In [1]:
```python
# Import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from imblearn.over_sampling import SMOTE
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score
from sklearn.metrics import precision_recall_curve, average_precision_score
```

In [2]:
```python
# Load data
data = pd.read_csv('creditcard.csv')
data.head()
```

Out[2]:

	Time	V1	V2	V3	V4	V5	V6	V7	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.0986
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.0851
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.2476
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.3774
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.2705

5 rows × 31 columns

In [3]:
```python
# Check dimension of data
data.shape
```

Out[3]:
```
(284807, 31)
```

In [4]:
```python
# Understand column types
data.dtypes
```

Out[4]:
```
Time      float64
V1        float64
V2        float64
V3        float64
V4        float64
V5        float64
V6        float64
V7        float64
V8        float64
V9        float64
V10       float64
V11       float64
V12       float64
V13       float64
V14       float64
V15       float64
V16       float64
V17       float64
V18       float64
V19       float64
V20       float64
V21       float64
V22       float64
V23       float64
V24       float64
V25       float64
V26       float64
V27       float64
V28       float64
Amount    float64
Class       int64
dtype: object
```

In [5]:
```
# Understand numerical data
data.describe()
```

Out[5]:

	Time	V1	V2	V3	V4	
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.8480
mean	94813.859575	1.168375e-15	3.416908e-16	-1.379537e-15	2.074095e-15	9.604C
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00	1.3802
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00	-1.1374
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01	-6.915
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02	-5.4335
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01	6.1192
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01	3.4801

8 rows × 31 columns

In [6]:
```
# Check for missing values
data.isna().sum()
```

Out[6]:
```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

There are no missing values in the dataset.

In [7]:
```
# Check for duplicates
data.duplicated().sum()
```

Out[7]:
```
1081
```

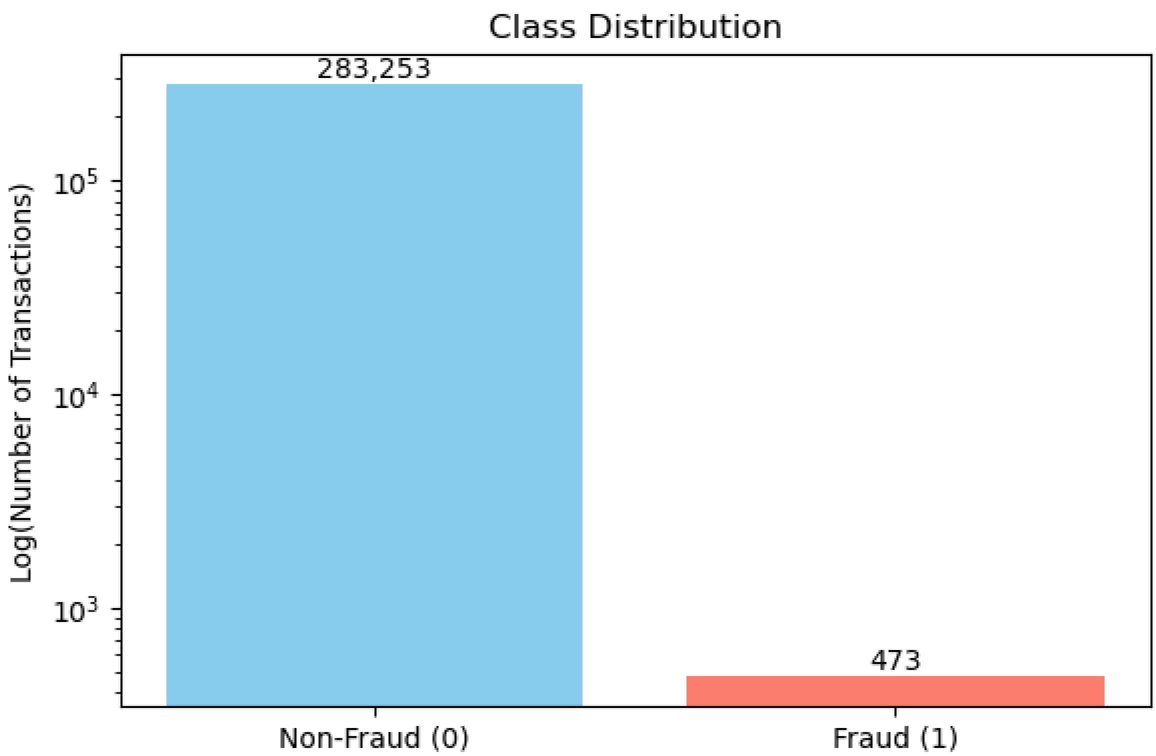
In [8]:
```
# Remove duplicated rows
data = data.drop_duplicates()
```

In [9]:
```
# Check for duplicates again
data.duplicated().sum()
```

Out[9]:
```
0
```

In [10]:
```
#Check imbalance within the dataset

# Count of each class
```

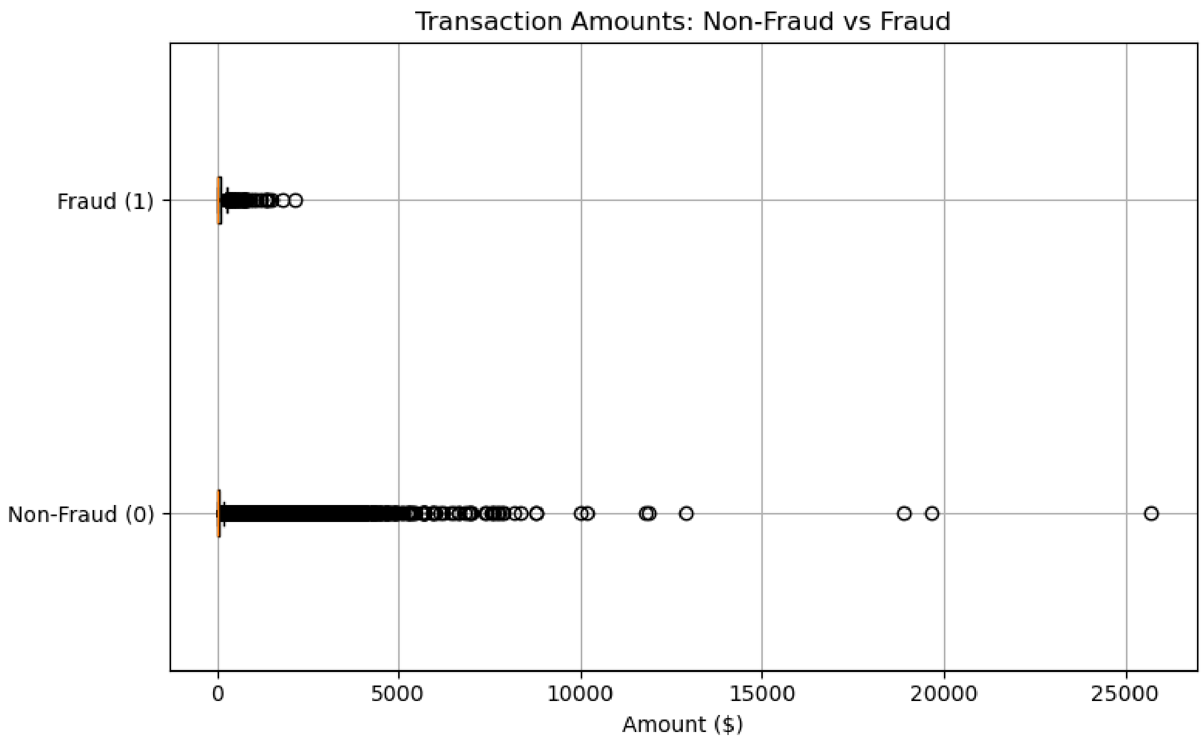
```
class_counts = data['Class'].value_counts()

# Bar chart
plt.figure(figsize=(6, 4))
bars = plt.bar(class_counts.index, class_counts.values, color=['skyblue', 'salmon']
plt.yscale('log')
plt.xticks([0, 1], ['Non-Fraud (0)', 'Fraud (1)'])
plt.ylabel('Log(Number of Transactions)')
plt.title('Class Distribution')

# Add value labels
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, height, f'{int(height):,}',
             ha='center', va='bottom', fontsize=10)

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



In [11]:

```
# Create boxplots of transaction amounds between fraudulent and non-fraudulent trac
# Split the data
fraud_amounts = data[data['Class'] == 1]['Amount']
nonfraud_amounts = data[data['Class'] == 0]['Amount']

# Boxplot
plt.figure(figsize=(8, 5))
plt.boxplot([nonfraud_amounts, fraud_amounts],
            vert=False,
            patch_artist=True,
            labels=['Non-Fraud (0)', 'Fraud (1)'],
            boxprops=dict(facecolor='skyblue'))
```

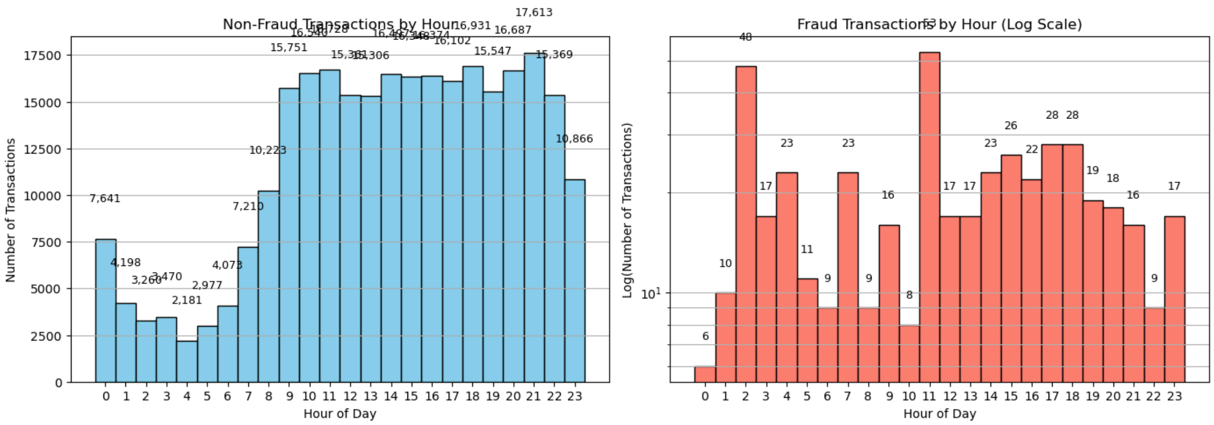
```python
plt.title('Transaction Amounts: Non-Fraud vs Fraud')
plt.xlabel('Amount ($)')
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [12]:

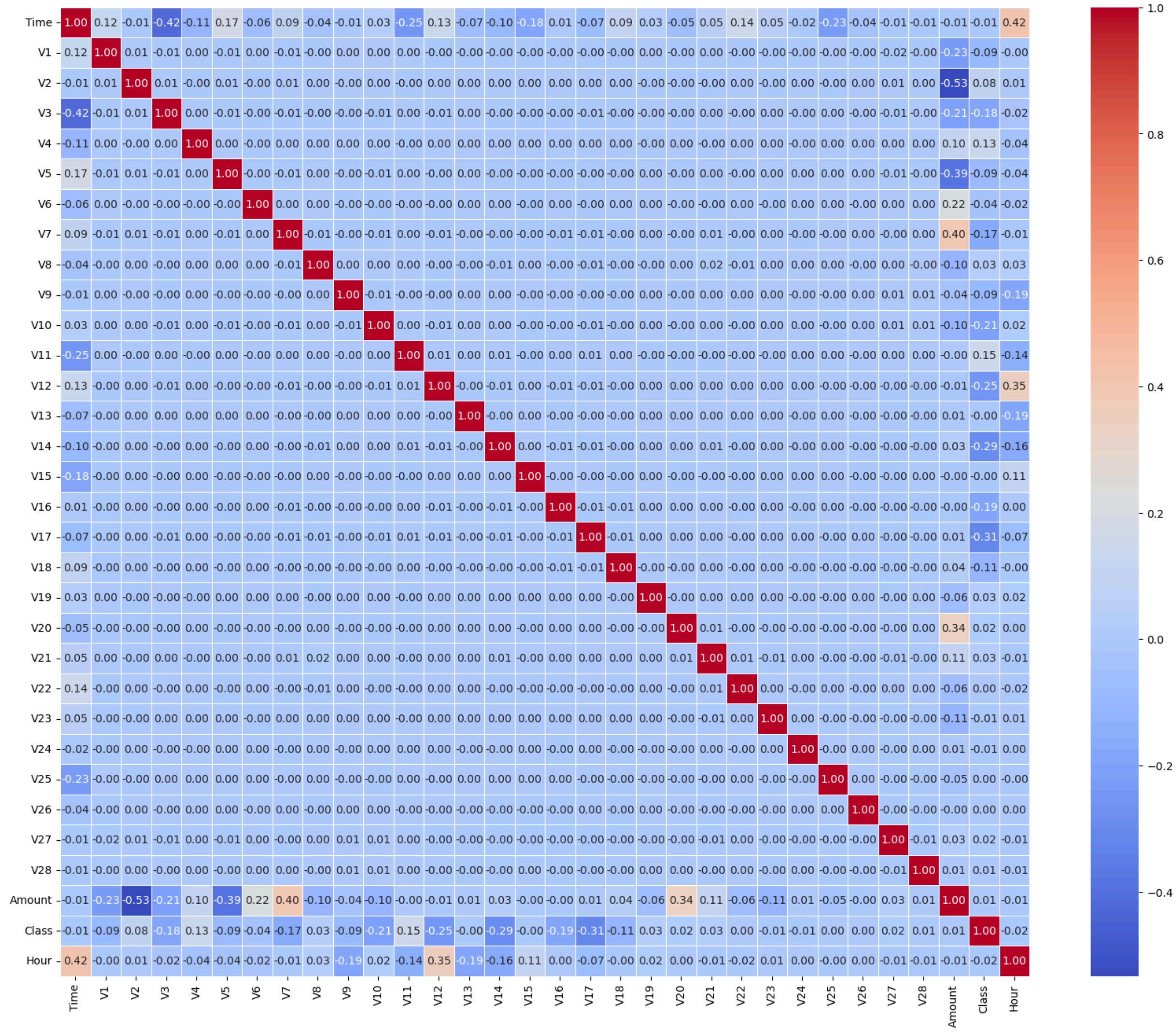
```python
# Understand timing of transactions

# Create Hour Column
data['Hour'] = (data['Time'] // 3600) % 24

# Split data
fraud = data[data['Class'] == 1]
nonfraud = data[data['Class'] == 0]

# Bins
bins = np.arange(25) - 0.5

# Set up figure
fig, axes = plt.subplots(1, 2, figsize=(14, 5), sharey=False)

# Non-Fraud Plot (Linear)
counts_nf, _, _ = axes[0].hist(nonfraud['Hour'], bins=bins, color='skyblue', edgeco
axes[0].set_title('Non-Fraud Transactions by Hour')
axes[0].set_xlabel('Hour of Day')
axes[0].set_ylabel('Number of Transactions')
axes[0].set_xticks(range(24))
axes[0].grid(axis='y')

# Add labels
for i, count in enumerate(counts_nf):
    if count > 0:
        axes[0].text(i, count + 2000, f'{int(count):,}', ha='center', fontsize=9)
```

```
# Fraud Plot (Log Scale)
counts_f, _, _ = axes[1].hist(fraud['Hour'], bins=bins, color='salmon', edgecolor='
axes[1].set_yscale('log')
axes[1].set_title('Fraud Transactions by Hour (Log Scale)')
axes[1].set_xlabel('Hour of Day')
axes[1].set_xticks(range(24))
axes[1].set_ylabel('Log(Number of Transactions)')
axes[1].grid(axis='y', which='both')

# Add value labels (adjusted for log scale visibility)
for i, count in enumerate(counts_f):
    if count > 0:
        axes[1].text(i, count * 1.2, str(int(count)), ha='center', fontsize=9)

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



In [13]:

```
# Create Correlation Heatmap to conduct preliminary analysis
plt.figure(figsize=(20, 16))
heatmap = sns.heatmap(data.corr(), annot=True, cmap='coolwarm', fmt=".2f", linewidt

plt.show()
```



In [14]:
```
# Time and Amount Columns before scaling
print(data[['Time', 'Amount']].describe())
```

```
                Time         Amount
count  283726.000000  283726.000000
mean    94811.077600      88.472687
std     47481.047891     250.399437
min         0.000000       0.000000
25%     54204.750000       5.600000
50%     84692.500000      22.000000
75%    139298.000000      77.510000
max    172792.000000   25691.160000
```

In [15]:
```
# Scale Amount and Time variables
scaler = StandardScaler()
data[['Time', 'Amount']] = scaler.fit_transform(data[['Time', 'Amount']])
```

In [16]:
```
# Time and Amount Columns after scaling
print(data[['Time', 'Amount']].describe())
```

```
              Time        Amount
count  2.837260e+05  2.837260e+05
mean   1.218105e-16 -5.409347e-17
std    1.000002e+00  1.000002e+00
min   -1.996823e+00 -3.533268e-01
25%   -8.552128e-01 -3.309625e-01
50%   -2.131081e-01 -2.654671e-01
75%    9.369423e-01 -4.378088e-02
max    1.642362e+00  1.022476e+02
```

In [17]:

```
# Create feature and target variables
X = data.drop('Class', axis=1)
y = data['Class']
```

In [18]:

```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)
```

In [19]:

```
# TEMP: Reduce dataset size (e.g., to 50k rows)
data_sampled = data.sample(n=50000, random_state=42)

# SMOTE on training data
smote = SMOTE(random_state=42)
X_train_res, y_train_res = smote.fit_resample(X_train, y_train)
```

In [20]:

```
# Define Models
# Logistic Regression
lr = LogisticRegression(max_iter=1000, random_state=42)
lr.fit(X_train_res, y_train_res)

# Random Forest
rf = RandomForestClassifier(n_estimators=50, max_depth=5, random_state=42, n_jobs=-
rf.fit(X_train_res, y_train_res)

# XGBoost
xgb = XGBClassifier(n_estimators=50, max_depth=3, use_label_encoder=False, eval_met
xgb.fit(X_train_res, y_train_res)
```

```
C:\Users\chris\anaconda3\Lib\site-packages\xgboost\training.py:183: UserWarning: [2
1:09:18] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

Out[20]:

▾ XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=
None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, feature_weights=None, gamma=None,
              grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=
None,
```

In [21]:

```python
# Evalute models

# Store results
results = []

models = {'Logistic Regression': lr, 'Random Forest': rf, 'XGBoost': xgb}

for name, model in models.items():
    y_pred = model.predict(X_test)
    y_proba = model.predict_proba(X_test)[:, 1]
    report = classification_report(y_test, y_pred, output_dict=True, zero_division=
    roc_auc = roc_auc_score(y_test, y_proba)

    results.append({
        'Model': name,
        'Precision': report['1']['precision'],
        'Recall': report['1']['recall'],
        'F1-Score': report['1']['f1-score'],
        'ROC AUC': roc_auc
    })

# Convert to DataFrame
results_df = pd.DataFrame(results)

# Display the table
results_df = results_df.round(4)
results_df
```

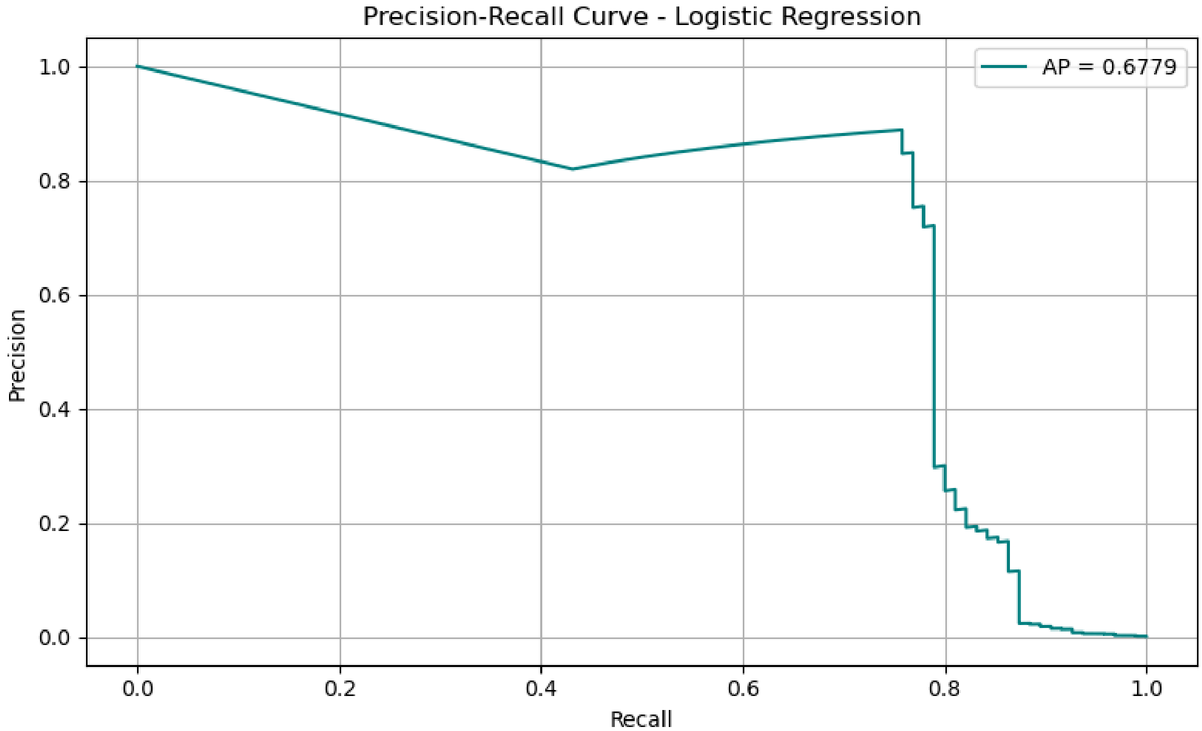
Out[21]:

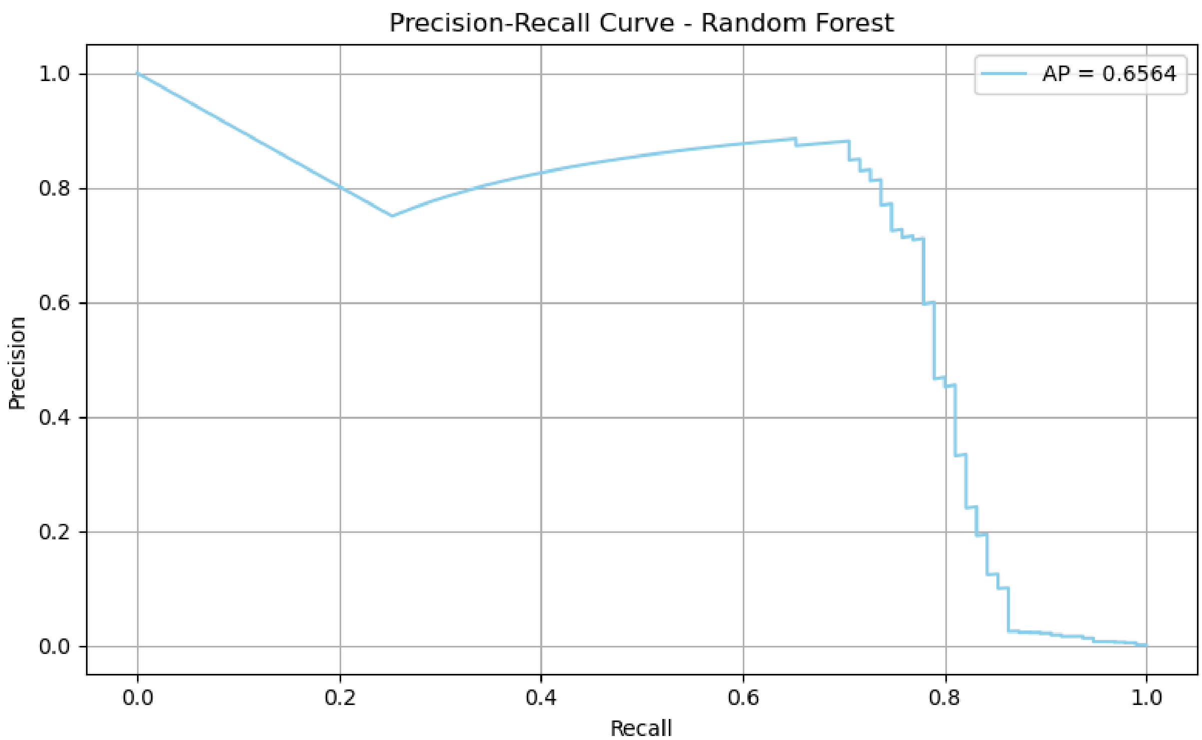
	Model	Precision	Recall	F1-Score	ROC AUC
0	Logistic Regression	0.0529	0.8737	0.0998	0.9659
1	Random Forest	0.2468	0.8211	0.3796	0.9728
2	XGBoost	0.1455	0.8421	0.2481	0.9718

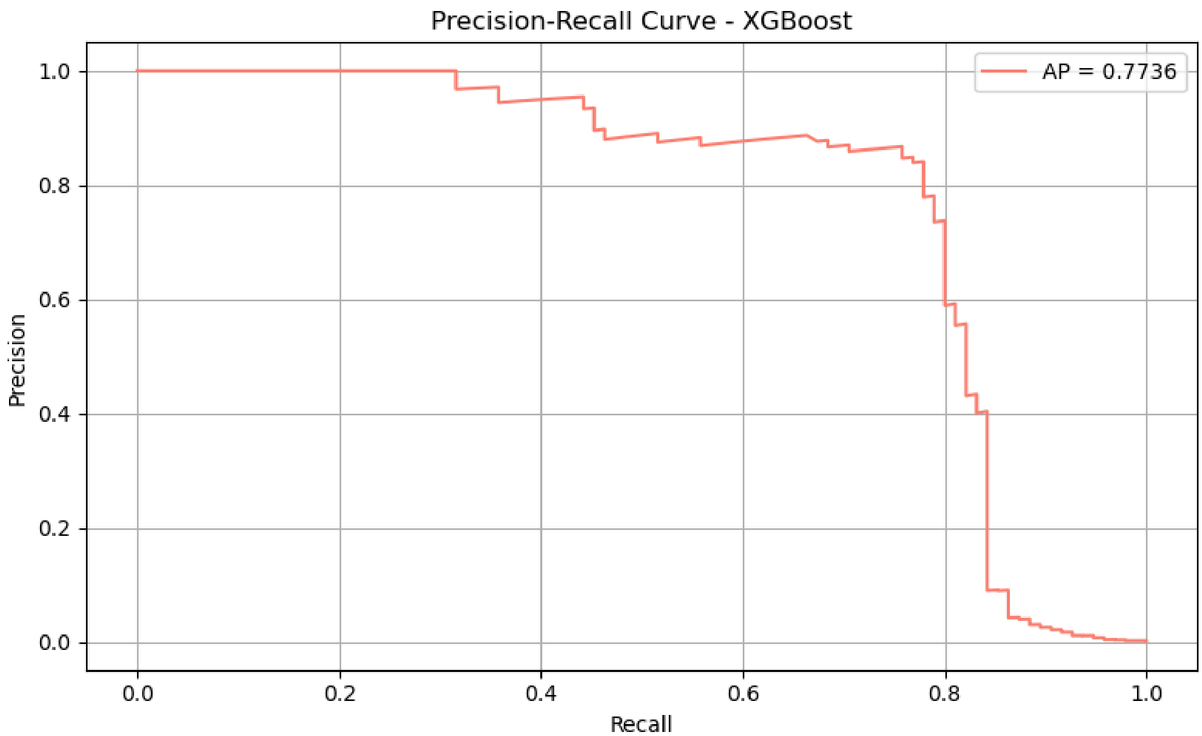
In [22]:

```python
# --- Get predicted probabilities ---
lr_probs = lr.predict_proba(X_test)[:, 1]
rf_probs = rf.predict_proba(X_test)[:, 1]
xgb_probs = xgb.predict_proba(X_test)[:, 1]
```

```python
# --- Compute precision-recall curves ---
lr_precision, lr_recall, _ = precision_recall_curve(y_test, lr_probs)
rf_precision, rf_recall, _ = precision_recall_curve(y_test, rf_probs)
xgb_precision, xgb_recall, _ = precision_recall_curve(y_test, xgb_probs)

# --- Compute Average Precision Scores ---
lr_ap = average_precision_score(y_test, lr_probs)
rf_ap = average_precision_score(y_test, rf_probs)
xgb_ap = average_precision_score(y_test, xgb_probs)

# --- Plot: Logistic Regression ---
plt.figure(figsize=(8, 5))
plt.plot(lr_recall, lr_precision, color='teal', label=f'AP = {lr_ap:.4f}')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve - Logistic Regression')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# --- Plot: Random Forest ---
plt.figure(figsize=(8, 5))
plt.plot(rf_recall, rf_precision, color='skyblue', label=f'AP = {rf_ap:.4f}')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve - Random Forest')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# --- Plot: XGBoost ---
plt.figure(figsize=(8, 5))
plt.plot(xgb_recall, xgb_precision, color='salmon', label=f'AP = {xgb_ap:.4f}')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve - XGBoost')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```


Precision-Recall Curve - Logistic Regression
AP = 0.6779
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0


Precision-Recall Curve - Random Forest
AP = 0.6564
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0



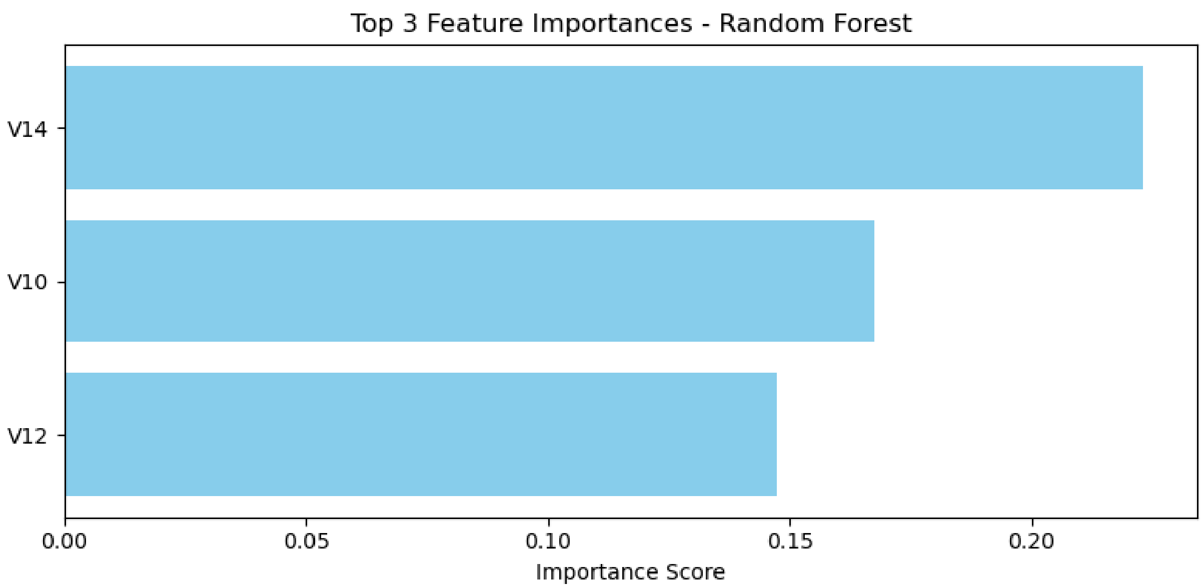
In [23]:
```python
# Make predictions with models
y_pred_lr = lr.predict(X_test)
y_pred_rf = rf.predict(X_test)
y_pred_xgb = xgb.predict(X_test)

# Generate confusion matrices
lr_cf = confusion_matrix(y_test, y_pred_lr)
rf_cf = confusion_matrix(y_test, y_pred_rf)
xgb_cf = confusion_matrix(y_test, y_pred_xgb)

# Set up vertical plot layout
fig, ax = plt.subplots(3, 1, figsize=(16, 20), dpi=150)

# Logistic Regression
sns.heatmap(lr_cf, ax=ax[0], annot=True, fmt='d', cmap='Blues', cbar=False,
            annot_kws={"size": 18})
ax[0].set_title("Logistic Regression\nConfusion Matrix", fontsize=18, fontweight='b
ax[0].set_xticklabels(['Non-Fraud', 'Fraud'], fontsize=14)
ax[0].set_yticklabels(['Non-Fraud', 'Fraud'], fontsize=14)

# Random Forest
sns.heatmap(rf_cf, ax=ax[1], annot=True, fmt='d', cmap='Blues', cbar=False,
            annot_kws={"size": 18})
ax[1].set_title("Random Forest\nConfusion Matrix", fontsize=18, fontweight='bold')
ax[1].set_xticklabels(['Non-Fraud', 'Fraud'], fontsize=14)
ax[1].set_yticklabels(['Non-Fraud', 'Fraud'], fontsize=14)

# XGBoost
sns.heatmap(xgb_cf, ax=ax[2], annot=True, fmt='d', cmap='Blues', cbar=False,
            annot_kws={"size": 18})
ax[2].set_title("XGBoost\nConfusion Matrix", fontsize=18, fontweight='bold')
ax[2].set_xticklabels(['Non-Fraud', 'Fraud'], fontsize=14)
ax[2].set_yticklabels(['Non-Fraud', 'Fraud'], fontsize=14)
```

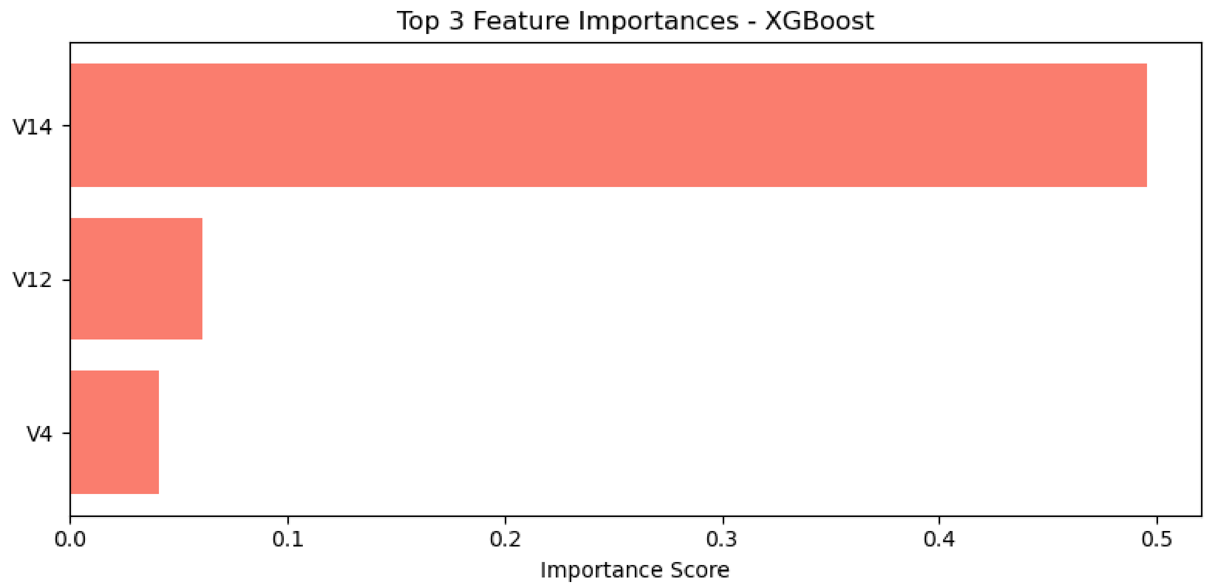
```python
plt.tight_layout()
plt.show()
```

In [24]:

```python
# --- Random Forest Top 3 ---
rf_importances = rf.feature_importances_
rf_df = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance': rf_importances
}).sort_values(by='Importance', ascending=False).head(3)
```

```python
# Plot Random Forest
plt.figure(figsize=(8, 4))
plt.barh(rf_df['Feature'], rf_df['Importance'], color='skyblue')
plt.gca().invert_yaxis()
plt.title('Top 3 Feature Importances - Random Forest')
plt.xlabel('Importance Score')
plt.tight_layout()
plt.show()

# --- XGBoost Top 3 ---
xgb_importances = xgb.feature_importances_
xgb_df = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance': xgb_importances
}).sort_values(by='Importance', ascending=False).head(3)

# Plot XGBoost
plt.figure(figsize=(8, 4))
plt.barh(xgb_df['Feature'], xgb_df['Importance'], color='salmon')
plt.gca().invert_yaxis()
plt.title('Top 3 Feature Importances - XGBoost')
plt.xlabel('Importance Score')
plt.tight_layout()
plt.show()
```




Top 3 Feature Importances - XGBoost
V14
V12
V4
0.0
0.1
0.2
0.3
0.4
0.5
Importance Score

In [ ]: