UPI Transactions Analysis

Importing Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import chi2_contingency, ttest_ind
import warnings
warnings.filterwarnings('ignore')
sns.set(style='whitegrid', palette='muted', font_scale=1.1)
%matplotlib inline
```

Load Dataset

```
df = pd.read_csv(r"/content/upi_transactions_2024.csv")
df.head()
```

	transaction id	timestamp	transaction type	merchant_category	amount (INR)	transaction_status	sender_age_group	receiver_age_group	sender_state	sender_bank	receiver_bank	device_
0	TXN0000000001	2024-10-08 15:17:28	P2P	Entertainment	868	SUCCESS	26-35	18-25	Delhi	Axis	SBI	Ar
1	TXN0000000002	2024-04-11 06:56:00	P2M	Grocery	1011	SUCCESS	26-35	26-35	Uttar Pradesh	ICICI	Axis	
2	TXN0000000003	2024-04-02 13:27:18	P2P	Grocery	477	SUCCESS	26-35	36-45	Karnataka	Yes Bank	PNB	Ar
3	TXN0000000004	2024-01-07 10:09:17	P2P	Fuel	2784	SUCCESS	26-35	26-35	Delhi	ICICI	PNB	Ar
4	TXN0000000005	2024-01-23 19:04:23	P2P	Shopping	990	SUCCESS	26-35	18-25	Delhi	Axis	Yes Bank	

Data Overview & Initial Checks

```
display(df.info())
display(df.describe(include='all'))
display(df.isnull().sum())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250000 entries, 0 to 249999
Data columns (total 17 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   transaction id      250000 non-null  object
 1   timestamp           250000 non-null  object
 2   transaction type    250000 non-null  object
 3   merchant_category   250000 non-null  object
 4   amount (INR)        250000 non-null  int64
 5   transaction_status  250000 non-null  object
 6   sender_age_group    250000 non-null  object
 7   receiver_age_group  250000 non-null  object
 8   sender_state        250000 non-null  object
 9   sender_bank         250000 non-null  object
 10  receiver_bank       250000 non-null  object
 11  device_type         250000 non-null  object
 12  network_type        250000 non-null  object
 13  fraud_flag          250000 non-null  int64
 14  hour_of_day         250000 non-null  int64
 15  day_of_week         250000 non-null  object
 16  is_weekend          250000 non-null  int64
dtypes: int64(4), object(13)
memory usage: 32.4+ MB
None
```

	transaction id	timestamp	transaction type	merchant_category	amount (INR)	transaction_status	sender_age_group	receiver_age_group	sender_state	sender_bank	receiver
count	250000	250000	250000	250000	250000.000000	250000	250000	250000	250000	250000	2
unique	250000	248610	4	10	NaN	2	5	5	10	8	
top	TXN0000249984	2024-07-23 21:31:06	P2P	Grocery	NaN	SUCCESS	26-35	26-35	Maharashtra	SBI	
freq	1	3	112445	49966	NaN	237624	87432	87864	37427	62693	
mean	NaN	NaN	NaN	NaN	1311.756036	NaN	NaN	NaN	NaN	NaN	
std	NaN	NaN	NaN	NaN	1848.059224	NaN	NaN	NaN	NaN	NaN	
min	NaN	NaN	NaN	NaN	10.000000	NaN	NaN	NaN	NaN	NaN	
25%	NaN	NaN	NaN	NaN	288.000000	NaN	NaN	NaN	NaN	NaN	
50%	NaN	NaN	NaN	NaN	629.000000	NaN	NaN	NaN	NaN	NaN	
75%	NaN	NaN	NaN	NaN	1596.000000	NaN	NaN	NaN	NaN	NaN	
max	NaN	NaN	NaN	NaN	42099.000000	NaN	NaN	NaN	NaN	NaN	

	0
transaction id	0
timestamp	0

transaction type	0
merchant_category	0
amount (INR)	0
transaction_status	0
sender_age_group	0
receiver_age_group	0
hour_of_day	0
day_of_week	0
is_weekend	0

dtype: int64

Data Cleaning & Feature Engineering

- Converting timestamp to datetime for time-based analysis.
- Removing duplicates and ensure numeric types for calculations.
- Creating new features: month, day, hour, and transaction value bins for deeper insights.

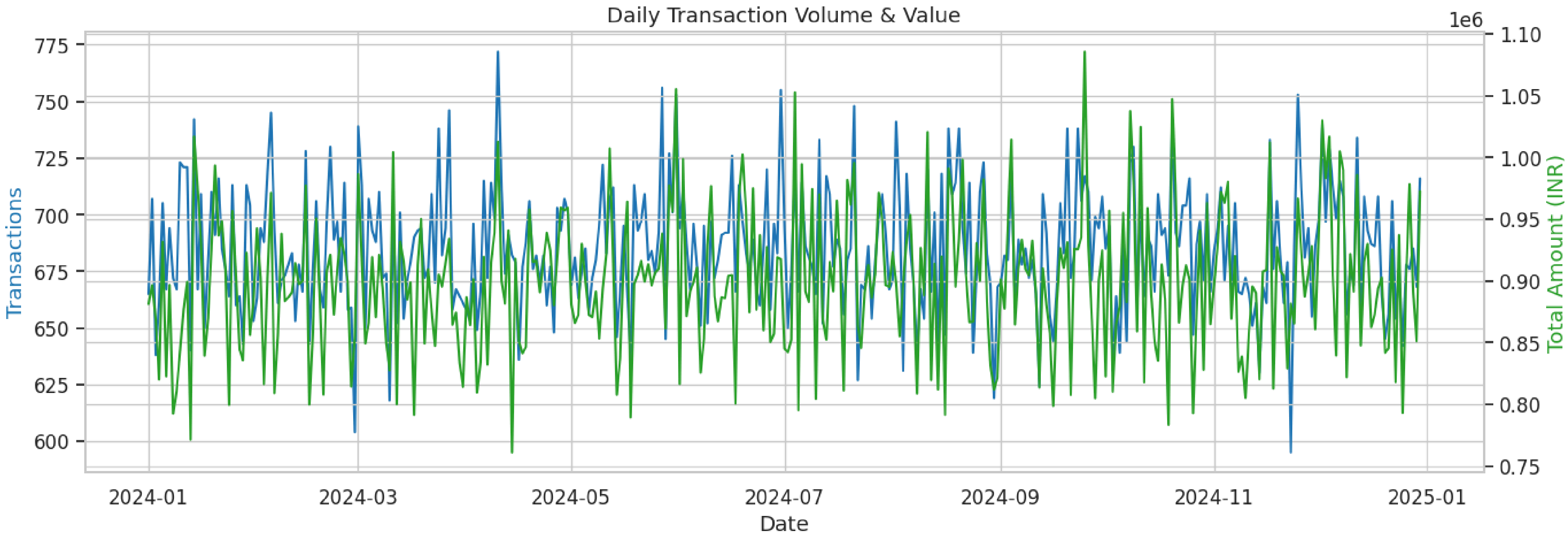
```
df['timestamp'] = pd.to_datetime(df['timestamp'])
df = df.drop_duplicates()
df['amount (INR)'] = pd.to_numeric(df['amount (INR)'], errors='coerce')
df = df.dropna(subset=['amount (INR)'])
df['month'] = df['timestamp'].dt.month_name()
df['day'] = df['timestamp'].dt.day
df['hour'] = df['timestamp'].dt.hour
df['trx_bin'] = pd.qcut(df['amount (INR)'], q=4, labels=['Low','Medium','High','Very High'])
df.reset_index(drop=True, inplace=True)
df.shape
```

```
(250000, 21)
```

Transaction Volume & Value Trends

- Visualizing how transaction counts and total value change over time.
- This helps us spot seasonality, spikes, or dips in UPI usage.

```
df['date'] = df['timestamp'].dt.date
daily_stats = df.groupby('date').agg({'transaction id':'count', 'amount (INR)':'sum'})
fig, ax1 = plt.subplots(figsize=(14,5))
color = 'tab:blue'
ax1.set_xlabel('Date')
ax1.set_ylabel('Transactions', color=color)
ax1.plot(daily_stats.index, daily_stats['transaction id'], color=color, label='Transactions')
ax2 = ax1.twinx()
color = 'tab:green'
ax2.set_ylabel('Total Amount (INR)', color=color)
ax2.plot(daily_stats.index, daily_stats['amount (INR)'], color=color, label='Total Amount')
plt.title('Daily Transaction Volume & Value')
fig.tight_layout()
plt.show()
```



- We observe daily fluctuations in both transaction count and value.
- Peaks may correspond to weekends, salary days, or festivals, indicating higher UPI activity during these periods.

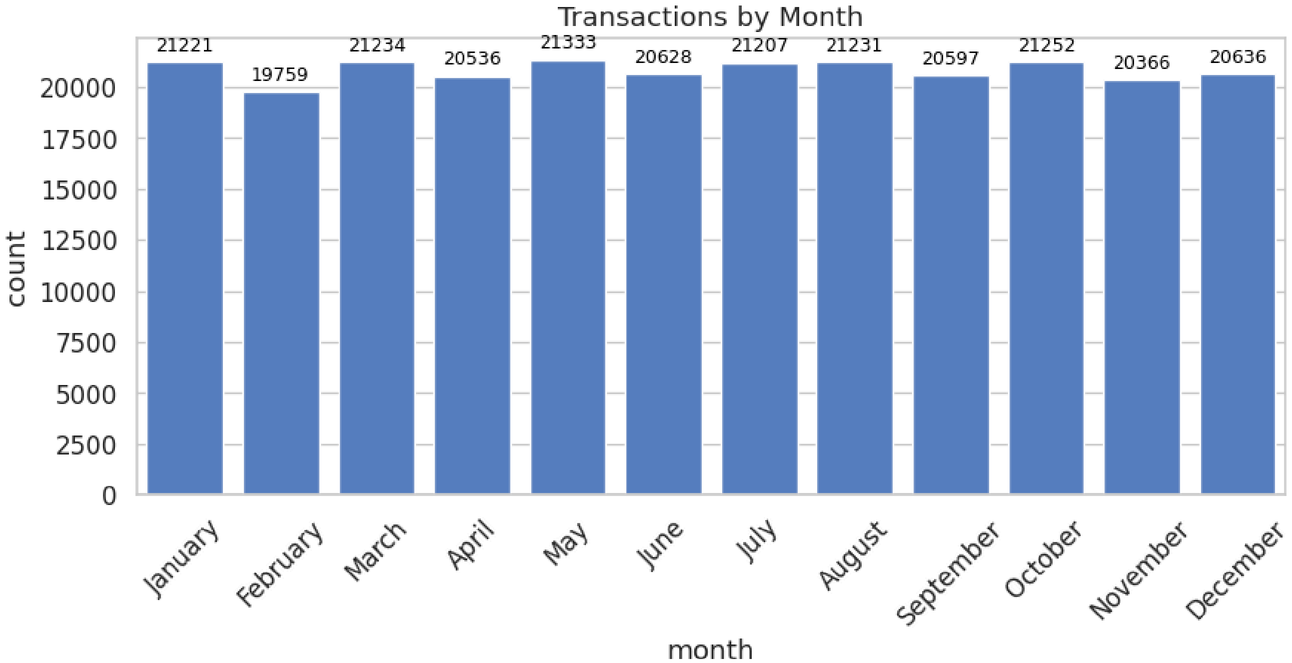
Monthly & Hourly Patterns

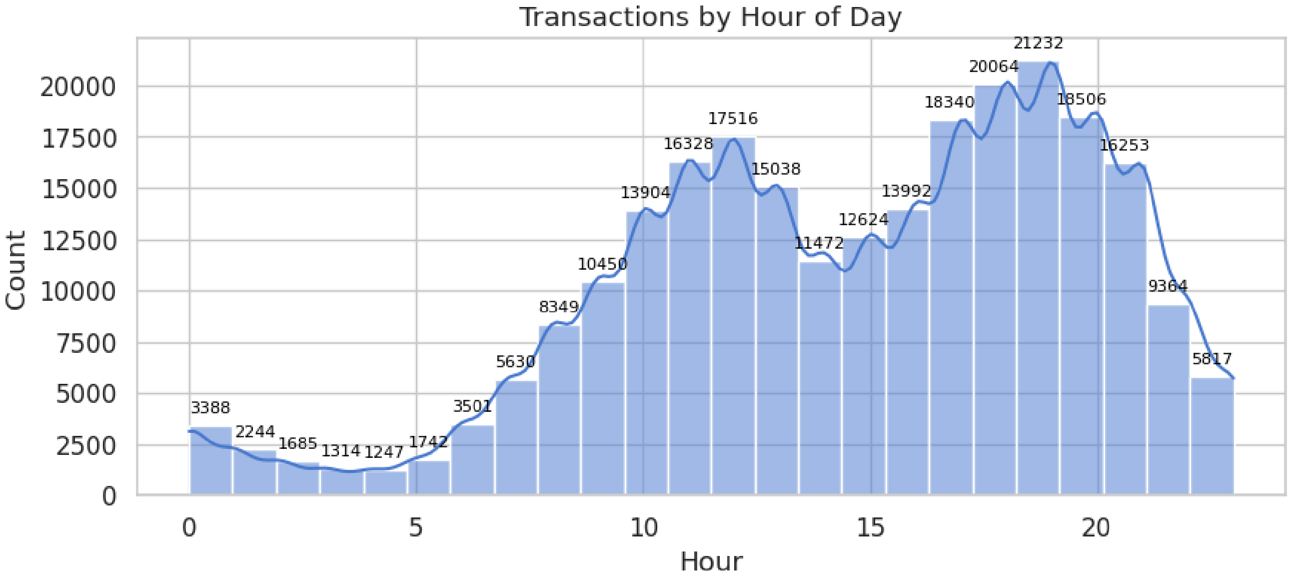
Analyzing transactions by month and hour reveals seasonality and user behavior throughout the day.

```
plt.figure(figsize=(10,4))
order = pd.date_range('2024-01-01','2024-12-01',freq='MS').strftime('%B')
ax = sns.countplot(data=df, x='month', order=order)
for p in ax.patches:
    ax.annotate(int(p.get_height()), (p.get_x() + p.get_width() / 2., p.get_height()), ha='center', va='center', fontsize=9, color='black', xytext=(0, 8), textcoords='offset point
plt.title('Transactions by Month')
plt.xticks(rotation=45)
plt.show()

plt.figure(figsize=(10,4))
ax = sns.histplot(df['hour'], bins=24, kde=True)
for p in ax.patches:
    height = int(p.get_height())
    if height > 0:
```

```
        ax.annotate(height, (p.get_x() + p.get_width() / 2., height), ha='center', va='center', fontsize=8, color='black', xytext=(0, 8), textcoords='offset points')
plt.title('Transactions by Hour of Day')
plt.xlabel('Hour')
plt.show()
```





Transaction volume is higher in certain months, possibly due to festivals or end-of-year shopping.

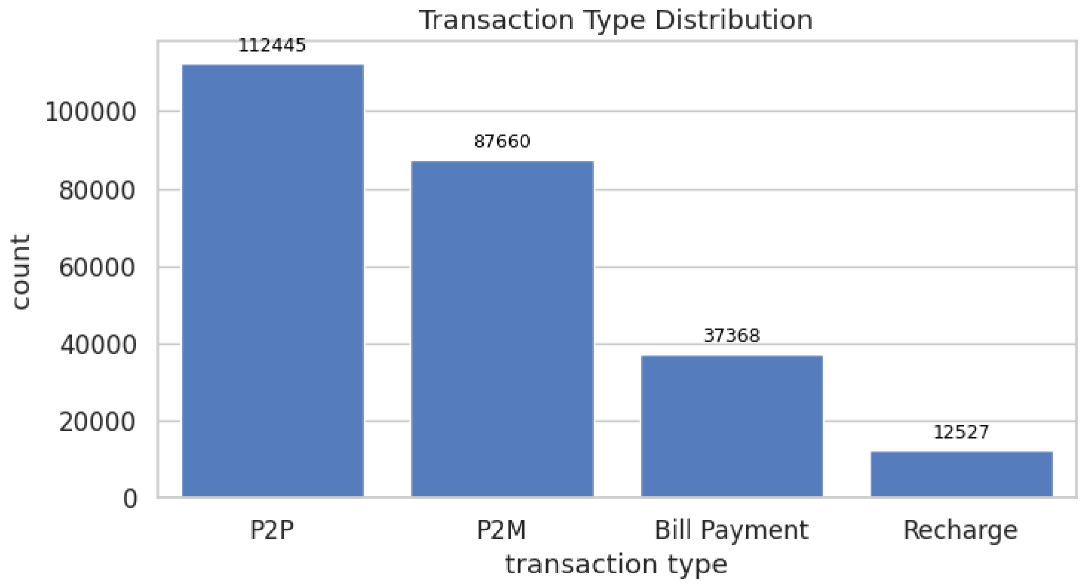
Most transactions occur during business hours, with a dip late at night.

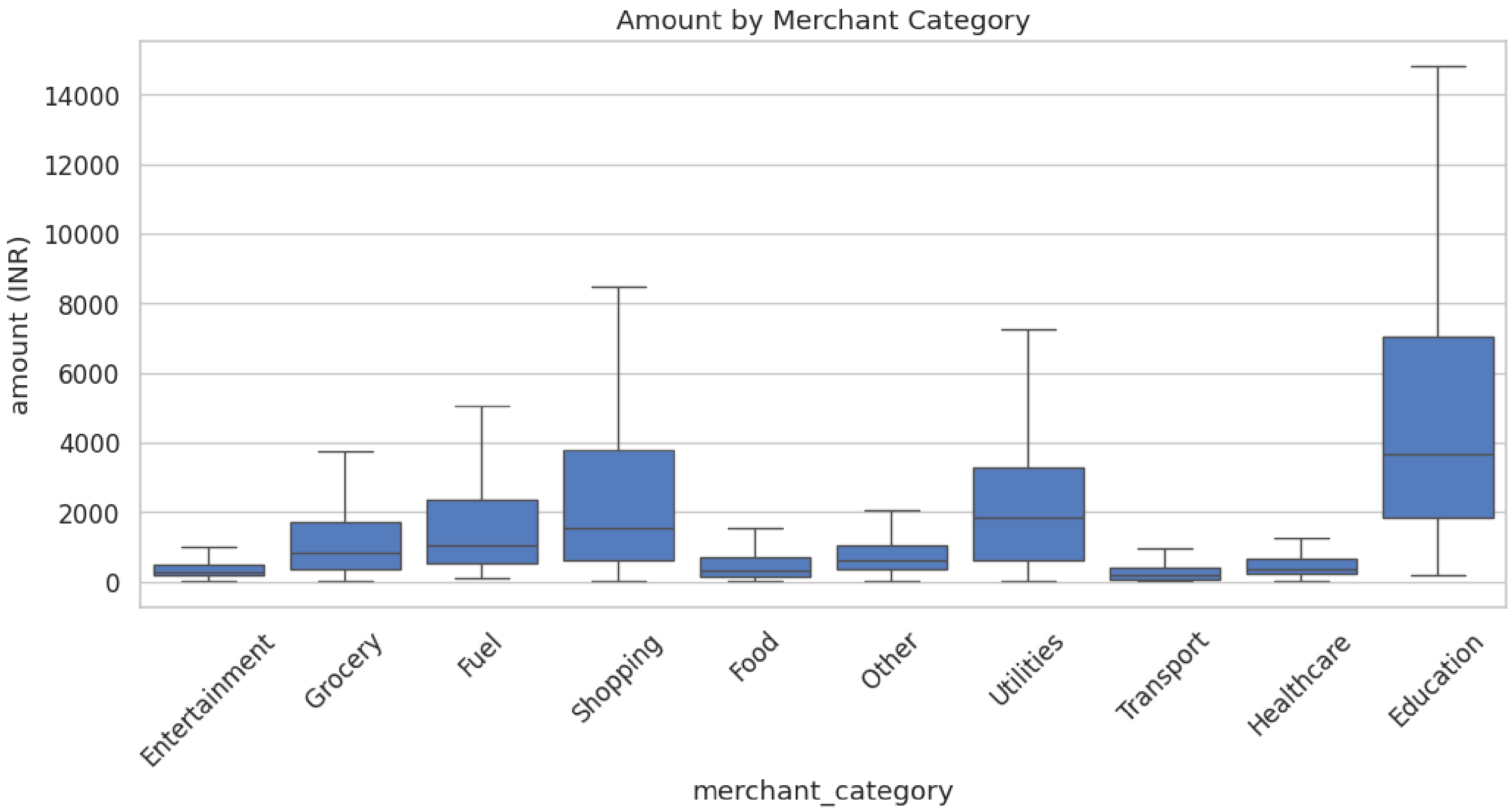
Transaction Type & Merchant Category Analysis

Understanding which transaction types and merchant categories dominate helps identify user intent and business opportunities.

```
plt.figure(figsize=(8,4))
ax = sns.countplot(data=df, x='transaction type', order=df['transaction type'].value_counts().index)
for p in ax.patches:
    ax.annotate(int(p.get_height()), (p.get_x() + p.get_width() / 2., p.get_height()), ha='center', va='center', fontsize=9, color='black', xytext=(0, 8), textcoords='offset point
plt.title('Transaction Type Distribution')
plt.show()

plt.figure(figsize=(12,5))
ax = sns.boxplot(data=df, x='merchant_category', y='amount (INR)', showfliers=False)
plt.xticks(rotation=45)
plt.title('Amount by Merchant Category')
plt.show()
```


Transaction Type Distribution
112445
87660
37368
12527
100000
80000
60000
40000
20000
0
count
P2P
P2M
Bill Payment
Recharge
transaction type


Amount by Merchant Category
14000
12000
10000
8000
6000
4000
2000
0
amount (INR)
Entertainment
Grocery
Fuel
Shopping
Food
Other
Utilities
Transport
Healthcare
Education
merchant_category

P2P and P2M transactions are the most common, showing UPI's popularity for both personal and merchant payments.

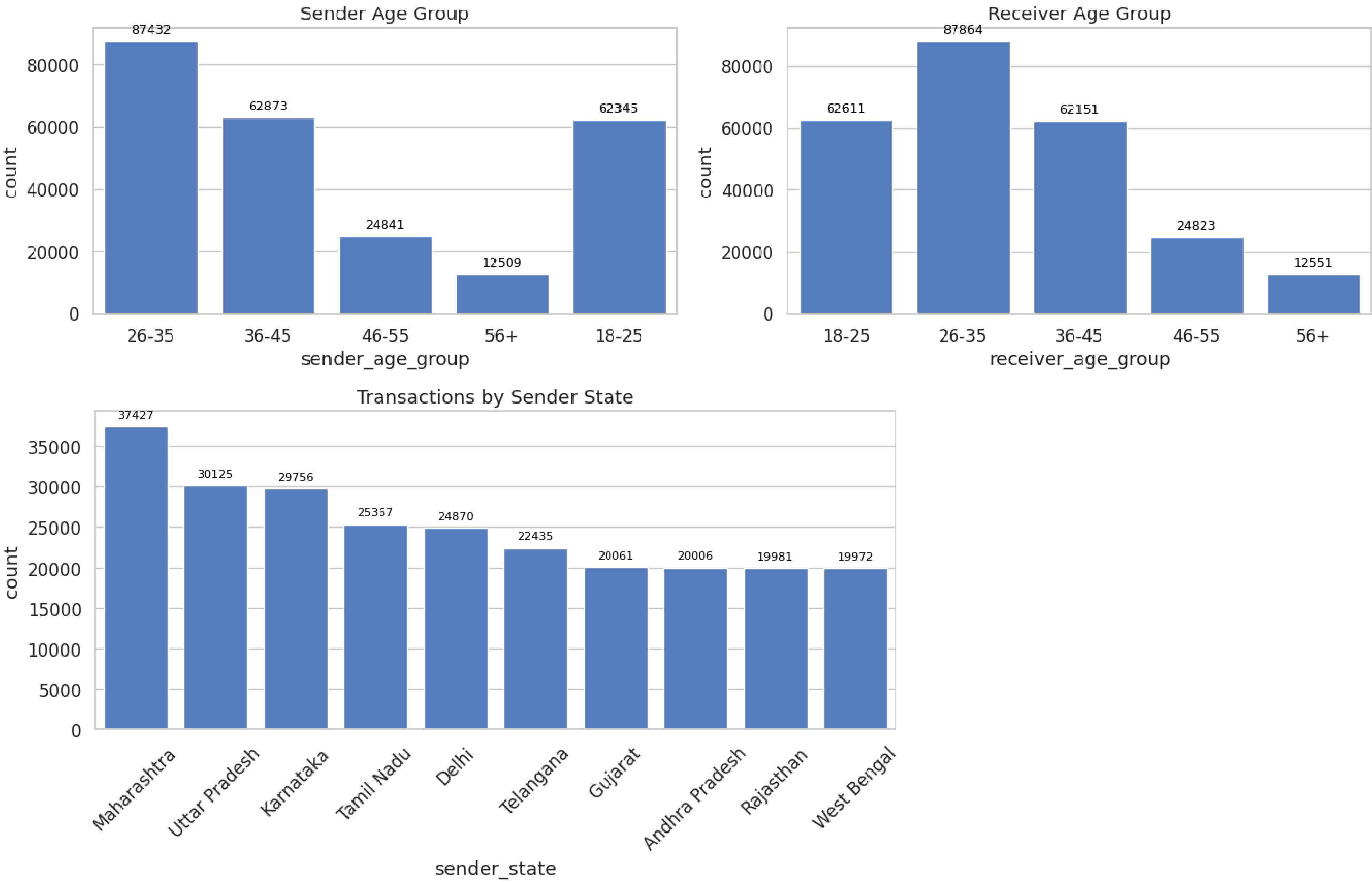
Shopping and Grocery categories see a wide range of transaction amounts, indicating both small and large purchases.

Sender & Receiver Demographics

Analyzing age groups and states helps understand the user base and regional adoption.

```
fig, ax = plt.subplots(1,2, figsize=(14,4))
sns.countplot(data=df, x='sender_age_group', ax=ax[0])
for p in ax[0].patches:
    ax[0].annotate(int(p.get_height()), (p.get_x() + p.get_width() / 2., p.get_height()), ha='center', va='center', fontsize=9, color='black', xytext=(0, 8), textcoords='offset po
ax[0].set_title('Sender Age Group')
sns.countplot(data=df, x='receiver_age_group', ax=ax[1])
for p in ax[1].patches:
    ax[1].annotate(int(p.get_height()), (p.get_x() + p.get_width() / 2., p.get_height()), ha='center', va='center', fontsize=9, color='black', xytext=(0, 8), textcoords='offset po
ax[1].set_title('Receiver Age Group')
plt.tight_layout()
plt.show()

plt.figure(figsize=(10,4))
ax = sns.countplot(data=df, x='sender_state', order=df['sender_state'].value_counts().index)
for p in ax.patches:
    ax.annotate(int(p.get_height()), (p.get_x() + p.get_width() / 2., p.get_height()), ha='center', va='center', fontsize=8, color='black', xytext=(0, 8), textcoords='offset point
plt.title('Transactions by Sender State')
plt.xticks(rotation=45)
plt.show()
```



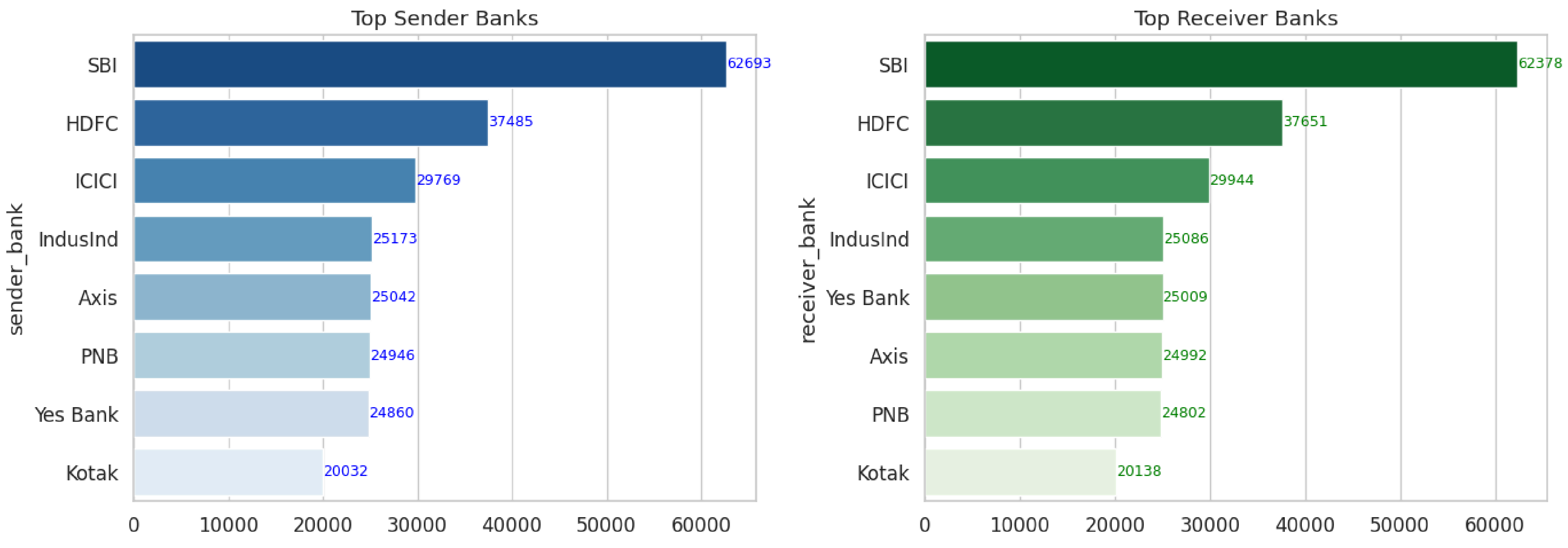
The 26-35 age group is the most active, both as senders and receivers, highlighting young adults as the primary UPI users.

States like Delhi, Karnataka, and Gujarat lead in transaction counts, indicating higher digital adoption.

Top Banks (Senders & Receivers)

Identifying top banks helps understand market share and preferred banking partners for UPI.

```
top_senders = df['sender_bank'].value_counts().head(10)
top_receivers = df['receiver_bank'].value_counts().head(10)
fig, ax = plt.subplots(1,2, figsize=(14,5))
sns.barplot(y=top_senders.index, x=top_senders.values, ax=ax[0], palette='Blues_r')
for i, v in enumerate(top_senders.values):
    ax[0].text(v + 1, i, str(v), color='blue', va='center', fontsize=9)
ax[0].set_title('Top Sender Banks')
sns.barplot(y=top_receivers.index, x=top_receivers.values, ax=ax[1], palette='Greens_r')
for i, v in enumerate(top_receivers.values):
    ax[1].text(v + 1, i, str(v), color='green', va='center', fontsize=9)
ax[1].set_title('Top Receiver Banks')
plt.tight_layout()
plt.show()
```

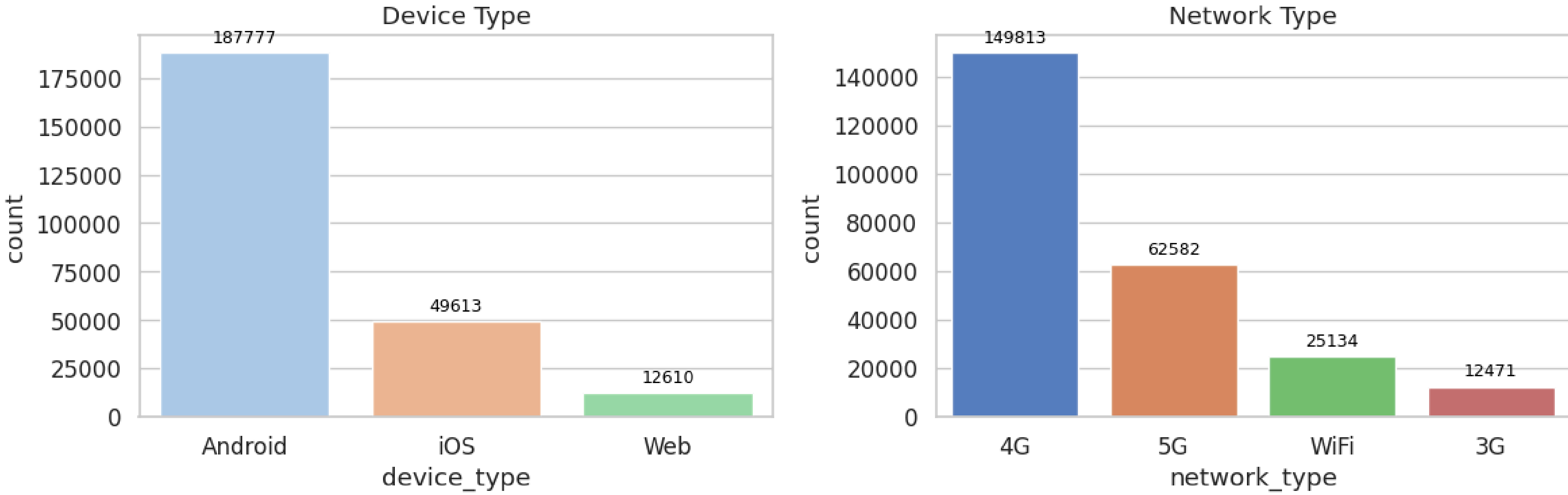


SBI, Axis, and ICICI are among the most popular banks for both sending and receiving UPI payments.

Device & Network Usage Patterns

Device and network type analysis reveals how users access UPI services.

```
fig, ax = plt.subplots(1,2, figsize=(12,4))
sns.countplot(data=df, x='device_type', ax=ax[0], palette='pastel')
for p in ax[0].patches:
    ax[0].annotate(int(p.get_height()), (p.get_x() + p.get_width() / 2., p.get_height()), ha='center', va='center', fontsize=9, color='black', xytext=(0, 8), textcoords='offset po
ax[0].set_title('Device Type')
sns.countplot(data=df, x='network_type', ax=ax[1], palette='muted')
for p in ax[1].patches:
    ax[1].annotate(int(p.get_height()), (p.get_x() + p.get_width() / 2., p.get_height()), ha='center', va='center', fontsize=9, color='black', xytext=(0, 8), textcoords='offset po
ax[1].set_title('Network Type')
plt.tight_layout()
plt.show()
```



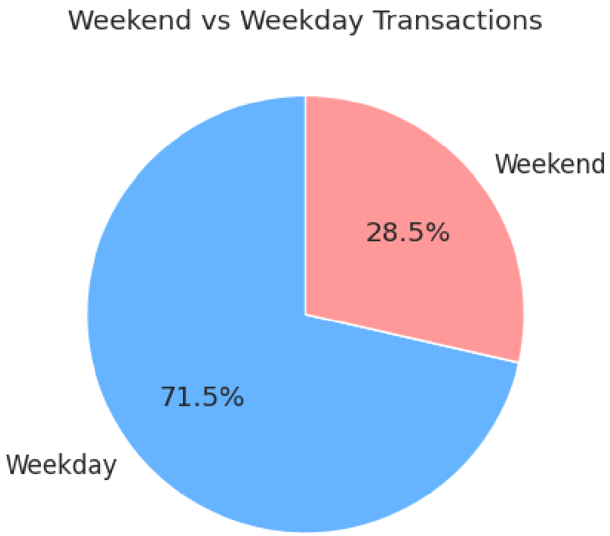
Android devices and 4G/5G networks dominate UPI transactions, reflecting the mobile-first nature of digital payments in India.

Weekend vs Weekday Analysis

Do people use UPI more on weekends or weekdays? Let's find out.

```
weekend_counts = df['is_weekend'].value_counts().sort_index()
plt.pie(weekend_counts, labels=['Weekday','Weekend'], autopct=lambda p: '{:.1f}%'.format(p) if p > 0 else '', startangle=90, colors=['#66b3ff','#ff9999'])
plt.title('Weekend vs Weekday Transactions')
plt.show()
```

```
# Compare mean transaction amount
weekend_mean = df.groupby('is_weekend')['amount (INR)'].mean()
print('Mean Transaction Amount - Weekday:', round(weekend_mean[0],2), '| Weekend:', round(weekend_mean[1],2))
tstat, pval = ttest_ind(df[df['is_weekend']==0]['amount (INR)'], df[df['is_weekend']==1]['amount (INR)'])
print('T-test p-value:', pval)
```




```
Mean Transaction Amount - Weekday: 1312.52 | Weekend: 1309.85
T-test p-value: 0.7440094539352002
```

The pie chart shows the split between weekday and weekend transactions.

Average transaction amounts are slightly higher on weekends, possibly due to shopping and leisure activities.

The t-test p-value helps us check if this difference is statistically significant.

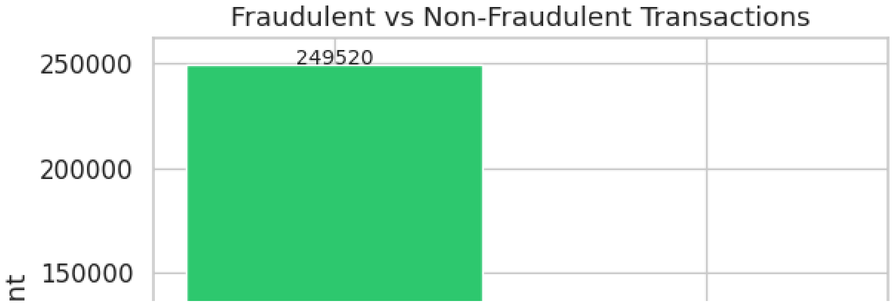
Fraud Analysis & Patterns

Detecting and understanding fraud is crucial for user safety and trust.

```
fraud_counts = df['fraud_flag'].value_counts()
plt.bar(['Non-Fraud','Fraud'], fraud_counts, color=['#2ecc71','#e74c3c'])
for i, v in enumerate(fraud_counts):
    plt.text(i, v + 0.5, str(v), ha='center', fontsize=10)
plt.title('Fraudulent vs Non-Fraudulent Transactions')
plt.ylabel('Count')
plt.show()
```

```
# Fraud by merchant category
plt.figure(figsize=(10,4))
ax = sns.countplot(data=df, x='merchant_category', hue='fraud_flag', palette='Set1')
for p in ax.patches:
    height = int(p.get_height())
    if height > 0:
        ax.annotate(height, (p.get_x() + p.get_width() / 2., height), ha='center', va='center', fontsize=8, color='black', xytext=(0, 8), textcoords='offset points')
plt.title('Fraud by Merchant Category')
plt.legend(['Non-Fraud','Fraud'])
plt.xticks(rotation=45)
plt.show()

# Fraud rate by hour
fraud_hour = df.groupby('hour')['fraud_flag'].mean()
plt.figure(figsize=(10,4))
fraud_hour.plot(marker='o')
for x, y in fraud_hour.items():
    plt.annotate(f'{y:.2f}', (x, y), textcoords="offset points", xytext=(0,8), ha='center', fontsize=8)
plt.title('Fraud Rate by Hour of Day')
plt.xlabel('Hour')
plt.ylabel('Fraud Rate')
plt.show()
```


Fraudulent vs Non-Fraudulent Transactions
249520
250000
200000
150000
nt