Financial Fraud Analysis

Import Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_scc
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier
```

Load DataSet

In [2]:
```
df = pd.read_csv("C:/Users/ankit/OneDrive/Desktop/Projects/Financial Fraud/finan
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   transaction_id     10000 non-null  int64
 1   user_id            10000 non-null  int64
 2   amount             10000 non-null  float64
 3   transaction_type   10000 non-null  object
 4   merchant_category  10000 non-null  object
 5   country            10000 non-null  object
 6   hour               10000 non-null  int64
 7   device_risk_score  10000 non-null  float64
 8   ip_risk_score      10000 non-null  float64
 9   is_fraud           10000 non-null  int64
dtypes: float64(3), int64(4), object(3)
memory usage: 781.4+ KB
```

In [4]:
```
df.head()
```

Out[4]:

	transaction_id	user_id	amount	transaction_type	merchant_category	country
0	9608	363	4922.587542	ATM	Travel	TR
1	456	692	48.018303	QR	Food	US
2	4747	587	136.881960	Online	Travel	TR
3	6934	445	80.534719	POS	Clothing	TR
4	1646	729	120.041158	Online	Grocery	FR

In [5]:
```
df.tail()
```

Out[5]:

	transaction_id	user_id	amount	transaction_type	merchant_category	country
9995	1076	482	58.366442	POS	Clothing	DE
9996	4995	904	139.502160	POS	Travel	DE
9997	3485	527	71.012122	Online	Travel	TR
9998	7922	771	21.031405	QR	Grocery	UK
9999	6451	429	54.028632	ATM	Electronics	DE

Size of data

In [6]:
```
df.dtypes
```

Out[6]:
```
transaction_id         int64
user_id                int64
amount               float64
transaction_type      object
merchant_category     object
country               object
hour                   int64
device_risk_score    float64
ip_risk_score        float64
is_fraud               int64
dtype: object
```

Field Information

In [7]:
```
df.columns
```

Out[7]:
```
Index(['transaction_id', 'user_id', 'amount', 'transaction_type',
       'merchant_category', 'country', 'hour', 'device_risk_score',
       'ip_risk_score', 'is_fraud'],
      dtype='object')
```

Missing values and Duplicates

In [8]:
```
print("Missing values per column:")
print(df.isnull().sum())

print("\nNumber of duplicate rows:", df.duplicated().sum())
```

```
Missing values per column:
transaction_id       0
user_id              0
amount               0
transaction_type     0
merchant_category    0
country              0
hour                 0
device_risk_score    0
ip_risk_score        0
is_fraud             0
dtype: int64

Number of duplicate rows: 0
```

In [9]:
```
df.describe().T
```

Out[9]:

	count	mean	std	min	25%	50%
transaction_id	10000.0	4999.500000	2886.895680	0.000000	2499.750000	4999.500000
user_id	10000.0	500.058700	288.328495	0.000000	247.000000	503.000000
amount	10000.0	178.142763	531.647950	1.000000	65.084753	101.686510
hour	10000.0	14.247100	5.347383	0.000000	10.000000	14.000000
device_risk_score	10000.0	0.183773	0.177381	0.000030	0.075721	0.156583
ip_risk_score	10000.0	0.184669	0.175772	0.000009	0.077762	0.158290
is_fraud	10000.0	0.050000	0.217956	0.000000	0.000000	0.000000

In [10]:
```
df.select_dtypes(include=np.number).corr()
```

Out[10]:

	transaction_id	user_id	amount	hour	device_risk_score	ip_ri
transaction_id	1.000000	-0.001360	0.242245	-0.070046	0.332211	(
user_id	-0.001360	1.000000	-0.008333	-0.022854	0.007316	(
amount	0.242245	-0.008333	1.000000	-0.100818	0.554977	(
hour	-0.070046	-0.022854	-0.100818	1.000000	-0.149832	-(
device_risk_score	0.332211	0.007316	0.554977	-0.149832	1.000000	(
ip_risk_score	0.332628	0.004433	0.549554	-0.161670	0.757978	'
is_fraud	0.377492	0.006165	0.638435	-0.181448	0.871989	(

Check the number of legitimate and fraudulent transactions and fraud ratio

In [11]:
```
# Count of fraud vs legitimate transactions
print(df['is_fraud'].value_counts())

# Fraud ratio
fraud_ratio = df['is_fraud'].mean()
print("Fraud ratio:", fraud_ratio)
```

```
is_fraud
0    9500
1     500
Name: count, dtype: int64
Fraud ratio: 0.05
```

Basic statistics for numeric columns and compare fraud vs legitimate transactions

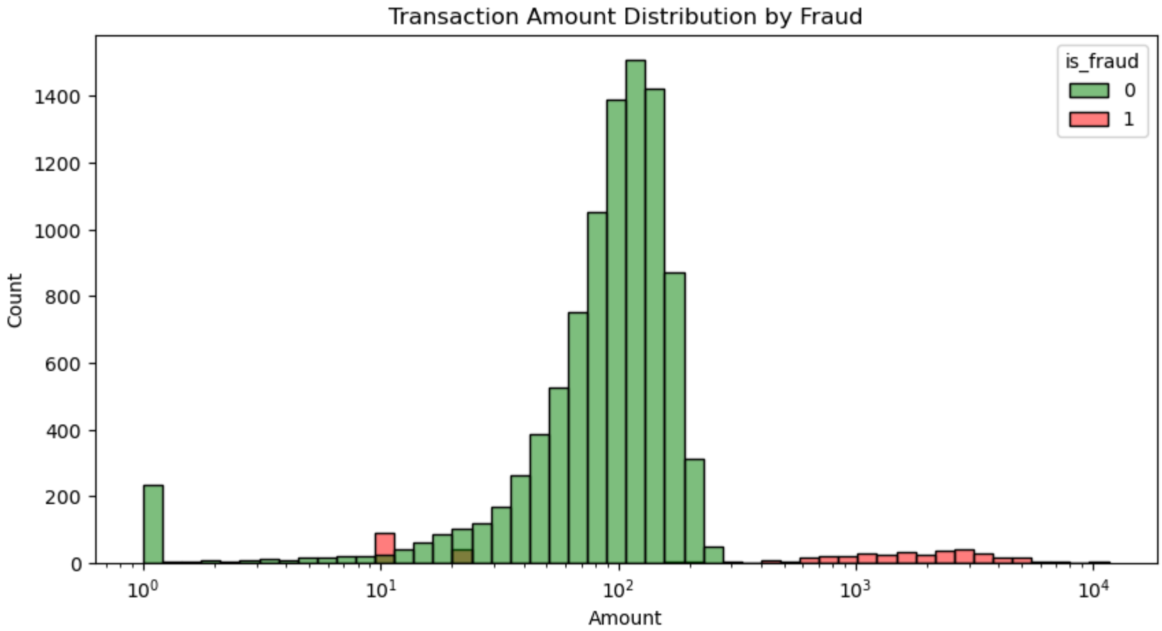
In [12]:
```
# Describe numeric columns
print(df[['amount', 'hour', 'device_risk_score', 'ip_risk_score']].describe())

# Group by fraud
print(df.groupby('is_fraud')[['amount', 'hour']].mean())
```

```
             amount          hour  device_risk_score  ip_risk_score
count  10000.000000  10000.000000       10000.000000   10000.000000
mean     178.142763     14.247100           0.183773       0.184669
std      531.647950      5.347383           0.177381       0.175772
min        1.000000      0.000000           0.000030       0.000009
25%       65.084753     10.000000           0.075721       0.077762
50%      101.686510     14.000000           0.156583       0.158290
75%      138.280872     19.000000           0.234939       0.236968
max    11628.213881     23.000000           0.998737       0.999603
               amount       hour
is_fraud
0          100.277751  14.469684
1         1657.577984  10.018000
```

Distribution of transaction amounts for fraud and legitimate transactions

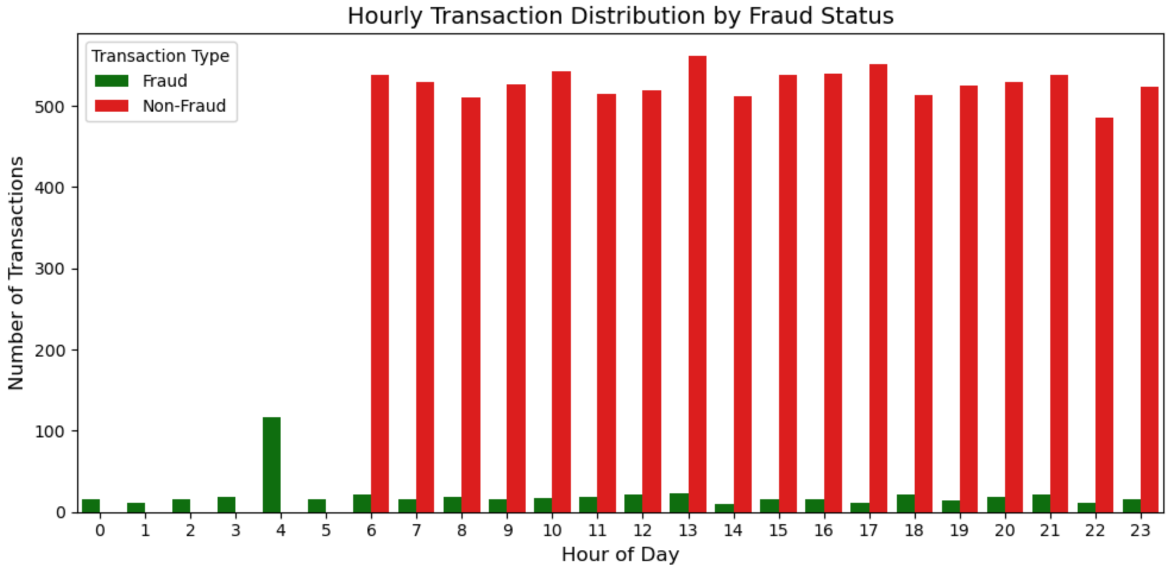
In [13]:
```
# Amount distribution by fraud
plt.figure(figsize=(10,5))
sns.histplot(data=df, x='amount', hue='is_fraud', bins=50, log_scale=True, palet
plt.title("Transaction Amount Distribution by Fraud")
plt.xlabel("Amount")
plt.ylabel("Count")
plt.show()
```

```
C:\Users\ankit\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarnin
g: use_inf_as_na option is deprecated and will be removed in a future version. Co
nvert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



Number of transactions per hour, separated by fraud and legitimate labels

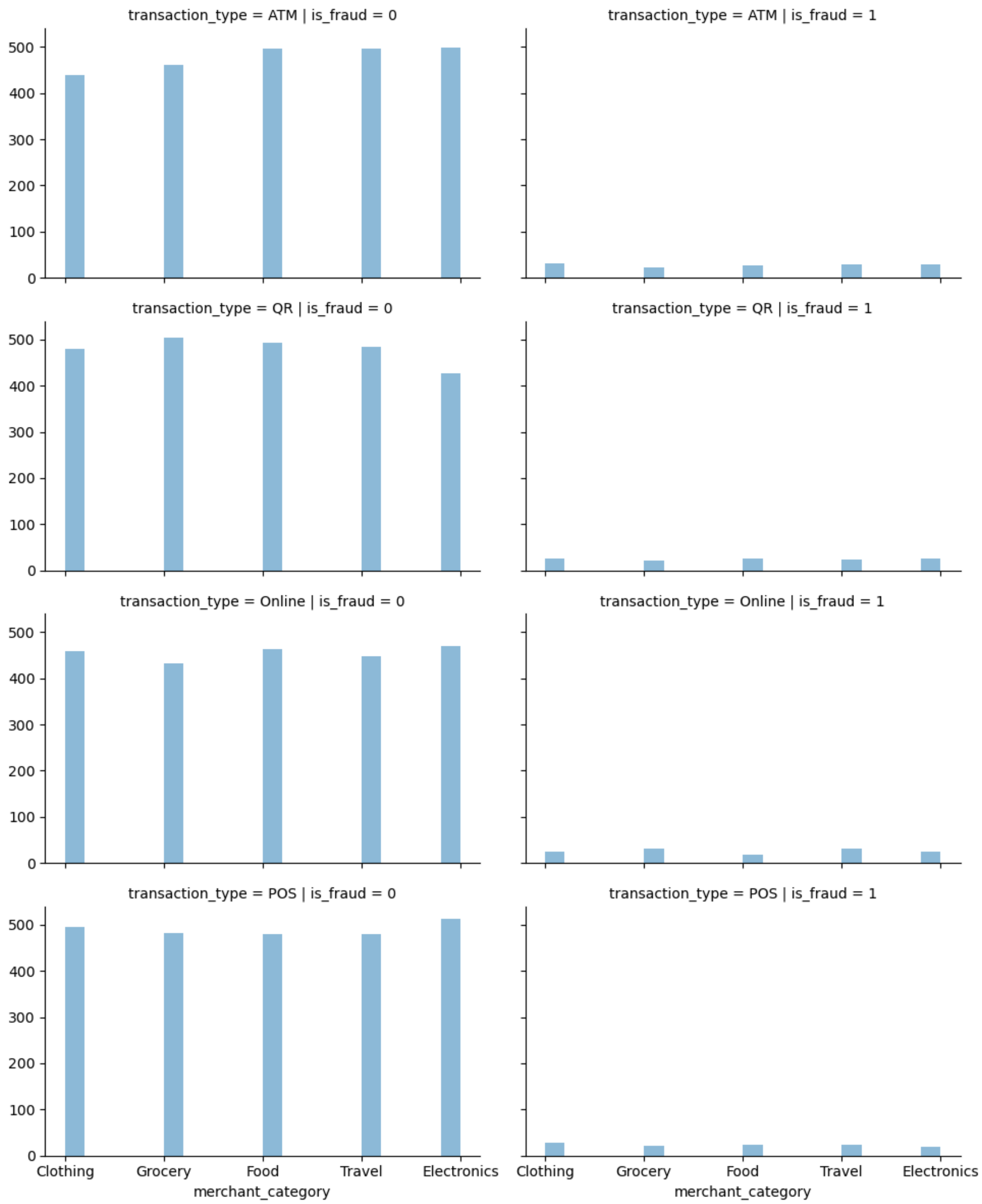
In [14]:
```
df['is_fraud_label'] = df['is_fraud'].map({0: 'Non-Fraud', 1: 'Fraud'})

# Plot
plt.figure(figsize=(10, 5))

ax = sns.countplot(
    data=df,
    x='hour',
    hue='is_fraud_label',
    palette=['green', 'red']
)

# Titles and Labels
plt.title("Hourly Transaction Distribution by Fraud Status", fontsize=14)
plt.xlabel("Hour of Day", fontsize=12)
plt.ylabel("Number of Transactions", fontsize=12)


ax.legend(title="Transaction Type")

plt.tight_layout()
plt.show()
```



Fraud vs Non-Fraud Distribution Across Transaction Types and Merchant Categories

In [15]:
```
grid = sns.FacetGrid(df, col='is_fraud', row='transaction_type', aspect=1.6)
grid.map(plt.hist, 'merchant_category', alpha=.5, bins=20)
grid.add_legend()
```

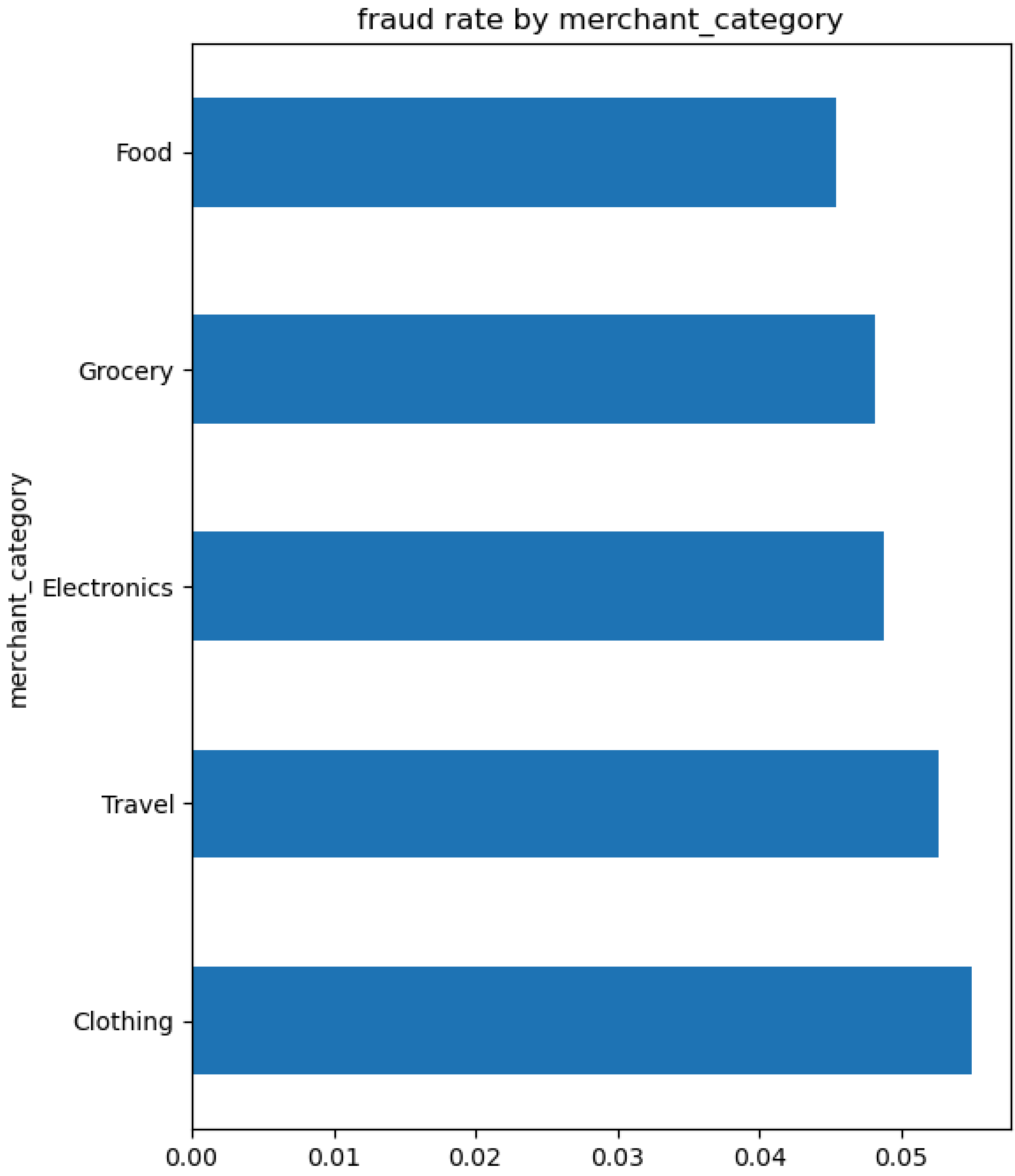
Out[15]: <seaborn.axisgrid.FacetGrid at 0x25188367550>



Fraud Rate by Merchant Category

In [16]:

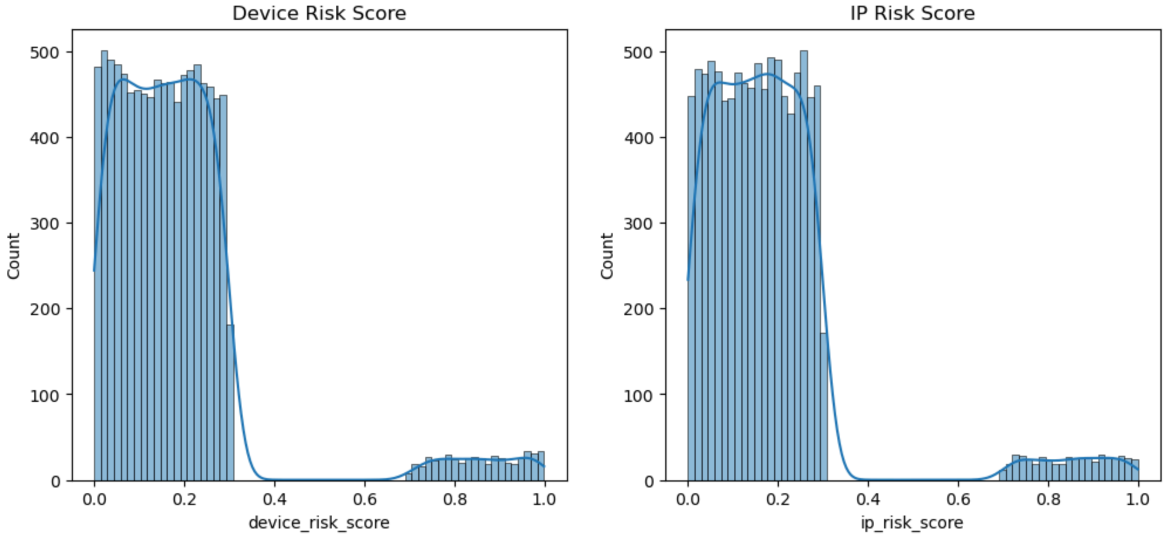
```
fraud_by_cat = df.groupby('merchant_category')['is_fraud'].mean().sort_values(as
fraud_by_cat.plot.barh(figsize=(6,8))
plt.title('fraud rate by merchant_category')
plt.show()
```



Distribution of Device and IP Risk Scores

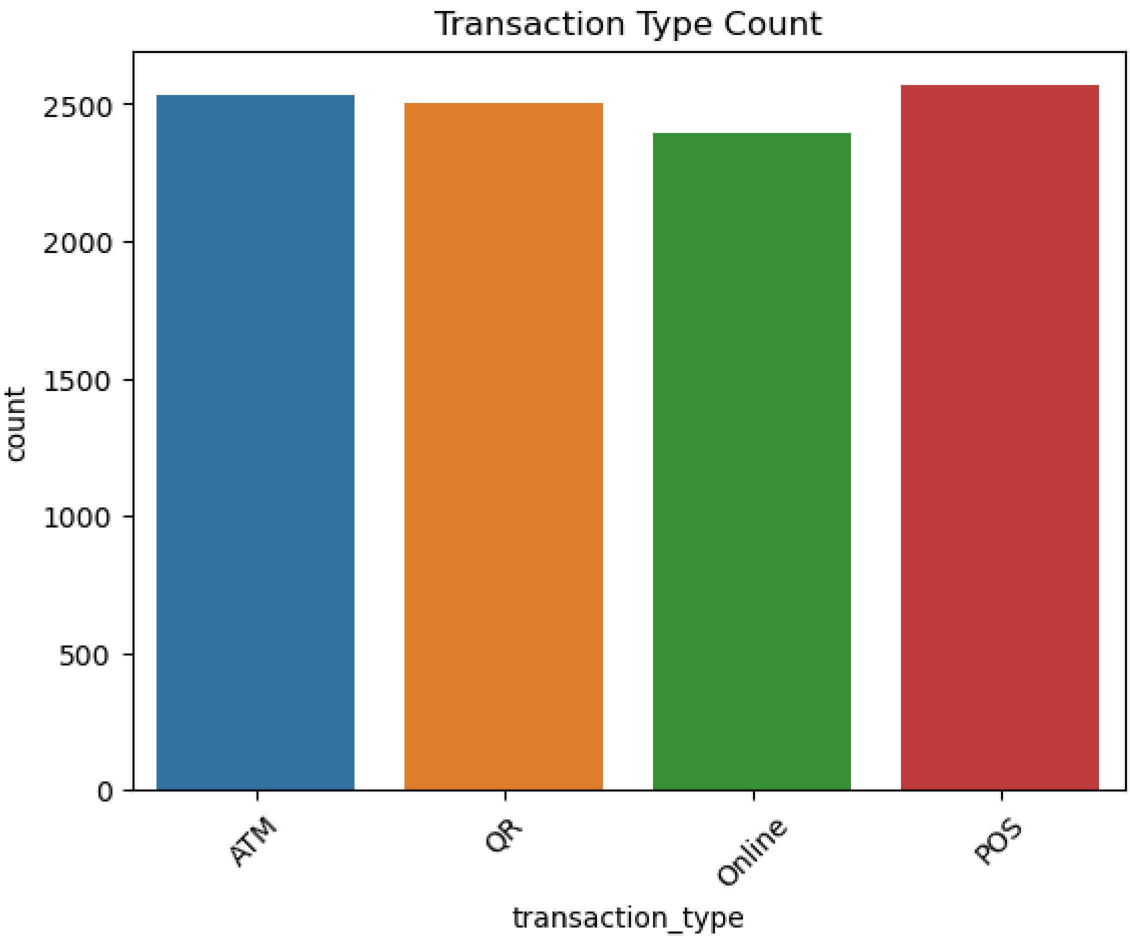
In [17]:
```
fig, ax = plt.subplots(1,2, figsize=(12,5))
sns.histplot(df['device_risk_score'], kde=True, ax=ax[0])
sns.histplot(df['ip_risk_score'], kde=True, ax=ax[1])
ax[0].set_title("Device Risk Score")
ax[1].set_title("IP Risk Score")
plt.show()
```

```
C:\Users\ankit\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarnin
g: use_inf_as_na option is deprecated and will be removed in a future version. Co
nvert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\ankit\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarnin
g: use_inf_as_na option is deprecated and will be removed in a future version. Co
nvert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



Distribution of Transaction Types

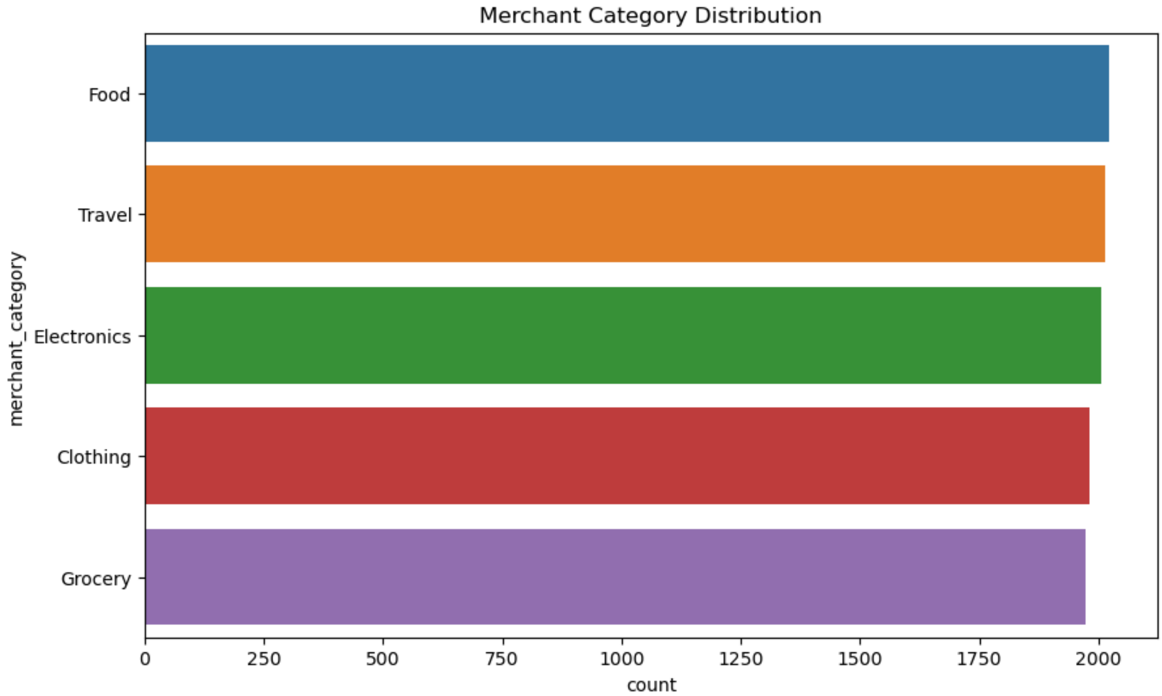
In [18]:
```
sns.countplot(data=df, x="transaction_type")
plt.title("Transaction Type Count")
plt.xticks(rotation=45)
plt.show()
```



Merchant Category Distribution

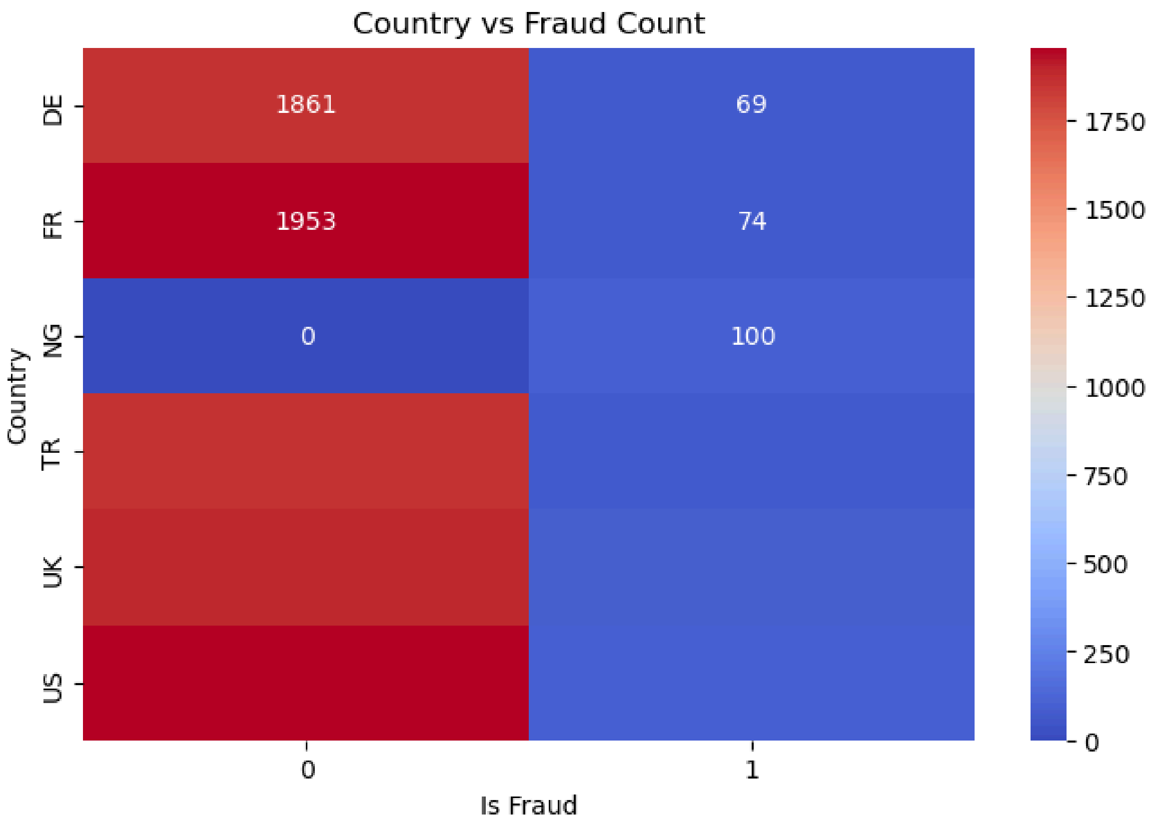
In [19]:
```
plt.figure(figsize=(10,6))
sns.countplot(data=df, y="merchant_category", order=df['merchant_category'].valu
```

```
plt.title("Merchant Category Distribution")
plt.show()
```



Fraud and legitimate transaction counts per country.

In [20]:
```
# Pivot table: country vs fraud
country_fraud = df.pivot_table(index='country', columns='is_fraud', values='tran

# Plot heatmap
plt.figure(figsize=(8,5))
sns.heatmap(country_fraud, annot=True, fmt='g', cmap='coolwarm')
plt.title("Country vs Fraud Count")
plt.xlabel("Is Fraud")
plt.ylabel("Country")
plt.show()
```



Data Modelling

In [21]:
```
# Feature Engineering

def time_range(x):
    if 5 <= x <= 11:
        return "Morning"
    elif 12 <= x <= 17:
        return "Afternoon"
    elif 18 <= x <= 22:
        return "Evening"
    else:
        return "Night"

df["time_range"] = df["hour"].apply(time_range)

cat_cols = ["transaction_type", "merchant_category", "country", "time_range"]
le = LabelEncoder()
for col in cat_cols:
    df[col] = le.fit_transform(df[col])
```

Prepare data

In [22]:
```
X = df.drop(
    columns=["is_fraud", "is_fraud_label", "transaction_id"],
    errors="ignore"
)
y = df["is_fraud"]


#Encode categorical columns FIRST
```

```
cat_cols = X.select_dtypes(include="object").columns
le = LabelEncoder()

for col in cat_cols:
    X[col] = le.fit_transform(X[col])


feature_names = X.columns


scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)


X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.25, random_state=42, stratify=y
)
```

Train Multiple Model

In [23]:
```
lr = LogisticRegression(max_iter=1000)
lr.fit(X_train, y_train)

rf = RandomForestClassifier(random_state=42)
rf.fit(X_train, y_train)

dt = DecisionTreeClassifier(random_state=42)
dt.fit(X_train, y_train)

knn = KNeighborsClassifier()
knn.fit(X_train, y_train)

xgb = XGBClassifier(eval_metric="logloss", random_state=42)
xgb.fit(X_train, y_train)
```

Out[23]:

▾ XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rou
nds=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=None, max_bin=None, max_cat_threshold=No
ne,
```

Evaluate Models

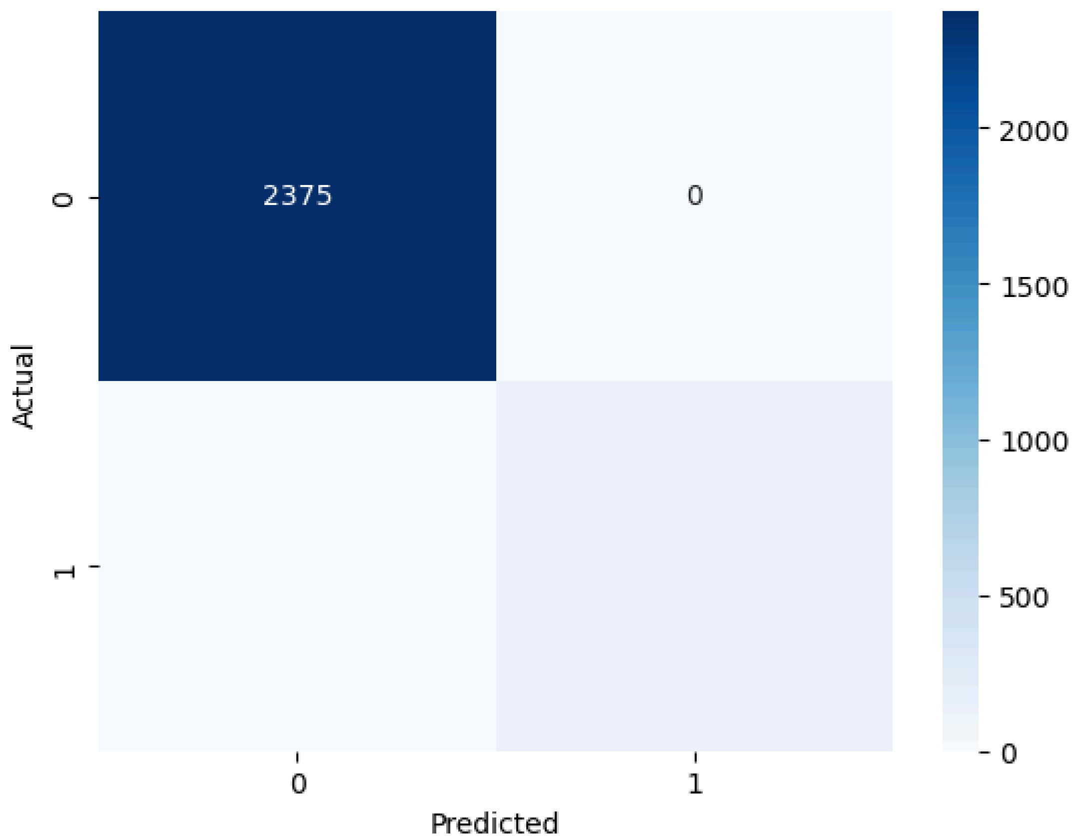
In [24]:
```
def evaluate_model(model):
    pred = model.predict(X_test)
    print(classification_report(y_test, pred))
    cm = confusion_matrix(y_test, pred)
```

```
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()
```

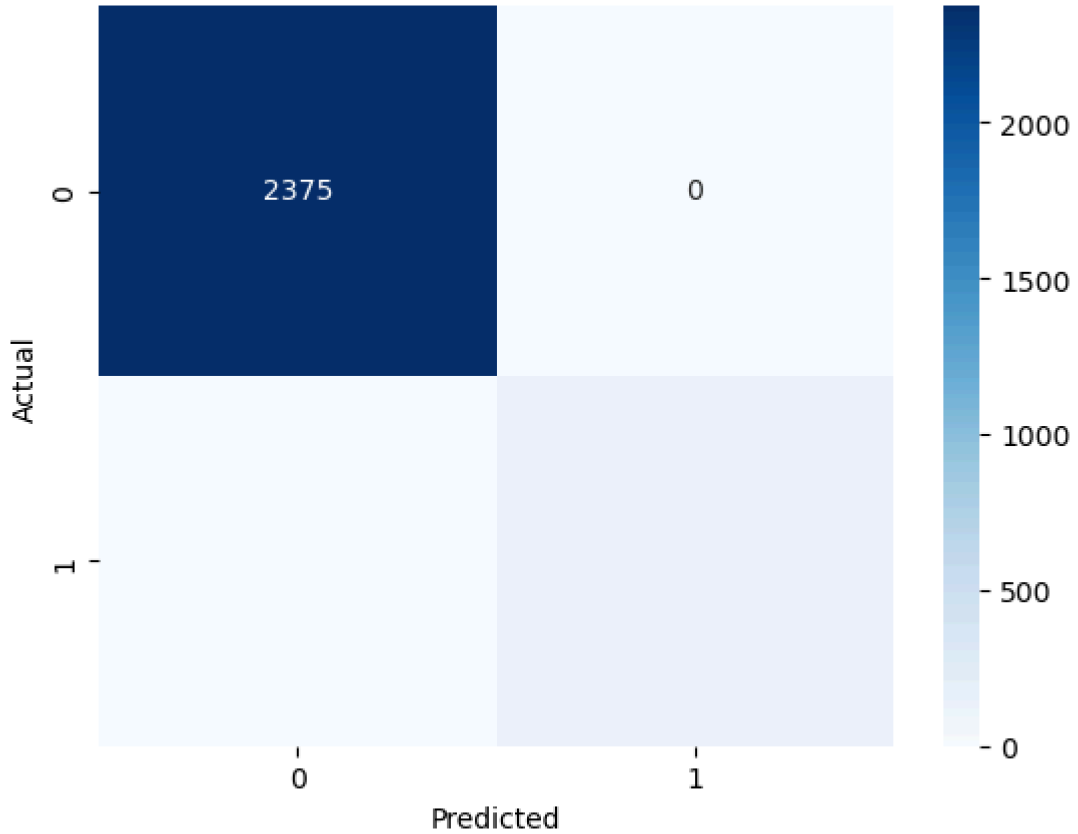
Evaluate all model

In [25]:
```
models = [lr, rf, dt, knn, xgb]
names = ["Logistic Regression", "Random Forest", "Decision Tree", "KNN", "XGBoos

for name, model in zip(names, models):
    print(f"----- {name} -----")
    evaluate_model(model)
```

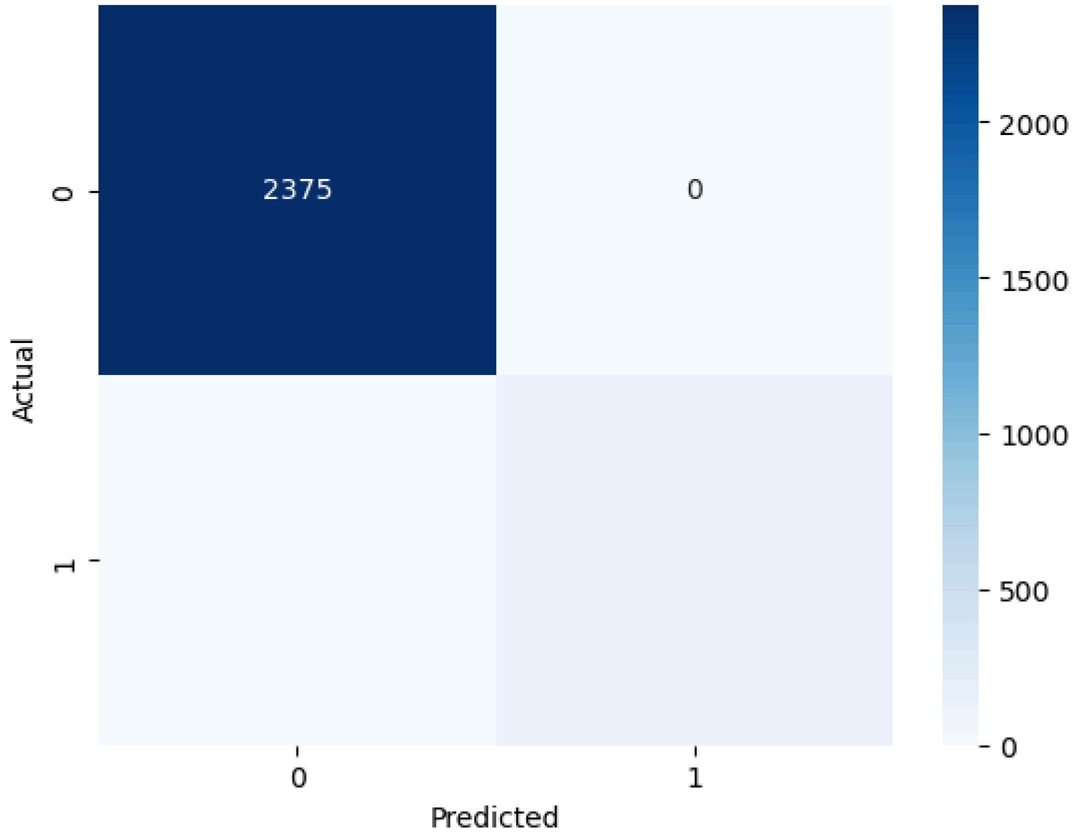
```
----- Logistic Regression -----
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2375
           1       1.00      1.00      1.00       125

    accuracy                           1.00      2500
   macro avg       1.00      1.00      1.00      2500
weighted avg       1.00      1.00      1.00      2500
```



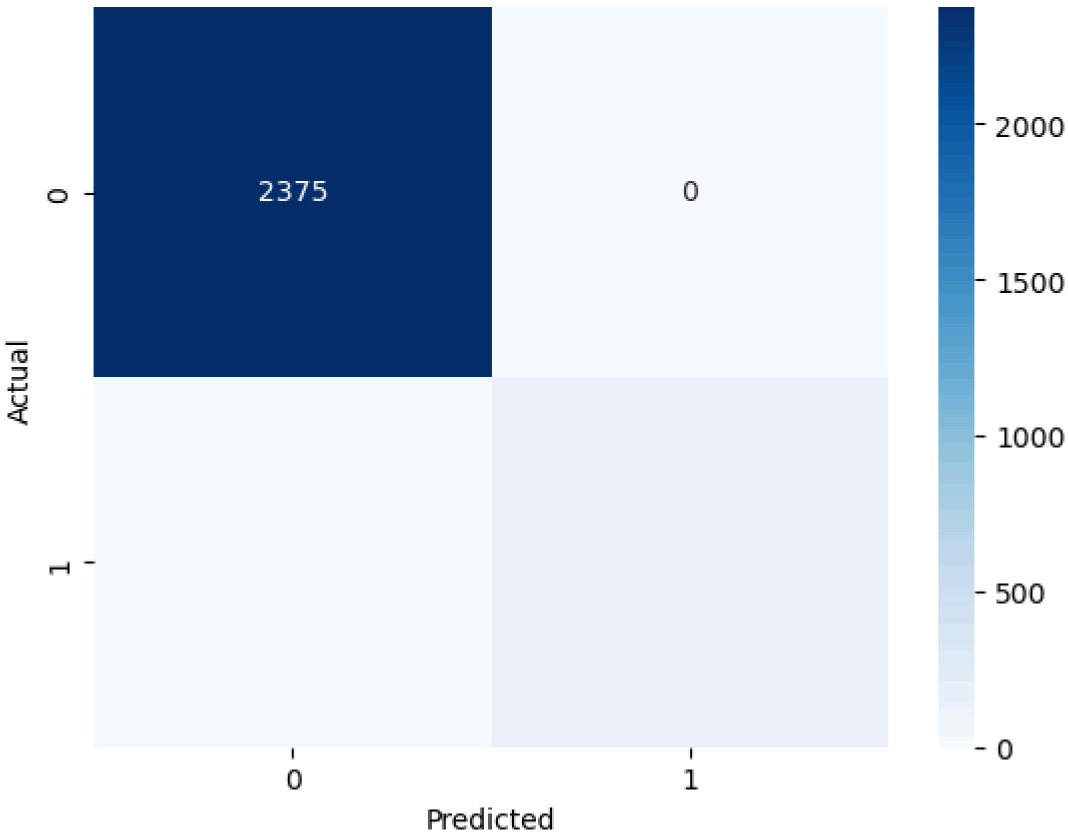
```
----- Random Forest -----
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2375
           1       1.00      1.00      1.00       125

    accuracy                           1.00      2500
   macro avg       1.00      1.00      1.00      2500
weighted avg       1.00      1.00      1.00      2500
```



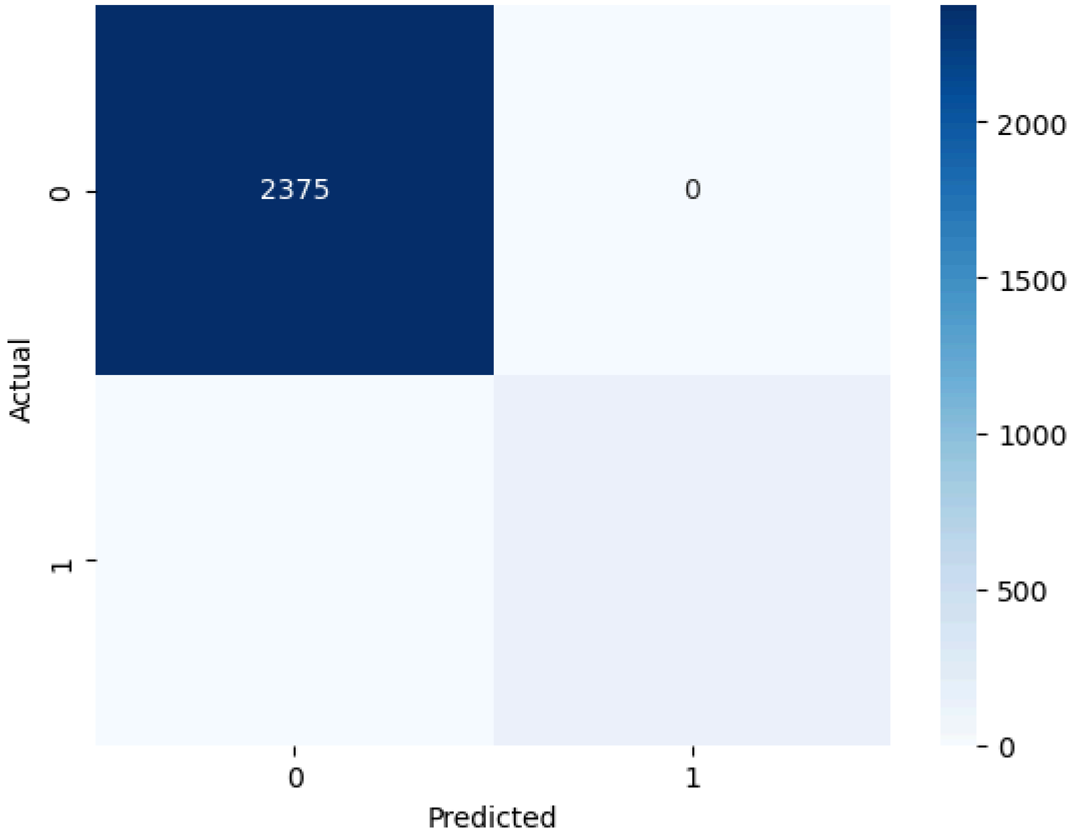

```
----- Decision Tree -----
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2375
           1       1.00      1.00      1.00       125

    accuracy                           1.00      2500
   macro avg       1.00      1.00      1.00      2500
weighted avg       1.00      1.00      1.00      2500
```




```
----- KNN -----
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2375
           1       1.00      1.00      1.00       125

    accuracy                           1.00      2500
   macro avg       1.00      1.00      1.00      2500
weighted avg       1.00      1.00      1.00      2500
```

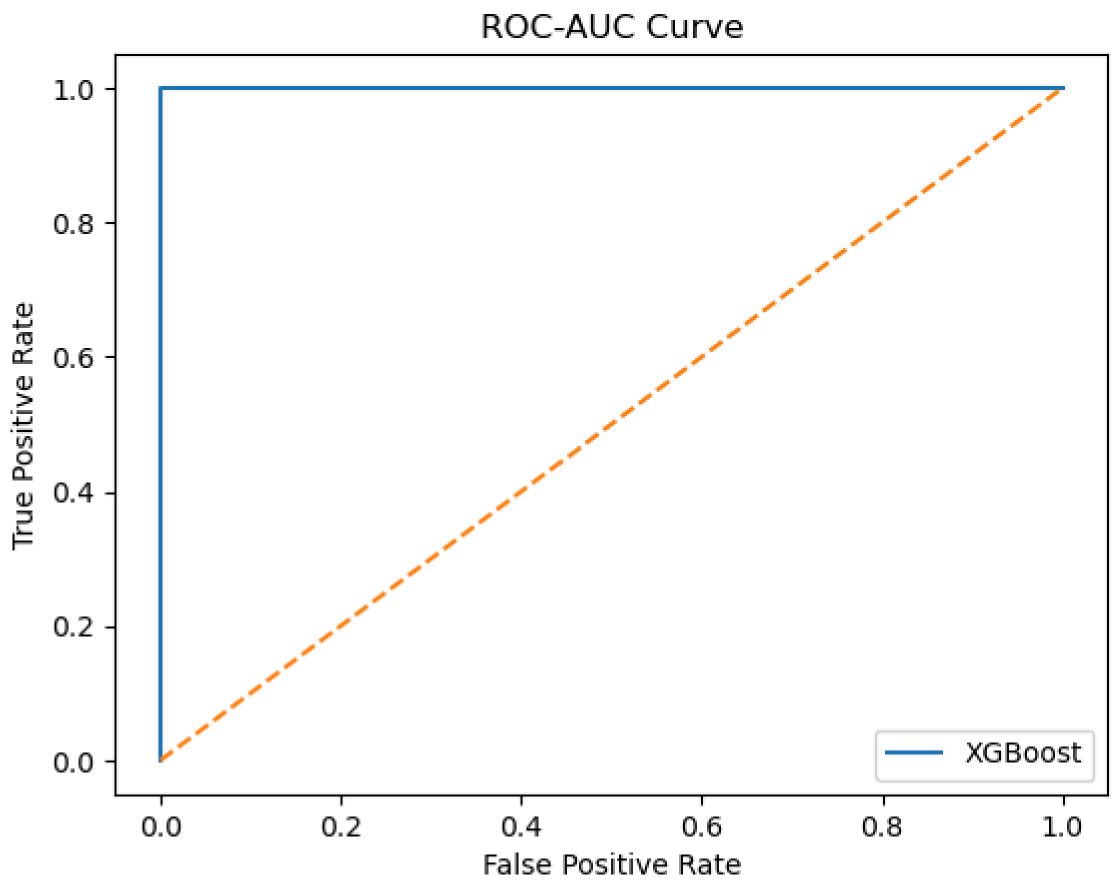



```
----- XGBoost -----
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2375
           1       1.00      1.00      1.00       125

    accuracy                           1.00      2500
   macro avg       1.00      1.00      1.00      2500
weighted avg       1.00      1.00      1.00      2500
```



ROC–AUC Curve (Best Model – XGBoost)

In [26]:
```
y_pred_prob = xgb.predict_proba(X_test)[:, 1]
fpr, tpr, _ = roc_curve(y_test, y_pred_prob)

plt.plot(fpr, tpr, label="XGBoost")
plt.plot([0, 1], [0, 1], '--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC-AUC Curve")
plt.legend()
plt.show()

roc_auc_score(y_test, y_pred_prob)
```



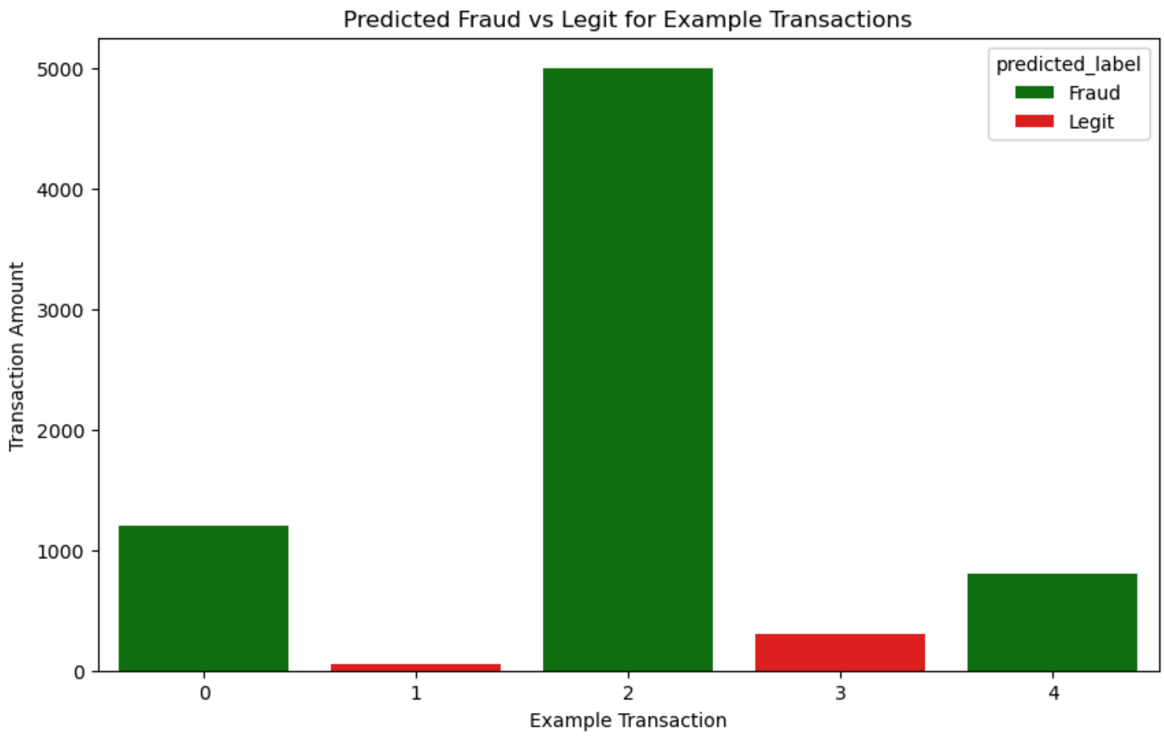
Out[26]: 1.0

Predict fraud for 5 example transactions and visualize the results

In [28]:
```
# Example new transactions
new_transactions = pd.DataFrame({
    'amount': [1200, 50, 5000, 300, 800],
    'hour': [2, 14, 23, 10, 1],
    'device_risk_score': [0.9, 0.1, 0.95, 0.2, 0.8],
    'ip_risk_score': [0.85, 0.05, 0.9, 0.15, 0.75]
})


# Create full feature frame using training features
new_X = pd.DataFrame(columns=X.columns)

# Fill known values
for col in new_transactions.columns:
    new_X[col] = new_transactions[col]

# Fill missing columns with 0
new_X = new_X.fillna(0)

new_X_scaled = scaler.transform(new_X)

# Make predictions
predictions = rf.predict(new_X_scaled)

new_transactions['predicted_is_fraud'] = predictions
new_transactions['predicted_label'] = new_transactions['predicted_is_fraud'].map
```

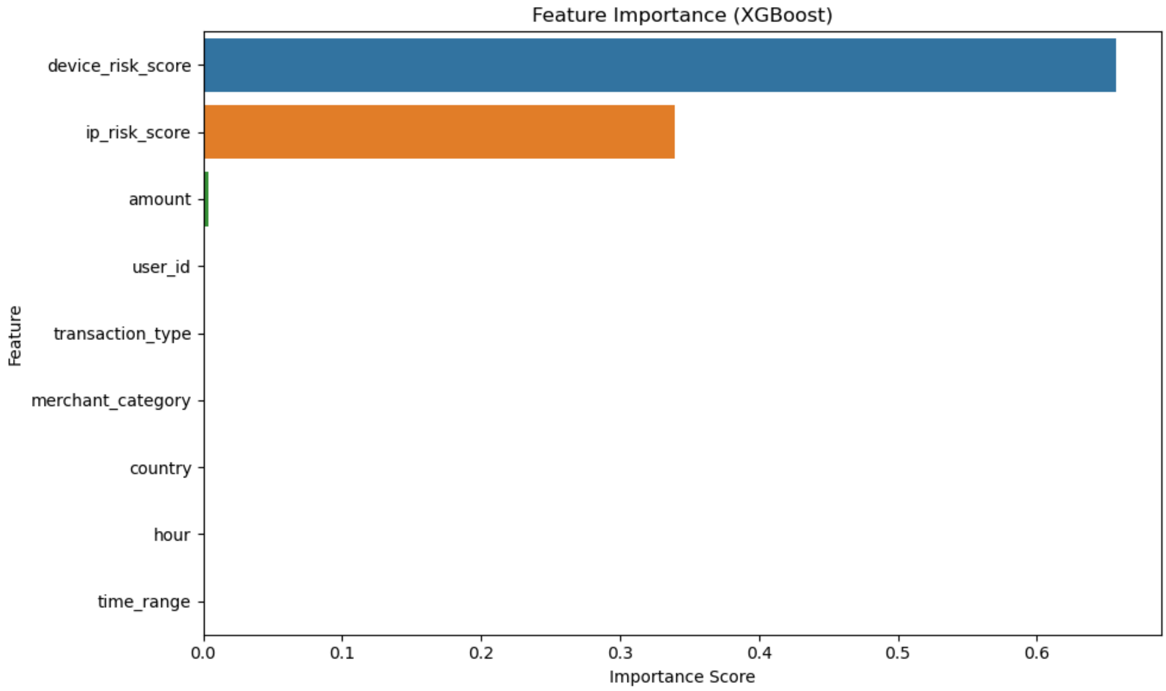
```
    {1: 'Fraud', 0: 'Legit'}
)

print(new_transactions)


# Visualization

plt.figure(figsize=(10,6))
sns.barplot(
    x=new_transactions.index,
    y='amount',
    hue='predicted_label',
    data=new_transactions,
    dodge=False,
    palette=['green','red']
)

plt.title("Predicted Fraud vs Legit for Example Transactions")
plt.xlabel("Example Transaction")
plt.ylabel("Transaction Amount")
plt.show()
```

```
   amount  hour  device_risk_score  ip_risk_score  predicted_is_fraud  \
0    1200     2               0.90           0.85                   1
1      50    14               0.10           0.05                   0
2    5000    23               0.95           0.90                   1
3     300    10               0.20           0.15                   0
4     800     1               0.80           0.75                   1

  predicted_label
0           Fraud
1           Legit
2           Fraud
3           Legit
4           Fraud
```



Feature Importance (XGBoost)

In [29]:
```
# Create feature importance DataFrame
importance_df = pd.DataFrame({
    "Feature": feature_names,
    "Importance": xgb.feature_importances_
}).sort_values(by="Importance", ascending=False)

plt.figure(figsize=(10,6))
sns.barplot(
    data=importance_df,
    x="Importance",
    y="Feature"
)
plt.title("Feature Importance (XGBoost)")
plt.xlabel("Importance Score")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```



In [ ]: