In [32]:
```
from google.cloud import bigquery

# Use raw string for the file path
key_path = r"C:\Phoenix Portfolio\phoenix-portfolio-461608-e794abe0cf71.json"

# Initialize the BigQuery client
client = bigquery.Client.from_service_account_json(key_path)

# Query table
query = """
    SELECT *
    FROM `bigquery-public-data.ml_datasets.credit_card_default`
    LIMIT 10000
"""
# Run the query and create a DataFrame
df = client.query(query).to_dataframe()

# Display the first few rows
print(df.head())
```

```
        id  limit_balance sex education_level marital_status   age  pay_0  \
0  27502.0        80000.0   1               6              1  54.0    0.0
1  26879.0       200000.0   1               4              1  49.0    0.0
2  18340.0        20000.0   2               6              2  22.0    0.0
3  13692.0       260000.0   2               4              2  33.0    0.0
4  20405.0       150000.0   1               4              2  32.0    0.0

   pay_2  pay_3  pay_4  ... bill_amt_5 bill_amt_6  pay_amt_1  pay_amt_2  \
0    0.0    0.0    0.0  ...    26210.0    17643.0     2545.0     2208.0
1    0.0    0.0    0.0  ...    50235.0    48984.0     1689.0     2164.0
2    0.0    0.0    0.0  ...      500.0        0.0     4641.0     1019.0
3    0.0    0.0    0.0  ...    30767.0    29890.0     5000.0     5000.0
4    0.0    0.0   -1.0  ...   143375.0   146411.0     4019.0   146896.0

   pay_amt_3  pay_amt_4  pay_amt_5  pay_amt_6  default_payment_next_month  \
0     1336.0     2232.0      542.0      348.0                           1
1     2500.0     3480.0     2500.0     3000.0                           0
2      900.0        0.0     1500.0        0.0                           1
3     1137.0     5000.0     1085.0     5000.0                           0
4   157436.0     4600.0     4709.0     5600.0                           0

                predicted_default_payment_next_month
0  [{'tables': {'score': 0.8667634129524231, 'val...
1  [{'tables': {'score': 0.9351968765258789, 'val...
2  [{'tables': {'score': 0.8572560548782349, 'val...
3  [{'tables': {'score': 0.9690881371498108, 'val...
4  [{'tables': {'score': 0.9349926710128784, 'val...

[5 rows x 26 columns]
```

In [33]:
```
#Initial Inspection
print("Dataset shape:", df.shape)
df.head()
print("\nInfo:")
print(df.info()) #understand the purpose of each function
```

```
print("\nSummary Statistics:")
print(df.describe())
print("\nMissing Values:")
print(df.isnull().sum())
print(type(df))
for col in df.columns:
    print(col, type(df[col].iloc[0]))
df_no_ndarray = df.drop(columns=["predicted_default_payment_next_month"])
print("Duplicated Rows:", df_no_ndarray.duplicated().sum())
print("\nData Types:")
print(df.dtypes)
```

```
Dataset shape: (2965, 26)

Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2965 entries, 0 to 2964
Data columns (total 26 columns):
 #   Column                              Non-Null Count  Dtype  
---  ------                              --------------  -----  
 0   id                                  2965 non-null   float64
 1   limit_balance                       2965 non-null   float64
 2   sex                                 2965 non-null   object 
 3   education_level                     2965 non-null   object 
 4   marital_status                      2965 non-null   object 
 5   age                                 2965 non-null   float64
 6   pay_0                               2965 non-null   float64
 7   pay_2                               2965 non-null   float64
 8   pay_3                               2965 non-null   float64
 9   pay_4                               2965 non-null   float64
 10  pay_5                               2965 non-null   object 
 11  pay_6                               2965 non-null   object 
 12  bill_amt_1                          2965 non-null   float64
 13  bill_amt_2                          2965 non-null   float64
 14  bill_amt_3                          2965 non-null   float64
 15  bill_amt_4                          2965 non-null   float64
 16  bill_amt_5                          2965 non-null   float64
 17  bill_amt_6                          2965 non-null   float64
 18  pay_amt_1                           2965 non-null   float64
 19  pay_amt_2                           2965 non-null   float64
 20  pay_amt_3                           2965 non-null   float64
 21  pay_amt_4                           2965 non-null   float64
 22  pay_amt_5                           2965 non-null   float64
 23  pay_amt_6                           2965 non-null   float64
 24  default_payment_next_month          2965 non-null   object 
 25  predicted_default_payment_next_month  2965 non-null   object 
dtypes: float64(19), object(7)
memory usage: 602.4+ KB
None

Summary Statistics:
                 id  limit_balance          age        pay_0        pay_2  \
count   2965.000000    2965.000000  2965.000000  2965.000000  2965.000000   
mean   14945.556155  163369.308600    35.193255     0.005059    -0.122428   
std     8700.288152  125030.415472     9.109439     1.114395     1.180784   
min       29.000000   10000.000000    21.000000    -2.000000    -2.000000   
25%     7499.000000   50000.000000    28.000000    -1.000000    -1.000000   
50%    14782.000000  140000.000000    34.000000     0.000000     0.000000   
75%    22571.000000  230000.000000    41.000000     0.000000     0.000000   
max    29995.000000  800000.000000    69.000000     8.000000     7.000000   

             pay_3        pay_4     bill_amt_1     bill_amt_2     bill_amt_3  \
count  2965.000000  2965.000000    2965.000000    2965.000000    2965.000000   
mean     -0.141653    -0.185160   52118.305228   50649.153120   48239.757504   
std       1.183630     1.178322   72328.670541   70785.001588   68145.710745   
min      -2.000000    -2.000000  -11545.000000  -67526.000000  -25443.000000   
25%      -1.000000    -1.000000    3958.000000    3390.000000    3302.000000   
50%       0.000000     0.000000   24257.000000   23111.000000   21520.000000   
```

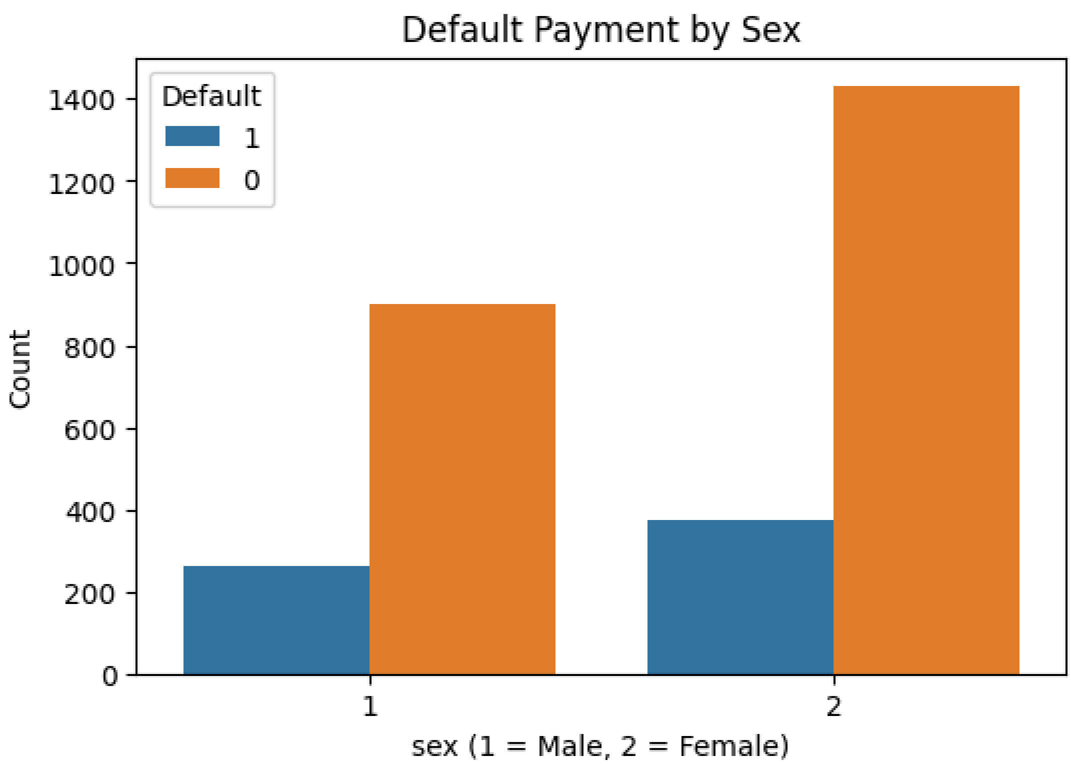
```
75%       0.000000     0.000000   69852.000000   67827.000000   63023.000000
max       7.000000     8.000000  613860.000000  512650.000000  578971.000000

          bill_amt_4     bill_amt_5     bill_amt_6      pay_amt_1  \
count    2965.000000    2965.000000    2965.000000    2965.000000
mean    44089.683305   40956.080607   39773.072513    6348.902867
std     61907.454056   58271.904751   57303.488981   20885.735336
min    -46627.000000  -46627.000000  -73895.000000       0.000000
25%      2582.000000    1958.000000    1430.000000    1013.000000
50%     19894.000000   18814.000000   18508.000000    2234.000000
75%     58622.000000   53373.000000   52287.000000    5087.000000
max    488808.000000  441981.000000  436172.000000  493358.000000

          pay_amt_2      pay_amt_3      pay_amt_4      pay_amt_5  \
count  2.965000e+03    2965.000000    2965.000000    2965.000000
mean   6.272494e+03    5150.497133    4561.376054    4913.286678
std    2.887967e+04   14287.079982   13281.499599   16734.340778
min    0.000000e+00       0.000000       0.000000       0.000000
25%    9.900000e+02     477.000000     313.000000     323.000000
50%    2.175000e+03    1994.000000    1600.000000    1646.000000
75%    5.000000e+03    4500.000000    4000.000000    4021.000000
max    1.227082e+06  199209.000000  202076.000000  388071.000000

           pay_amt_6
count    2965.000000
mean     5382.701518
std     17275.953029
min         0.000000
25%       173.000000
50%      1615.000000
75%      4081.000000
max    403500.000000

Missing Values:
id                                0
limit_balance                     0
sex                               0
education_level                   0
marital_status                    0
age                               0
pay_0                             0
pay_2                             0
pay_3                             0
pay_4                             0
pay_5                             0
pay_6                             0
bill_amt_1                        0
bill_amt_2                        0
bill_amt_3                        0
bill_amt_4                        0
bill_amt_5                        0
bill_amt_6                        0
pay_amt_1                         0
pay_amt_2                         0
pay_amt_3                         0
pay_amt_4                         0
```

```
pay_amt_5                               0
pay_amt_6                               0
default_payment_next_month              0
predicted_default_payment_next_month    0
dtype: int64
<class 'pandas.core.frame.DataFrame'>
id <class 'numpy.float64'>
limit_balance <class 'numpy.float64'>
sex <class 'str'>
education_level <class 'str'>
marital_status <class 'str'>
age <class 'numpy.float64'>
pay_0 <class 'numpy.float64'>
pay_2 <class 'numpy.float64'>
pay_3 <class 'numpy.float64'>
pay_4 <class 'numpy.float64'>
pay_5 <class 'str'>
pay_6 <class 'str'>
bill_amt_1 <class 'numpy.float64'>
bill_amt_2 <class 'numpy.float64'>
bill_amt_3 <class 'numpy.float64'>
bill_amt_4 <class 'numpy.float64'>
bill_amt_5 <class 'numpy.float64'>
bill_amt_6 <class 'numpy.float64'>
pay_amt_1 <class 'numpy.float64'>
pay_amt_2 <class 'numpy.float64'>
pay_amt_3 <class 'numpy.float64'>
pay_amt_4 <class 'numpy.float64'>
pay_amt_5 <class 'numpy.float64'>
pay_amt_6 <class 'numpy.float64'>
default_payment_next_month <class 'str'>
predicted_default_payment_next_month <class 'numpy.ndarray'>
Duplicated Rows: 0

Data Types:
id                                      float64
limit_balance                           float64
sex                                      object
education_level                          object
marital_status                           object
age                                     float64
pay_0                                   float64
pay_2                                   float64
pay_3                                   float64
pay_4                                   float64
pay_5                                    object
pay_6                                    object
bill_amt_1                              float64
bill_amt_2                              float64
bill_amt_3                              float64
bill_amt_4                              float64
bill_amt_5                              float64
bill_amt_6                              float64
pay_amt_1                               float64
pay_amt_2                               float64
pay_amt_3                               float64
```

```
pay_amt_4                                float64
pay_amt_5                                float64
pay_amt_6                                float64
default_payment_next_month                object
predicted_default_payment_next_month      object
dtype: object
```

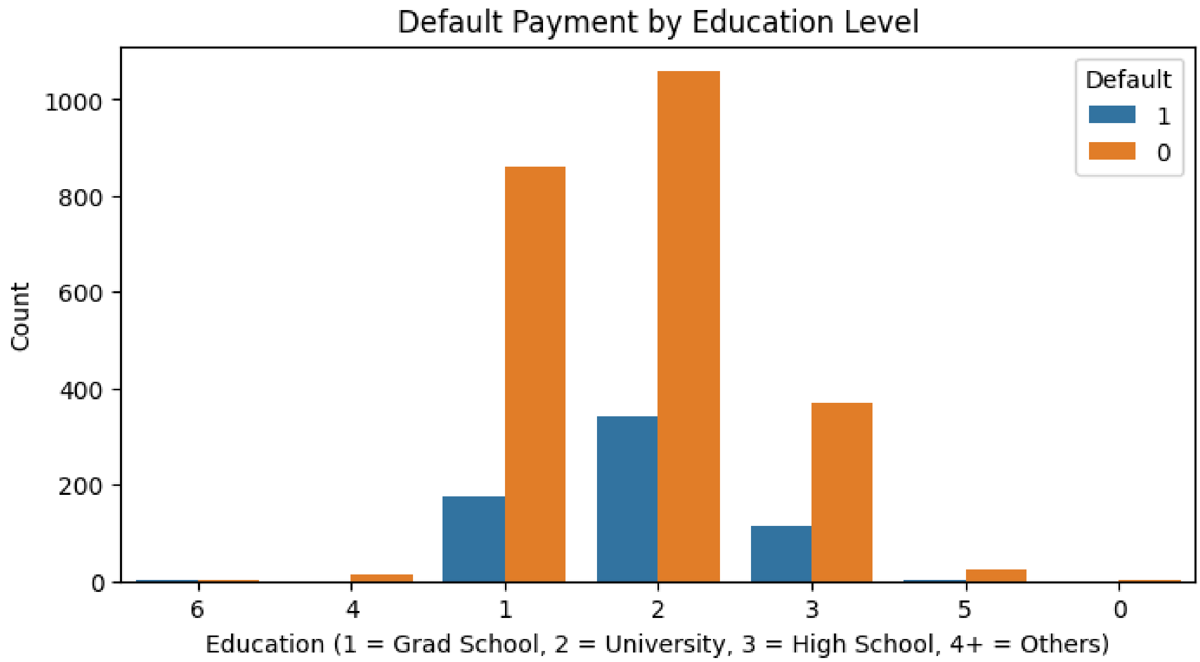
In [34]:

```python
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(6, 4))
sns.countplot(x='sex', hue='default_payment_next_month', data=df)
plt.title("Default Payment by Sex")
plt.xlabel("sex (1 = Male, 2 = Female)")
plt.ylabel("Count")
plt.legend(title='Default')
plt.show()
```

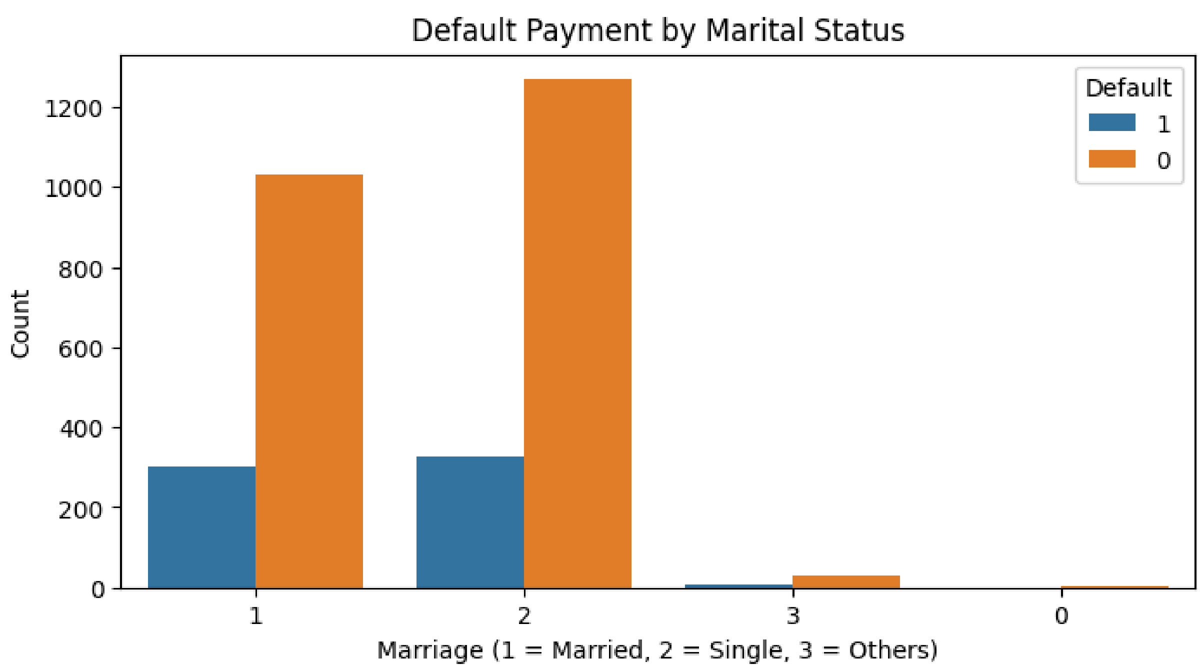


In [35]:

```python
plt.figure(figsize=(8, 4))
sns.countplot(x='education_level', hue='default_payment_next_month', data=df)
plt.title("Default Payment by Education Level")
plt.xlabel("Education (1 = Grad School, 2 = University, 3 = High School, 4+ = Other
plt.ylabel("Count")
plt.legend(title='Default')
plt.show()
```



In [36]:
```
plt.figure(figsize=(8, 4))
sns.countplot(x='marital_status', hue='default_payment_next_month', data=df)
plt.title("Default Payment by Marital Status")
plt.xlabel("Marriage (1 = Married, 2 = Single, 3 = Others)")
plt.ylabel("Count")
plt.legend(title='Default')
plt.show()
```



In [37]:
```
import numpy as np
import pandas as pd

# Function to clean values
def clean_binary_column(val):
    # Handle lists/arrays with a single item
```

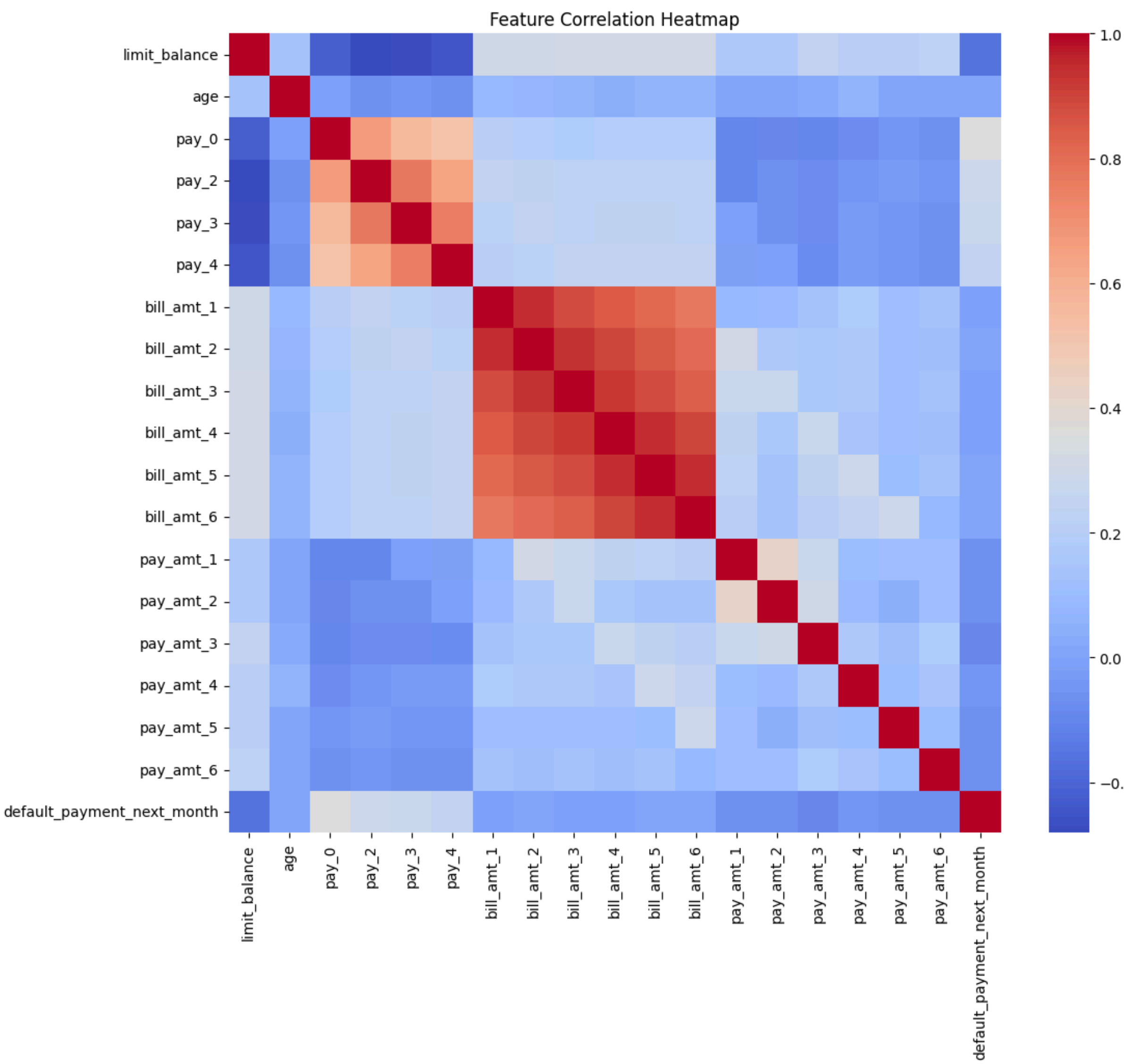
```
    if isinstance(val, (list, np.ndarray)) and len(val) == 1:
        val = val[0]
    elif isinstance(val, dict) and 'value' in val:
        val = val['value']
    # Try converting to numeric
    try:
        return int(float(val))
    except (ValueError, TypeError):
        return np.nan

# Apply cleaning
df['default_payment_next_month'] = df['default_payment_next_month'].apply(clean_bin
df['default_payment_next_month'] = pd.to_numeric(df['default_payment_next_month'],

# Drop invalid values and cast to int
df = df.dropna(subset=['default_payment_next_month'])
df['default_payment_next_month'] = df['default_payment_next_month'].astype(int)

# Confirm it worked
print(df['default_payment_next_month'].unique())
print(df['default_payment_next_month'].dtype)
```

```
[1 0]
int64
```

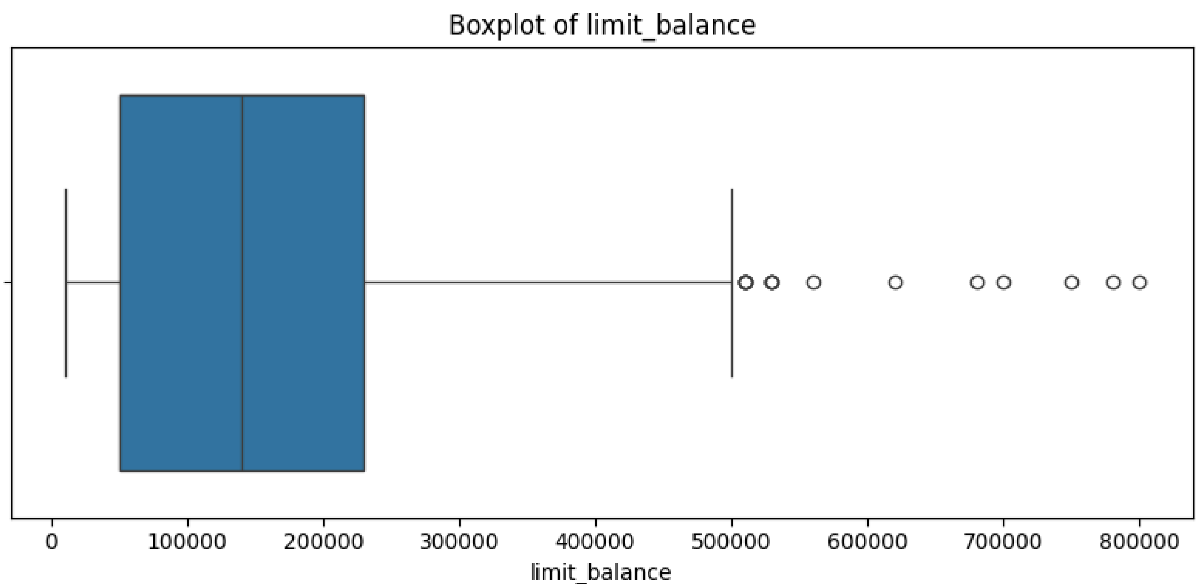
In [38]:

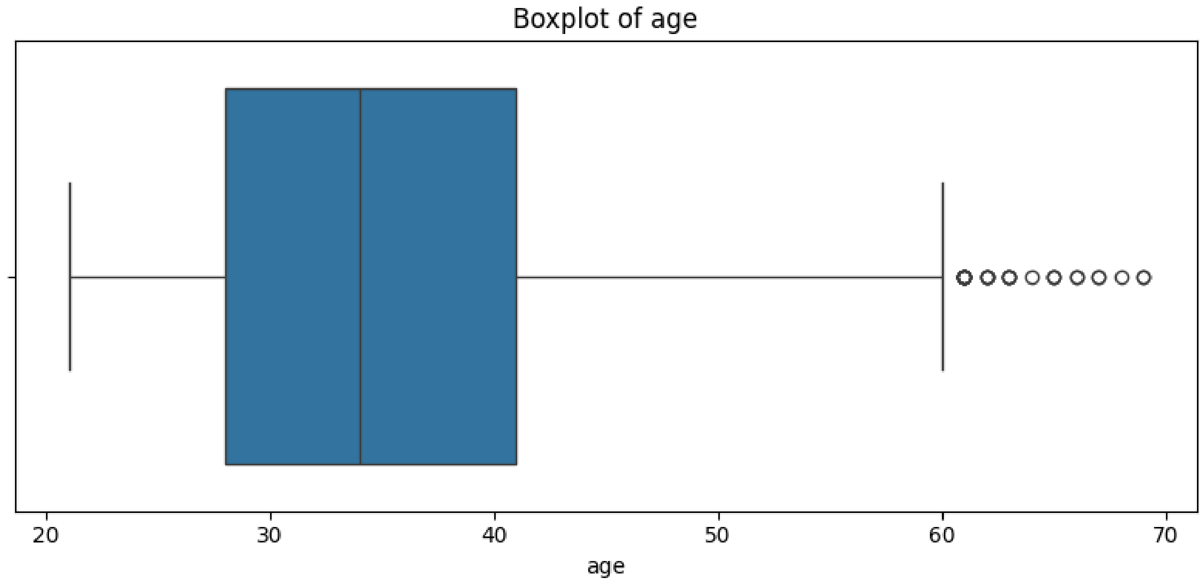
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# 1. Accept only numeric values
df_numeric = df.select_dtypes(include=[np.number]).copy()

# 2. Drop ID column if present
if 'id' in df_numeric.columns:
    df_numeric.drop(columns=['id'], inplace=True)

# 3. Drop missing values
df_numeric.dropna(inplace=True)

# 4. Plot correlation heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(df_numeric.corr(), cmap='coolwarm', annot=False)
plt.title("Feature Correlation Heatmap")
plt.show()

# 5. Correlation with target variable
target_col = "default_payment_next_month"
if target_col in df_numeric.columns:
    correlation = df_numeric.corr()[target_col].sort_values(ascending=False)
    print(f"\nCorrelation with '{target_col}':")
    print(correlation)
else:
    print(f"\nColumn '{target_col}' not found in df_numeric.")

# 6. Drop highly correlated features (multicollinearity filter)
```

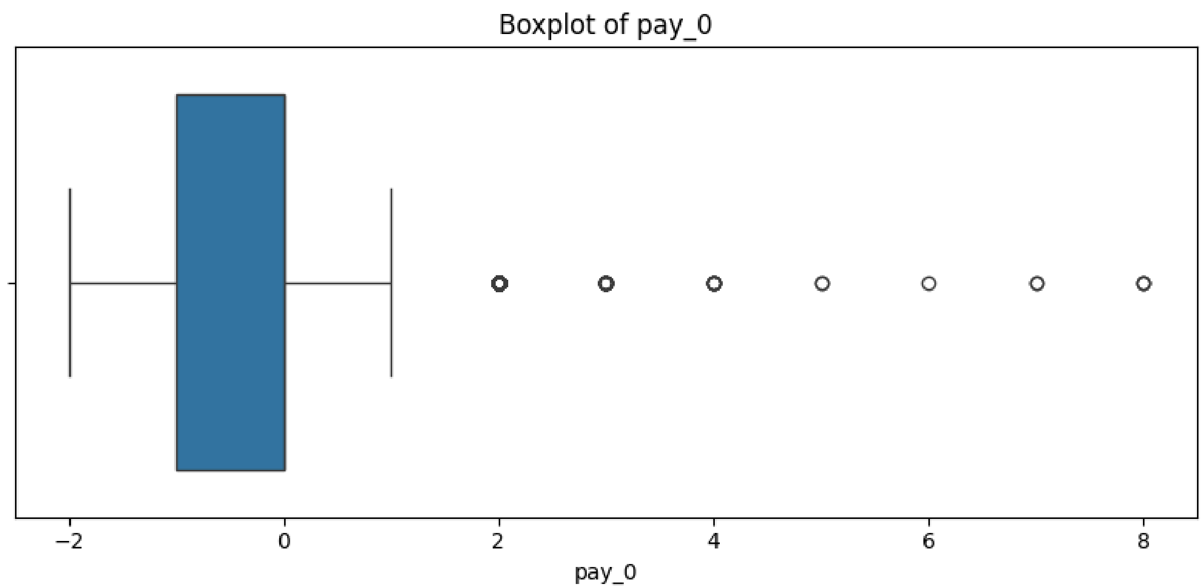
```
#    Threshold can be adjusted (e.g., 0.8 or 0.9)
corr_matrix = df_numeric.corr().abs()
upper_tri = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool)
to_drop = [column for column in upper_tri.columns if any(upper_tri[column] > 0.8)]

print(f"\nDropping highly correlated features:\n{to_drop}")
df_reduced = df_numeric.drop(columns=to_drop)


# 7. Box plots for outlier detection
print("\nBoxplots for numeric columns (checking for outliers)...")
for column in df_reduced.columns:
    plt.figure(figsize=(8, 4))
    sns.boxplot(data=df_reduced, x=column)
    plt.title(f"Boxplot of {column}")
    plt.tight_layout()
    plt.show()
```

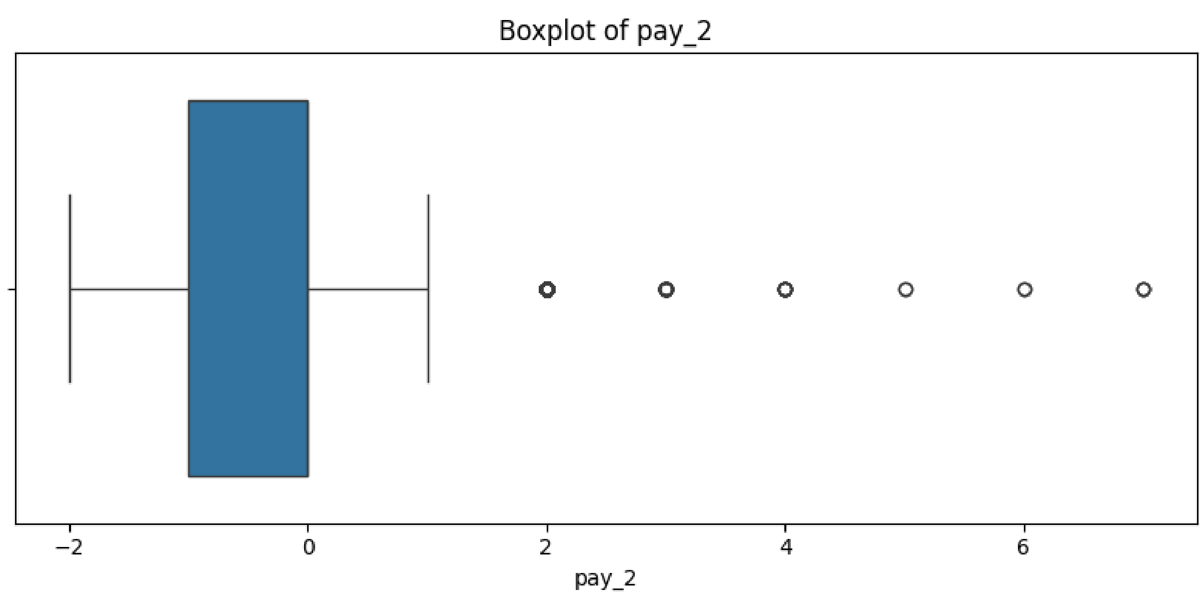


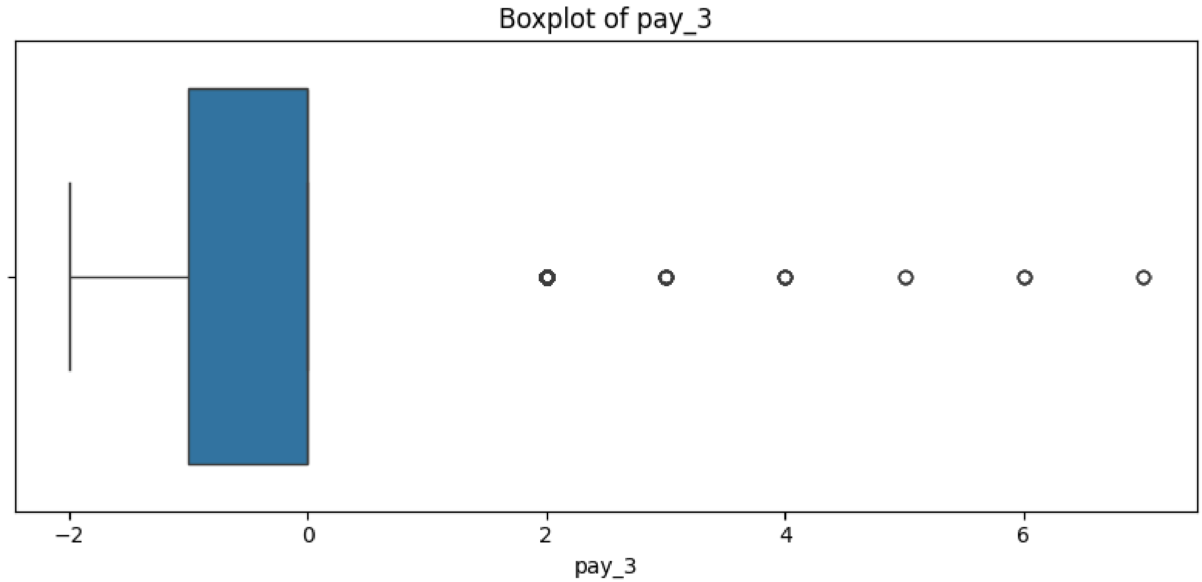
```
Correlation with 'default_payment_next_month':
default_payment_next_month    1.000000
pay_0                         0.356963
pay_2                         0.288813
pay_3                         0.275758
pay_4                         0.255805
age                           0.016905
bill_amt_6                    0.006116
bill_amt_5                    0.005930
bill_amt_2                    0.000877
bill_amt_3                   -0.001075
bill_amt_4                   -0.004718
bill_amt_1                   -0.005961
pay_amt_4                    -0.053684
pay_amt_2                    -0.059265
pay_amt_5                    -0.066159
pay_amt_1                    -0.066163
pay_amt_6                    -0.066966
pay_amt_3                    -0.090248
limit_balance                -0.161909
Name: default_payment_next_month, dtype: float64

Dropping highly correlated features:
['bill_amt_2', 'bill_amt_3', 'bill_amt_4', 'bill_amt_5', 'bill_amt_6']

Boxplots for numeric columns (checking for outliers)...
```

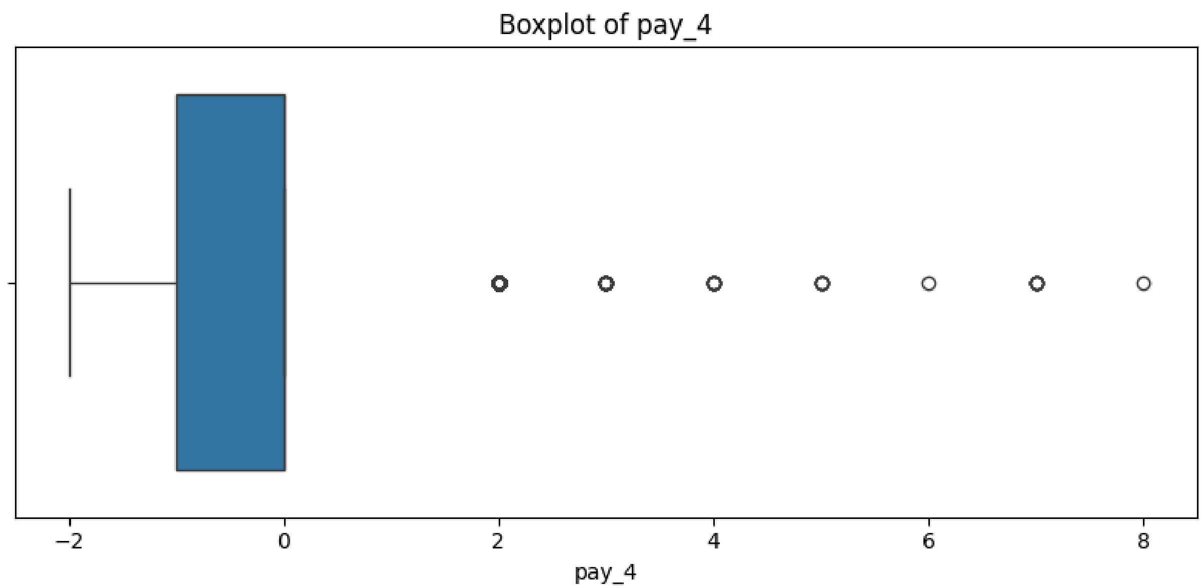


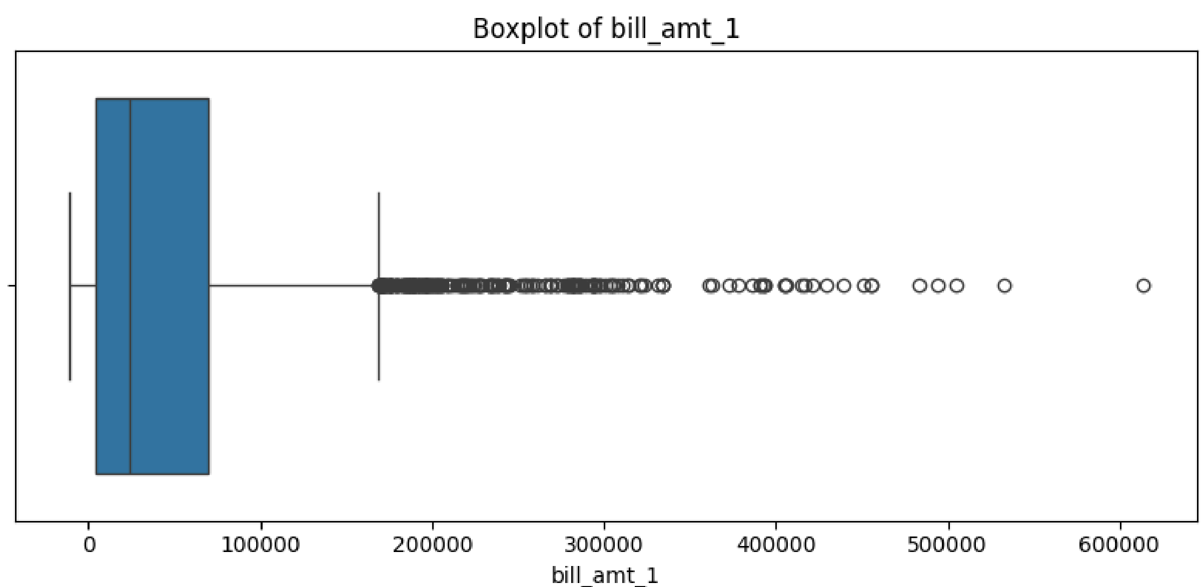

Boxplot of age
20
30
40
50
60
70
age

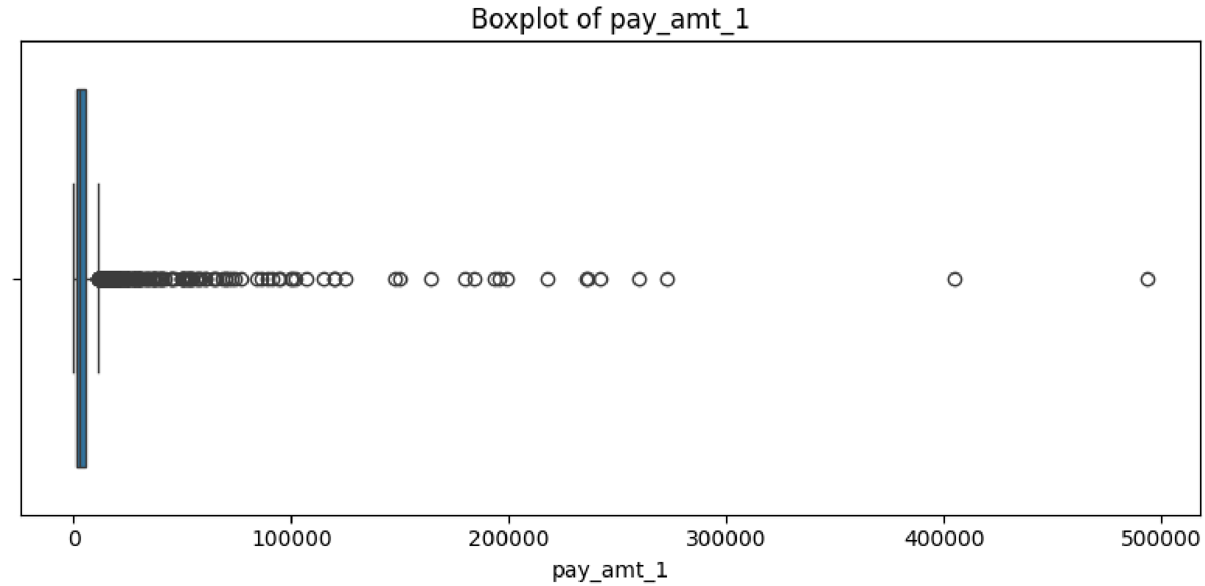

Boxplot of pay_0
−2
0
2
4
6
8
pay_0

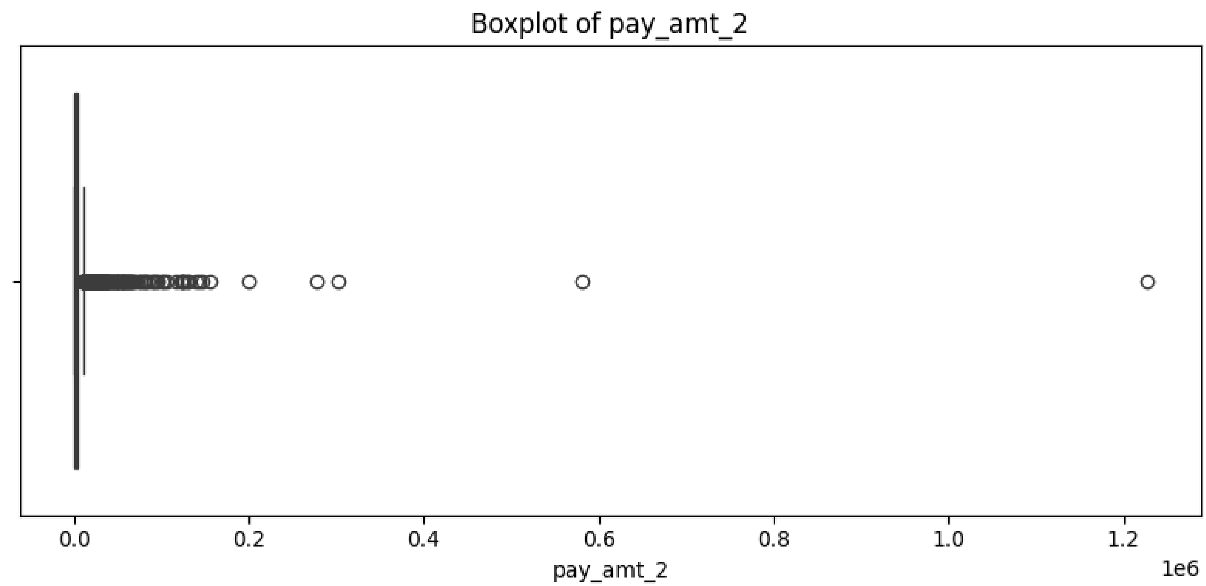

Boxplot of pay_2
−2
0
2
4
6
pay_2

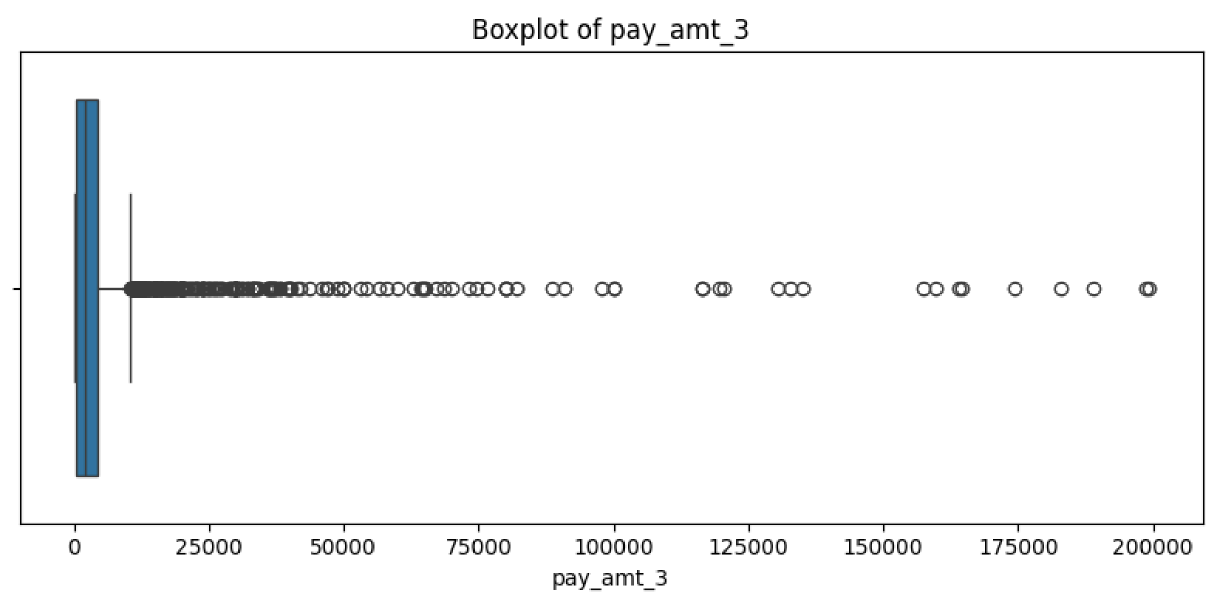

Boxplot of pay_3
−2
0
2
4
6
pay_3

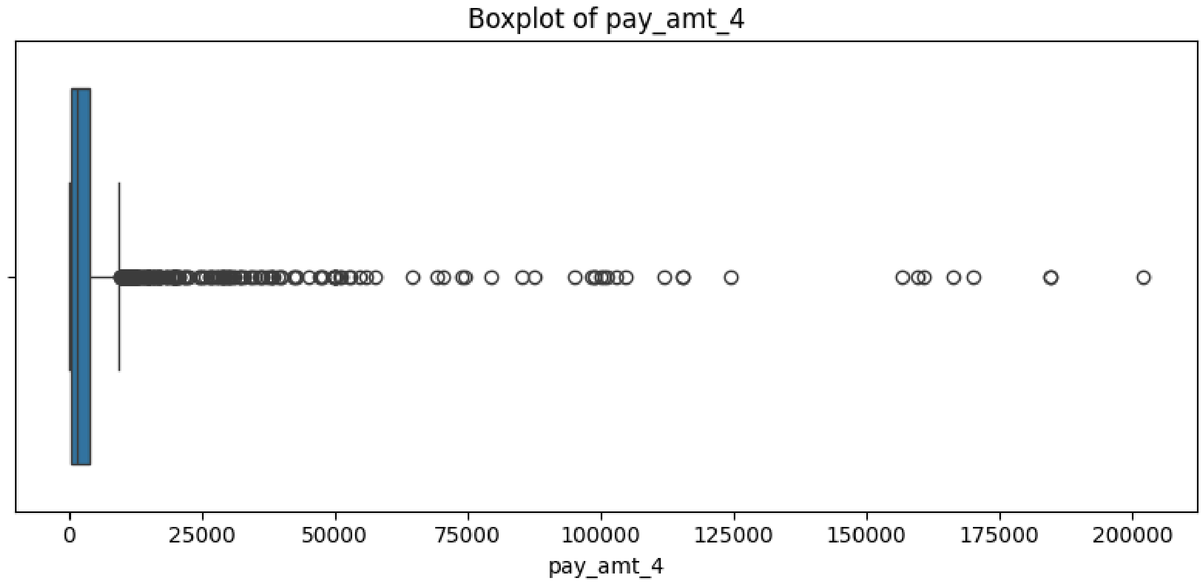

Boxplot of pay_4
−2
0
2
4
6
8
pay_4

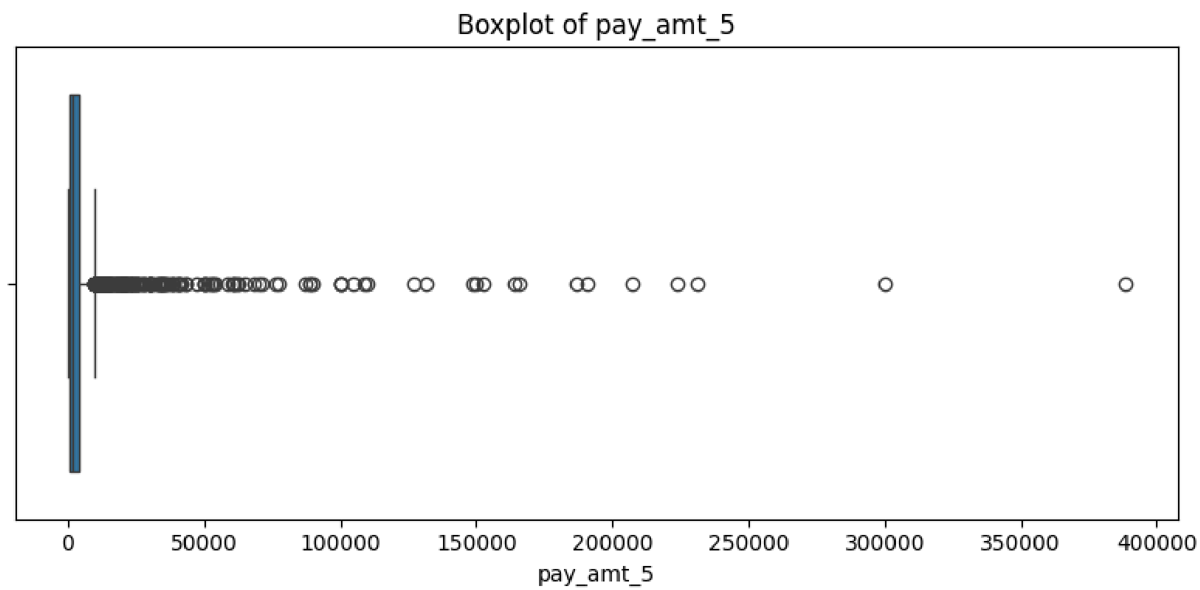

Boxplot of bill_amt_1
0
100000
200000
300000
400000
500000
600000
bill_amt_1

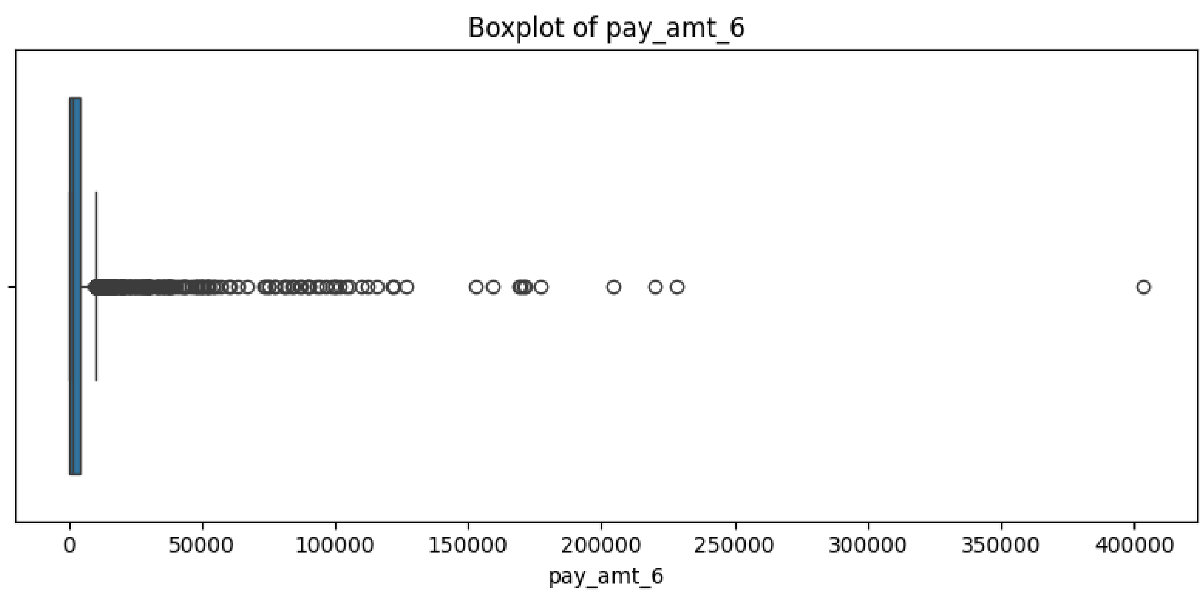

Boxplot of pay_amt_1
0
100000
200000
300000
400000
500000
pay_amt_1

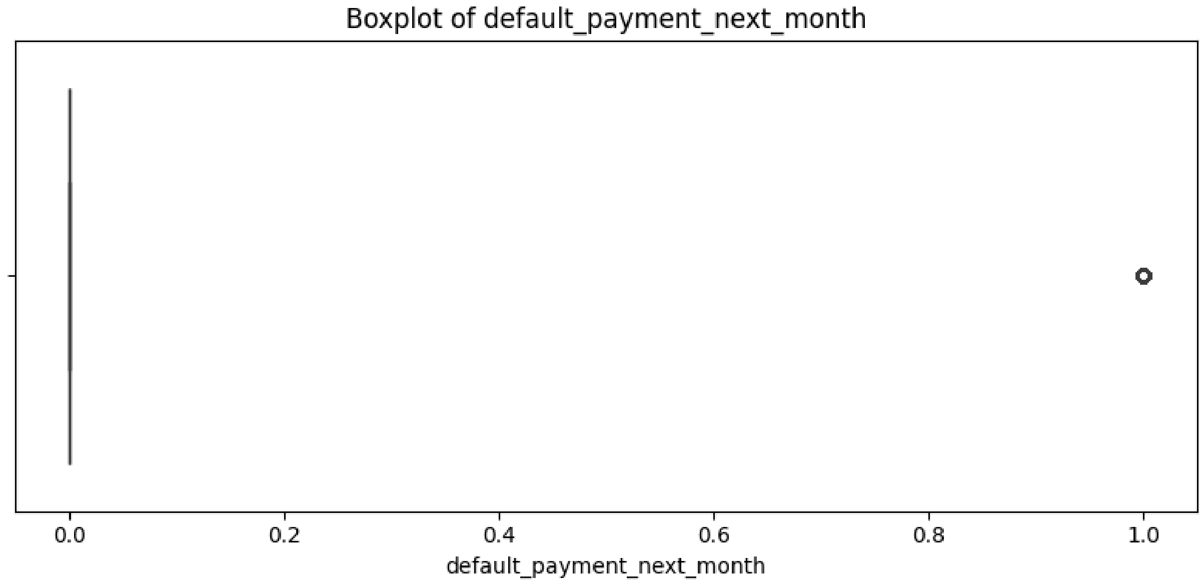

Boxplot of pay_amt_2
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1e6
pay_amt_2


Boxplot of pay_amt_3
0
25000
50000
75000
100000
125000
150000
175000
200000
pay_amt_3


Boxplot of pay_amt_4
0
25000
50000
75000
100000
125000
150000
175000
200000
pay_amt_4


Boxplot of pay_amt_5
0
50000
100000
150000
200000
250000
300000
350000
400000
pay_amt_5


Boxplot of pay_amt_6
0
50000
100000
150000
200000
250000
300000
350000
400000
pay_amt_6



In [39]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
import xgboost as xgb


# Rename target column
df.rename(columns={"default_payment_next_month": "default"}, inplace=True)

# Drop ID column
if 'id' in df.columns:
    df.drop(columns=["id"], inplace=True)

# Drop rows with missing values
df.dropna(inplace=True)

# Split features and target
X = df.drop("default", axis=1)
y = df[["default"]]

# Keep only numeric features
X = X.select_dtypes(include=["number"])

# Split dataset
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# Scale features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train model
model = xgb.XGBClassifier(use_label_encoder=False, eval_metric='logloss')
model.fit(X_train_scaled, y_train)
```

```python
# Predict
y_pred = model.predict(X_test_scaled)

# Evaluate
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
c:\Users\ADMIN\Desktop\Phoenix Analytics\venv\Lib\site-packages\xgboost\training.py:
183: UserWarning: [08:43:26] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\le
arner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
Accuracy: 0.7892074198988196

Confusion Matrix:
 [[420  46]
 [ 79  48]]

Classification Report:
               precision    recall  f1-score   support

           0       0.84      0.90      0.87       466
           1       0.51      0.38      0.43       127

    accuracy                           0.79       593
   macro avg       0.68      0.64      0.65       593
weighted avg       0.77      0.79      0.78       593
```

In [40]:

```python
from sklearn.model_selection import GridSearchCV
import xgboost as xgb

# Define the model
xgb_clf = xgb.XGBClassifier(use_label_encoder=False, eval_metric='logloss')

# Define parameter grid to search
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [3, 5, 7],
    'learning_rate': [0.01, 0.1, 0.2],
    'subsample': [0.8, 1.0],
    'colsample_bytree': [0.8, 1.0]
}

# Set up GridSearchCV
grid_search = GridSearchCV(
    estimator=xgb_clf,
    param_grid=param_grid,
    scoring='accuracy',      # You can change to 'roc_auc', 'f1', etc.
    cv=5,                     # 5-fold cross-validation
    verbose=1,                # Shows progress
    n_jobs=-1               # Use all CPU cores
)
```

```
# Fit the grid search to the training data
grid_search.fit(X_train_scaled, y_train.values.ravel())

# Best parameters and score
print("Best Parameters:\n", grid_search.best_params_)
print("\nBest Accuracy Score:", grid_search.best_score_)
```

```
Fitting 5 folds for each of 108 candidates, totalling 540 fits
Best Parameters:
 {'colsample_bytree': 1.0, 'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 10
0, 'subsample': 0.8}

Best Accuracy Score: 0.8398010215411947
```

```
c:\Users\ADMIN\Desktop\Phoenix Analytics\venv\Lib\site-packages\xgboost\training.py:
183: UserWarning: [08:45:26] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\le
arner.cc:738:
Parameters: { "use_label_encoder" } are not used.

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

In [41]:
```
best_model = grid_search.best_estimator_

# Predict
y_pred = best_model.predict(X_test_scaled)

# Evaluate
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

print("Accuracy:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.8026981450252951
Confusion Matrix:
 [[428  38]
 [ 79  48]]
Classification Report:
               precision    recall  f1-score   support

           0       0.84      0.92      0.88       466
           1       0.56      0.38      0.45       127

    accuracy                           0.80       593
   macro avg       0.70      0.65      0.67       593
weighted avg       0.78      0.80      0.79       593
```