# Library Import

```
# 1. Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

# Data Loading

```
# 2. Load Dataset
df = pd.read_csv("Diwali_Sales_Data.csv",encoding="latin1")

df.shape
```

```
(11251, 15)
```

# Data Inspection

```
df.head()
```

```
   User_ID  Cust_name Product_ID Gender Age Group  Age  Marital_Status
\
0  1002903  Sanskriti  P00125942      F     26-35   28               0

1  1000732     Kartik  P00110942      F     26-35   35               1

2  1001990      Bindu  P00118542      F     26-35   35               1

3  1001425     Sudevi  P00237842      M      0-17   16               0

4  1000588       Joni  P00057942      M     26-35   28               1


            State      Zone       Occupation Product_Category  Orders
\
0     Maharashtra   Western       Healthcare             Auto       1

1  Andhra Pradesh  Southern             Govt             Auto       3

2   Uttar Pradesh   Central       Automobile             Auto       3

3       Karnataka  Southern     Construction             Auto       2

4         Gujarat   Western  Food Processing             Auto       2
```

```
    Amount  Status  unnamed1
0  23952.0     NaN       NaN
1  23934.0     NaN       NaN
2  23924.0     NaN       NaN
3  23912.0     NaN       NaN
4  23877.0     NaN       NaN

df.tail()

       User_ID    Cust_name Product_ID Gender Age Group  Age
Marital_Status  \
11246  1000695      Manning  P00296942      M     18-25   19
1
11247  1004089  Reichenbach  P00171342      M     26-35   33
0
11248  1001209        Oshin  P00201342      F     36-45   40
0
11249  1004023       Noonan  P00059442      M     36-45   37
0
11250  1002744      Brumley  P00281742      F     18-25   19
0

                State      Zone   Occupation Product_Category  Orders
Amount  \
11246     Maharashtra   Western     Chemical           Office       4
370.0
11247         Haryana  Northern   Healthcare       Veterinary       3
367.0
11248  Madhya Pradesh   Central      Textile           Office       4
213.0
11249       Karnataka  Southern  Agriculture           Office       3
206.0
11250     Maharashtra   Western   Healthcare           Office       3
188.0

       Status  unnamed1
11246     NaN       NaN
11247     NaN       NaN
11248     NaN       NaN
11249     NaN       NaN
11250     NaN       NaN

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11251 entries, 0 to 11250
Data columns (total 15 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
```

```
 0   User_ID           11251 non-null  int64
 1   Cust_name         11251 non-null  object
 2   Product_ID        11251 non-null  object
 3   Gender            11251 non-null  object
 4   Age Group         11251 non-null  object
 5   Age               11251 non-null  int64
 6   Marital_Status    11251 non-null  int64
 7   State             11251 non-null  object
 8   Zone              11251 non-null  object
 9   Occupation        11251 non-null  object
 10  Product_Category  11251 non-null  object
 11  Orders            11251 non-null  int64
 12  Amount            11239 non-null  float64
 13  Status            0 non-null      float64
 14  unnamed1          0 non-null      float64
dtypes: float64(3), int64(4), object(8)
memory usage: 1.3+ MB
```

```
df.describe()
```

```
            User_ID           Age  Marital_Status        Orders
Amount  \
count  1.125100e+04  11251.000000    11251.000000  11251.000000
11239.000000
mean   1.003004e+06     35.421207        0.420318      2.489290
9453.610858
std    1.716125e+03     12.754122        0.493632      1.115047
5222.355869
min    1.000001e+06     12.000000        0.000000      1.000000
188.000000
25%    1.001492e+06     27.000000        0.000000      1.500000
5443.000000
50%    1.003065e+06     33.000000        0.000000      2.000000
8109.000000
75%    1.004430e+06     43.000000        1.000000      3.000000
12675.000000
max    1.006040e+06     92.000000        1.000000      4.000000
23952.000000

       Status  unnamed1
count     0.0       0.0
mean      NaN       NaN
std       NaN       NaN
min       NaN       NaN
25%       NaN       NaN
50%       NaN       NaN
75%       NaN       NaN
max       NaN       NaN
```

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

```
User_ID                 0
Cust_name               0
Product_ID              0
Gender                  0
Age Group               0
Age                     0
Marital_Status          0
State                   0
Zone                    0
Occupation              0
Product_Category        0
Orders                  0
Amount                 12
Status              11251
unnamed1            11251
dtype: int64
```

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

```
8
```

# Data Cleaning

```
# Drop useless columns
df.drop(columns=['Status', 'unnamed1'], inplace=True)
df.head(3)
```

```
   User_ID  Cust_name Product_ID Gender Age Group  Age  Marital_Status
\
0  1002903  Sanskriti  P00125942      F     26-35   28               0

1  1000732     Kartik  P00110942      F     26-35   35               1

2  1001990      Bindu  P00118542      F     26-35   35               1


            State      Zone  Occupation Product_Category  Orders
Amount
0     Maharashtra   Western  Healthcare             Auto       1
23952.0
1  Andhra Pradesh  Southern        Govt             Auto       3
23934.0
2   Uttar Pradesh   Central  Automobile             Auto       3
23924.0
```

```
df['Amount'] = df['Amount'].fillna(df['Amount'].median())
```

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

```
User_ID             0
Cust_name           0
Product_ID          0
Gender              0
Age Group           0
Age                 0
Marital_Status      0
State               0
Zone                0
Occupation          0
Product_Category    0
Orders              0
Amount              0
dtype: int64
```

```
df.drop_duplicates(inplace=True)
```

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

```
0
```

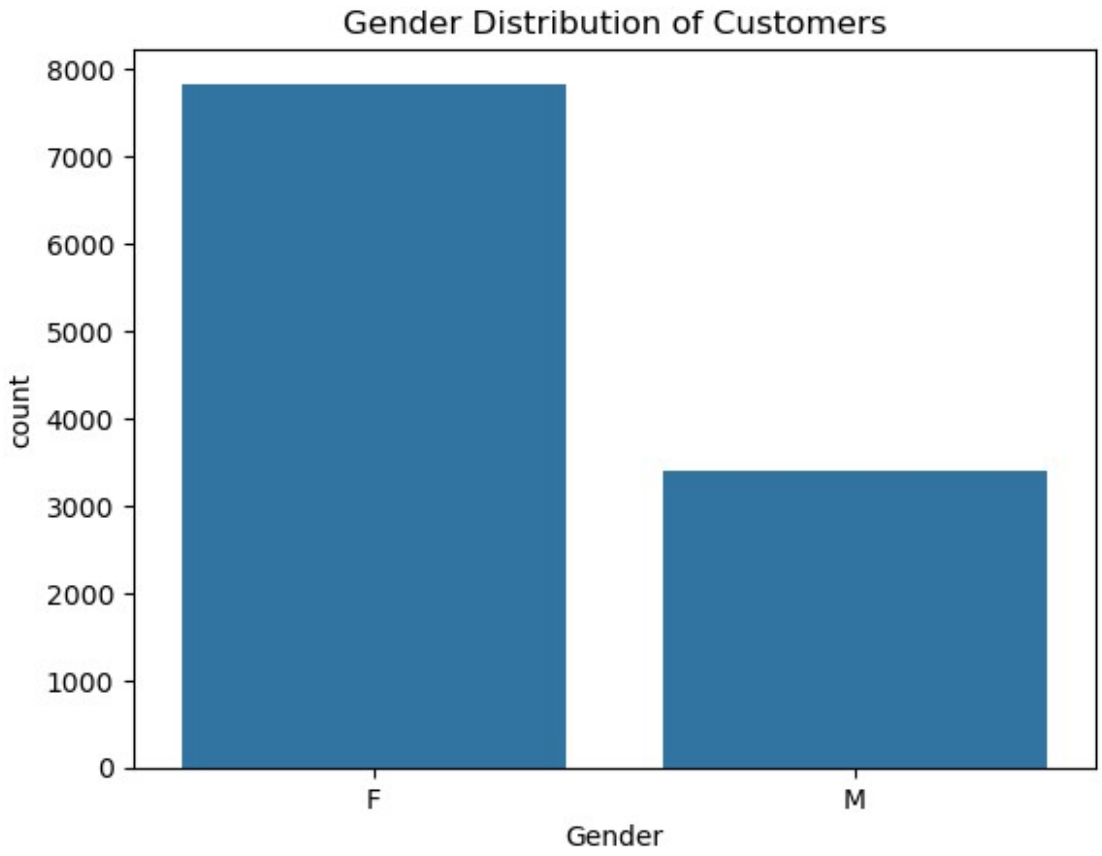
# Univariate EDA Steps

What is the distribution of customers based on Gender, and which gender forms the majority of buyers ?

```
print(df['Gender'].value_counts())
```

```
Gender
F    7838
M    3405
Name: count, dtype: int64
```

```
sns.countplot(x="Gender", data=df)
plt.title("Gender Distribution of Customers")
plt.show()
```

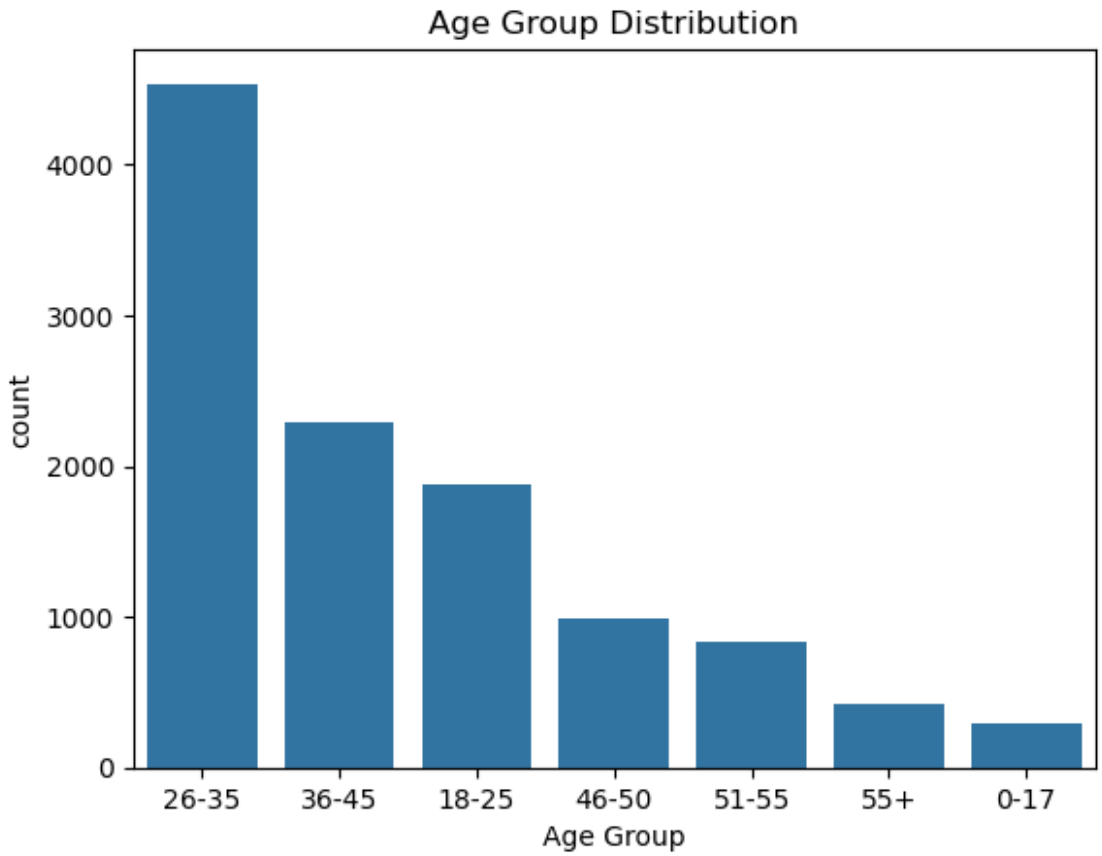



What is the distribution of customers across different Age Groups, and which age group contributes the most buyers?

```
print(df['Age Group'].value_counts())
```

```
Age Group
26-35    4538
36-45    2285
18-25    1878
46-50     987
51-55     831
55+       428
0-17      296
Name: count, dtype: int64
```

```
sns.countplot(x="Age Group", data=df, order=df["Age
Group"].value_counts().index)
plt.title("Age Group Distribution")
plt.show()
```

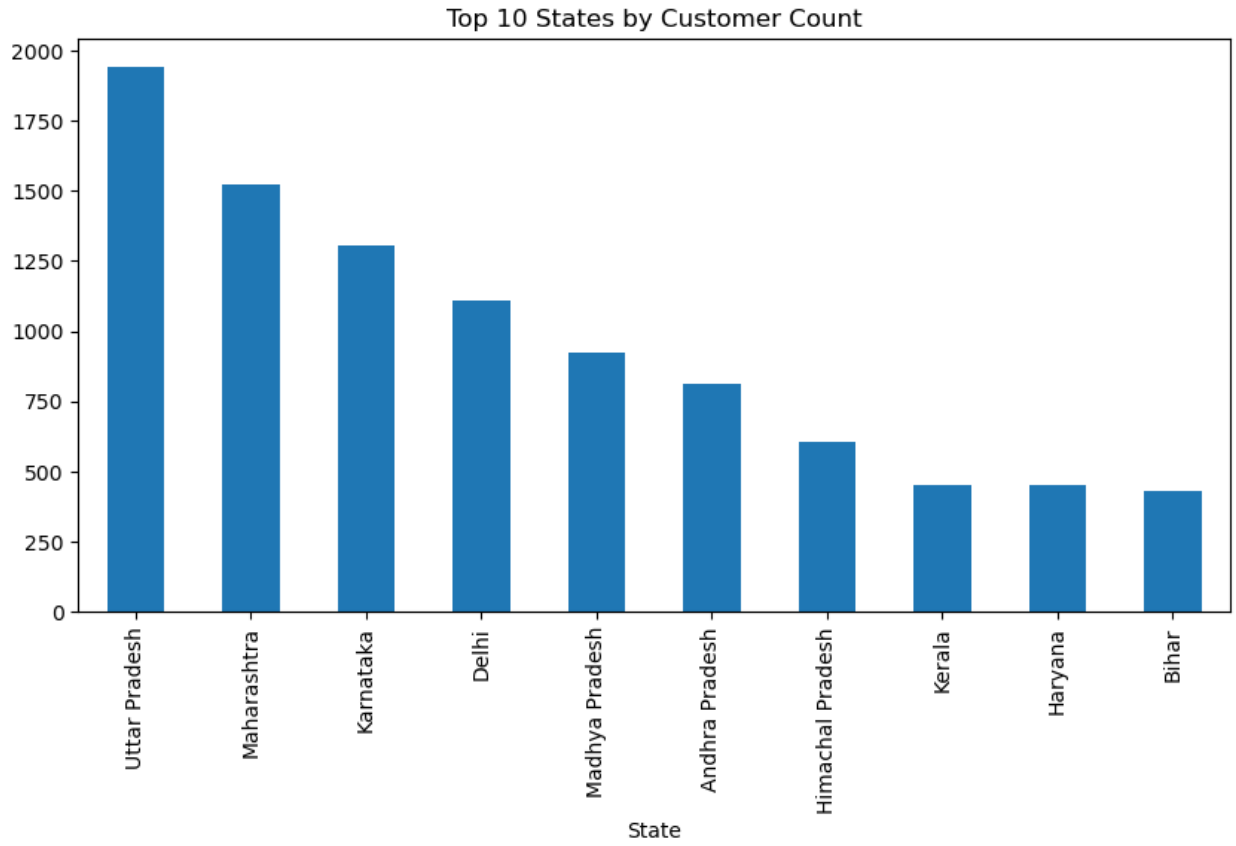



Which states have the highest number of customers ?

```
print(df['State'].value_counts())
```

```
State
Uttar Pradesh       1944
Maharashtra         1523
Karnataka           1305
Delhi               1107
Madhya Pradesh       923
Andhra Pradesh       812
Himachal Pradesh     608
Kerala               453
Haryana              451
Bihar                433
Gujarat              428
Jharkhand            380
Uttarakhand          320
Rajasthan            231
Punjab               200
Telangana            125
Name: count, dtype: int64
```

```
df['State'].value_counts().head(10).plot(kind='bar', figsize=(10,5))
plt.title("Top 10 States by Customer Count")
plt.show()
```



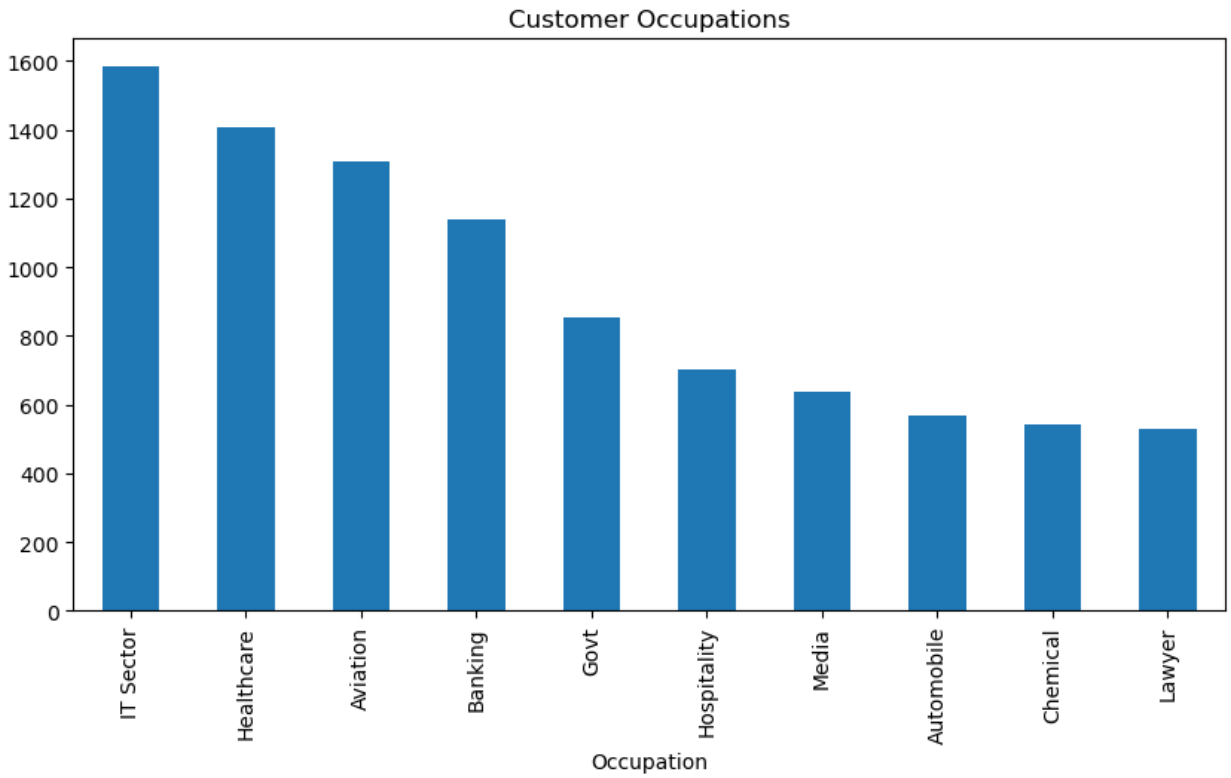

What is the distribution of customers across different Occupations, and which occupation group dominates the customer base?

```
print(df['Occupation'].value_counts())
```

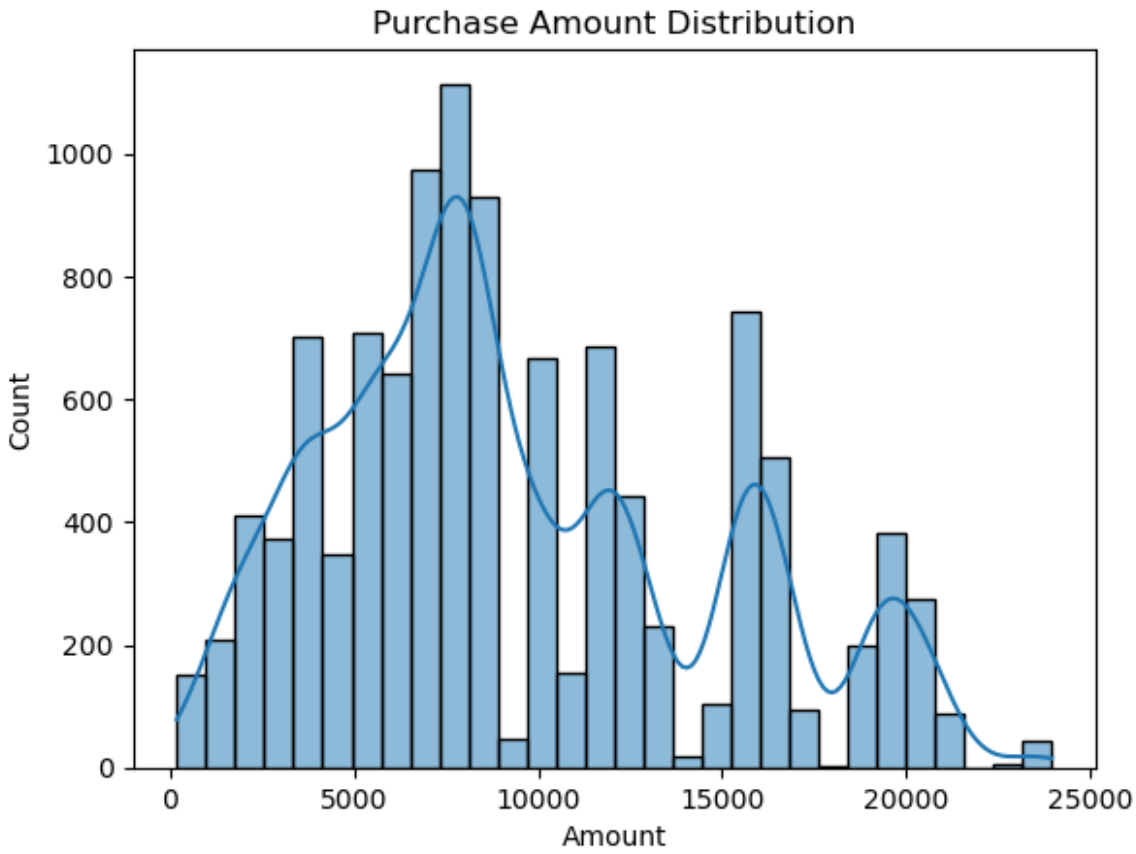
```
Occupation
IT Sector          1586
Healthcare         1408
Aviation           1309
Banking            1139
Govt                854
Hospitality         702
Media               637
Automobile          566
Chemical            542
Lawyer              531
Retail              501
Food Processing     423
Construction        413
```

```
Textile             350
Agriculture         282
Name: count, dtype: int64
```

```
df['Occupation'].value_counts().head(10).plot(kind='bar',
figsize=(10,5))
plt.title("Customer Occupations")
plt.show()
```




```
# Amount Distribution
sns.histplot(df['Amount'], bins=30, kde=True)
plt.title("Purchase Amount Distribution")
plt.show()
```




Who are the top 10 customers by total purchase amount?

# Bivariate Analysis

```
df.head()
```

```
   User_ID  Cust_name Product_ID Gender Age Group  Age  Marital_Status
\
0  1002903  Sanskriti  P00125942      F     26-35   28               0

1  1000732     Kartik  P00110942      F     26-35   35               1

2  1001990      Bindu  P00118542      F     26-35   35               1

3  1001425     Sudevi  P00237842      M      0-17   16               0

4  1000588       Joni  P00057942      M     26-35   28               1


             State      Zone       Occupation Product_Category  Orders
Amount
0     Maharashtra   Western       Healthcare             Auto       1
23952.0
1  Andhra Pradesh  Southern             Govt             Auto       3
```

```
23934.0
2   Uttar Pradesh   Central       Automobile              Auto       3
23924.0
3       Karnataka  Southern     Construction             Auto       2
23912.0
4         Gujarat   Western  Food Processing             Auto       2
23877.0
```

# gender

Which product categories are purchased the most by male and female customers, and what are the top 5 categories based on purchase frequency?

```
counts = df[['Product_Category',
'Gender']].value_counts().unstack(fill_value=0)

print("\nTop 5 Product Categories by Gender:")
print(counts.sort_values(by=['M','F'], ascending=False).head(5))


Top 5 Product Categories by Gender:
Gender                    F    M
Product_Category
Clothing & Apparel     1854  799
Food                   1774  719
Electronics & Gadgets  1472  610
Footwear & Shoes        786  278
Household items         284  236
```

## insight

Clothing and Apparel and Food products category are mostly purchased by Female and Male .Female customers dominate purchases across all top 5 categories, especially in Clothing & Apparel and Food, making them the key buyers. Male purchases are comparatively lower but closer in Household items.

Which gender contributes more in terms of orders and total purchase amount?

```
df.groupby('Gender')['Orders'].sum()

Gender
F    19554
M     8427
Name: Orders, dtype: int64

df.groupby('Gender')['Amount'].sum().head(5)
```

```
Gender
F    74388772.43
M    31887364.00
Name: Amount, dtype: float64
```

### Insight

Female customers not only placed more orders but also contributed a significantly higher purchase amount compared to male customers.

This indicates that female buyers are the dominant customer segment in this dataset, both in terms of volume (orders) and value (amount).

# age_group

### How do different Age Groups compare in terms of product category preferences, total orders, total purchase amount, and average purchase amount?

```
counts = df[['Age Group', 'Product_Category']].value_counts().head()
print("\nCount of Product Categories by Age Group:")
print(counts)


Count of Product Categories by Age Group:
Age Group  Product_Category
26-35      Clothing & Apparel       1056
           Food                      992
           Electronics & Gadgets     828
36-45      Clothing & Apparel        532
18-25      Food                      478
Name: count, dtype: int64

print("\nTotal Orders by Age Group:")
print(df.groupby('Age Group')
['Orders'].sum().sort_values(ascending=False))


Total Orders by Age Group:
Age Group
26-35    11381
36-45     5693
18-25     4646
46-50     2379
51-55     2115
55+       1077
```

```
0-17       690
Name: Orders, dtype: int64
```

```
print("\nTotal Amount by Age Group:")
print(df.groupby('Age Group')
['Amount'].sum().sort_values(ascending=False))
```

```
Total Amount by Age Group:
Age Group
26-35    42597986.94
36-45    22159463.49
18-25    17235530.00
46-50     9240280.00
51-55     8254127.00
55+       4089096.00
0-17      2699653.00
Name: Amount, dtype: float64
```

```
print("\nAverage Amount by Age Group:")
print(df.groupby('Age Group')
['Amount'].mean().sort_values(ascending=False))
```

```
Average Amount by Age Group:
Age Group
51-55    9932.764140
36-45    9697.795838
55+      9553.962617
26-35    9386.951728
46-50    9361.985816
18-25    9177.598509
0-17     9120.449324
Name: Amount, dtype: float64
```

### Insights on Age Groups

Product Category Preference: Clothing & Apparel and Food are the most purchased categories, especially among the 26–35 and 36–45 age groups.

Total Orders: The 26–35 age group placed the maximum number of orders (11,381), making them the most active buyers.

Total Purchase Amount: The 26–35 age group also contributed the highest total revenue (₹42,59,4899.0 approx).

Average purchase amount is highest for the 51-55 age group (₹9.9k), followed by 36-45 (₹9.6k) and 55+ (₹9.5k).

# Marital_status

## How do married vs unmarried customers differ in terms of product category preference, total orders, and total purchase amount?

```
print("\nCount of Product Categories by Marital Status:")
# counts = df[['Marital_Status',
'Product_Category']].value_counts().unstack(fill_value=0
counts = df[['Marital_Status',
'Product_Category']].value_counts().sort_values(ascending=False).head(
)
print(counts)
```

```
Count of Product Categories by Marital Status:
Marital_Status  Product_Category
0               Clothing & Apparel       1533
                Food                     1501
                Electronics & Gadgets    1172
1               Clothing & Apparel       1120
                Food                      992
Name: count, dtype: int64
```

```
print("\nTotal Orders by Marital Status:")
print(df.groupby('Marital_Status')
['Orders'].sum().sort_values(ascending=False))
```

```
Total Orders by Marital Status:
Marital_Status
0    16243
1    11738
Name: Orders, dtype: int64
```

```
print("\nTotal Amount Spent by Marital Status:")
print(df.groupby('Marital_Status')
['Amount'].sum().sort_values(ascending=False))
```

```
Total Amount Spent by Marital Status:
Marital_Status
0    62131172.44
1    44144963.99
Name: Amount, dtype: float64
```

insight by Marital_Status

Product Category Preference: Clothing & Apparel and Food are the most purchased categories across both married and unmarried customers.

Total Orders: Unmarried customers placed the maximum number of orders (16,243), compared to married customers (11,738).

Total Purchase Amount: Unmarried customers contributed the highest total revenue (₹62M approx), while married customers contributed around ₹44M.

# zone

## How do Product Categories, Orders, Revenue (Amount), and Occupations vary across different Zones ?

```
print("\nCount of Product Categories by Zone:")
zone_product = df[['Zone',
'Product_Category']].value_counts().sort_values(ascending=False).head(
)
print(zone_product)
```

```
Count of Product Categories by Zone:
Zone      Product_Category
Central   Food                990
          Clothing & Apparel    913
Western   Food                582
Southern  Clothing & Apparel    578
Central   Footwear & Shoes      577
Name: count, dtype: int64
```

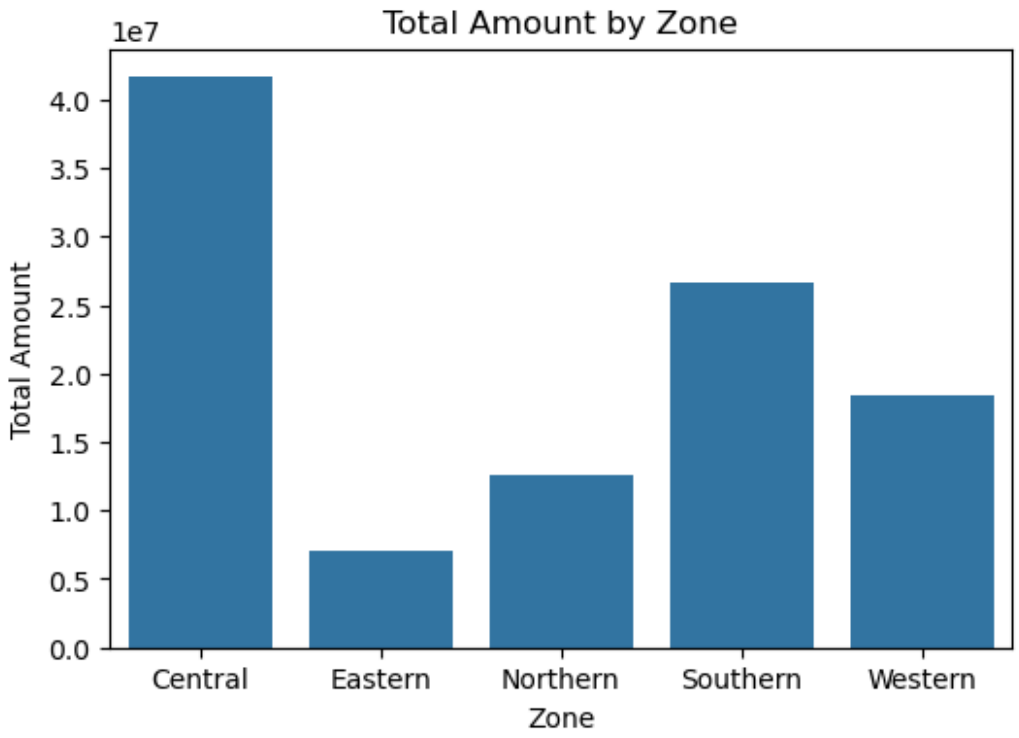
```
print("\nTotal Orders by Zone:")
zone_orders = df.groupby('Zone')['Orders'].sum()
print(zone_orders.sort_values(ascending=False))
```

```
Total Orders by Zone:
Zone
Central     10636
Southern     6744
Western      4866
Northern     3724
Eastern      2011
Name: Orders, dtype: int64
```

```
print("\nTotal Amount by Zone:")
zone_amount = df.groupby('Zone')['Amount'].sum()
print(zone_amount.sort_values(ascending=False))
```

```
Total Amount by Zone:
Zone
Central     41628723.45
Southern    26622886.98
Western     18366953.00
Northern    12616448.00
Eastern      7041125.00
Name: Amount, dtype: float64
```

```
plt.figure(figsize=(6,4))
sns.barplot(x=zone_amount.index, y=zone_amount.values)
plt.title("Total Amount by Zone")
plt.ylabel("Total Amount")
plt.xlabel("Zone")
plt.show()
```




```
print("\nCount of Occupations by Zone:")
zone_occ = df[['Zone', 'Occupation']].value_counts().head(10)
print(zone_occ.sort_values(ascending=False))
```

```
Count of Occupations by Zone:
Zone      Occupation
Central   IT Sector      638
          Healthcare     532
          Aviation       501
          Banking        405
Southern  IT Sector      364
          Healthcare     344
Central   Govt           337
Southern  Aviation       320
          Banking        284
Central   Hospitality    270
Name: count, dtype: int64
```

### insights by zone

Product Preference: Food and Clothing & Apparel dominate (Central & Western zones).

Orders: Central leads (10k), followed by Southern (6.7k).

Revenue: Central highest (₹41.6M), Southern (₹26.6M).

Occupations: IT, Healthcare, Banking buyers dominate (mostly Central).

Overall: Central strongest, Eastern weakest.

# occupation

How do Product Categories, Total Orders, and Total Revenue vary across different Occupations?

```
print("\nCount of Product Categories by Occupation:")
occ_product = df[['Occupation',
'Product_Category']].value_counts().head(10)
print(occ_product.sort_values(ascending=False))
```

```
Count of Product Categories by Occupation:
Occupation  Product_Category
Healthcare  Clothing & Apparel       361
IT Sector   Clothing & Apparel       351
            Food                    344
Healthcare  Food                    330
Aviation    Food                    312
IT Sector   Electronics & Gadgets    293
Aviation    Clothing & Apparel       281
Banking     Clothing & Apparel       274
            Electronics & Gadgets    252
Aviation    Electronics & Gadgets    241
Name: count, dtype: int64
```

```
df.groupby('Occupation')
['Orders'].sum().sort_values(ascending=False).head(5)
```

```
Occupation
IT Sector     4002
Healthcare    3455
Aviation      3212
Banking       2819
Govt          2155
Name: Orders, dtype: int64
```

```
df.groupby('Occupation')
['Amount'].sum().sort_values(ascending=False).head(5)
```

```
Occupation
IT Sector     14782407.00
Healthcare    13034587.49
Aviation      12599994.00
Banking       10786828.95
Govt           8517212.00
Name: Amount, dtype: float64
```

Insights by Occupation

Product Preference: Clothing & Apparel and Food are most purchased, especially by Healthcare and IT Sector professionals.

Orders: IT Sector placed the maximum orders (4002), followed by Healthcare (3455) and Aviation (3212).

Revenue: IT Sector generated the highest revenue (₹14.7M), followed by Healthcare (₹13.0M) and Aviation (₹12.6M).

# product_id

How do Orders and Revenue vary across different Product IDs and Which are the top 10 products by revenue

```
print("\nTotal Orders by Product ID:")
prod_orders = df.groupby('Product_ID')['Orders'].sum().head()
print(prod_orders)
```

```
Total Orders by Product ID:
Product_ID
P00000142    57
P00000242    15
P00000342    16
P00000442     1
P00000542     6
Name: Orders, dtype: int64
```

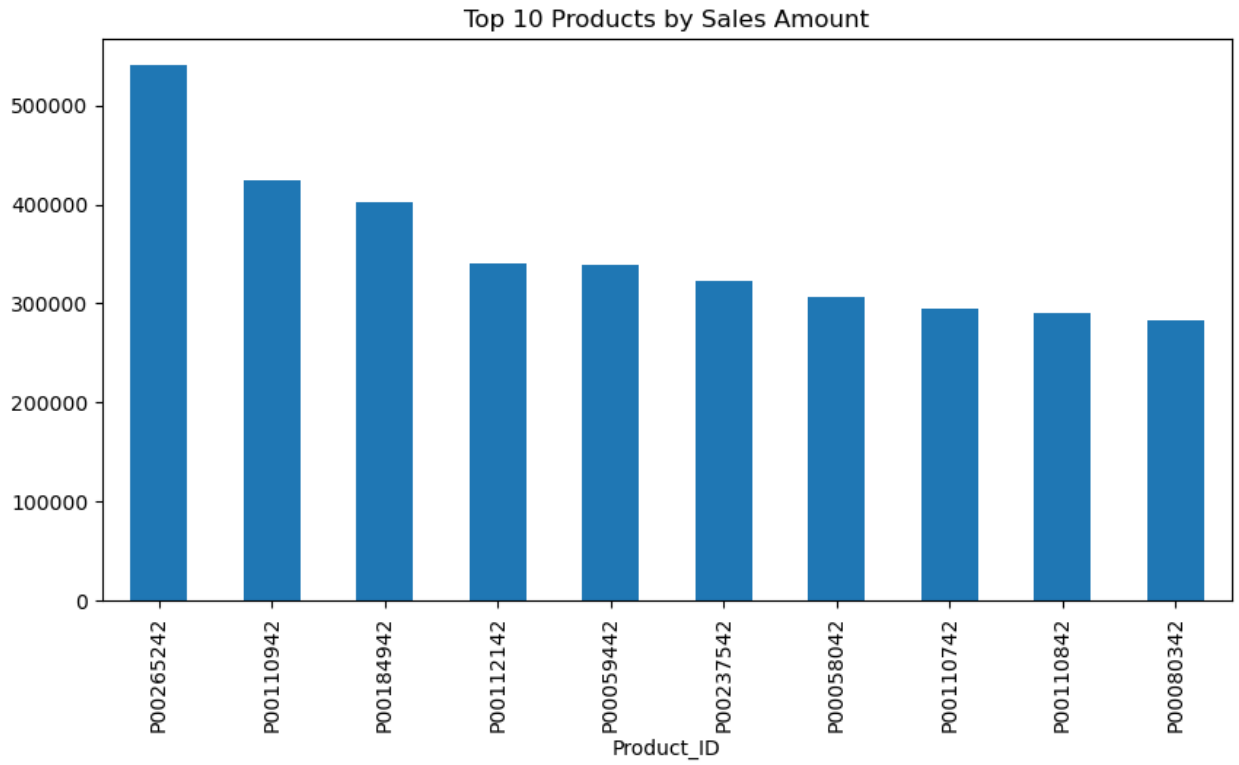
```
print("\nTotal Amount by Product ID:")
prod_amount = df.groupby('Product_ID')
['Amount'].sum().sort_values(ascending=False).head()
print(prod_amount)
```

```
Total Amount by Product ID:
Product_ID
P00265242    540136.0
P00110942    424833.0
P00184942    401816.0
P00112142    341020.0
P00059442    338571.0
Name: Amount, dtype: float64
```

```
# Top 10 Products by Amount
top_products = df.groupby("Product_ID")
["Amount"].sum().sort_values(ascending=False).head(10)
print("Top 10 Products:\n", top_products)
```

```
Top 10 Products:
 Product_ID
P00265242    540136.0
P00110942    424833.0
P00184942    401816.0
P00112142    341020.0
P00059442    338571.0
P00237542    322363.0
P00058042    307040.0
P00110742    294548.0
P00110842    290661.0
P00080342    283309.0
Name: Amount, dtype: float64
```

```
top_products.plot(kind="bar", figsize=(10,5))
plt.title("Top 10 Products by Sales Amount")
plt.show()
```




insight by product_id

Orders: Product P00000142 leads with 57 orders, followed by P00000242 (15 orders).

Revenue: Product P00265242 also generates the highest revenue (₹540136.0), followed by P00110942 (₹424833.0).

Top Revenue Products: IDs like P00265242, P00119442, P00295442, P00257442 .

# State

How do Product Category counts, total Orders, and total Amount vary across different States?

```
print("\nCount of Product Categories by State:")
counts = df[['State',
'Product_Category']].value_counts().sort_values(ascending=False).head(
)
print(counts)
```

```
Count of Product Categories by State:
State          Product_Category
Uttar Pradesh  Food                 569
               Clothing & Apparel   489
Maharashtra    Food                 480
Karnataka      Footwear & Shoes     339
Delhi          Footwear & Shoes     338
Name: count, dtype: int64
```

```
df.groupby('State')['Orders'].sum().sort_values(ascending=False)
```

```
State
Uttar Pradesh       4809
Maharashtra         3799
Karnataka           3241
Delhi               2744
Madhya Pradesh      2259
Andhra Pradesh      2054
Himachal Pradesh    1568
Kerala              1137
Haryana             1106
Gujarat             1067
Bihar               1058
Jharkhand            953
Uttarakhand          824
Rajasthan            555
Punjab               495
Telangana            312
Name: Orders, dtype: int64
```

```
df.groupby('State')['Amount'].sum().sort_values(ascending=False)
```

```
State
Uttar Pradesh       19362273.00
Maharashtra         14412576.00
Karnataka           13531649.00
Delhi               11628146.45
Madhya Pradesh       8117360.00
Andhra Pradesh       8045255.99
Himachal Pradesh     4963368.00
Haryana              4217871.00
Bihar                4014669.00
Gujarat              3954377.00
Kerala               3894491.99
Jharkhand            3026456.00
Uttarakhand          2520944.00
Rajasthan            1909409.00
Punjab               1525800.00
```

```
Telangana             1151490.00
Name: Amount, dtype: float64
```

insight by state

Product Preference: Food and Clothing & Apparel are most purchased, especially in Uttar Pradesh, Maharashtra, Delhi, and Karnataka.

Orders :Uttar Pradesh placed the maximum orders (4813), followed by Maharashtra (3811) and Karnataka (3241).

Revenue: Uttar Pradesh generated the highest revenue (₹19.3M), followed by Maharashtra (₹14.4M) and Delhi (₹13.5M).

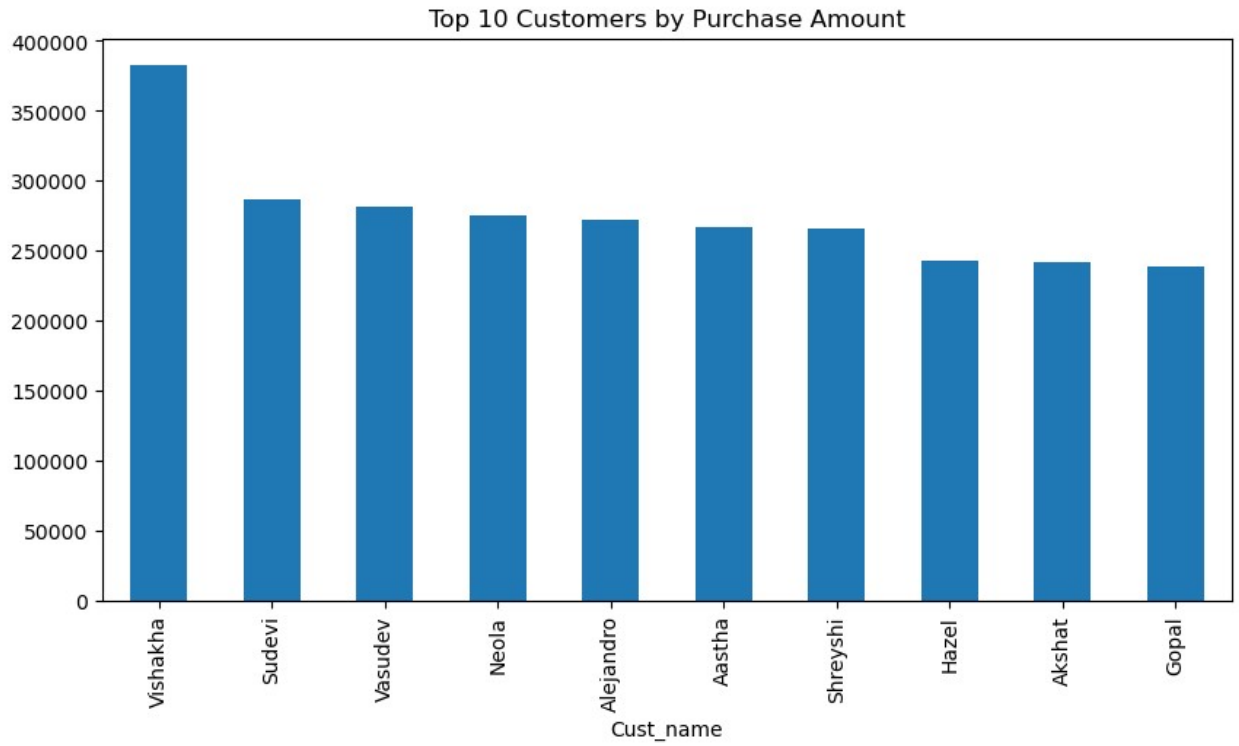
# customer name

## Find out top 10 customer by Amount

```
# Top 10 Customers by Amount
top_customers = df.groupby("Cust_name")
["Amount"].sum().sort_values(ascending=False).head(10)
print("Top 10 Customers:\n", top_customers)
```

```
Top 10 Customers:
 Cust_name
Vishakha     382782.0
Sudevi       287142.0
Vasudev      281034.0
Neola        275234.0
Alejandro    272517.0
Aastha       266961.0
Shreyshi     265603.0
Hazel        242343.0
Akshat       241349.0
Gopal        239147.0
Name: Amount, dtype: float64
```

```
top_customers.plot(kind="bar", figsize=(10,5))
plt.title("Top 10 Customers by Purchase Amount")
plt.show()
```




# Multivariate Analysis

```
df.head()
```

```
   User_ID  Cust_name Product_ID Gender Age Group  Age  Marital_Status
\
0  1002903  Sanskriti  P00125942      F     26-35   28               0

1  1000732     Kartik  P00110942      F     26-35   35               1

2  1001990      Bindu  P00118542      F     26-35   35               1

3  1001425     Sudevi  P00237842      M      0-17   16               0

4  1000588       Joni  P00057942      M     26-35   28               1


             State      Zone       Occupation Product_Category  Orders
Amount
0     Maharashtra   Western       Healthcare             Auto       1
23952.0
1  Andhra Pradesh  Southern             Govt             Auto       3
23934.0
2   Uttar Pradesh   Central       Automobile             Auto       3
23924.0
3       Karnataka  Southern     Construction             Auto       2
```

```
23912.0
4         Gujarat   Western  Food Processing             Auto       2
23877.0
```

## How do total Orders and Revenue vary across different Age Groups and Gender, and which segment contributes the most?

```
df.groupby(["Age Group", "Gender"])[["Orders",
"Amount"]].sum().sort_values(by=["Amount", "Orders"],
ascending=[False, False]).head()
```

```
                  Orders       Amount
Age Group Gender
26-35     F         8210  30961857.94
36-45     F         3908  15524425.49
18-25     F         3261  11887003.00
26-35     M         3171  11636129.00
46-50     F         1682   6767720.00
```

Insight

The female customers aged 26–35 are the biggest drivers of sales, both in terms of order volume and revenue. Younger females (18–25) and middle-aged females (36–45) also contribute significantly

## How do total Orders and Revenue vary across different States and Zones, and which State–Zone combinations contribute the most?

```
df.groupby(["State", "Zone"])[["Orders", "Amount"]].sum().sort_values(
    by=["Amount", "Orders"], ascending=[False, False]
).head()
```

```
                         Orders       Amount
State          Zone
Uttar Pradesh  Central     4809  19362273.00
Maharashtra    Western     3799  14412576.00
Karnataka      Southern    3241  13531649.00
Delhi          Central     2744  11628146.45
Madhya Pradesh Central     2259   8117360.00
```

Insight

Uttar Pradesh – Central Zone is the top-performing state–zone combination in both revenue and orders.

Other high contributors include Maharashtra (Western) and Karnataka (Southern).

## How do Orders and Revenue vary across different Occupations and Gender, and which segment generates the highest sales

```
df.groupby(["Occupation", "Gender"])[["Orders",
"Amount"]].sum().sort_values(
    by="Amount", ascending=False).head()
```

```
                    Orders       Amount
Occupation Gender
IT Sector  F          2701  10217271.00
Aviation   F          2299   9005089.00
Healthcare F          2403   8968232.49
Banking    F          2034   7808513.95
Govt       F          1507   6002907.00
```

Insight

Female professionals in the IT Sector generate the highest sales, followed by those in Aviation and Healthcare. This indicates that working women in high-income and service-oriented professions are key buyers

## Which Product Categories generate the highest Revenue and Orders, and which category is the top performer overall

```
df.groupby("Product_Category")[["Orders",
"Amount"]].sum().reset_index().sort_values(
    by="Amount", ascending=False).head()
```

```
        Product_Category  Orders       Amount
6                   Food    6120  33958210.50
3     Clothing & Apparel    6627  16484472.00
7       Footwear & Shoes    2654  15615754.45
5  Electronics & Gadgets    5208  15607657.00
8              Furniture     890   5448160.99
```

Insight

Food is the highest revenue generator, while Clothing & Apparel leads in order volume.

Footwear & Shoes and Electronics & Gadgets also perform strongly, showing balanced demand.

Furniture has the least contribution among the top categories.