UPI_Transaction_Analysis

December 22, 2025

[1]:
```
#NAME MOHAN MOLLI
```

[2]:
```
#Import Required Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

[3]:
```
#Upload dataset
df=pd.read_csv("UPI_Sample_Dataset.csv")
df
```

[3]:
```
        Date  User ID Transaction ID Transaction Type  Transaction Value  \
0    16:39.4  User_52          Txn_1         Recharge            2990.60
1    16:39.4  User_93          Txn_2     Peer-to-Peer            2022.00
2    16:39.4  User_15          Txn_3         Recharge            2243.63
3    16:39.4  User_72          Txn_4         Recharge            4530.38
4    16:39.4  User_61          Txn_5         Recharge            1806.45
..       …      …              …                …                 …
400      NaN      NaN        Txn_396              NaN                NaN
401      NaN      NaN        Txn_397              NaN                NaN
402      NaN      NaN        Txn_398              NaN                NaN
403      NaN      NaN        Txn_399              NaN                NaN
404      NaN      NaN        Txn_400              NaN                NaN

     Revenue  User Age User Gender       City Device Used User Retention  \
0      38.79      52.0        Male       Pune      Tablet       Retained
1      73.31      43.0       Other      Delhi      Tablet            New
2      33.23      25.0       Other    Chennai     Desktop            New
3      58.81      53.0        Male    Chennai     Desktop       Retained
4      50.22      47.0       Other  Hyderabad     Desktop        Churned
..       …        …          …          …          …            …
400      NaN       NaN         NaN        NaN         NaN        Churned
401      NaN       NaN         NaN        NaN         NaN       Retained
402      NaN       NaN         NaN        NaN         NaN       Retained
403      NaN       NaN         NaN        NaN         NaN            NaN
```

```
404       NaN        NaN          NaN         NaN          NaN              NaN

     Time of Day Day of the Week  User Type
0           15.0          Monday        New
1            8.0       Wednesday  Returning
2            8.0       Wednesday        New
3            5.0        Saturday        New
4           10.0          Monday  Returning
..           …               …         …
400          NaN          Friday        NaN
401          NaN          Monday        NaN
402          NaN         Tuesday        NaN
403          NaN             NaN        NaN
404          NaN             NaN        NaN

[405 rows x 14 columns]
```

1 Business Problem

[4]:
```
# Title : Analysis of UPI Transaction Patterns to Improve Revenue and User
↪Retention
```

[5]:
```
# Domain : Financial
```

[6]:
```
# Description :The organization needs to analyze UPI transaction data to
↪understand user behavior, revenue patterns, and retention trends.
```

[7]:
```
# Objective :The primary objective of this project is to perform Exploratory
↪Data Analysis (EDA) on UPI transaction data to generate actionable business
↪insights.
            #Specifically, the project aims to:
# 1.Analyze transaction behavior across cities, devices, and time periods
# 2.Identify high-revenue transaction types and user segments
# 3.Compare transaction patterns between retained and churned users
# 4.Understand factors influencing transaction value and revenue
# 5.Support data-driven decision-making for improving user retention and
↪revenue growth
```

2 Data Understanding and Exploration

[8]:
```
#Top 5 rows
df.head()
```

[8]:
```
      Date  User ID Transaction ID Transaction Type  Transaction Value  \
0  16:39.4  User_52          Txn_1         Recharge            2990.60
1  16:39.4  User_93          Txn_2     Peer-to-Peer            2022.00
```

```
2  16:39.4  User_15          Txn_3         Recharge            2243.63
3  16:39.4  User_72          Txn_4         Recharge            4530.38
4  16:39.4  User_61          Txn_5         Recharge            1806.45

   Revenue  User Age User Gender       City Device Used User Retention  \
0    38.79      52.0        Male       Pune      Tablet       Retained
1    73.31      43.0       Other      Delhi      Tablet            New
2    33.23      25.0       Other    Chennai     Desktop            New
3    58.81      53.0        Male    Chennai     Desktop       Retained
4    50.22      47.0       Other  Hyderabad     Desktop        Churned

   Time of Day Day of the Week  User Type
0         15.0          Monday        New
1          8.0       Wednesday  Returning
2          8.0       Wednesday        New
3          5.0        Saturday        New
4         10.0          Monday  Returning
```

[9]:
```
#Bottom 5 rows
df.tail()
```

[9]:
```
    Date User ID Transaction ID Transaction Type  Transaction Value  Revenue  \
400  NaN     NaN        Txn_396              NaN                NaN      NaN
401  NaN     NaN        Txn_397              NaN                NaN      NaN
402  NaN     NaN        Txn_398              NaN                NaN      NaN
403  NaN     NaN        Txn_399              NaN                NaN      NaN
404  NaN     NaN        Txn_400              NaN                NaN      NaN

     User Age User Gender City Device Used User Retention  Time of Day  \
400       NaN         NaN  NaN         NaN        Churned          NaN
401       NaN         NaN  NaN         NaN       Retained          NaN
402       NaN         NaN  NaN         NaN       Retained          NaN
403       NaN         NaN  NaN         NaN            NaN          NaN
404       NaN         NaN  NaN         NaN            NaN          NaN

    Day of the Week User Type
400          Friday       NaN
401          Monday       NaN
402         Tuesday       NaN
403             NaN       NaN
404             NaN       NaN
```

[11]:
```
df.shape
```

[11]: (405, 14)

[12]:
```
df.dtypes
```

[12]:
```
Date                   object
User ID                object
Transaction ID         object
Transaction Type       object
Transaction Value     float64
Revenue               float64
User Age              float64
User Gender            object
City                   object
Device Used            object
User Retention         object
Time of Day           float64
Day of the Week        object
User Type              object
dtype: object
```

[13]:
```
df.describe()
```

[13]:

	Transaction Value	Revenue	User Age	Time of Day
count	400.000000	400.000000	400.000000	400.000000
mean	2396.698200	54.188300	40.822500	11.557500
std	1385.685822	28.239135	14.116983	6.966565
min	122.700000	5.610000	18.000000	0.000000
25%	1124.017500	28.455000	28.000000	5.000000
50%	2312.490000	56.450000	41.000000	11.000000
75%	3526.560000	78.375000	53.000000	18.000000
max	4984.680000	99.800000	64.000000	23.000000

[14]:
```
df.isnull().sum()
```

[14]:
```
Date                 5
User ID              5
Transaction ID       0
Transaction Type     5
Transaction Value    5
Revenue              5
User Age             5
User Gender          5
City                 5
Device Used          5
User Retention       2
Time of Day          5
Day of the Week      2
User Type            5
dtype: int64
```

[16]:
```python
# replacing null values with median in the Transaction value, Revenue, User Age␣
↪Columns
df['Transaction Value'].fillna(df['Transaction Value'].median(), inplace=True)
df['Revenue'].fillna(df['Revenue'].median(), inplace=True)
df['User Age'].fillna(df['User Age'].median(), inplace=True)
```

[17]:
```python
# replacing null values with mode in the Transaction Type, City, Device Used,␣
↪User Retention, Time of the Day, User Type
df['Transaction Type'].fillna(df['Transaction Type'].mode()[0], inplace=True)
df['City'].fillna(df['City'].mode()[0], inplace=True)
df['Device Used'].fillna(df['Device Used'].mode()[0], inplace=True)
df['User Retention'].fillna(df['User Retention'].mode()[0], inplace=True)
df['Time of Day'].fillna(df['Time of Day'].mode()[0], inplace=True)
df['User Type'].fillna(df['User Type'].mode()[0], inplace=True)
```

[18]:
```python
# rows where date or user id has null(NaN) were removed
df.dropna(subset=['Date', 'User ID'], inplace=True)
```

[19]:
```python
df.isnull().sum()
```

[19]:
```
Date                 0
User ID              0
Transaction ID       0
Transaction Type     0
Transaction Value    0
Revenue              0
User Age             0
User Gender          0
City                 0
Device Used          0
User Retention       0
Time of Day          0
Day of the Week      0
User Type            0
dtype: int64
```

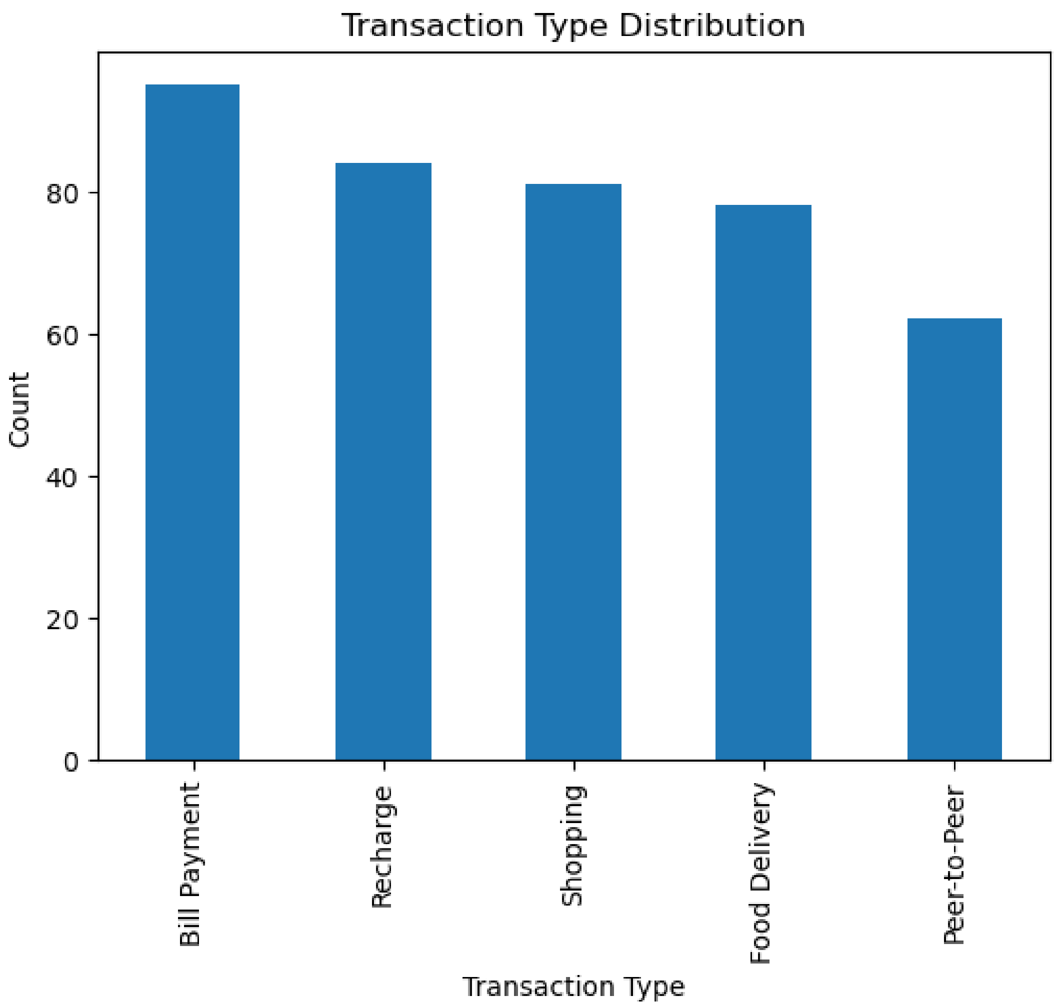
[20]:
```python
df.duplicated().sum()
```

[20]:
```
0
```

3 Univariate Analysis

3.1 Transaction Type Distribution

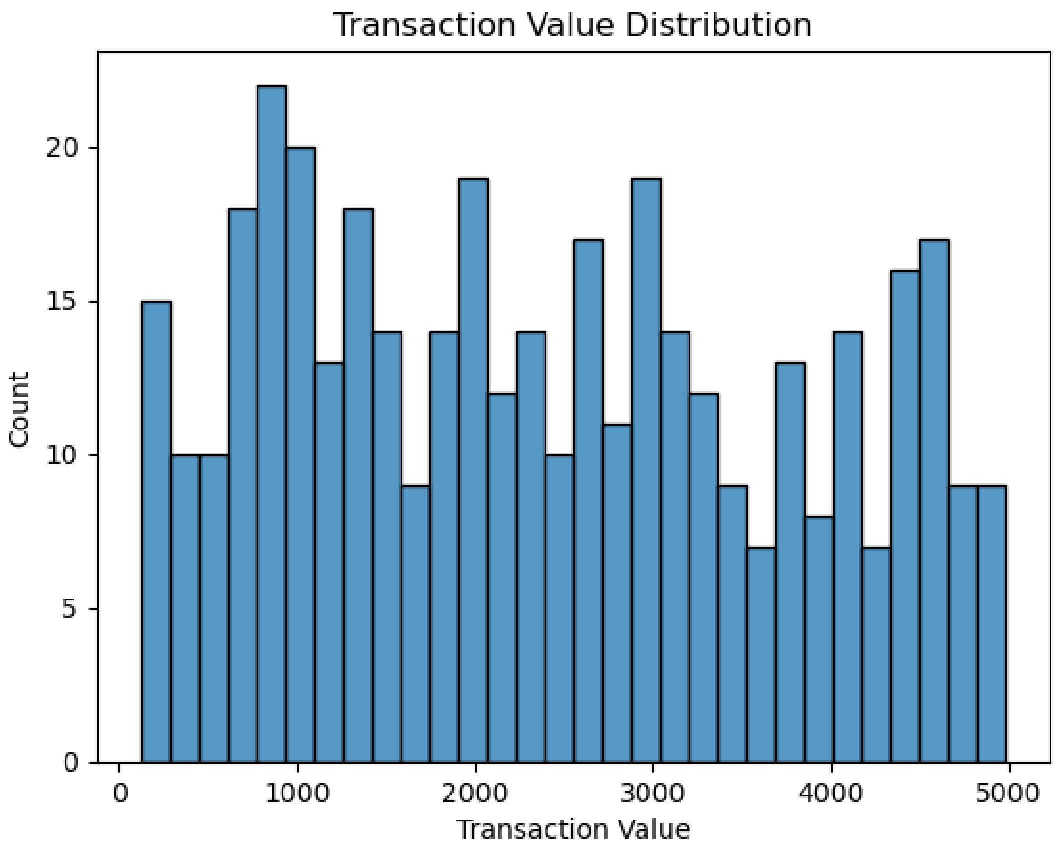
[21]:
```python
# Plot to analyze the frequency of each transaction type in the dataset
plt.figure()
df['Transaction Type'].value_counts().plot(kind='bar')
plt.title("Transaction Type Distribution")
plt.xlabel("Transaction Type")
plt.ylabel("Count")
plt.show()
```



[22]:
```python
#Observation
# 1.Bill Payments and Recharges are the most frequent transaction types
# 2.Shopping and Food Delivery show strong user engagement
# 3.Peer-to-Peer (P2P) transactions have the lowest transaction count
```

3.2 Transaction Value Distribution

[23]:
```
#  histogram to visualize the distribution of transaction values.
plt.figure()
sns.histplot(df['Transaction Value'], bins=30)
plt.title("Transaction Value Distribution")
plt.show()
```

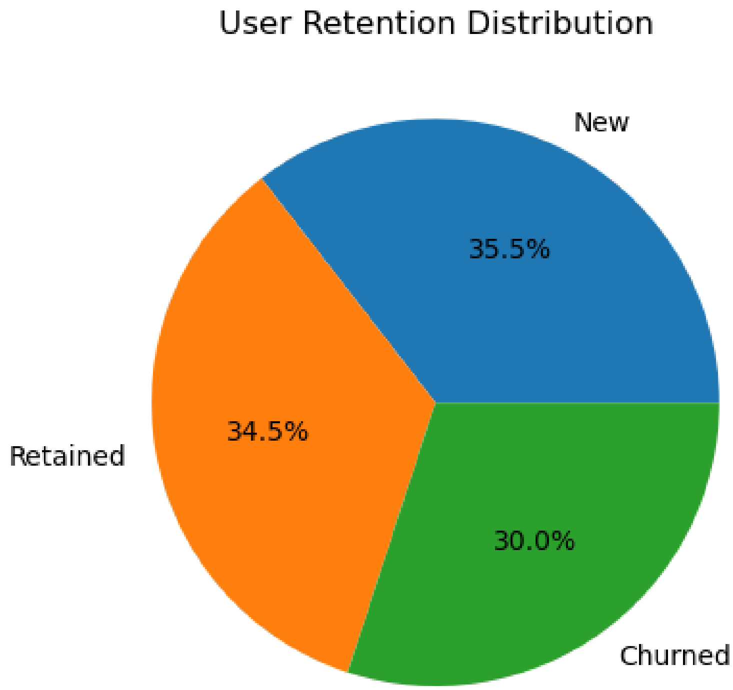


[24]:
```
# Observation
# 1.Transaction values range approximately from  100 to  5,000
# 2.Majority of transactions fall in the  500- 3,000 range
# 3.Presence of high-value transactions (> 4,000) indicates premium or power␣
↪users
```

3.3 User Retention Status

[25]:
```
# pie chart showing the percentage distribution of user retention categories.
plt.figure()
df['User Retention'].value_counts().plot(kind='pie', autopct='%1.1f%%')
plt.title("User Retention Distribution")
```

```
plt.ylabel("")
plt.show()
```

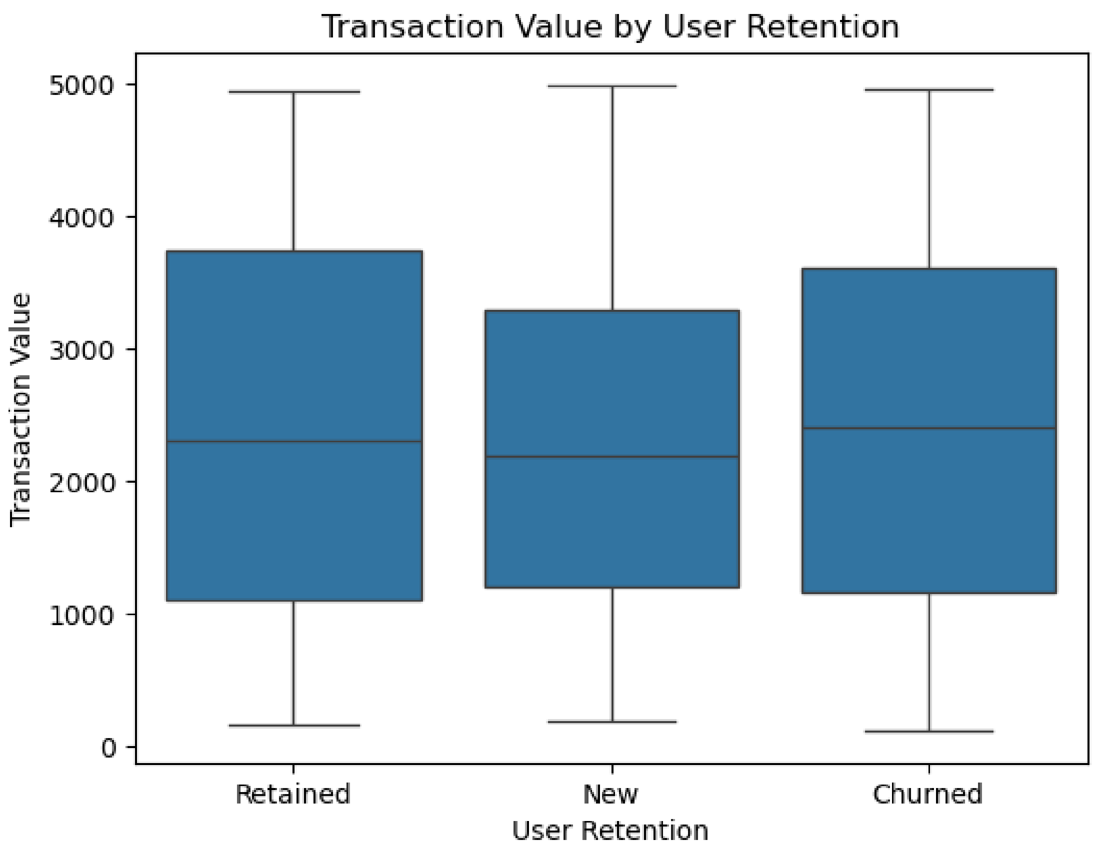


[26]:
```
# Observation
# 1.New Users: 35.5%
# 2.Retained Users: 34.5%
# 3.Churned Users: 30%
```

4 Bivariate Analysis

4.1 Transaction Value vs User Retention

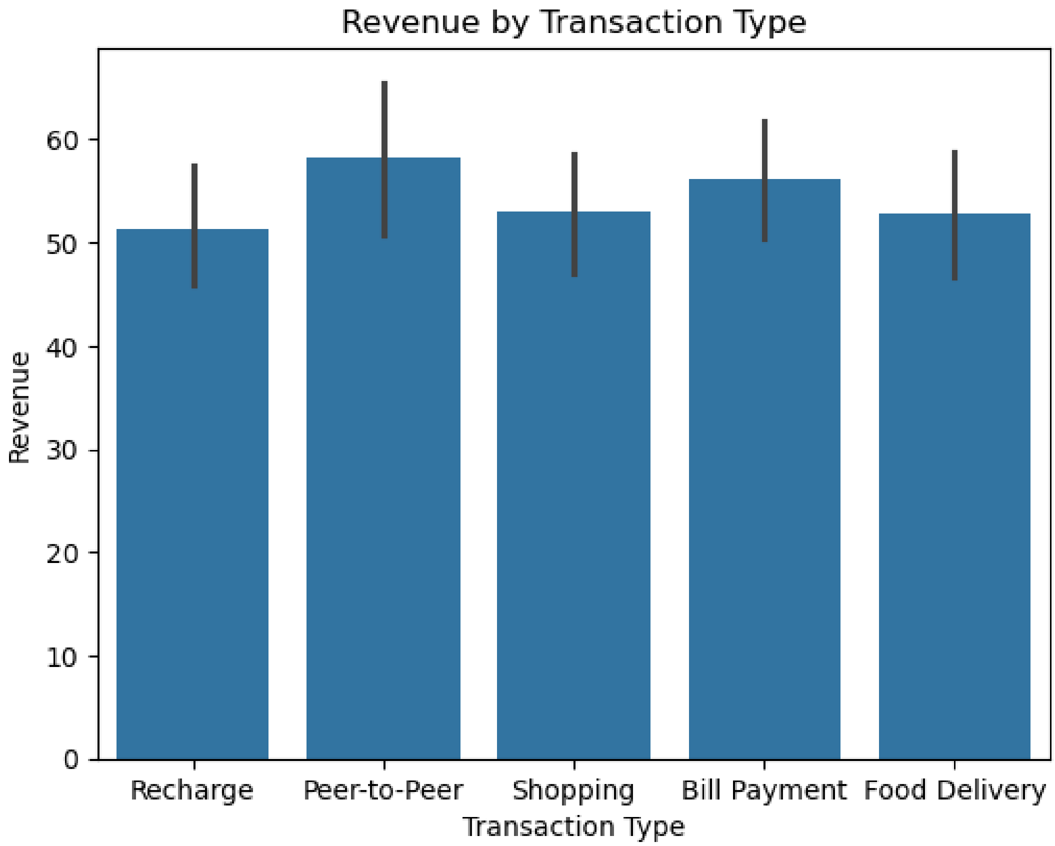
[27]:
```
# box plot to compare transaction value distributions across user retention␣
↪categories.
plt.figure()
sns.boxplot(x='User Retention', y='Transaction Value', data=df)
plt.title("Transaction Value by User Retention")
plt.show()
```



[28]:
```
#Observation
# 1.Retained users have higher median transaction values
# 2.New users show comparatively lower transaction values
```

4.2 Revenue by Transaction Type

[29]:
```
# bar chart to compare total revenue across different transaction types.
plt.figure()
sns.barplot(x='Transaction Type', y='Revenue', data=df)
plt.title("Revenue by Transaction Type")
plt.show()
```

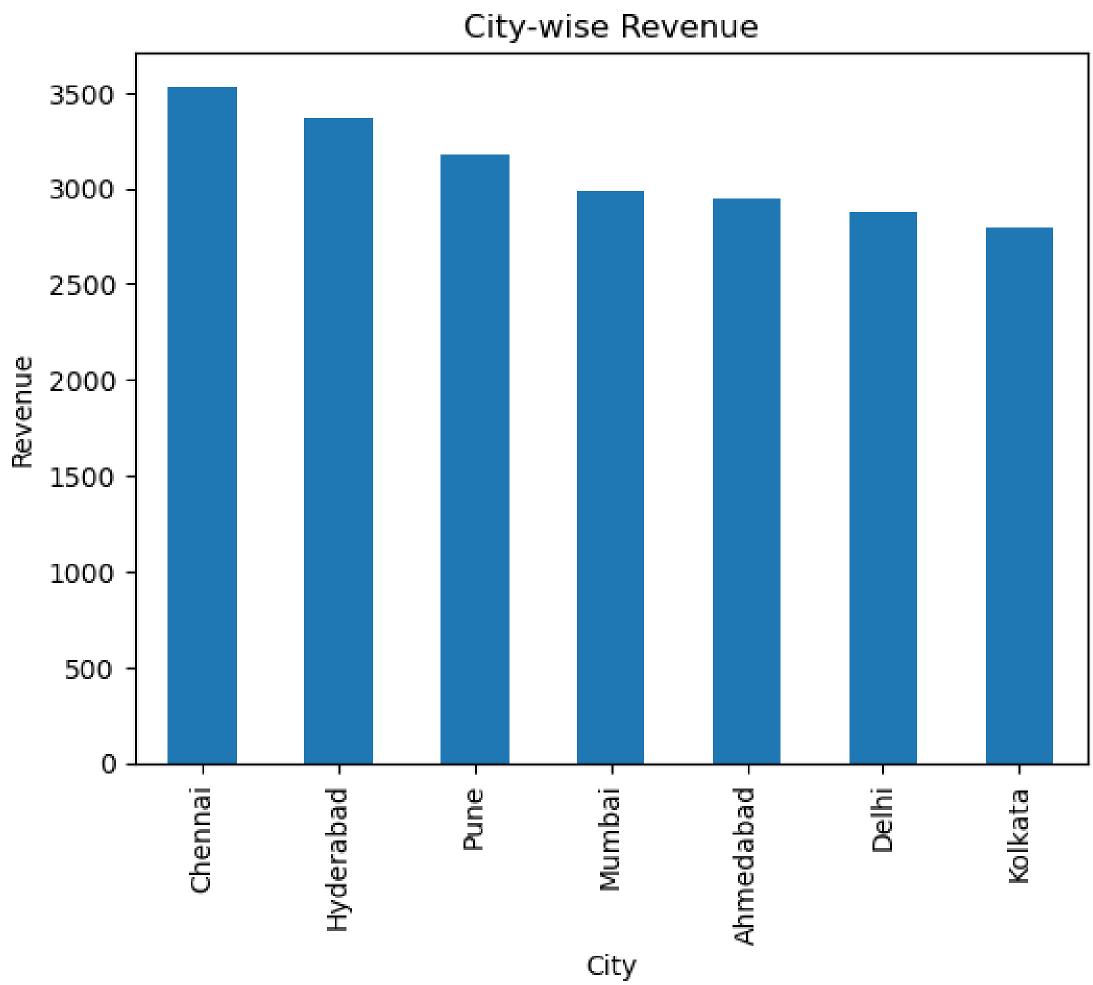


[30]:
```
#Observation
# 1.Peer-to-Peer and Bill Payment transactions generate the highest revenue
# 2.Recharge transactions generate comparatively lower revenue
```

4.3 Revenue by Cities

[31]:
```
# bar chart calculates total revenue per city
city_revenue = df.groupby('City')['Revenue'].sum().sort_values(ascending=False)

plt.figure()
city_revenue.plot(kind='bar')
plt.title("City-wise Revenue")
plt.xlabel("City")
plt.ylabel("Revenue")
plt.show()
```

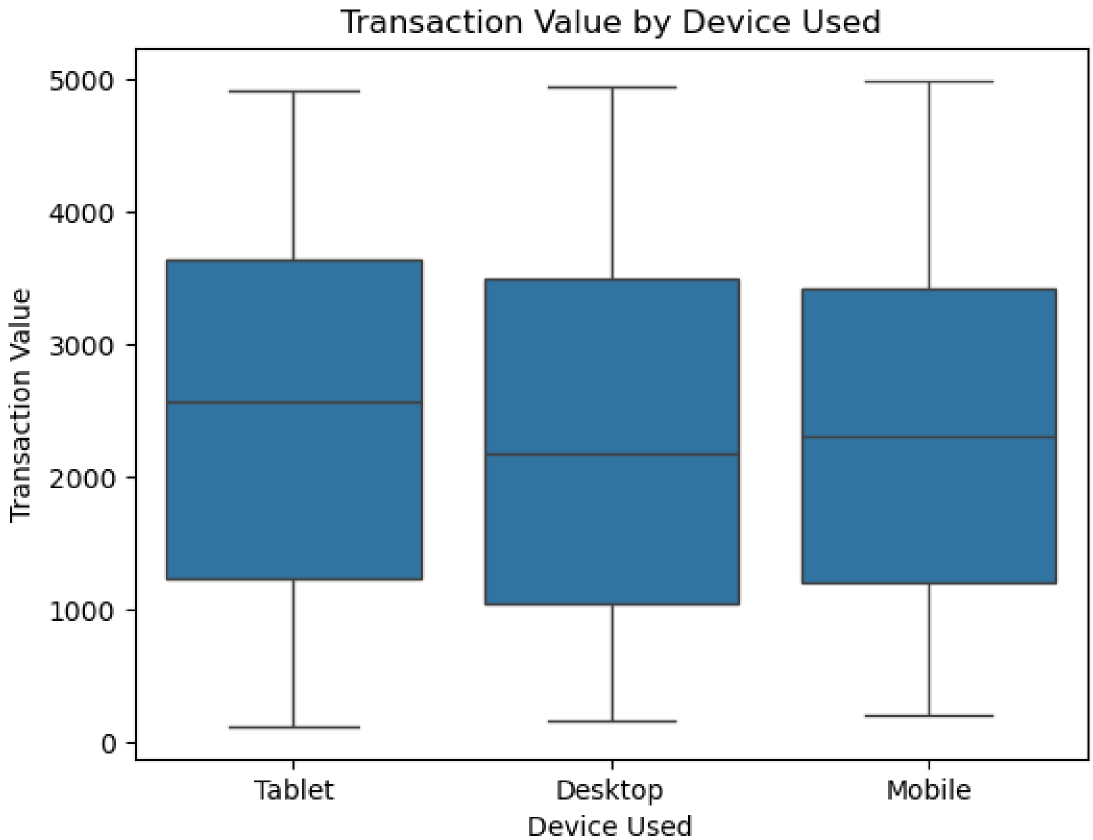


[32]:
```
#Observation
# 1.Chennai and Hyderabad generate the highest revenue
# 2.Kolkata contributes the lowest revenue among the listed cities
```

5 Multivariate Analysis

5.1 Device Used VS Transaction Type

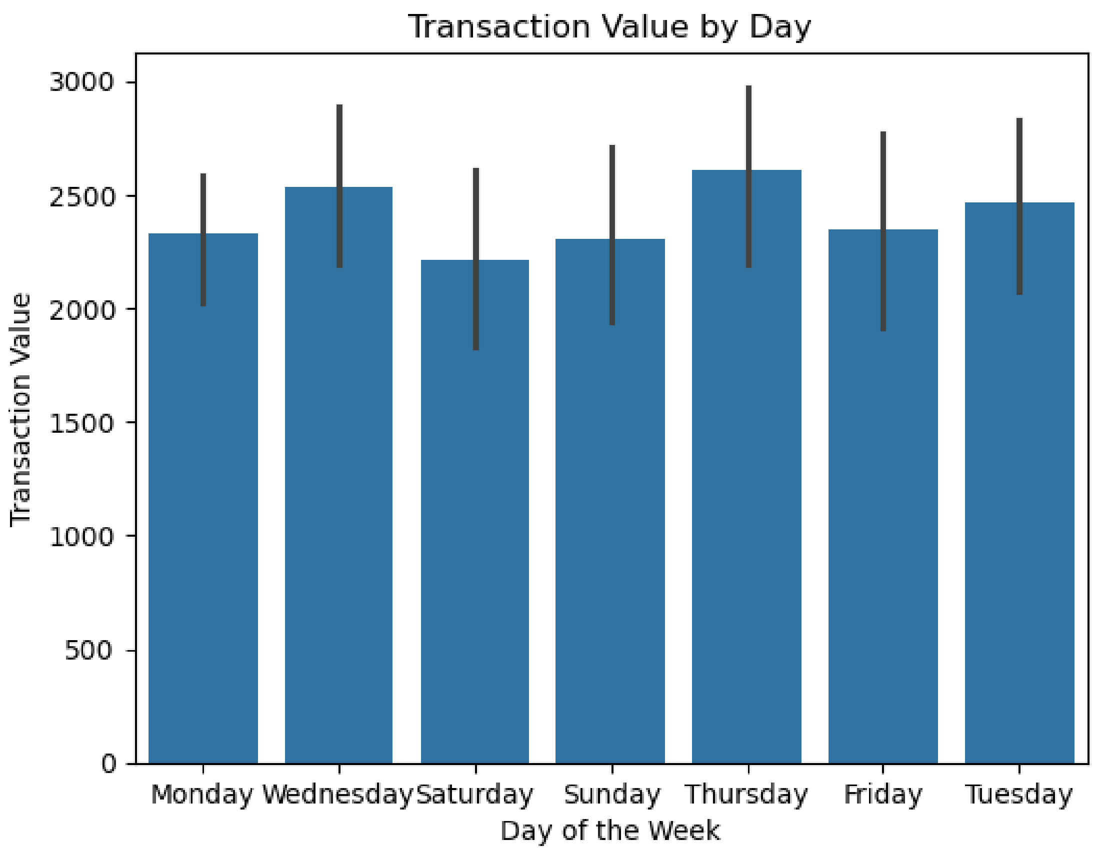
[33]:
```
# box plot to compare transaction value distributions across different devices.
plt.figure()
sns.boxplot(x='Device Used', y='Transaction Value', data=df)
plt.title("Transaction Value by Device Used")
plt.show()
```



[34]:
```
#Observation
# 1.Tablet users show slightly higher median transaction values
# 2.Desktop and Mobile users display similar patterns with wider variation
```

5.2 Transaction activity by Day of week

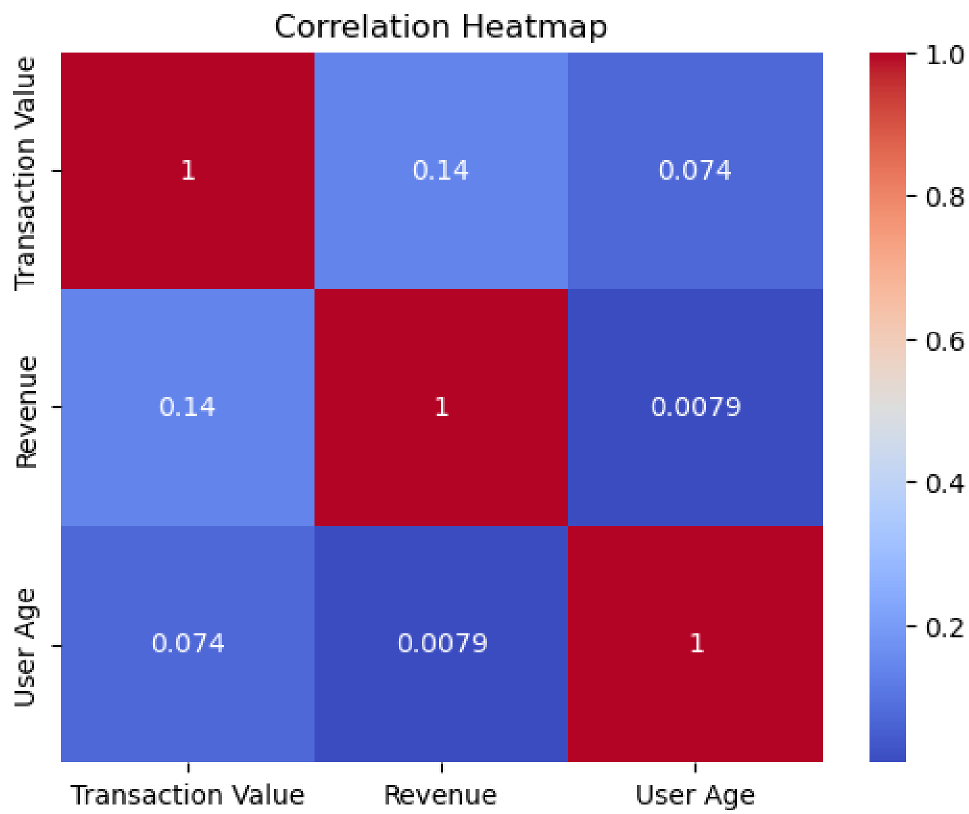
[35]:
```
# bar chart to show how transaction values vary across days of the week.
plt.figure()
sns.barplot(x='Day of the Week', y='Transaction Value', data=df)
plt.title("Transaction Value by Day")
plt.show()
```



[36]:
```
#Observation
# 1.Wednesday and Thursday show the highest average transaction values
# 2.Saturday has the lowest average transaction value
```

5.3 Correlation Analysis

[37]:
```
# heatmap to visualize correlations between transaction value, revenue, and␣
↪user age.
plt.figure()
sns.heatmap(df[['Transaction Value', 'Revenue', 'User Age']].corr(),
            annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```



[38]:
```
#Observation
# 1.Transaction Value and Revenue show a weak positive correlation (~0.14)
# 2.User Age has minimal correlation with Transaction Value or Revenue
```

6 Business Insights

[41]:
```
#Insights

# 1. Bill Payments and Recharges dominate transaction types, while P2P has the lowest usage.
# 2. Most transactions fall in  500- 3,000, with a small segment of high-value users contributing significantly.
# 3. New, retained, and churned users are fairly balanced, but churn is notable.
# 4. Retained users consistently have higher transaction values than new users.
# 5. Peer-to-Peer and Bill Payment transactions generate the highest revenue.
# 6. Revenue is concentrated in major cities like Chennai and Hyderabad.
# 7. Tablet users show slightly higher median transaction values compared to other devices.
# 8. Mid-week days, especially Wednesday and Thursday, have higher average transaction values.
```

```
# 9.Transaction value and revenue are weakly correlated, and user age has␣
↪minimal impact.
```

7 Final Conclusion

[ ]:
```
# The analysis indicates that bill payments, recharges, and P2P transactions,␣
↪along with high-value and retained users, are the primary revenue drivers.
# Focusing on user retention, key transaction types, and revenue-rich cities␣
↪like Chennai and Hyderabad can significantly enhance business performance.
```