Loading The Dataset

In [1]:
```
import pandas as pd
df=pd.read_csv("E:\\R.P 2\\Data-Credit Card Transactions Fraud Detection 2019-2020\
df.head()
```

Out[1]:

	trans_date_trans_time	cc_num	merchant	category	amt	gender	
0	2019-01-01 12:47:00	6.041621e+10	fraud_Jones, Sawayn and Romaguera	misc_net	7.27	F	Wash
1	2019-01-02 08:44:00	6.041621e+10	fraud_Berge LLC	gas_transport	52.94	F	Wash
2	2019-01-02 08:47:00	6.041621e+10	fraud_Luettgen PLC	gas_transport	82.08	F	Wash
3	2019-01-02 12:38:00	6.041621e+10	fraud_Daugherty LLC	kids_pets	34.79	F	Wash
4	2019-01-02 13:10:00	6.041621e+10	fraud_Beier and Sons	home	27.18	F	Wash

5 rows × 24 columns

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1048575 entries, 0 to 1048574
Data columns (total 24 columns):
 #   Column                 Non-Null Count    Dtype
---  ------                 --------------    -----
 0   trans_date_trans_time  1048575 non-null  object
 1   cc_num                 1048575 non-null  float64
 2   merchant               1048575 non-null  object
 3   category               1048575 non-null  object
 4   amt                    1048575 non-null  float64
 5   gender                 1048575 non-null  object
 6   city                   1048575 non-null  object
 7   state                  1048575 non-null  object
 8   zip                    1048575 non-null  int64
 9   lat                    1048575 non-null  float64
 10  long                   1048575 non-null  float64
 11  city_pop               1048575 non-null  int64
 12  job                    1048575 non-null  object
 13  dob                    1048575 non-null  object
 14  unix_time              1048575 non-null  int64
 15  merch_lat              1048575 non-null  float64
 16  merch_long             1048575 non-null  float64
 17  is_fraud               1048575 non-null  int64
 18  hour                   1048575 non-null  int64
 19  day                    1048575 non-null  int64
 20  month                  1048575 non-null  int64
 21  weekday                1048575 non-null  int64
 22  time_gap               1048575 non-null  float64
 23  age                    1048575 non-null  int64
dtypes: float64(7), int64(9), object(8)
memory usage: 192.0+ MB
```

In [2]:
```
df.shape
```

Out[2]:
```
(1048575, 24)
```

In [3]:
```
num_cols = df.select_dtypes(include=['int64', 'float64'])
num_cols
```

Out[3]:

	cc_num	amt	zip	lat	long	city_pop	unix_time	merch_lat
0	6.041621e+10	7.27	82514	43.0048	-108.8964	1645	1325422035	43.974711
1	6.041621e+10	52.94	82514	43.0048	-108.8964	1645	1325493897	42.018766
2	6.041621e+10	82.08	82514	43.0048	-108.8964	1645	1325494056	42.961335
3	6.041621e+10	34.79	82514	43.0048	-108.8964	1645	1325507894	42.228227
4	6.041621e+10	27.18	82514	43.0048	-108.8964	1645	1325509846	43.321745
...	...	...	...	...	...	...	...	...
1048570	4.990000e+18	120.04	29127	34.1832	-81.5324	8333	1362874452	35.137752
1048571	4.990000e+18	17.52	61335	41.1730	-89.2187	532	1362876979	40.445215
1048572	4.990000e+18	3.54	61335	41.1730	-89.2187	532	1362883539	41.562968
1048573	4.990000e+18	172.50	29127	34.1832	-81.5324	8333	1362895897	34.218730
1048574	4.990000e+18	16.20	61335	41.1730	-89.2187	532	1362905882	40.548748

1048575 rows × 16 columns

In [4]:

```
num_cols.describe()
```

Out[4]:

	cc_num	amt	zip	lat	long	city_p
count	1.048575e+06	1.048575e+06	1.048575e+06	1.048575e+06	1.048575e+06	1.048575e+
mean	4.171800e+17	7.027910e+01	4.880159e+04	3.853336e+01	-9.022626e+01	8.905776e+
std	1.308893e+18	1.599518e+02	2.689804e+04	5.076852e+00	1.375858e+01	3.024351e+
min	6.041621e+10	1.000000e+00	1.257000e+03	2.002710e+01	-1.656723e+02	2.300000e+
25%	1.800000e+14	9.640000e+00	2.623700e+04	3.462050e+01	-9.679800e+01	7.430000e+
50%	3.520000e+15	4.745000e+01	4.817400e+04	3.935430e+01	-8.747690e+01	2.456000e+
75%	4.640000e+15	8.305000e+01	7.204200e+04	4.194040e+01	-8.015800e+01	2.032800e+
max	4.990000e+18	2.894890e+04	9.978300e+04	6.669330e+01	-6.795030e+01	2.906700e+

E D A

Target Distribution (1)

In [9]:
```
#Count of Fraud and Non-Fraud
df['is_fraud'].value_counts()
```

Out[9]:
```
is_fraud
0    1042569
1       6006
Name: count, dtype: int64
```

In [10]:
```
df['is_fraud'].value_counts(normalize=True) * 100
```

Out[10]:
```
is_fraud
0    99.427223
1     0.572777
Name: proportion, dtype: float64
```

- **Insights:Fraudulent transactions constitute a very small proportion of total transactions. Class Imbalance is confirmed.**

Transaction Amount – Fraud vs Non-Fraud (1)

In [11]:
```
df.groupby('is_fraud')['amt'].describe()
```

Out[11]:

is_fraud	count	mean	std	min	25%	50%	75%	max
0	1042569.0	67.627445	153.695606	1.00	9.6000	47.220	82.47	28948.90
1	6006.0	530.573492	391.333069	1.18	241.5775	391.165	901.95	1371.81

- **insights:Fraudulent transactions generally involve much higher transaction amounts compared to genuine transactions. While most genuine transactions are of low value, fraudulent transactions tend to occur in a higher amount range.**

Time Gap Analysis (2)

In [12]:
```
df.groupby('is_fraud')['time_gap'].describe()
```

Out[12]:

is_fraud	count	mean	std	min	25%	50%	75%	max
0	1042569.0	187.480501	421.411011	0.0	15.0	52.0	176.0	20095.0
1	6006.0	126.903430	305.115645	0.0	10.0	29.0	86.0	8388.0

- **Fraudulent transactions tend to occur within shorter time intervals compared to genuine transactions. This indicates that fraud often happens as a quick sequence of multiple transactions.**

To test whether the time gap between transactions differs for fraudulent and genuine transactions (2)

In [13]:
```
from scipy.stats import mannwhitneyu

fraud_gap = df[df['is_fraud'] == 1]['time_gap']
nonfraud_gap = df[df['is_fraud'] == 0]['time_gap']

stat, p = mannwhitneyu(fraud_gap, nonfraud_gap, alternative='two-sided')

print("Mann-Whitney U Statistic:", stat)
print("p-value:", p)
```

```
Mann-Whitney U Statistic: 2597440318.0
p-value: 4.172204050961408e-115
```

Since the p-value < level of significance (0.05),

- we reject the null hypothesis and conclude that there is a statistically significant difference in the time gap between fraudulent and genuine transactions.
- This indicates that fraudulent transactions tend to occur with different transaction timing patterns compared to normal transactions. In particular, fraud transactions are more likely to happen with shorter time gaps, suggesting rapid or suspicious transaction behaviour.
- Therefore, time gap between transactions is an important indicator for identifying potential credit card fraud.

Hour-wise Fraud Pattern (2)

In [14]:
```
df.groupby('hour')['is_fraud'].mean()
```

Out[14]:
```
hour
0     0.015198
1     0.015450
2     0.014648
3     0.014093
4     0.001178
5     0.001407
6     0.000845
7     0.001259
8     0.001343
9     0.001147
10    0.000905
11    0.000851
12    0.001063
13    0.001227
14    0.001427
15    0.001208
16    0.001243
17    0.001192
18    0.001049
19    0.001092
20    0.000950
21    0.001117
22    0.028224
23    0.027933
Name: is_fraud, dtype: float64
```

- **Fraudulent transactions are more likely to occur during late night hours, especially between 10 PM and 12 AM, while daytime transactions show significantly lower fraud rates.**

Day-wise / Weekday Pattern (2)

In [15]:
```
df.groupby('weekday')['is_fraud'].mean()
```

Out[15]:
```
weekday
0    0.004716
1    0.006084
2    0.006135
3    0.006328
4    0.007098
5    0.006184
6    0.004801
Name: is_fraud, dtype: float64
```

- **Fraudulent transactions are more frequent towards the end of the week, especially on Fridays, while the beginning and end of the week show lower fraud occurrence.**

Category-wise Fraud (3)

In [16]:
```
category_fraud_count = (
    df[df['is_fraud'] == 1]
    .groupby('category')
    .size()
    .sort_values(ascending=False))

print(category_fraud_count)
```

```
category
grocery_pos       1396
shopping_net      1375
misc_net           742
shopping_pos       662
gas_transport      498
kids_pets          194
misc_pos           194
entertainment      185
personal_care      172
home               153
food_dining        121
grocery_net        110
health_fitness     104
travel             100
dtype: int64
```

In [17]:
```
#proportion
df.groupby('category')['is_fraud'].mean().sort_values(ascending=False)
```

Out[17]:
```
category
shopping_net      0.017427
misc_net          0.014526
grocery_pos       0.013973
shopping_pos      0.007016
gas_transport     0.004679
travel            0.003046
misc_pos          0.003008
grocery_net       0.002996
entertainment     0.002435
personal_care     0.002340
kids_pets         0.002122
food_dining       0.001634
home              0.001536
health_fitness    0.001499
Name: is_fraud, dtype: float64
```

- **Fraudulent transactions are significantly more common in online shopping categories compared to point-of-sale transactions, indicating higher risk in card-not-present environments.**

In [18]:
```
import numpy as np
```

Distance calculate Function

In [19]:
```
def haversine(lat1, lon1, lat2, lon2):
    R = 6371  # Earth radius in KM

    lat1, lon1, lat2, lon2 = map(np.radians, [lat1, lon1, lat2, lon2])

    dlat = lat2 - lat1
    dlon = lon2 - lon1

    a = np.sin(dlat/2)**2 + np.cos(lat1)*np.cos(lat2)*np.sin(dlon/2)**2
    c = 2 * np.arcsin(np.sqrt(a))

    return R * c
```

distance_km column

In [20]:
```
df['distance_km'] = haversine(
    df['lat'],
    df['long'],
    df['merch_lat'],
    df['merch_long']
)
```

In [21]:
```
df["distance_km"].head()
```

Out[21]:
```
0    127.606239
1    110.308921
2     21.787261
3     87.204215
4     74.212965
Name: distance_km, dtype: float64
```

Distance vs Fraud

In [22]:
```
df.groupby('is_fraud')['distance_km'].describe()
```

Out[22]:

	count	mean	std	min	25%	50%	75%	
is_fraud								
0	1042569.0	76.101398	29.114996	0.022255	55.330371	78.212461	98.480836	152.1
1	6006.0	76.237524	28.698942	0.738769	55.623008	77.869499	98.372391	144.52

- The average distance for fraudulent and non-fraudulent transactions is almost the same, suggesting that transaction distance alone is not a strong indicator of fraud.

Correlation Check

In [23]:
```
df[['amt','time_gap','distance_km','is_fraud']].corr()
```

Out[23]:

	amt	time_gap	distance_km	is_fraud
amt	1.000000	-0.003498	-0.001679	0.218417
time_gap	-0.003498	1.000000	0.001569	-0.010862
distance_km	-0.001679	0.001569	1.000000	0.000353
is_fraud	0.218417	-0.010862	0.000353	1.000000

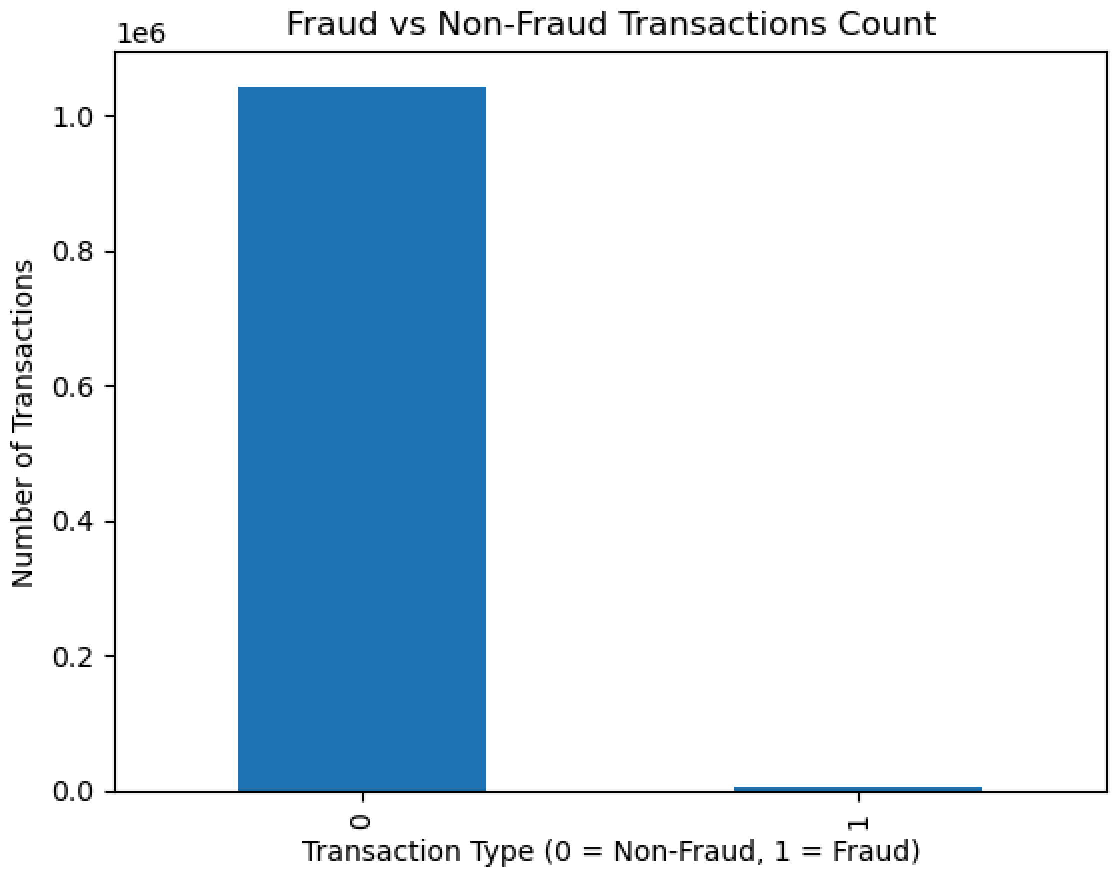
- Transaction amount shows a moderate positive correlation with fraud, indicating higher amounts are more likely to be fraudulent. Time gap and transaction distance have negligible correlation with fraud, suggesting they are not strong indicators on their own.

📊 EDA – Graphs

Fraud vs Non-Fraud Count (Class Imbalance) (1)

In [14]:
```
import matplotlib.pyplot as plt

df['is_fraud'].value_counts().plot(kind='bar')
plt.title('Fraud vs Non-Fraud Transactions Count')
plt.xlabel('Transaction Type (0 = Non-Fraud, 1 = Fraud)')
plt.ylabel('Number of Transactions')
plt.show()
```

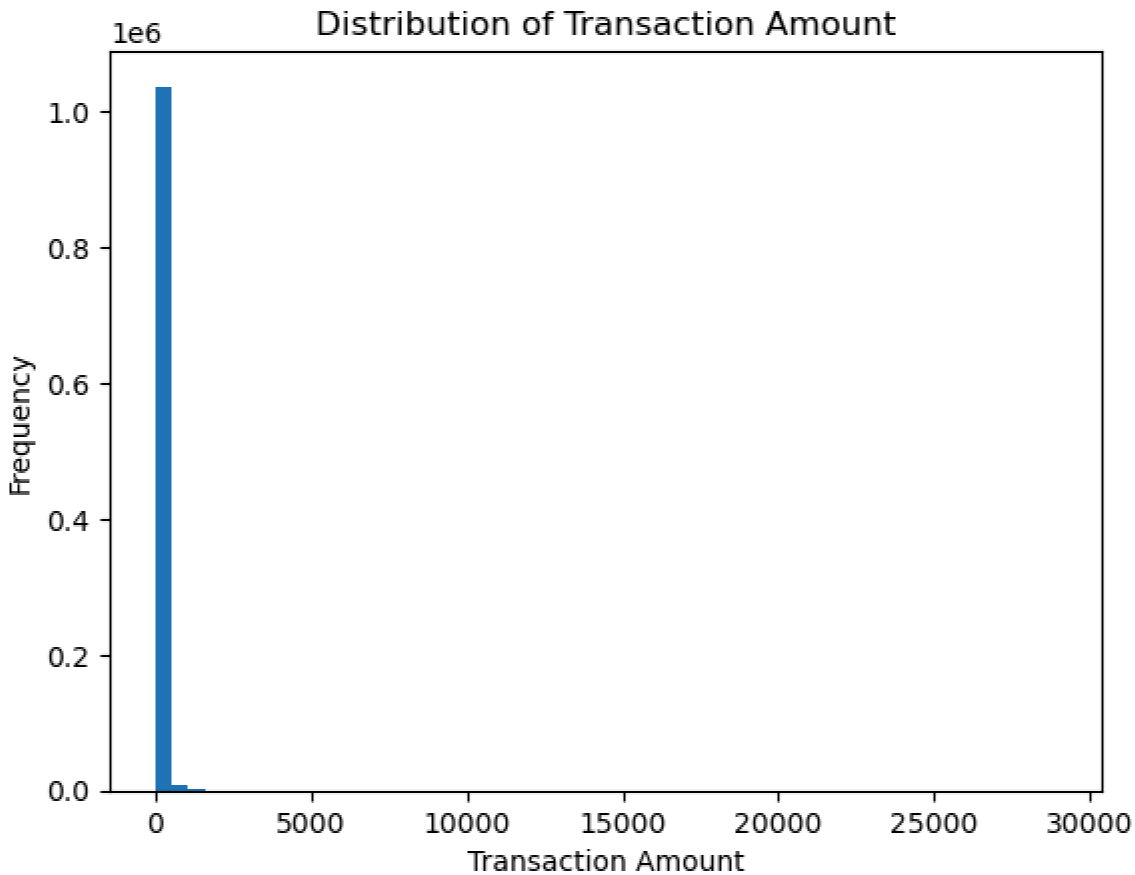


- **The dataset is highly imbalanced, with fraudulent transactions forming a very small proportion of total transactions.**

Transaction Amount Distribution (1)

(a) Histogram

In [15]:
```
df['amt'].plot(kind='hist', bins=55)
plt.title('Distribution of Transaction Amount')
plt.xlabel('Transaction Amount')
plt.ylabel('Frequency')
plt.show()
```

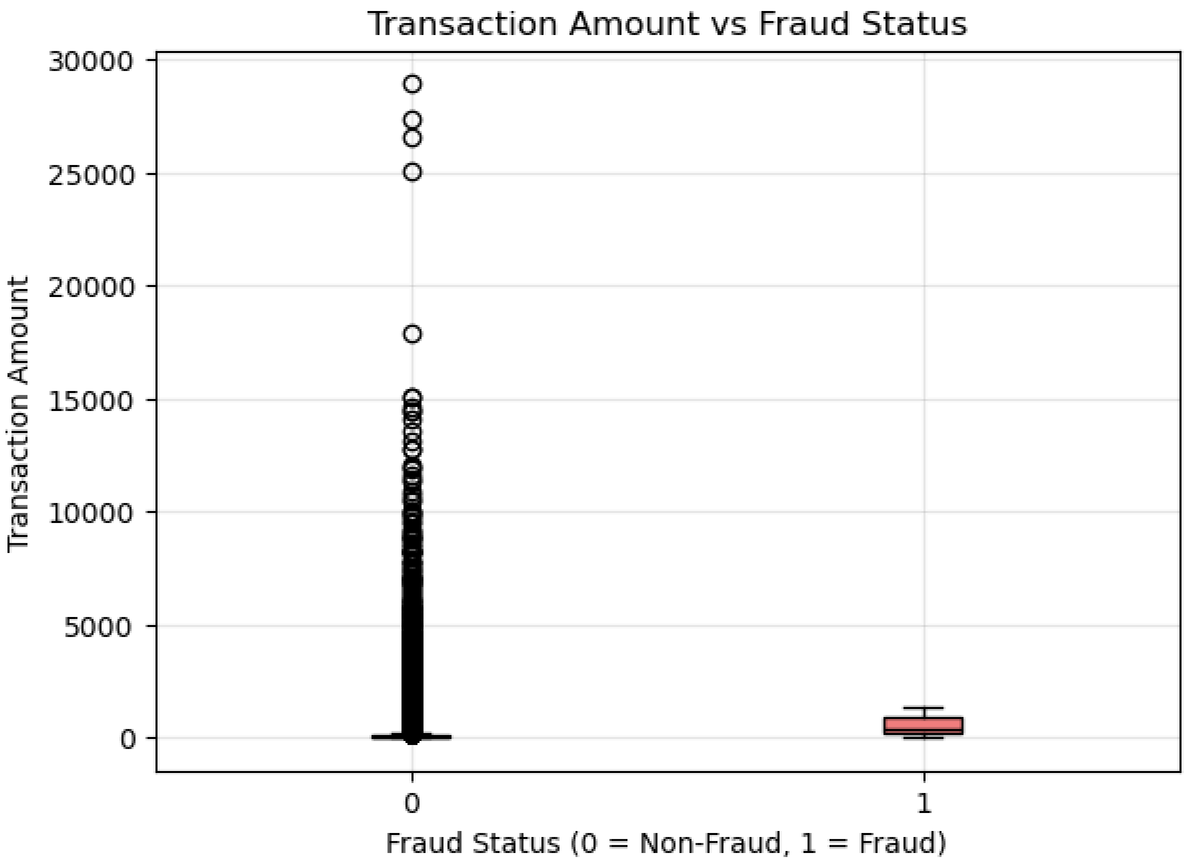


Amount vs Fraud (Boxplot)(1)

In [7]:

```
import matplotlib.pyplot as plt
plt.figure(figsize=(7,5))
df.boxplot(
    column='amt',
    by='is_fraud',
    patch_artist=True,
    boxprops=dict(facecolor='lightcoral'),
    medianprops=dict(color='black'),
    whiskerprops=dict(color='black'),
    capprops=dict(color='black')
)
plt.title('Transaction Amount vs Fraud Status')
plt.suptitle('')
plt.xlabel('Fraud Status (0 = Non-Fraud, 1 = Fraud)')
plt.ylabel('Transaction Amount')
plt.grid(alpha=0.3)
plt.show()
```

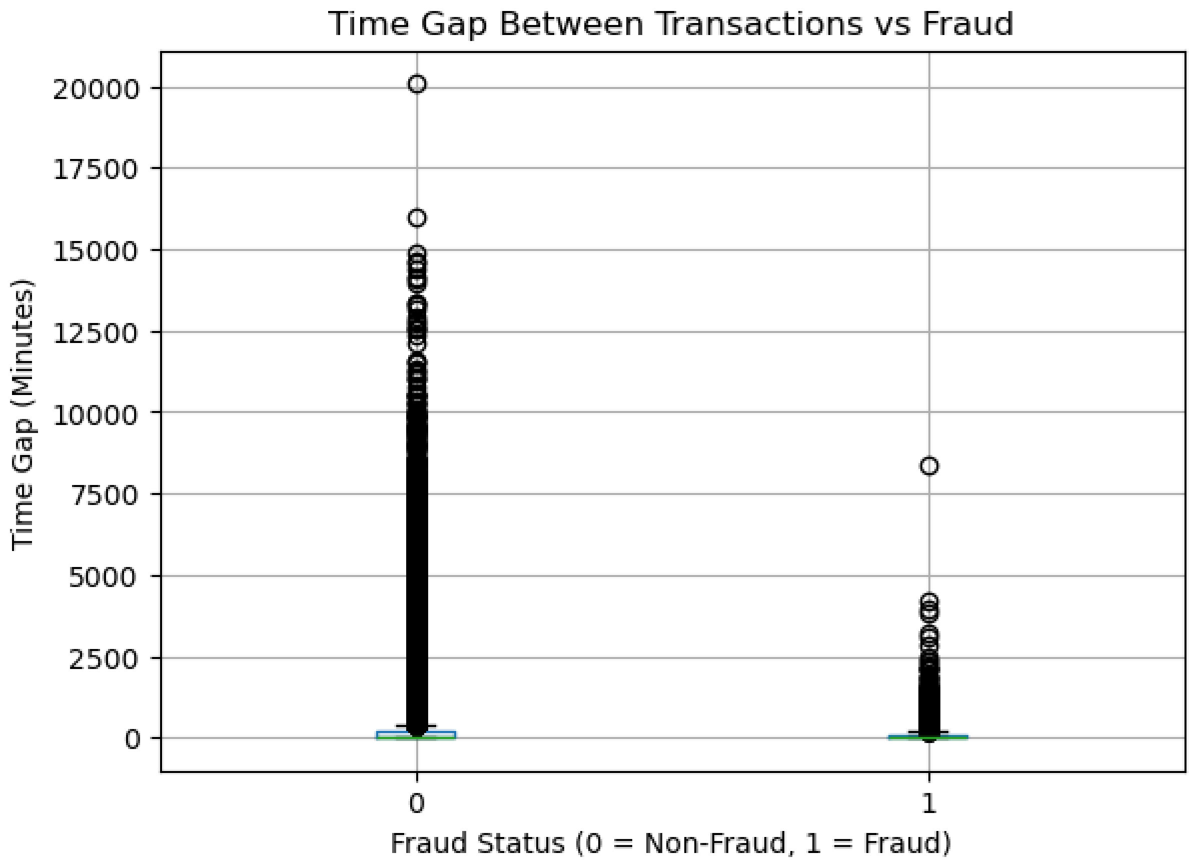
```
<Figure size 700x500 with 0 Axes>
```



- Fraudulent transactions tend to involve higher amounts compared to legitimate ones. While most non-fraud transactions are low in value, fraud cases include several high-amount outliers. This means transaction amount is a useful indicator for spotting potential fraud.

Time Gap vs Fraud (2)

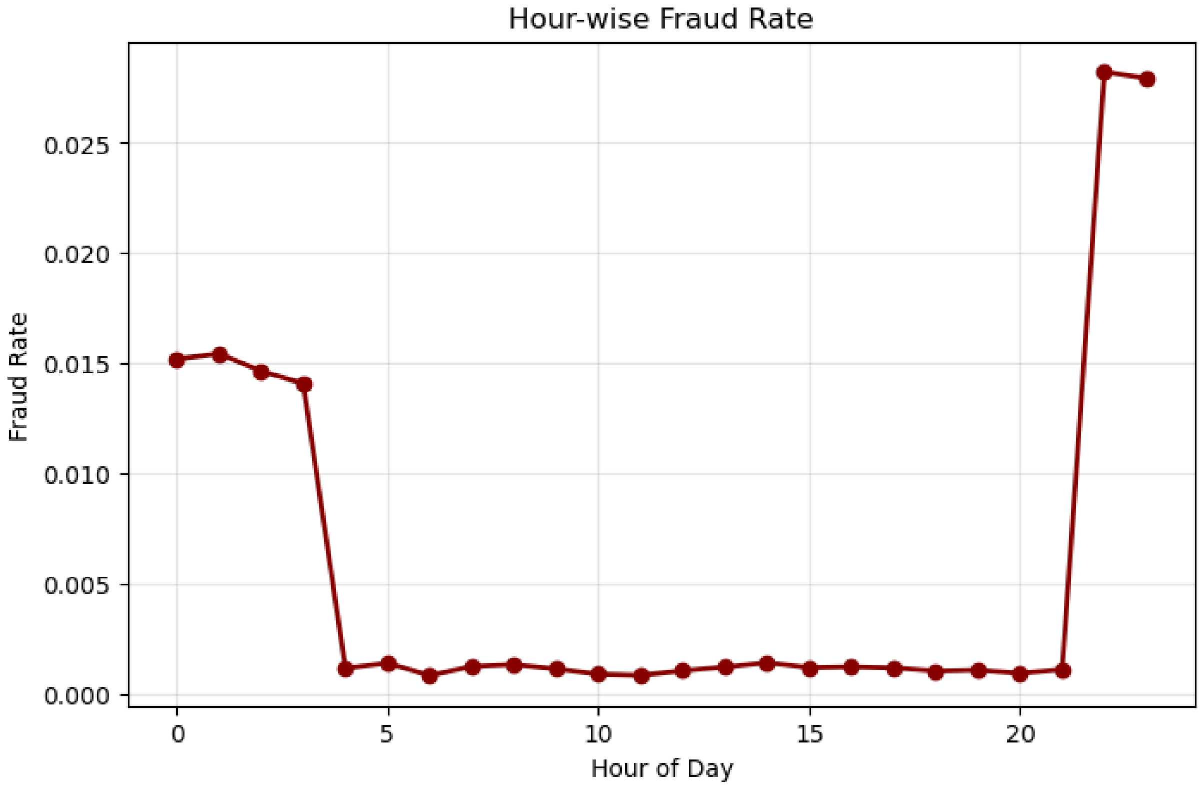
In [24]:
```
df.boxplot(column='time_gap', by='is_fraud')
plt.title('Time Gap Between Transactions vs Fraud')
plt.suptitle('')
plt.xlabel('Fraud Status (0 = Non-Fraud, 1 = Fraud)')
plt.ylabel('Time Gap (Minutes)')
plt.show()
```



- **Fraudulent transactions often occur with shorter time gaps between them compared to legitimate ones. This suggests fraudsters may act quickly in succession, while normal transactions are more spread out. Time between transactions could help flag suspicious activity.**

Hour-wise Fraud Pattern (2)

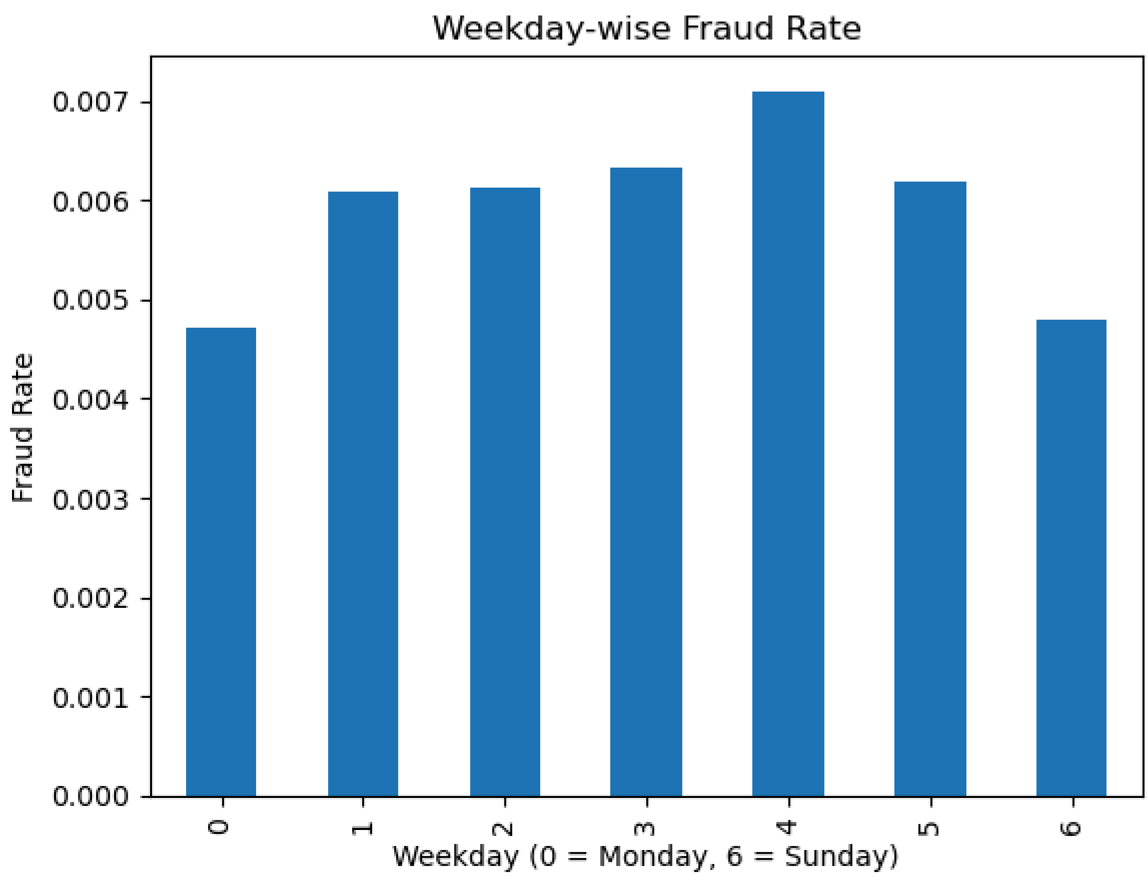
In [26]:
```
plt.figure(figsize=(8,5))
df.groupby('hour')['is_fraud'].mean().plot(
    kind='line',
    marker='o',
    color='darkred',     # 🔴 color added
    linewidth=2
)
plt.title('Hour-wise Fraud Rate')
plt.xlabel('Hour of Day')
plt.ylabel('Fraud Rate')
plt.grid(alpha=0.3)
plt.show()
```



- **Fraud happens more during certain hours, especially late at night and early morning, with lower rates during daytime and evening hours. This pattern suggests fraudulent activity peaks when monitoring may be lower or less expected.**

Weekday-wise Fraud Pattern (2)

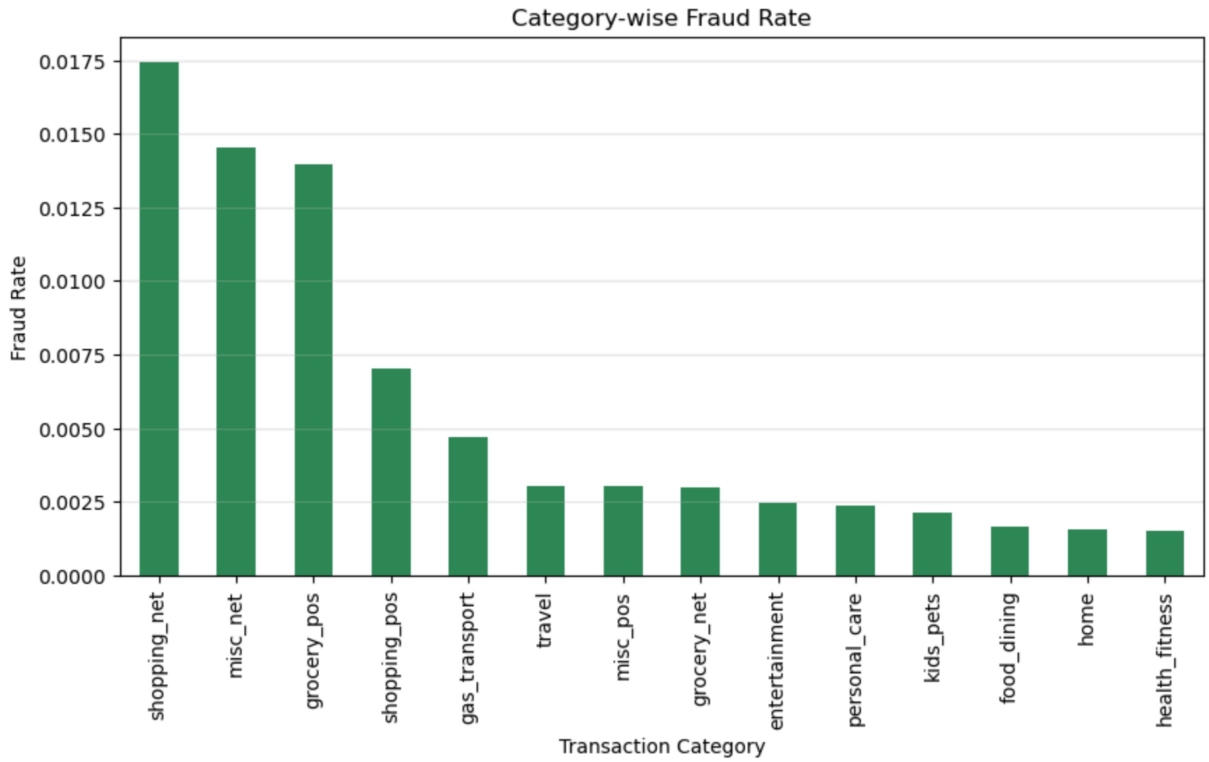
In [19]:
```
df.groupby('weekday')['is_fraud'].mean().plot(kind='bar')
plt.title('Weekday-wise Fraud Rate')
plt.xlabel('Weekday (0 = Monday, 6 = Sunday)')
plt.ylabel('Fraud Rate')
plt.show()
```



- **Fraud occurs slightly more often on weekends, especially Sunday, compared to weekdays. Weekday fraud is lower and more stable. This suggests fraudsters may take advantage of lower banking activity on weekends.**

Category-wise Fraud Rate (3)

In [27]:
```
plt.figure(figsize=(10,5))
df.groupby('category')['is_fraud'].mean().sort_values(ascending=False).plot(
    kind='bar',
    color='seagreen'     # 🟢 color added
)
plt.title('Category-wise Fraud Rate')
plt.xlabel('Transaction Category')
plt.ylabel('Fraud Rate')
plt.xticks(rotation=90)
plt.grid(axis='y', alpha=0.3)
plt.show()
```



In [21]:

```
fraud_rate = df.groupby('category')['is_fraud'].mean()

high_risk = fraud_rate.sort_values(ascending=False).head(5)
low_risk  = fraud_rate.sort_values().head(5)

print("high risk:", high_risk)
print("low risk:", low_risk)
```

```
high risk: category
shopping_net     0.017427
misc_net         0.014526
grocery_pos      0.013973
shopping_pos     0.007016
gas_transport    0.004679
Name: is_fraud, dtype: float64
low risk: category
health_fitness    0.001499
home              0.001536
food_dining       0.001634
kids_pets         0.002122
personal_care     0.002340
Name: is_fraud, dtype: float64
```

- **Some shopping and online purchase categories have a higher fraud rate than others. Online shopping and miscellaneous net purchases are riskier, while in-person grocery and gas transactions are safer. This helps focus fraud checks on high-risk categories.**

Correlation Heatmap

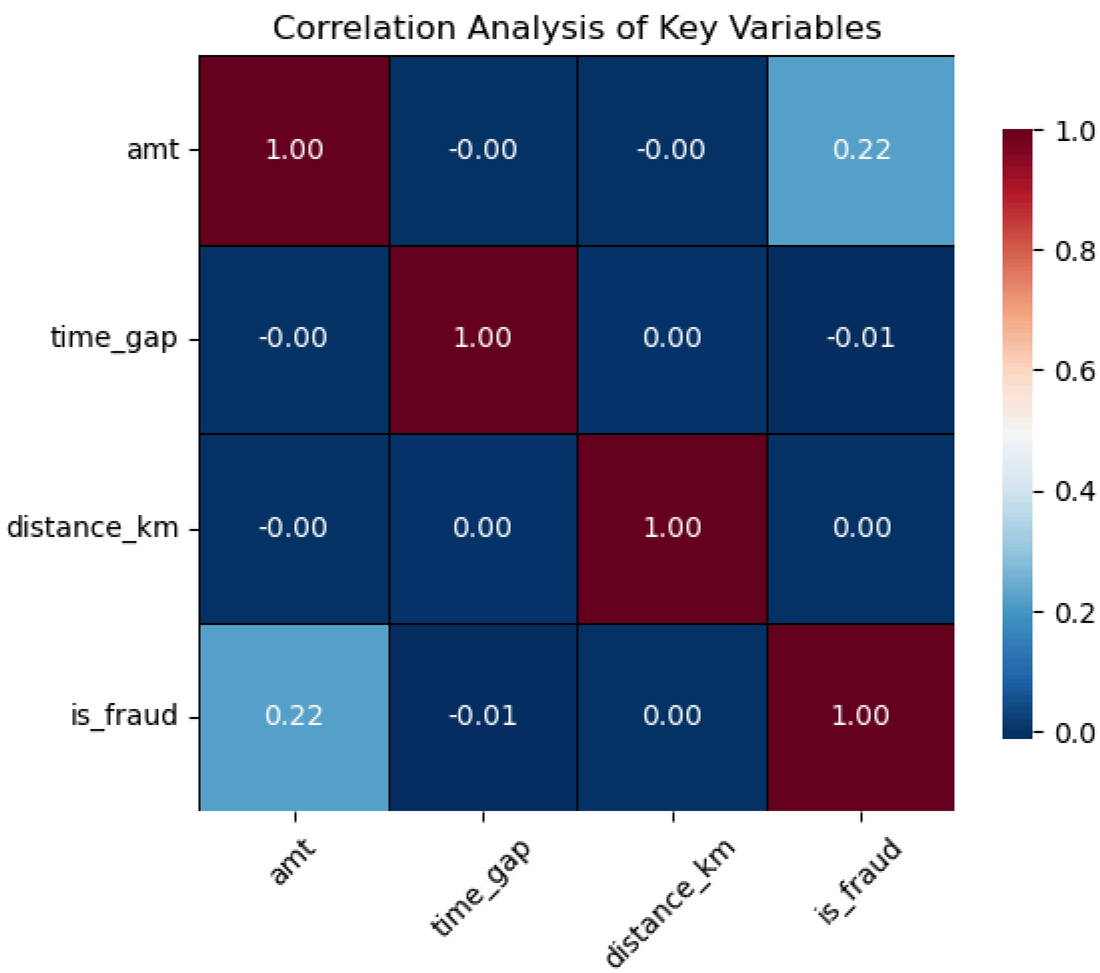
In [25]:
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(6,5))

corr = df[['amt','time_gap','distance_km','is_fraud']].corr()

sns.heatmap(
    corr,
    annot=True,
    fmt=".2f",
    cmap="RdBu_r",
    linewidths=0.5,
    linecolor="black",
    square=True,
    cbar_kws={"shrink": 0.8}
)

plt.title("Correlation Analysis of Key Variables", fontsize=12)
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()
```



- **The correlation matrix shows that is_fraud has a weak negative link with time_gap and distance_km, meaning fraud is slightly more likely when less time passes between transactions and when the distance is shorter. However, none of the variables are strongly correlated with fraud on their own.**

Noramality Check for time_gap variable

In [7]:
```
from scipy.stats import shapiro

# Take random samples (Shapiro is not suitable for very large data)
fraud_sample = df[df['is_fraud'] == 1]['time_gap'].sample(5000, random_state=42)
nonfraud_sample = df[df['is_fraud'] == 0]['time_gap'].sample(5000, random_state=42)

# Shapiro-Wilk Test
stat_fraud, p_fraud = shapiro(fraud_sample)
stat_nonfraud, p_nonfraud = shapiro(nonfraud_sample)

print("Fraud Time Gap p-value:", p_fraud)
print("Non-Fraud Time Gap p-value:", p_nonfraud)
```

```
Fraud Time Gap p-value: 7.534054174248599e-84
Non-Fraud Time Gap p-value: 3.9808530691501024e-84
```

Since the p-value < level of significance (0.05),

- time_gap data is Non Normal

In [ ]: