all payment methods, suggesting lower spending or fewer transactions compared to females.

Revenue By Gender

```
temp5=df.groupby('Gender')['Total Purchase
Amount'].sum().reset_index()
temp5
```

| | Gender | Total Purchase Amount |
|---|---|---|
| 0 | Female | 397618791 |
| 1 | Male | 284144689 |

```
plt.figure(figsize=(10,6))
temp5['Total Purchase Amount'].plot(kind='pie',autopct='%1.f%
%',labels=temp5['Gender'],explode=[0,0.07],shadow=True,colors=sns.colo
r_palette('Blues'))
plt.title("Total Revenue By Gender")
plt.ylabel("Total Revenue")
plt.show()
```




- Females contribute 58% of total revenue, which is higher than males.
- Males account for 42% of total revenue, indicating a lower spending pattern compared to females.
- The revenue distribution suggests female customers are the dominant buyers in this dataset.
- The slight gap between male and female revenue implies a potential opportunity to increase male customer engagement.

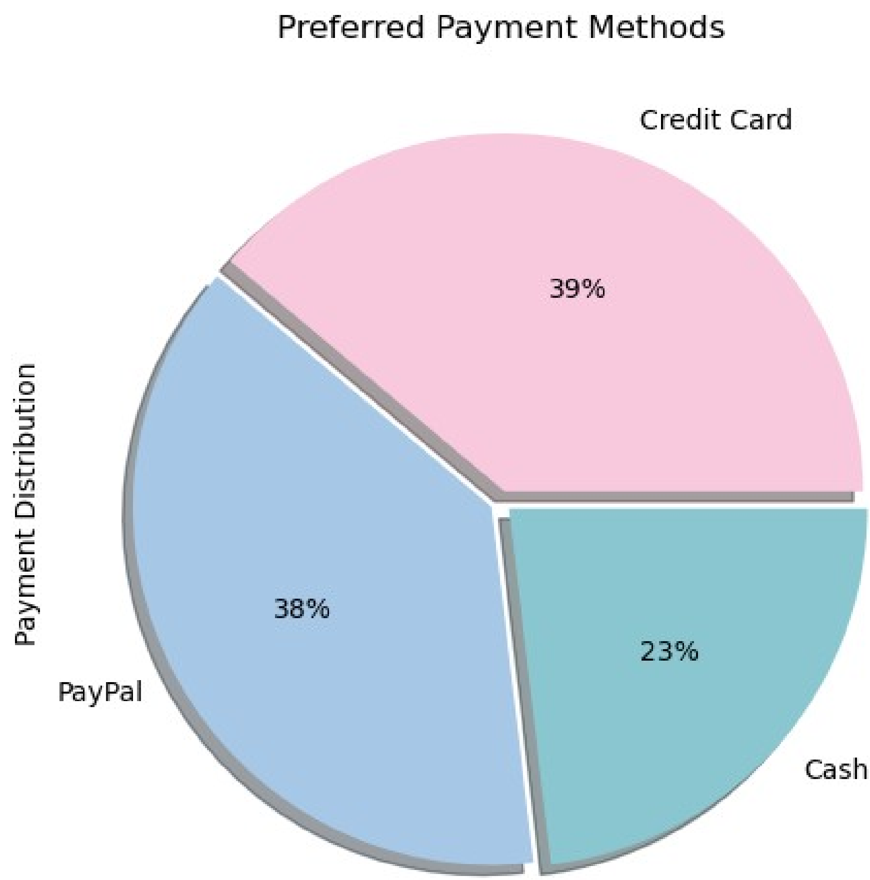
Preferred Payment Methods

```
temp6=df['Payment Method'].value_counts().reset_index()
temp6
```

| | Payment Method | count |
|---|---|---|
| 0 | Credit Card | 97194 |
| 1 | PayPal | 94965 |
| 2 | Cash | 57841 |

```
plt.figure(figsize=(10,6))
temp6['count'].plot(kind='pie',labels=temp6['Payment 
Method'],autopct="%1.0f%%",explode=[0.03,0.03,0.03],
```

```
                    colors=sns.color_palette(["#F8C8DC",
"#A7C7E7","#8AC6D0"]),shadow=True)
plt.title('Preferred Payment Methods')
plt.ylabel('Payment Distribution')
plt.show()
```

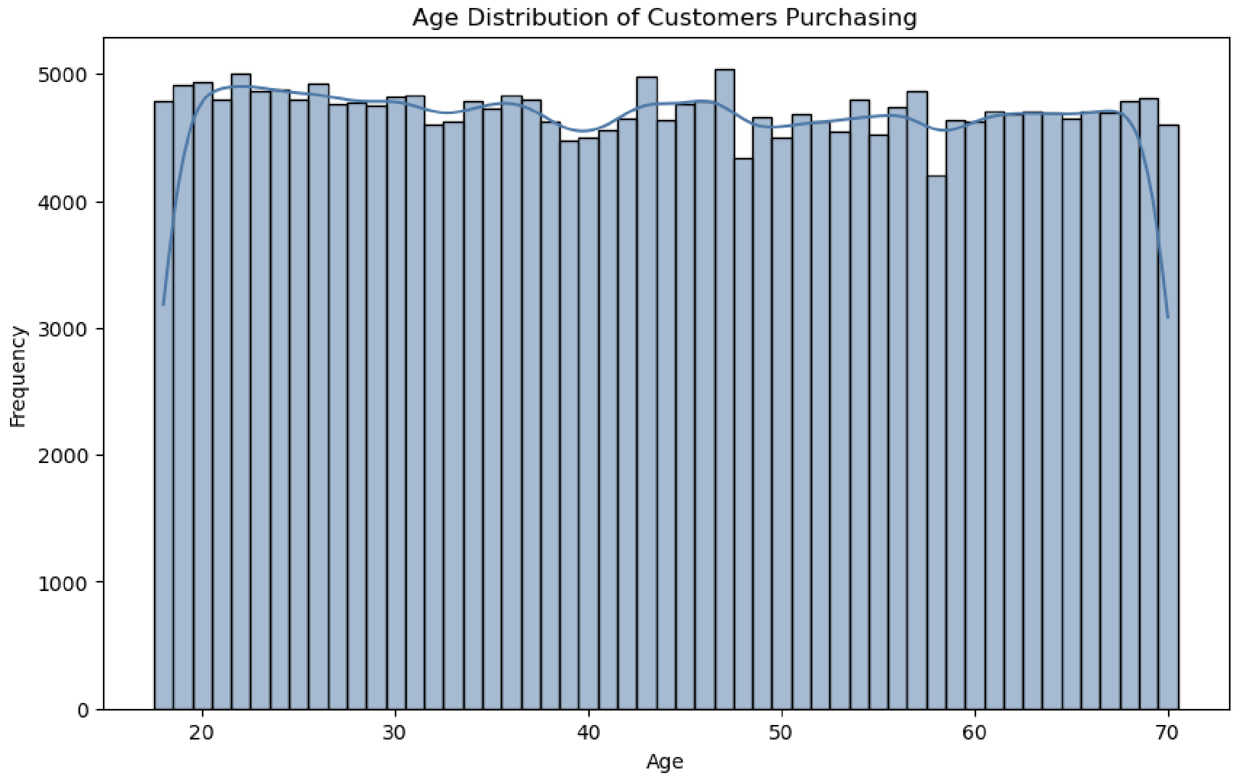



- Credit Card is the most used payment method, contributing 39% of total transactions.
- PayPal follows closely behind at 38%, indicating a strong preference for digital payments.
- Cash payments account for only 23%, showing that fewer customers prefer cash transactions.
- The high preference for digital payments (Credit Card & PayPal) suggests a shift towards online transactions.

Age Distribution of Customers Purchasing

```
plt.figure(figsize=(10,6))
sns.histplot(df['Age'],kde=True,discrete=True,color='#4E79A7')
plt.xlabel('Age')
plt.ylabel('Frequency')
```

```
plt.title('Age Distribution of Customers Purchasing')
plt.show()
```




- Customer purchases are evenly distributed across different age groups, with no significant peaks.
- Most customers fall between the ages of 18 and 70, indicating a broad customer base.
- The frequency of purchases remains relatively stable, suggesting age is not a major factor in purchasing behavior.
- A slight decline at the lower and upper age ranges suggests fewer younger and older shoppers.

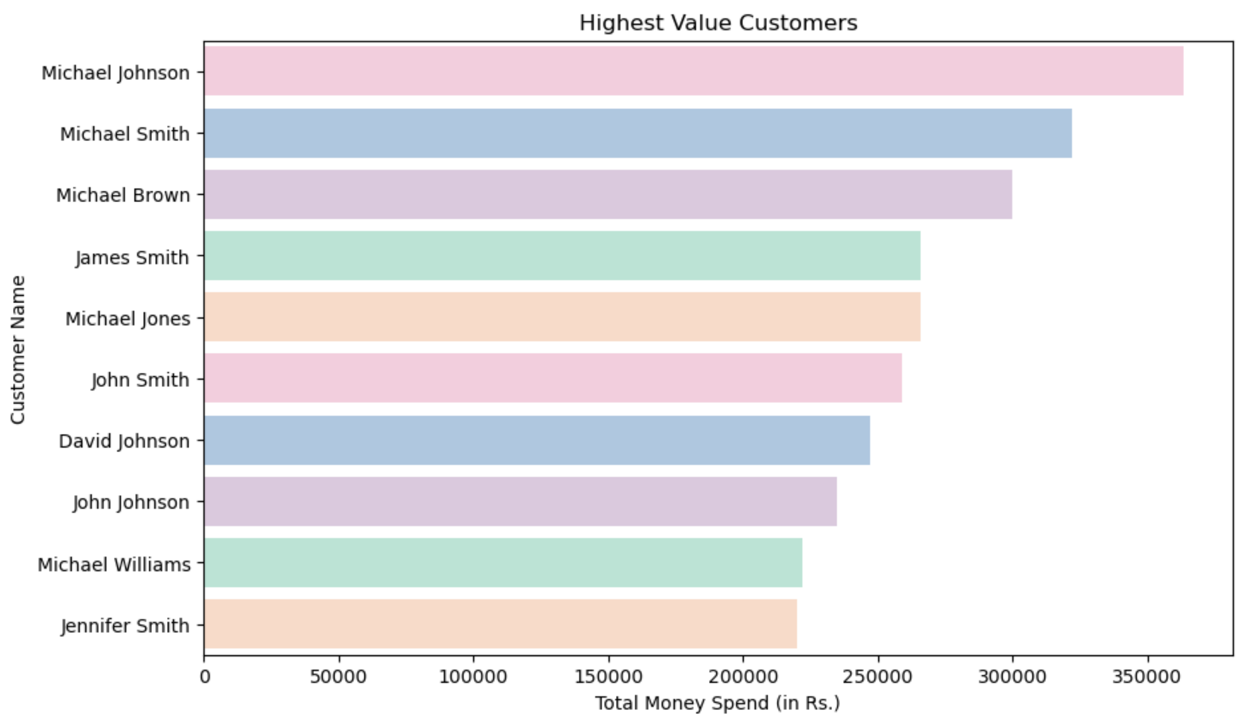
Highest Value Customers

```
temp7=df.groupby('Customer Name')['Total Purchase
Amount'].sum().sort_values(ascending=False).head(10).reset_index()
temp7
```

| | Customer Name | Total Purchase Amount |
|---|---|---|
| 0 | Michael Johnson | 363400 |
| 1 | Michael Smith | 321691 |
| 2 | Michael Brown | 299694 |
| 3 | James Smith | 265814 |
| 4 | Michael Jones | 265805 |
| 5 | John Smith | 258797 |
| 6 | David Johnson | 247292 |
| 7 | John Johnson | 234897 |

```
8  Michael Williams                          221734
9    Jennifer Smith                          220167
```

```
plt.figure(figsize=(10,6))
sns.barplot(temp7,y='Customer Name',x='Total Purchase
Amount',palette=["#F8C8DC", "#A7C7E7", "#DCC6E0", "#B5EAD7",
"#FFDAC1"])
plt.xlabel('Total Money Spend (in Rs.)')
plt.ylabel('Customer Name')
plt.title('Highest Value Customers')
plt.show()
```



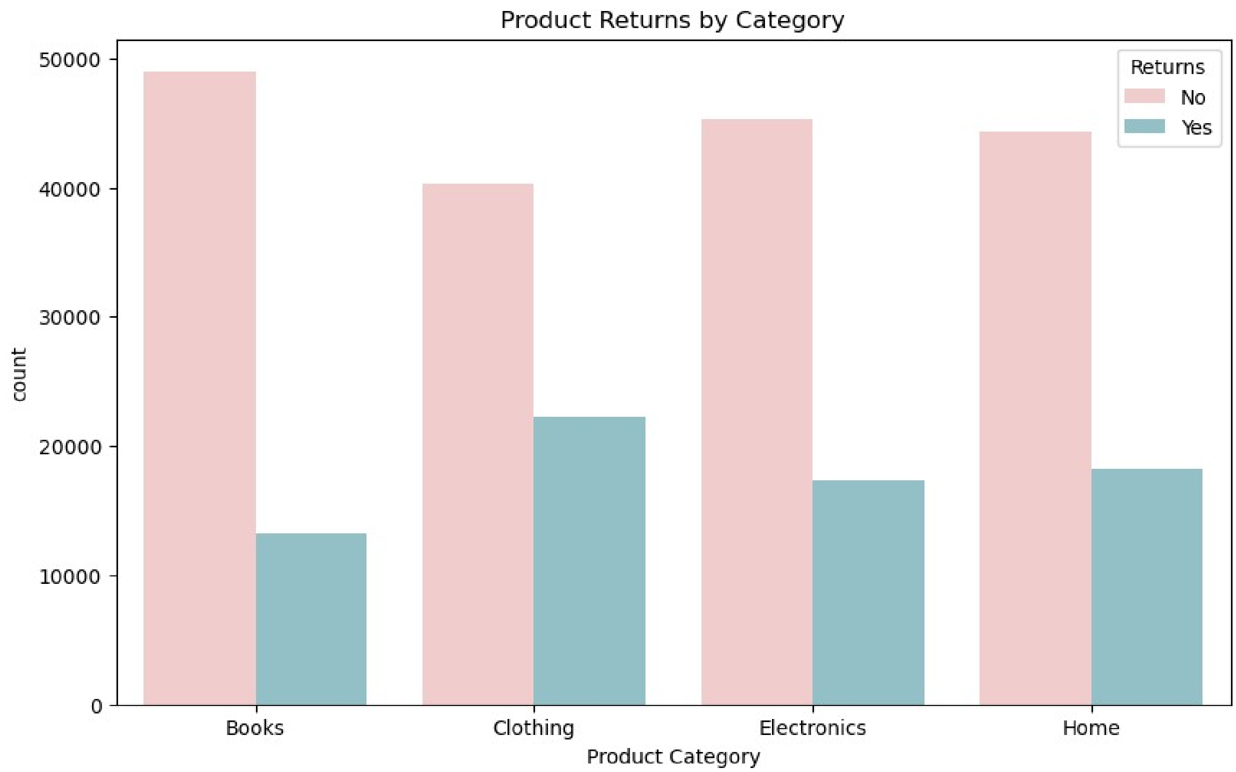

- This horizontal bar chart displays the top 10 customers ranked by their total spending. Michael Johnson leads with the highest total spend, significantly outpacing other customers in this group. The chart allows for quick visual comparison of customer value and highlights the relative contribution of top spenders.

Product Returns by Category

```
temp8=df.groupby('Product Category')
['Returns'].value_counts().reset_index()
temp8
```

| | Product Category | Returns | count |
|---|---|---|---|
| 0 | Books | No | 48996 |
| 1 | Books | Yes | 13251 |
| 2 | Clothing | No | 40300 |
| 3 | Clothing | Yes | 22281 |

```
4       Electronics      No  45289
5       Electronics     Yes  17341
6              Home      No  44299
7              Home     Yes  18243

plt.figure(figsize=(10,6))
sns.barplot(temp8,x='Product
Category',y='count',hue='Returns',palette=["#F7C6C7", "#8AC6D0"])
plt.xlabel('Product Category')
plt.title('Product Returns by Category')
plt.show()
```

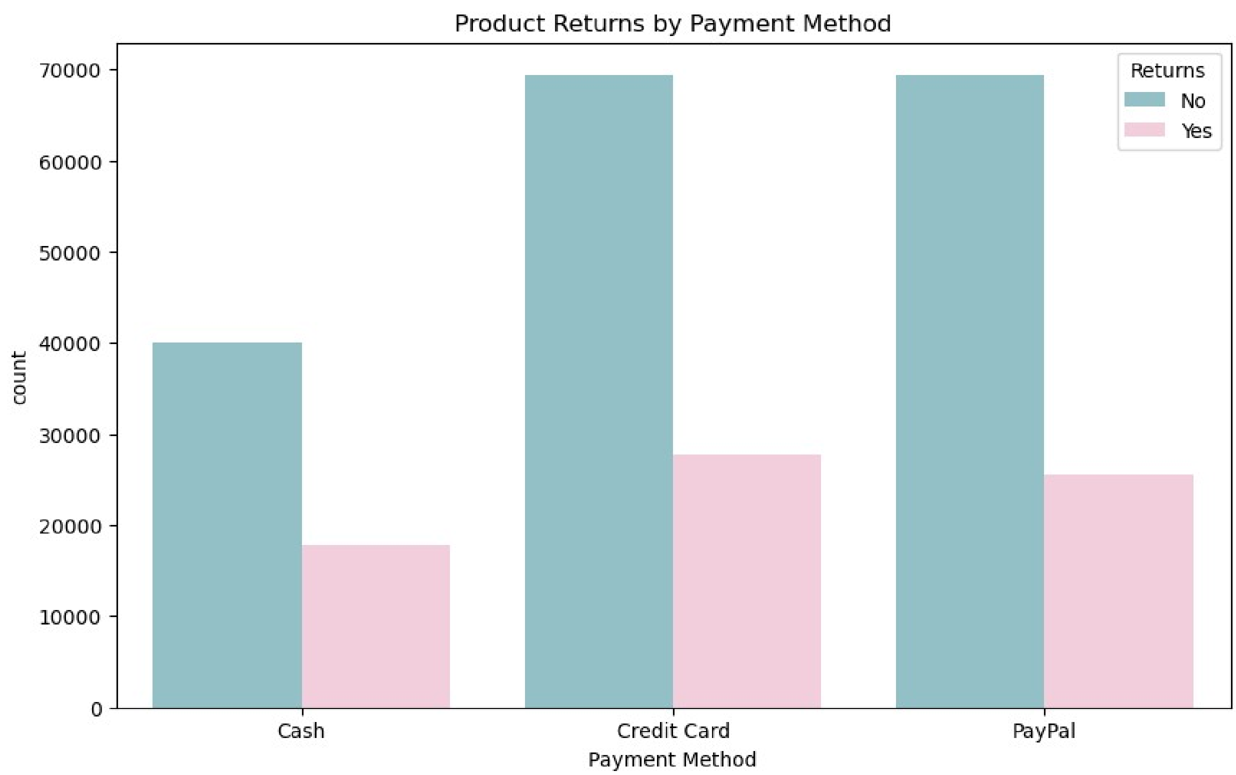



- Books have the lowest return rate, with significantly fewer returns compared to other categories.
- Clothing has the highest return rate, indicating frequent size or style mismatches.
- Electronics and Home products have moderate return rates, suggesting potential issues like defects or customer dissatisfaction.
- Overall, most products are not returned, as indicated by the larger proportion of "No" bars across all categories.

Product Returns by Payment Method

```
temp9=df.groupby('Payment Method')
['Returns'].value_counts().reset_index()
temp9
```

```
  Payment Method Returns  count
0           Cash      No  40035
1           Cash     Yes  17806
2    Credit Card      No  69381
3    Credit Card     Yes  27813
4         PayPal      No  69468
5         PayPal     Yes  25497

plt.figure(figsize=(10,6))
sns.barplot(temp9,x='Payment
Method',y='count',hue='Returns',palette=["#8AC6D0","#F8C8DC"])
plt.title('Product Returns by Payment Method')
plt.show()
```

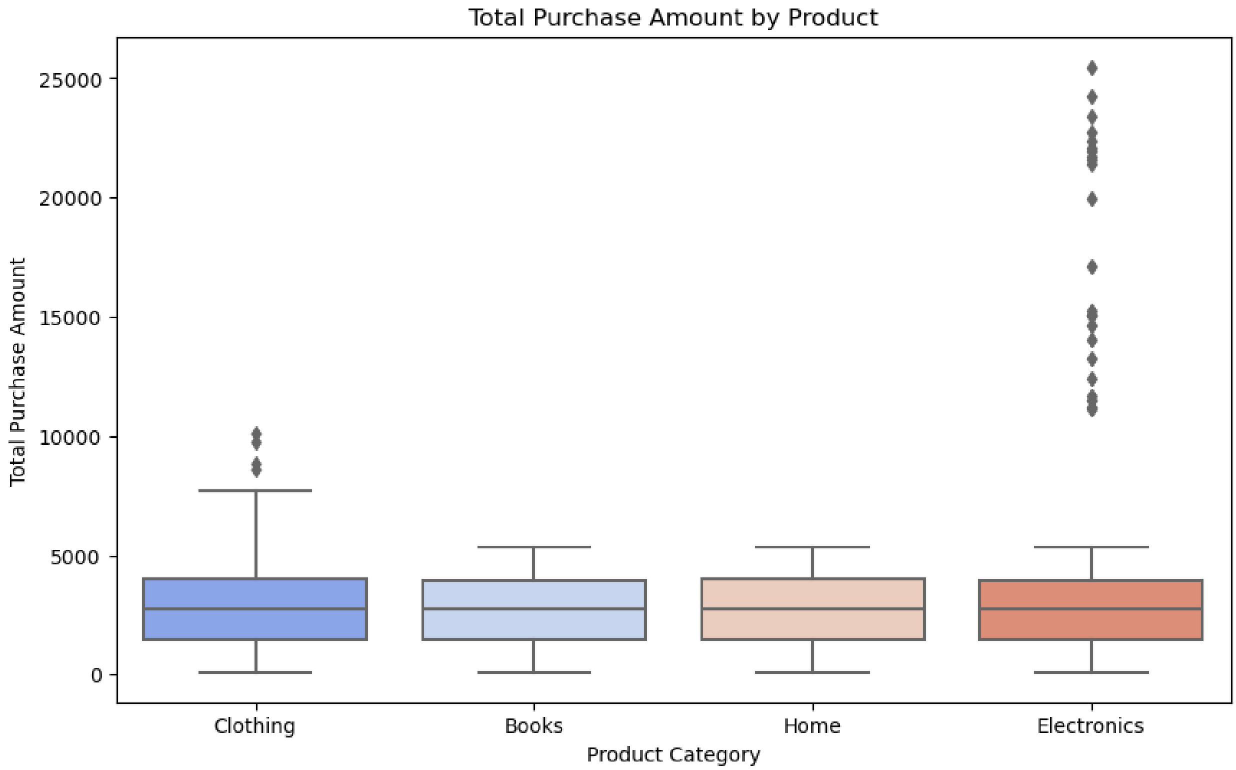



- Credit Card and PayPal have the highest number of purchases, with both having significantly more transactions than cash.
- Returns are highest for Credit Card purchases, followed by PayPal, while cash purchases have fewer returns.
- Cash purchases have the lowest total count, but the proportion of returns is still notable.
- Customers paying with digital methods (Credit Card & PayPal) tend to return more items, possibly due to the ease of online refunds and return policies.

Total Purchase Amount by Product

```
plt.figure(figsize=(10,6))
sns.boxplot(x='Product Category',y='Total Purchase
```

```
Amount',data=df,palette='coolwarm')
plt.title('Total Purchase Amount by Product')
plt.show()
```




- Electronics have the highest purchase amounts, with several extreme outliers exceeding 20,000. This suggests that some high-value items significantly increase the total purchase amount.
- Clothing, Books, and Home categories have relatively similar purchase distributions, with interquartile ranges (IQRs) showing moderate variation.
- The median purchase amount is similar across all categories, except for Electronics, which shows higher outliers.
- Presence of outliers in Clothing and Electronics: Some purchases are significantly higher than the usual range, which might indicate premium products or bulk purchases.
- Books and Home have a more consistent purchase pattern, with fewer outliers compared to Electronics and Clothing.

## CONCLUSION

- The eCommerce data analysis provided key insights into sales trends, customer behavior, and revenue drivers. Discount strategies played a crucial role in influencing purchases, while category-wise and gender-based trends helped in targeted marketing. Overall, data-driven decisions can enhance customer experience and boost business growth.