Problem Statement

The objective of this project is to build a predictive model that determines how likely an individual is to be a user of **illicit drugs** based on their demographic attributes, personality traits, and behavioral characteristics. The study leverages a dataset containing information on drug usage patterns (e.g., cannabis, cocaine, heroin, etc.), demographic variables (age, gender, education, etc.), and psychometric scores (e.g., neuroticism, extraversion, sensation-seeking).

This project focuses on answering the following key questions:

1. Which features—demographics, personality traits, or behavioral metrics—are the strongest predictors of illicit drug use?
2. How well can a supervised learning model predict the likelihood of illicit drug use, and what are its key performance metrics?

Scope of Illicit Drugs

"Illicit drugs" in this analysis refer to substances such as cannabis, cocaine, heroin, LSD, ketamine, methamphetamines, and similar drugs, excluding legal substances like alcohol and nicotine.

Significance

Substance abuse is a significant public health issue, with illicit drug usage often leading to adverse social, psychological, and economic consequences. Identifying predictors of illicit drug use can help inform targeted interventions, educational programs, and public health policies to prevent and reduce substance abuse.

This predictive model will provide insights into the attributes associated with illicit drug use and offer a tool to predict such behaviors, which could be utilized in further research or by public health organizations.

Project Goals

1. Perform **exploratory data analysis (EDA)** to uncover patterns and relationships in the data, particularly focusing on predictors of illicit drug use.
2. Build and evaluate a **classification model** to predict illicit drug use (binary classification: user vs. non-user).
3. Identify and interpret the most influential features contributing to predictions, using techniques like feature importance analysis or SHAP (SHapley Additive Explanations).
4. Address issues like **class imbalance** using techniques such as SMOTE, undersampling, or class-weighted models.

Deliverables

1. A cleaned and preprocessed dataset, with binary labels indicating illicit drug use.
2. Visualizations and analysis summarizing the relationships between predictors and drug use (e.g., correlation matrices, pair plots, bar charts).
3. A machine learning model (e.g., logistic regression, random forest, or XGBoost) that achieves acceptable performance based on evaluation metrics (e.g., precision, recall, F1 score, ROC-AUC).
4. A discussion of insights derived from the analysis and model, including the implications for public health.

In [1]:

```
from ucimlrepo import fetch_ucirepo
import pandas as pd
import seaborn as sns
from matplotlib import pyplot as plt
```

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, roc_auc_score, confusion_matrix, roc_c
urve, auc


# Fetch dataset
drug_consumption_quantified = fetch_ucirepo(id=373)

# Load data as Pandas DataFrames
X = drug_consumption_quantified.data.features
y = drug_consumption_quantified.data.targets

# Merge features and targets into a single DataFrame
df = pd.concat([X, y], axis=1)
```

In [2]:

```
# Slight cleaning
df = df.rename(columns={'impuslive': 'impulsive'})
df = df.drop(columns=['semer'])
```

Load and Preview the Data

Understand the dataset structure by summarizing it

In [3]:

```
# Check the structure of the dataset
print(df.info())

# Check for missing values
print(df.isnull().sum())

# Preview the dataset
print(df.head())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1885 entries, 0 to 1884
Data columns (total 30 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   age        1885 non-null   float64
 1   gender     1885 non-null   float64
 2   education  1885 non-null   float64
 3   country    1885 non-null   float64
 4   ethnicity  1885 non-null   float64
 5   nscore     1885 non-null   float64
 6   escore     1885 non-null   float64
 7   oscore     1885 non-null   float64
 8   ascore     1885 non-null   float64
 9   cscore     1885 non-null   float64
 10  impulsive  1885 non-null   float64
 11  ss         1885 non-null   float64
 12  alcohol    1885 non-null   object 
 13  amphet     1885 non-null   object 
 14  amyl       1885 non-null   object 
 15  benzos     1885 non-null   object 
 16  caff       1885 non-null   object 
 17  cannabis   1885 non-null   object 
 18  choc       1885 non-null   object 
 19  coke       1885 non-null   object 
 20  crack      1885 non-null   object 
 21  ecstasy    1885 non-null   object 
 22  heroin     1885 non-null   object 
 23  ketamine   1885 non-null   object 
 24  legalh     1885 non-null   object 
 25  lsd        1885 non-null   object 
 26  meth       1885 non-null   object 
 27  mushrooms  1885 non-null   object 
 28  nicotine   1885 non-null   object 
```

```
 28  nicotine    1885 non-null   object
 29  vsa         1885 non-null   object
dtypes: float64(12), object(18)
memory usage: 441.9+ KB
None
age          0
gender       0
education    0
country      0
ethnicity    0
nscore       0
escore       0
oscore       0
ascore       0
cscore       0
impulsive    0
ss           0
alcohol      0
amphet       0
amyl         0
benzos       0
caff         0
cannabis     0
choc         0
coke         0
crack        0
ecstasy      0
heroin       0
ketamine     0
legalh       0
lsd          0
meth         0
mushrooms    0
nicotine     0
vsa          0
dtype: int64
       age   gender  education  country  ethnicity   nscore   escore   oscore  \
0  0.49788  0.48246   -0.05921  0.96082    0.12600  0.31287 -0.57545 -0.58331
1 -0.07854 -0.48246    1.98437  0.96082   -0.31685 -0.67825  1.93886  1.43533
2  0.49788 -0.48246   -0.05921  0.96082   -0.31685 -0.46725  0.80523 -0.84732
3 -0.95197  0.48246    1.16365  0.96082   -0.31685 -0.14882 -0.80615 -0.01928
4  0.49788  0.48246    1.98437  0.96082   -0.31685  0.73545 -1.63340 -0.45174

    ascore   cscore  ...  crack  ecstasy heroin ketamine legalh  lsd meth  \
0 -0.91699 -0.00665  ...    CL0      CL0    CL0      CL0    CL0  CL0  CL0
1  0.76096 -0.14277  ...    CL0      CL4    CL0      CL2    CL0  CL2  CL3
2 -1.62090 -1.01450  ...    CL0      CL0    CL0      CL0    CL0  CL0  CL0
3  0.59042  0.58489  ...    CL0      CL0    CL0      CL2    CL0  CL0  CL0
4 -0.30172  1.30612  ...    CL0      CL1    CL0      CL0    CL1  CL0  CL0

  mushrooms nicotine  vsa
0       CL0      CL2  CL0
1       CL0      CL4  CL0
2       CL1      CL0  CL0
3       CL0      CL2  CL0
4       CL2      CL2  CL0

[5 rows x 30 columns]
```

In [4]:

```
df.columns
```

Out[4]:

```
Index(['age', 'gender', 'education', 'country', 'ethnicity', 'nscore',
       'escore', 'oscore', 'ascore', 'cscore', 'impulsive', 'ss', 'alcohol',
       'amphet', 'amyl', 'benzos', 'caff', 'cannabis', 'choc', 'coke', 'crack',
       'ecstasy', 'heroin', 'ketamine', 'legalh', 'lsd', 'meth', 'mushrooms',
       'nicotine', 'vsa'],
      dtype='object')
```

Understand the Target Variable

Before diving into predictors, analyze the distribution of the target variable (`y`).

In [5]:

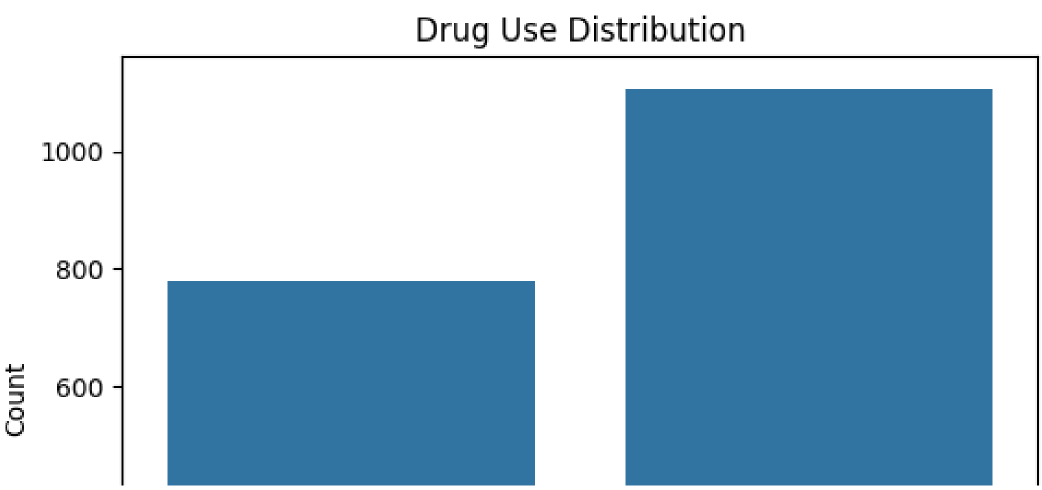
```
# Define a list of drugs (update based on your analysis)
drugs = ['cannabis', 'coke', 'crack', 'heroin', 'meth', 'ecstasy',
         'lsd', 'amyl', 'ketamine', 'mushrooms', 'vsa']

# Use at least once in last year
drug_user = ['CL3', 'CL4', 'CL5', 'CL6']

# Define a binary target variable for any drug use in the last year
def check_drug_use(row):
    for user in drug_user:  # Iterate over the drug_user codes
        if user in row.values:  # Check if the code is in the row's values
            return 1  # Return 1 if a match is found
    return 0  # Return 0 if no matches are found

# Apply the function only to the specified drug columns
df['drug_use'] = df[drugs].apply(check_drug_use, axis=1)

dfDrugUse = df.drop(columns={'alcohol',
        'amphet', 'amyl', 'benzos', 'caff', 'cannabis', 'choc', 'coke', 'crack',
        'ecstasy', 'heroin', 'ketamine', 'legalh', 'lsd', 'meth', 'mushrooms',
        'nicotine', 'vsa'})
dfDrugUse.head()
```

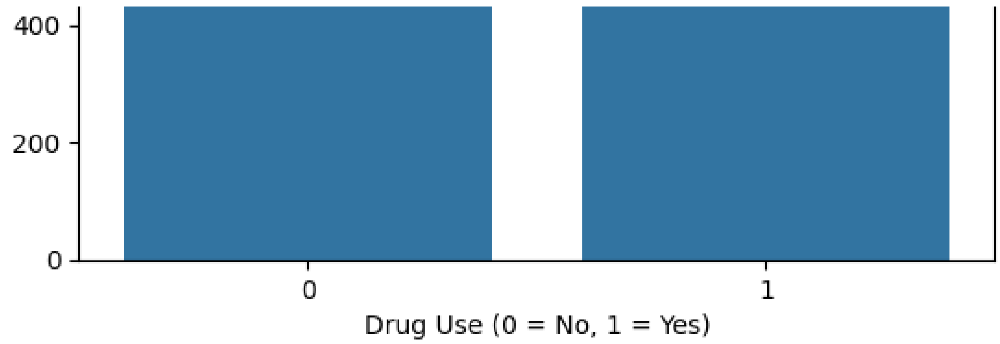
Out[5]:

	age	gender	education	country	ethnicity	nscore	escore	oscore	ascore	cscore	impulsive	ss	drug_use
0	0.49788	0.48246	-0.05921	0.96082	0.12600	0.31287	-0.57545	-0.58331	-0.91699	-0.00665	-0.21712	-1.18084	0
1	-0.07854	-0.48246	1.98437	0.96082	-0.31685	-0.67825	1.93886	1.43533	0.76096	-0.14277	-0.71126	-0.21575	1
2	0.49788	-0.48246	-0.05921	0.96082	-0.31685	-0.46725	0.80523	-0.84732	-1.62090	-1.01450	-1.37983	0.40148	1
3	-0.95197	0.48246	1.16365	0.96082	-0.31685	-0.14882	-0.80615	-0.01928	0.59042	0.58489	-1.37983	-1.18084	0
4	0.49788	0.48246	1.98437	0.96082	-0.31685	0.73545	-1.63340	-0.45174	-0.30172	1.30612	-0.21712	-0.21575	1

In [6]:

```
# Plot the new binary target variable
sns.countplot(x=df['drug_use'], y=None, hue=None, data=df)
plt.title("Drug Use Distribution")
plt.xlabel("Drug Use (0 = No, 1 = Yes)")
plt.ylabel("Count")
plt.show()
```





Overview of the Target Variable

- **Start by checking the distribution of the binary target variable to ensure no severe class imbalance.**

In [7]:

```
# Check class distribution
print(df['drug_use'].value_counts(normalize=True))
```

```
drug_use
1    0.587268
0    0.412732
Name: proportion, dtype: float64
```

Mapping Fields for Better Interpretability

In [8]:

```
# Mapping age values to age groups
age_mapping = {
    -0.95197: "18-24",
    -0.07854: "25-34",
     0.49788: "35-44",
     1.09449: "45-54",
     1.82213: "55-64",
     2.59171: "65+"
}

gender_mapping = {
    0.48246: "Female",
   -0.48246: "Male"
}

education_mapping = {
    -2.43591: "Left before 16",
    -1.73790: "Left at 16",
    -1.43719: "Left at 17",
    -1.22751: "Left at 18",
    -0.61113: "Some college",
    -0.05921: "Professional cert",
     0.45468: "University degree",
     1.16365: "Masters degree",
     1.98437: "Doctorate"
}

country_mapping = {
    -0.09765: "Australia",
     0.24923: "Canada",
    -0.46841: "New Zealand",
    -0.28519: "Other",
     0.21128: "Ireland",
     0.96082: "UK",
    -0.57009: "USA"
}

ethnicity_mapping = {
```

```
    -0.50212: "Asian",
    -1.10702: "Black",
     1.90725: "Mixed-Black/Asian",
     0.12600: "Mixed-White/Asian",
    -0.22166: "Mixed-White/Black",
     0.11440: "Other",
    -0.31685: "White"
}
```

Create a Mapped DataFrame for Visualizations

Copy the original `df` to a new DataFrame, `dfMapped`, and apply the mappings only to this new DataFrame.

In [9]:

```
# Create a separate DataFrame for mapped values
dfMapped = df.copy()

# Apply mappings to the copied DataFrame for visualizations
dfMapped['age'] = dfMapped['age'].map(age_mapping)
dfMapped['gender'] = dfMapped['gender'].map(gender_mapping)
dfMapped['education'] = dfMapped['education'].map(education_mapping)
dfMapped['country'] = dfMapped['country'].map(country_mapping)
dfMapped['ethnicity'] = dfMapped['ethnicity'].map(ethnicity_mapping)
```

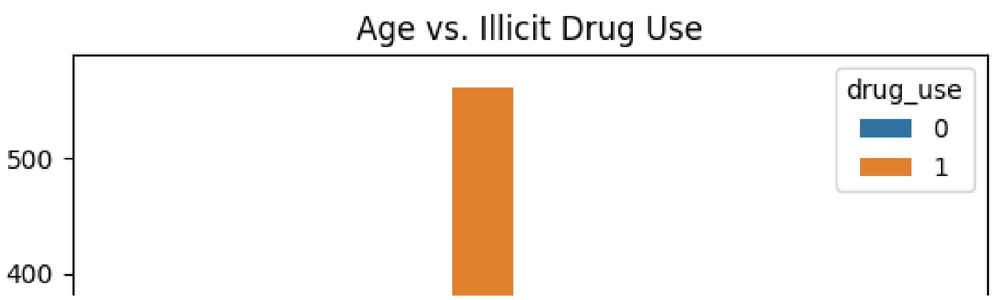
Feature Distribution by Illicit Drug Use

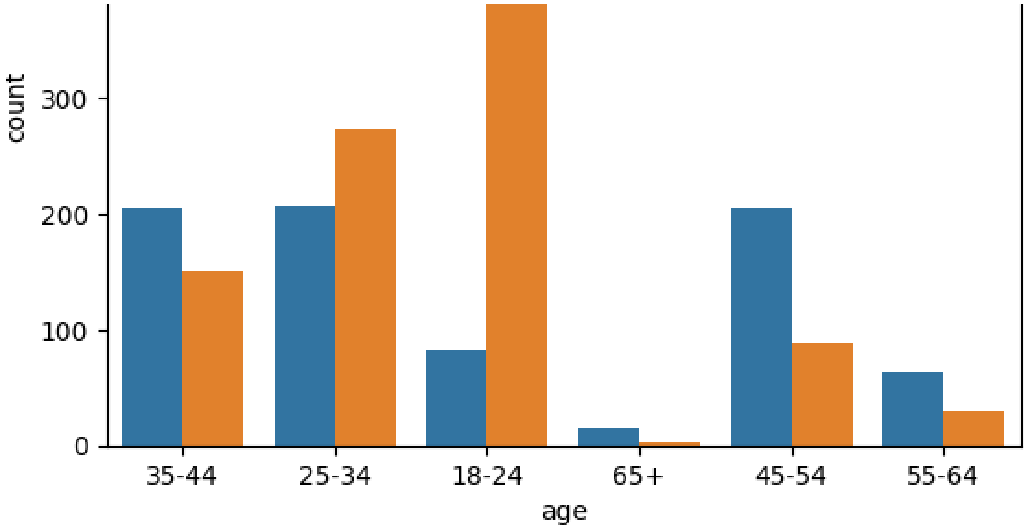
- **Analyze the distribution of demographic and personality traits with respect to `illicit_drug_use`.**

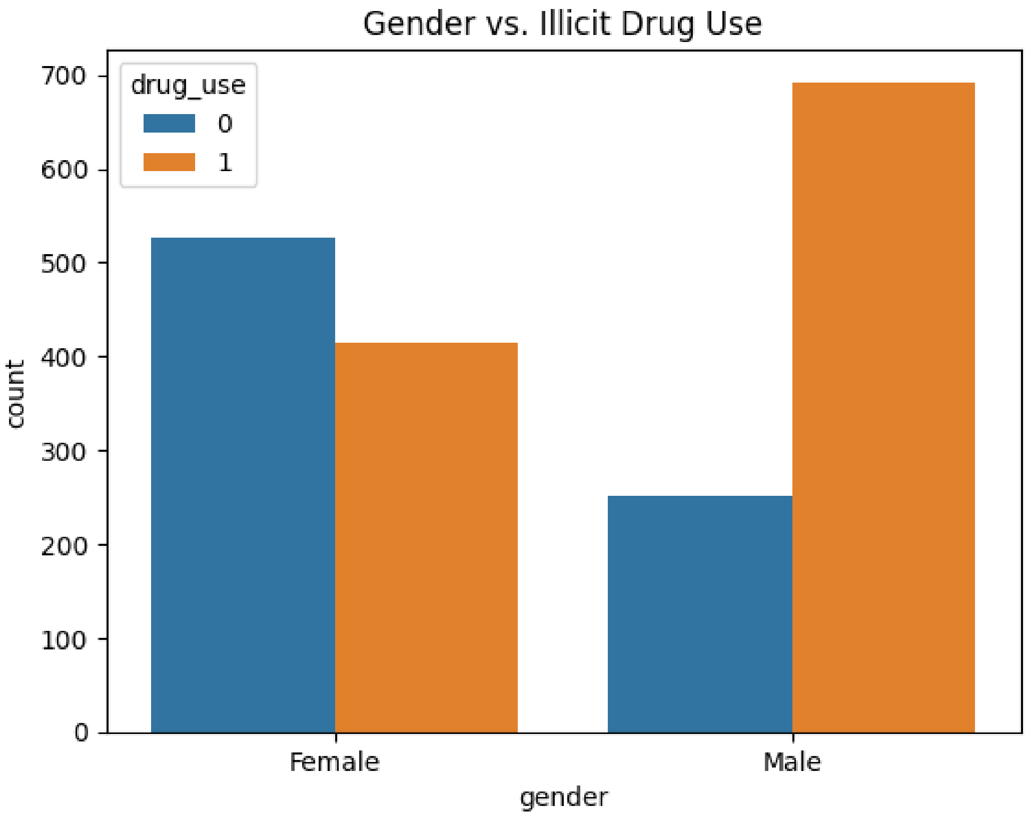
a. Demographics

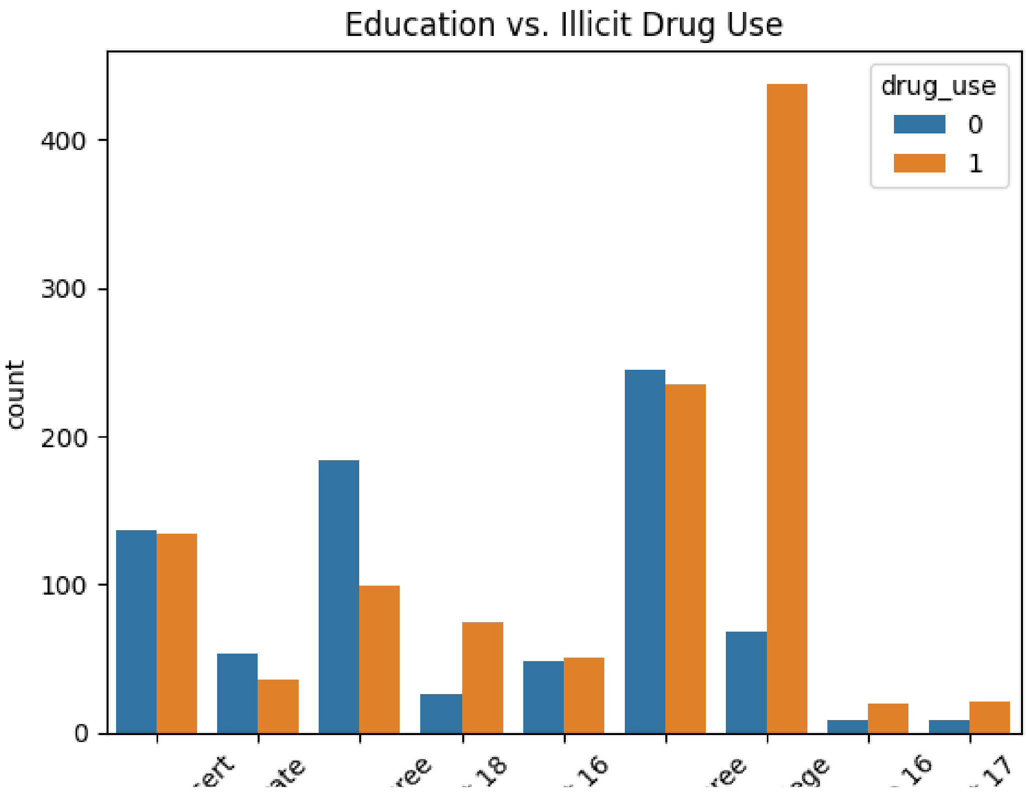
In [10]:

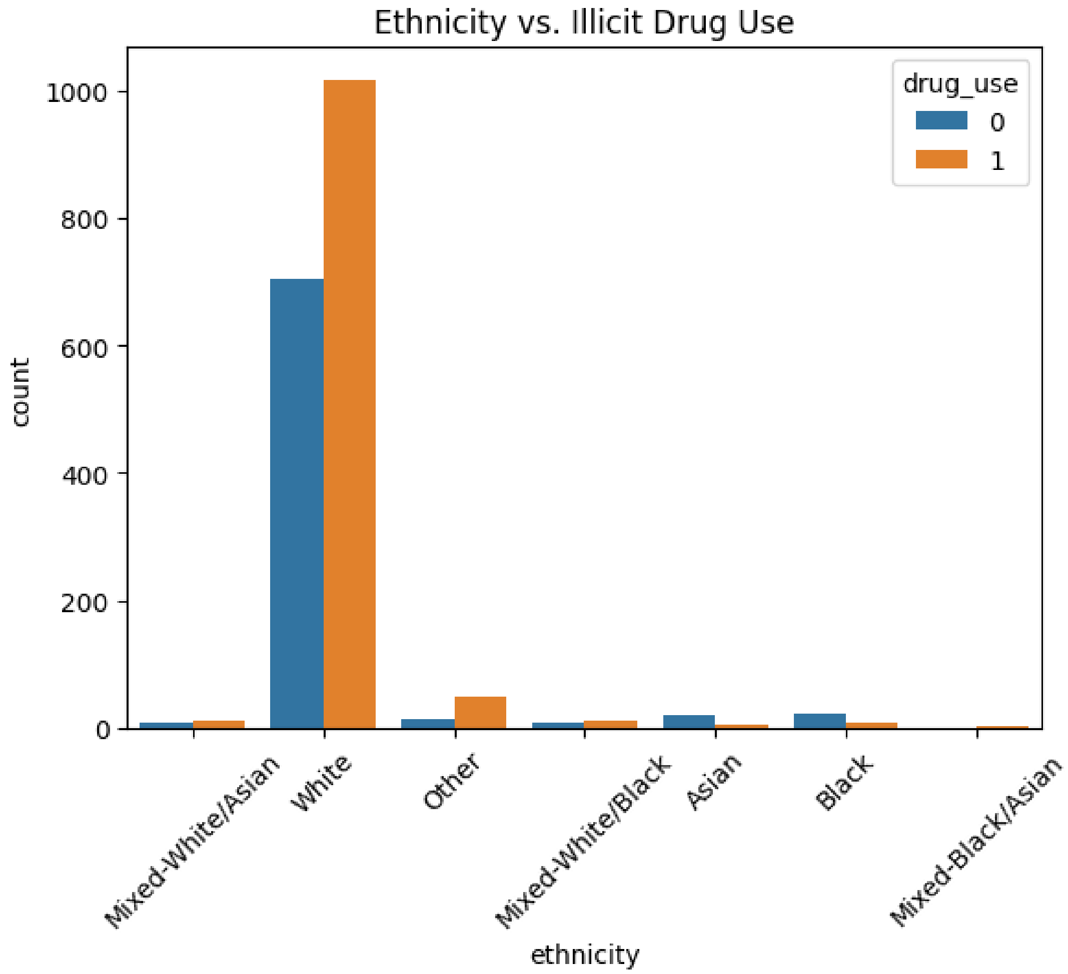
```
import seaborn as sns
import matplotlib.pyplot as plt

# Visualize age distribution by illicit drug use
sns.countplot(data=dfMapped, x='age', hue=df['drug_use'])
plt.title("Age vs. Illicit Drug Use")
plt.show()

# Visualize gender distribution by illicit drug use
sns.countplot(data=dfMapped, x='gender', hue=df['drug_use'])
plt.title("Gender vs. Illicit Drug Use")
plt.show()

# Visualize education distribution by illicit drug use
sns.countplot(data=dfMapped, x='education', hue=df['drug_use'])
plt.title("Education vs. Illicit Drug Use")
plt.xticks(rotation=45)
plt.show()

# Visualize ethnicity distribution by illicit drug use
sns.countplot(data=dfMapped, x='ethnicity', hue=df['drug_use'])
plt.title("Ethnicity vs. Illicit Drug Use")
plt.xticks(rotation=45)
plt.show()
```




count
300
200
100
0
35-44
25-34
18-24
65+
45-54
55-64
age


Gender vs. Illicit Drug Use
drug_use
0
1
700
600
500
400
300
200
100
0
count
Female
Male
gender

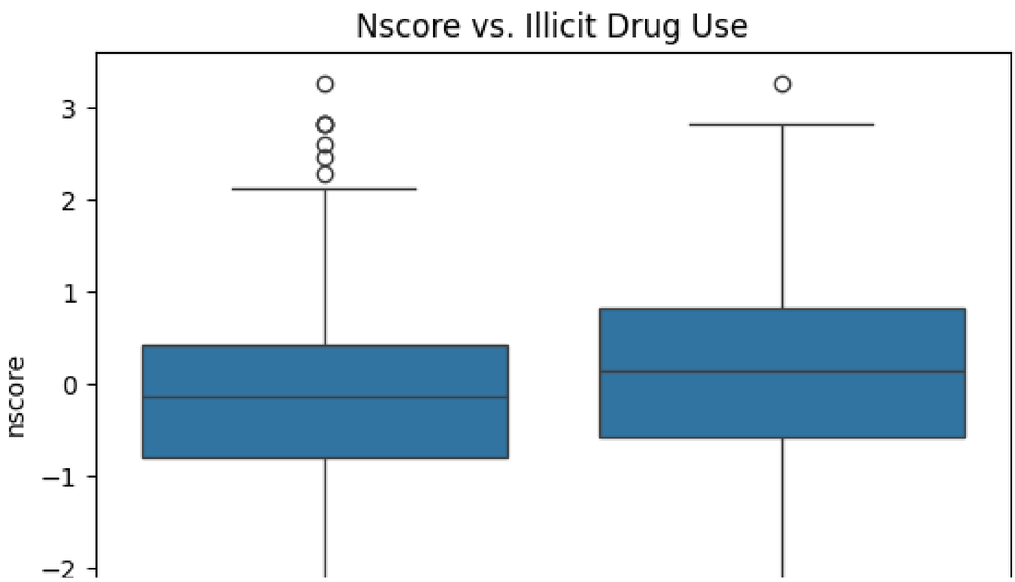

Education vs. Illicit Drug Use
drug_use
0
1
400
300
200
100
0
count

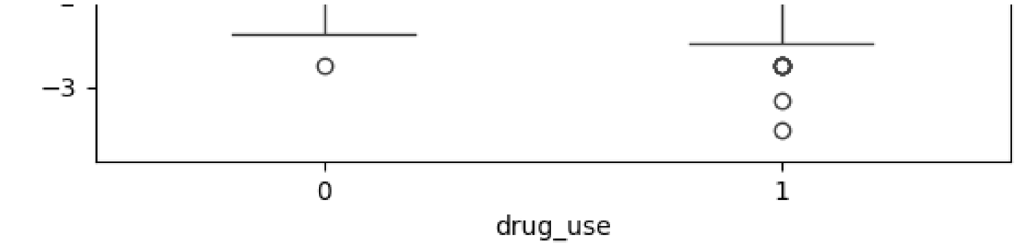


b. Personality Traits

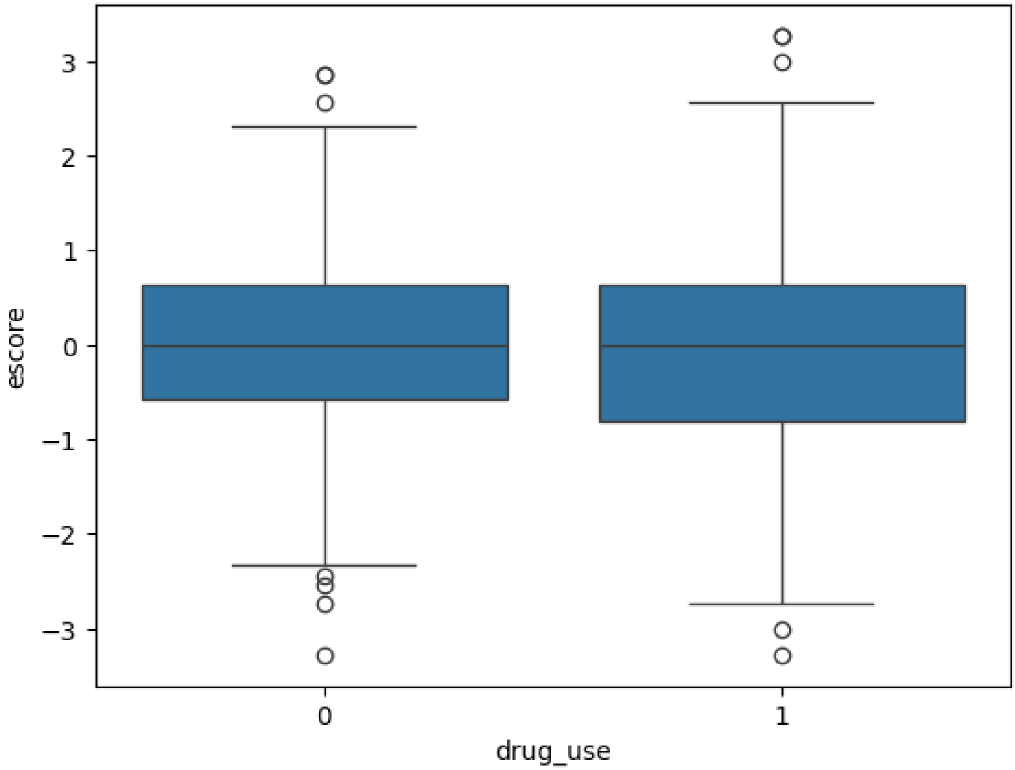
In [11]:

```
# Box plots for personality traits by illicit drug use
traits = ['nscore', 'escore', 'oscore', 'ascore', 'cscore', 'impulsive', 'ss']

for trait in traits:
    sns.boxplot(data=df, x=df['drug_use'], y=trait)
    plt.title(f"{trait.capitalize()} vs. Illicit Drug Use")
    plt.show()
```

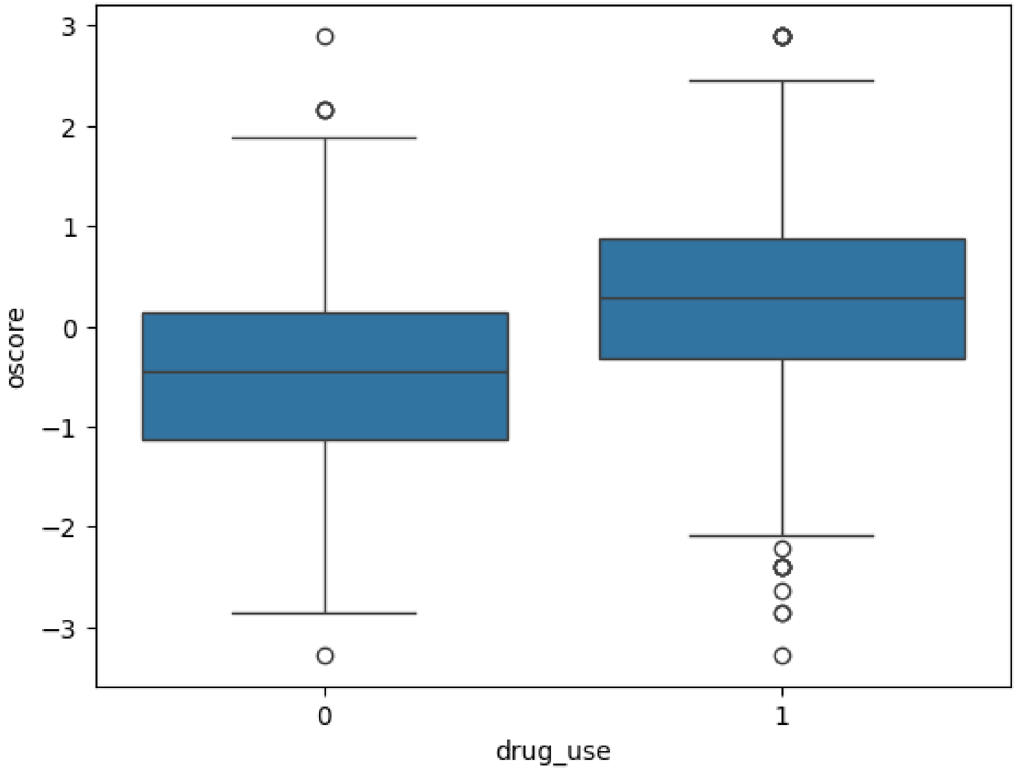




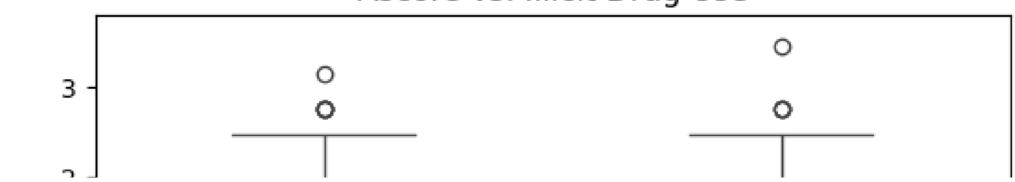
Escore vs. Illicit Drug Use

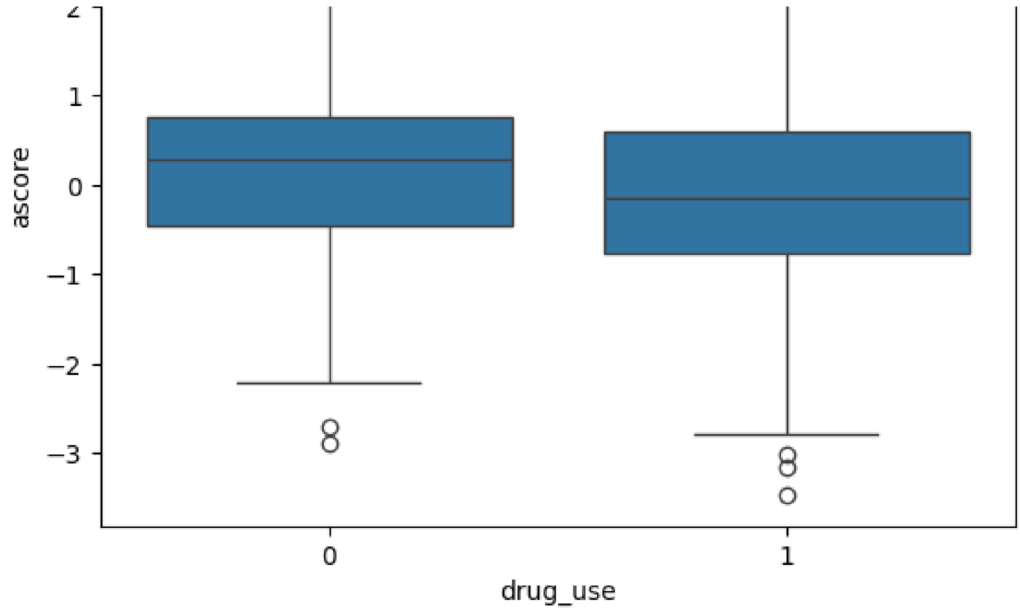


Oscore vs. Illicit Drug Use

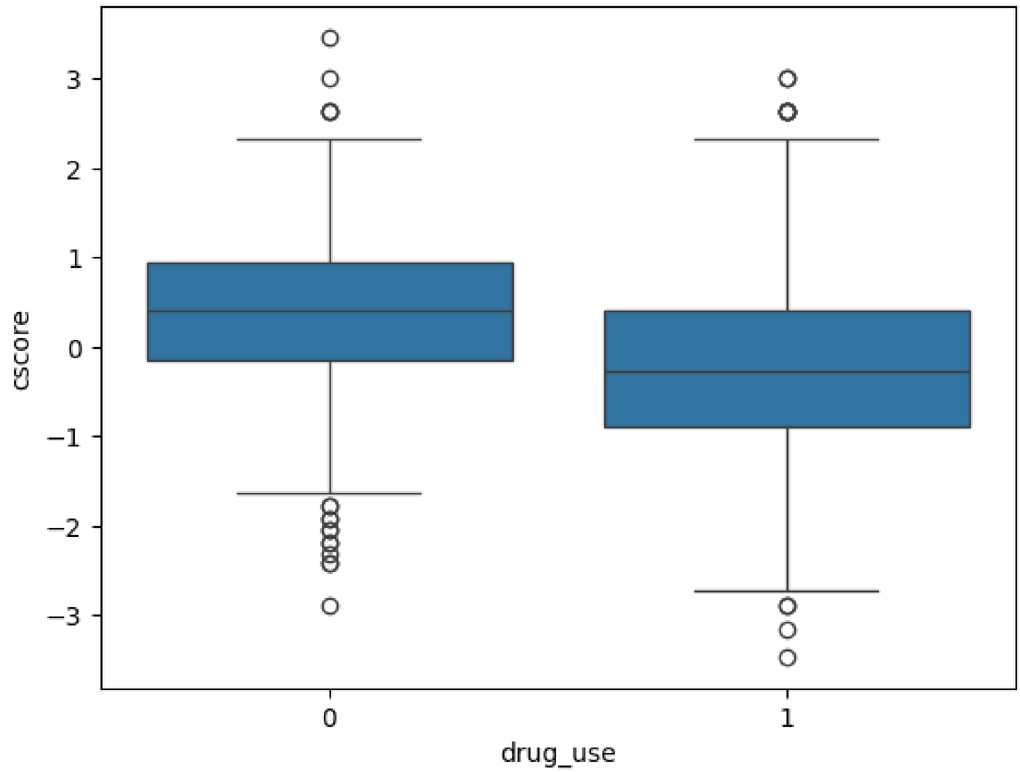


Ascore vs. Illicit Drug Use

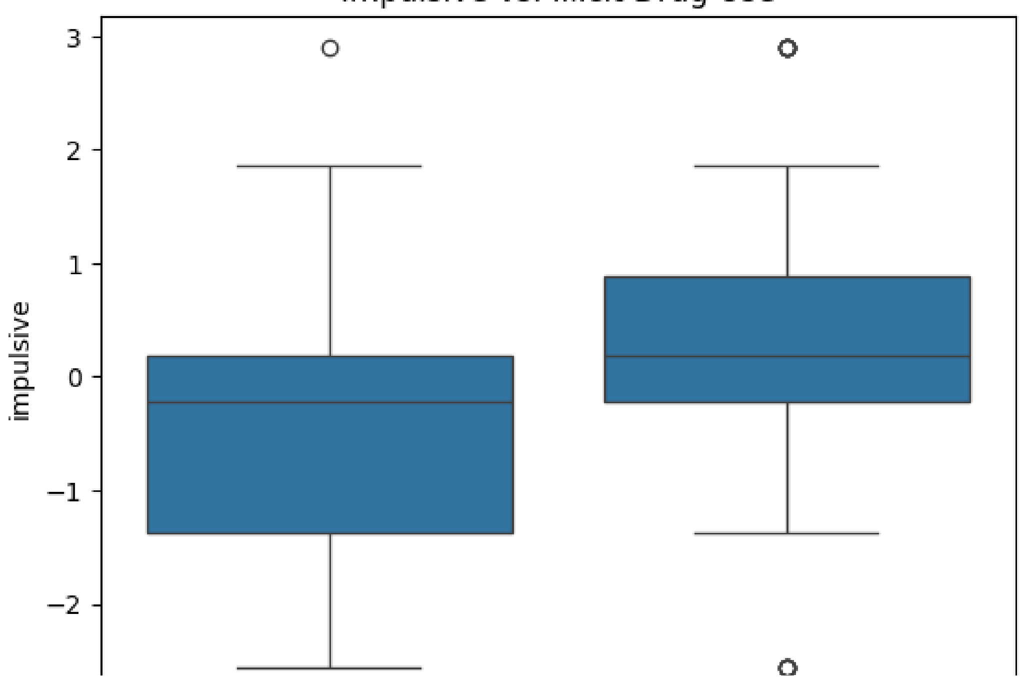


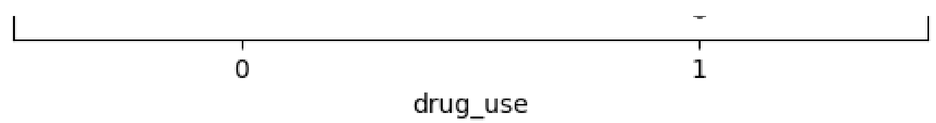


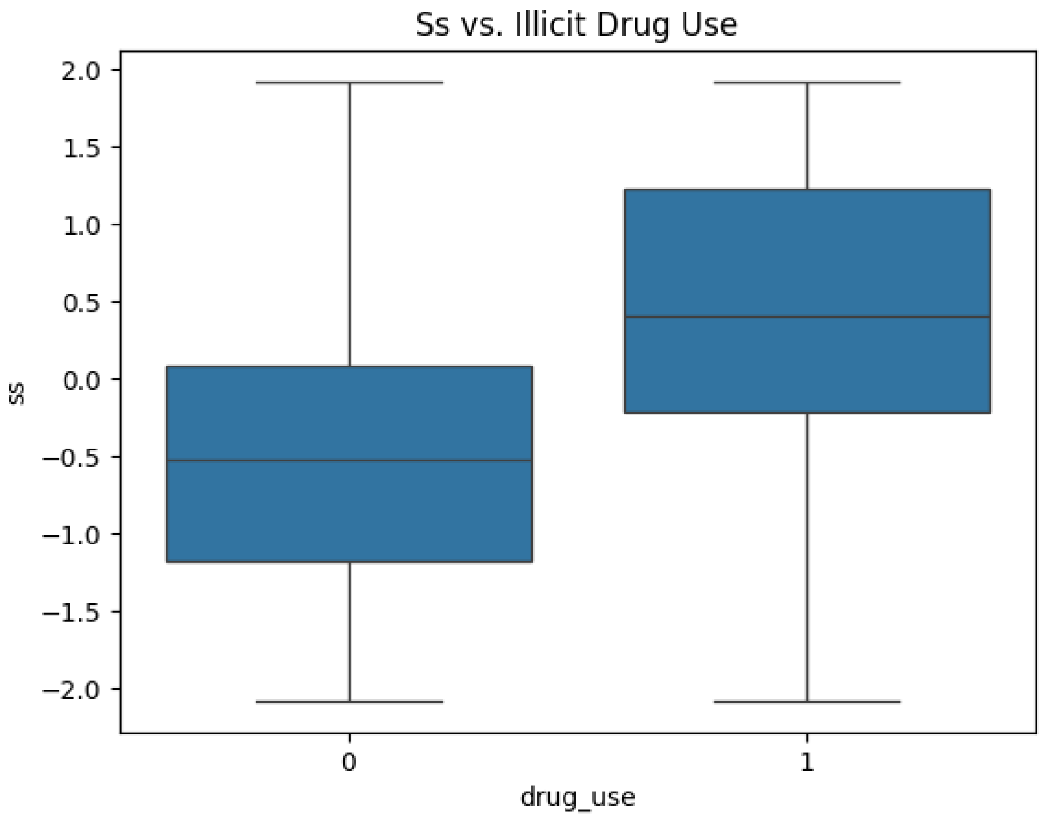
Cscore vs. Illicit Drug Use



Impulsive vs. Illicit Drug Use





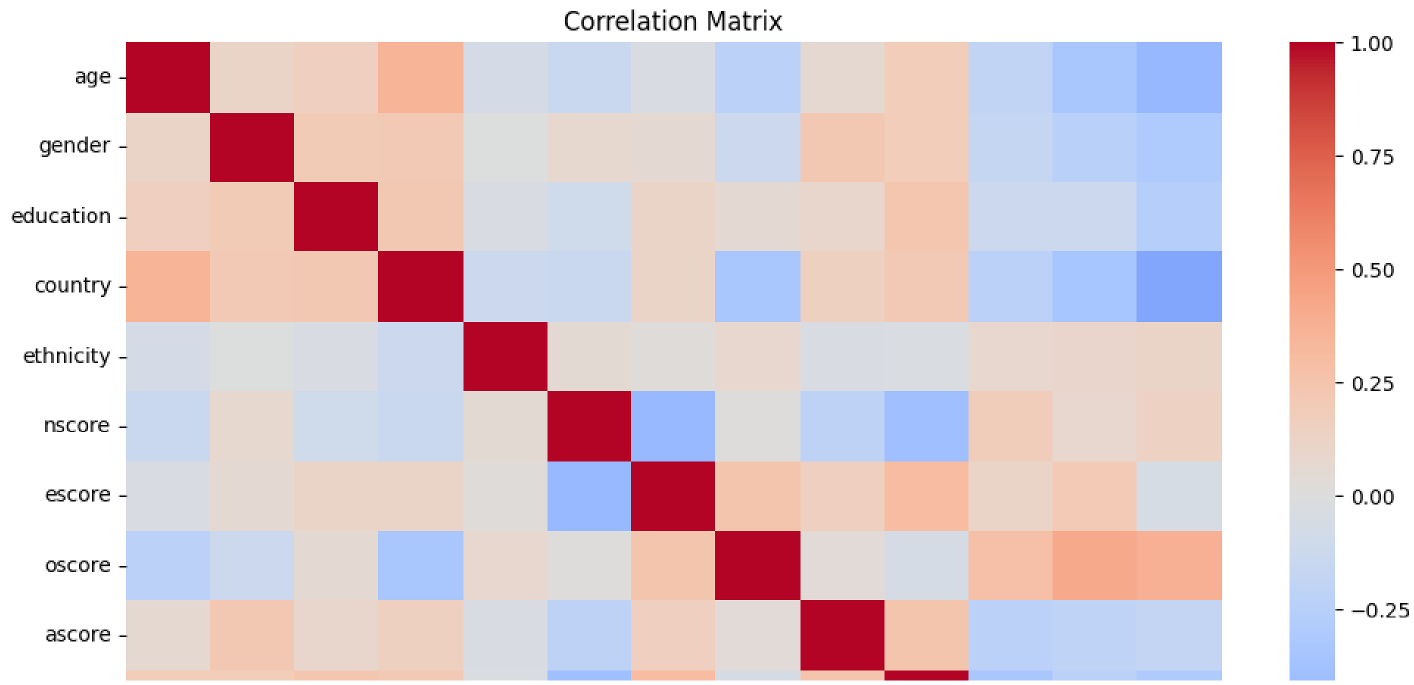


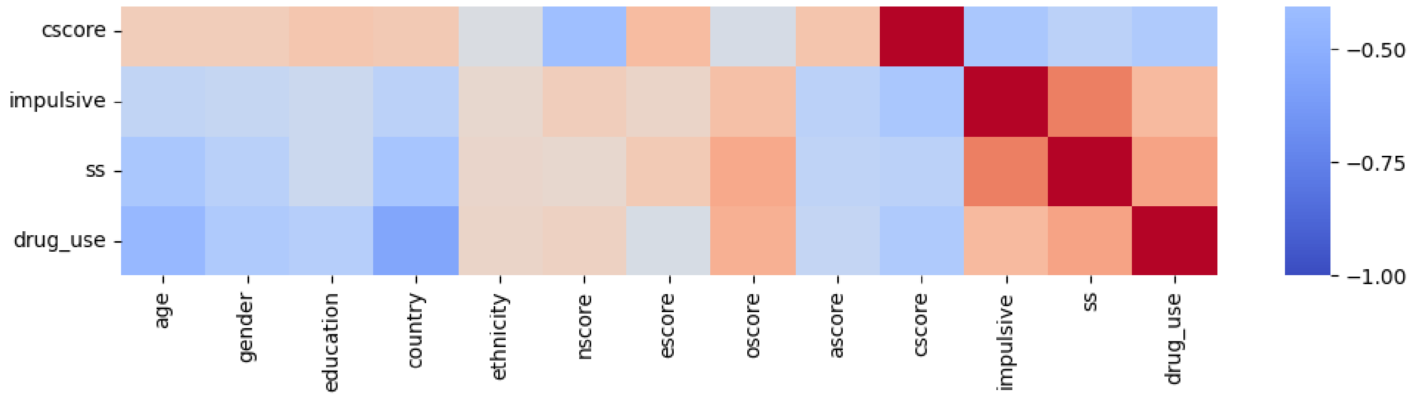
Correlation Analysis

- **Analyze the correlation between numerical features and `illicit_drug_use` to identify strong predictors.**

In [12]:

```
# Compute correlation matrix
correlation_matrix = dfDrugUse.corr()

# Plot heatmap for correlations
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=False, cmap='coolwarm', vmin=-1, vmax=1)
plt.title("Correlation Matrix")
plt.show()
```



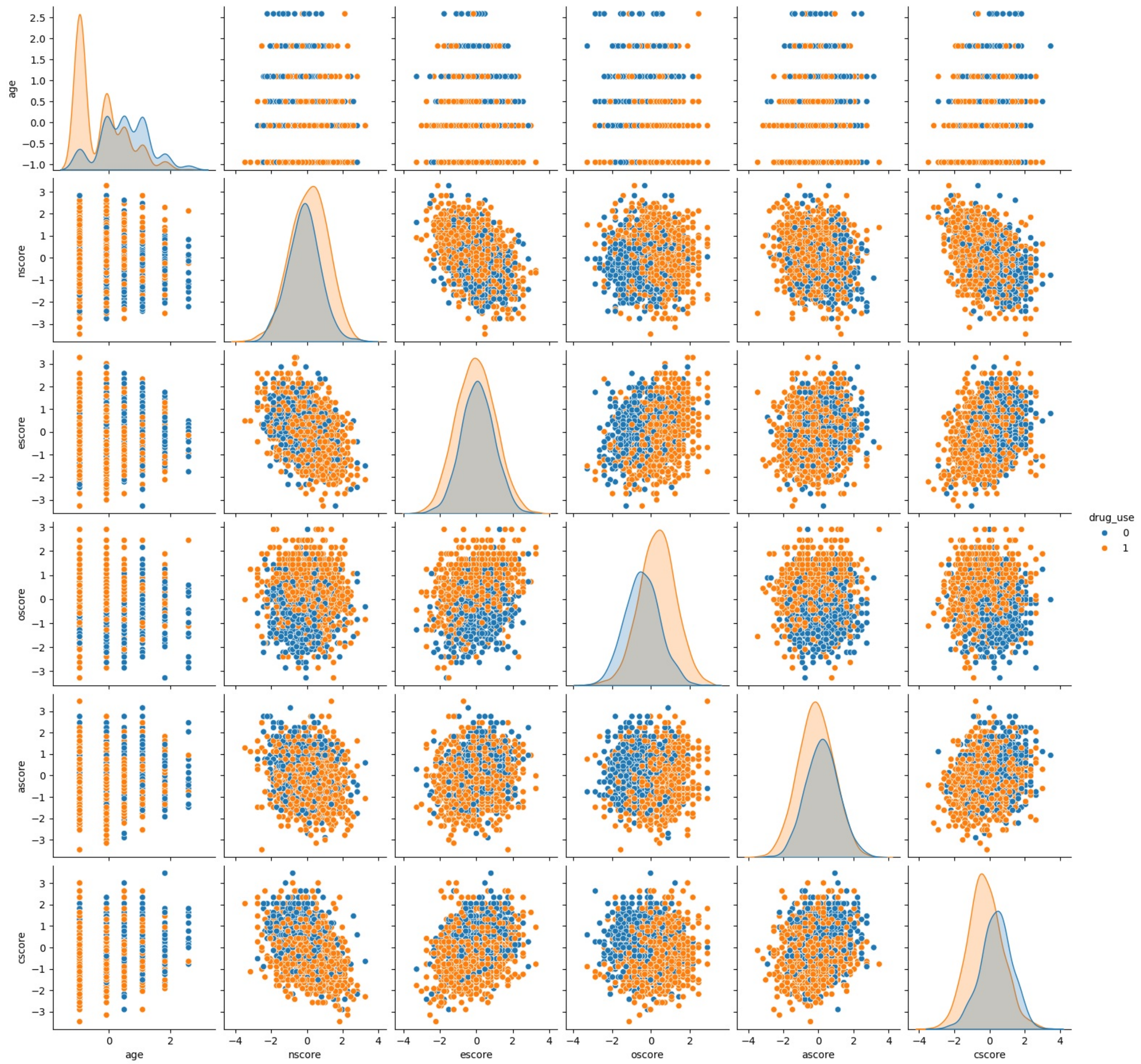


Pairwise Relationships

- **Use pair plots to explore how key features relate to** `illicit_drug_use`**.**

In [13]:

```
# Pair plot for selected features
selected_features = ['age', 'nscore', 'escore', 'oscore', 'ascore', 'cscore', 'drug_use']
sns.pairplot(df[selected_features], hue='drug_use', diag_kind='kde')
plt.show()
```



Relationships Between Features and `illicit_drug_use`:

In [14]:

```
for col in ['age', 'gender', 'education']:
    print(f"Distribution of {col} by illicit_drug_use:")
    print(dfMapped.groupby([col, 'drug_use']).size().unstack())
```

```
Distribution of age by illicit_drug_use:
drug_use    0    1
age
18-24      82  561
25-34     207  274
35-44     205  151
45-54     205   89
55-64      63   30
65+        16    2
Distribution of gender by illicit_drug_use:
drug_use    0    1
gender
Female    527  415
Male      251  692
Distribution of education by illicit_drug_use:
drug_use              0    1
education
Doctorate            53   36
Left at 16           48   51
Left at 17            9   21
Left at 18           26   74
Left before 16        9   19
Masters degree      184   99
Professional cert   136  134
Some college         68  438
University degree   245  235
```

Logistic Regression

- **Type: Linear Model**
- **Best For:**
  - **Simple relationships between predictors and the target variable.**
  - **Interpretable models with clear feature importance (via coefficients).**
  - **Problems with linearly separable data.**
- **Pros:**
  - **Easy to implement and interpret.**
  - **Computationally efficient and fast to train.**
  - **Performs well with simple or moderately complex datasets.**
  - **Naturally outputs probabilities for classification.**
- **Cons:**
  - **Assumes linearity between predictors and the target.**
  - **Sensitive to multicollinearity among features.**
  - **May struggle with non-linear decision boundaries.**

In [15]:

```
# Define features (X) and target (y)
X = dfDrugUse.drop('drug_use', axis=1)  # Features
y = dfDrugUse['drug_use']        # Target

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
, stratify=y)
```

In [16]:

```
# Initialize Logistic Regression model
logistic_model = LogisticRegression(solver='liblinear', max_iter=1000, random_state=42,
class_weight='balanced')
```

```python
# Train the model
logistic_model.fit(X_train, y_train)
```

Out[16]:

```
▼                       LogisticRegression
                                                          i ?
LogisticRegression(class_weight='balanced', max_iter=1000, random_state=42,
                   solver='liblinear')
```

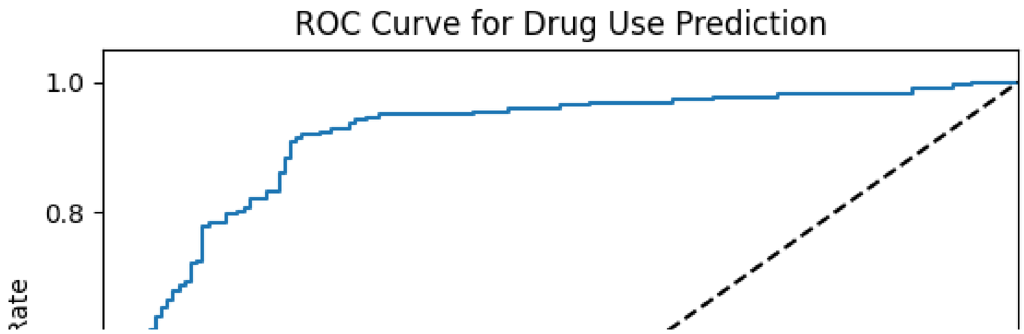
In [17]:

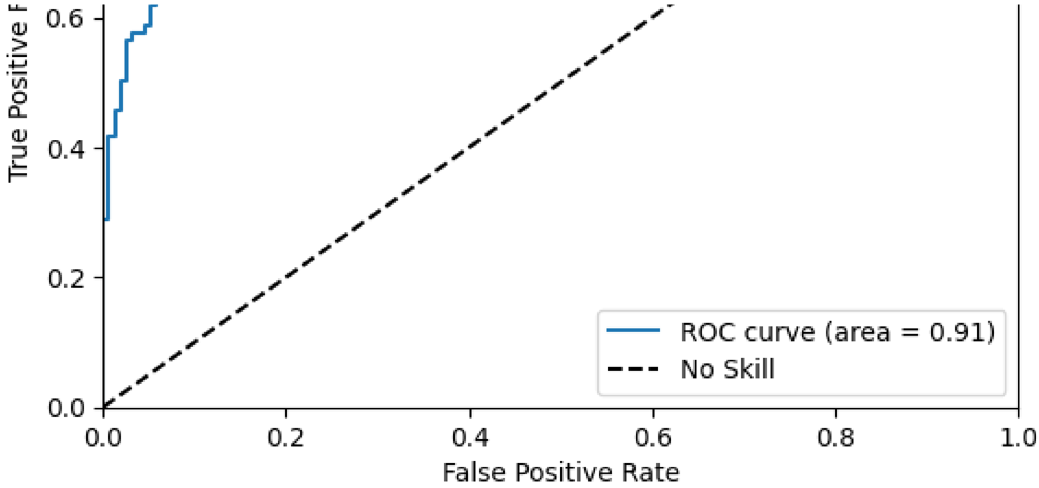
```python
# Predict on the test set
y_pred = logistic_model.predict(X_test)
y_proba = logistic_model.predict_proba(X_test)[:, 1]  # Probability estimates for ROC-AUC

# Classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.76      0.84      0.80       156
           1       0.88      0.81      0.84       221

    accuracy                           0.82       377
   macro avg       0.82      0.82      0.82       377
weighted avg       0.83      0.82      0.82       377

Confusion Matrix:
[[131  25]
 [ 42 179]]
```

In [18]:

```python
# Predict probabilities on the test set
y_pred_proba = logistic_model.predict_proba(X_test)[:, 1]

# Calculate ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
roc_auc = auc(fpr, tpr)
# Plot the ROC curve
plt.figure()
plt.plot(fpr, tpr, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], 'k--', label='No Skill')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Drug Use Prediction')
plt.legend()
plt.show()
```





In [19]:

```
from sklearn.model_selection import GridSearchCV

param_grid = {'C': [0.01, 0.1, 1, 10], 'penalty': ['l2'], 'solver': ['lbfgs']}
grid = GridSearchCV(LogisticRegression(max_iter=1000, class_weight='balanced'), param_gri
d, scoring='roc_auc', cv=5)
grid.fit(X_train, y_train)
print(f"Best Parameters: {grid.best_params_}")
print(f"Best ROC-AUC Score: {grid.best_score_}")
```

```
Best Parameters: {'C': 10, 'penalty': 'l2', 'solver': 'lbfgs'}
Best ROC-AUC Score: 0.9136074623778778
```

In [20]:

```
best_logistic_model = LogisticRegression(C=10, penalty='l2', solver='lbfgs')
best_logistic_model.fit(X_train, y_train)
# Predict on the test set
y_pred = best_logistic_model.predict(X_test)
y_proba = best_logistic_model.predict_proba(X_test)[:, 1]  # Probability estimates for RO
C-AUC

# Classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.81      0.81       156
           1       0.86      0.86      0.86       221

    accuracy                           0.84       377
   macro avg       0.83      0.83      0.83       377
weighted avg       0.84      0.84      0.84       377

Confusion Matrix:
[[126  30]
 [ 31 190]]
```

Random Forest

- **Type: Ensemble Model (Bagging)**
- **Best For:**
  - **Complex, non-linear relationships.**
  - **Handling missing data and unbalanced datasets.**
  - **Feature importance analysis.**

- **Pros:**
  - **Can capture non-linear patterns and interactions between features.**
  - **Robust to overfitting with enough trees.**
  - **Automatically handles feature scaling and normalization.**
  - **Resistant to outliers and noise.**
- **Cons:**
  - **Can be slower to train for large datasets.**
  - **Interpretability is lower compared to simpler models like Logistic Regression.**
  - **May require hyperparameter tuning (e.g., number of trees, max depth) for optimal performance.**

In [21]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, roc_auc_score, confusion_matrix
from sklearn.model_selection import cross_val_score

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

# Initialize Random Forest model
rf_model = RandomForestClassifier(
    n_estimators=100,  # Number of trees
    random_state=42,
    class_weight='balanced',  # Handle class imbalance
    max_depth=None,   # Allow trees to grow fully
)

# Train the model
rf_model.fit(X_train, y_train)
```

Out[21]:

```
▾                    RandomForestClassifier
                                                        i ?
RandomForestClassifier(class_weight='balanced', random_state=42)
```

In [22]:

```
# Predict on the test set
y_pred = rf_model.predict(X_test)
y_proba = rf_model.predict_proba(X_test)[:, 1]  # Probability estimates for ROC-AUC

# Classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))

# ROC-AUC score
roc_auc = roc_auc_score(y_test, y_proba)
print(f"ROC-AUC Score: {roc_auc}")

# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.79      0.82       156
           1       0.86      0.89      0.88       221

    accuracy                           0.85       377
   macro avg       0.85      0.84      0.85       377
weighted avg       0.85      0.85      0.85       377

ROC-AUC Score: 0.9092992226476388
Confusion Matrix:
[[124  32]
 [ 24 197]]
```

[24 197]]

In [23]:

```
from sklearn.model_selection import GridSearchCV

# Define hyperparameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Grid search
grid_search = GridSearchCV(
    estimator=RandomForestClassifier(random_state=42, class_weight='balanced'),
    param_grid=param_grid,
    scoring='roc_auc',
    cv=5,
    verbose=1,
    n_jobs=2
)
grid_search.fit(X_train, y_train)

# Best parameters and score
print(f"Best Parameters: {grid_search.best_params_}")
print(f"Best ROC-AUC Score: {grid_search.best_score_}")
```

```
Fitting 5 folds for each of 108 candidates, totalling 540 fits
Best Parameters: {'max_depth': 10, 'min_samples_leaf': 2, 'min_samples_split': 10, 'n_est
imators': 200}
Best ROC-AUC Score: 0.9102986413238237
```

In [24]:

```
best_rf_model = RandomForestClassifier(
    n_estimators=200,  # Number of trees
    random_state=42,
    min_samples_leaf=2,  # Minimum samples in leaf nodes
    min_samples_split=10,  # Minimum samples to split nodes
    class_weight='balanced',  # Handle class imbalance
    max_depth=10,
)

# Train the model
best_rf_model.fit(X_train, y_train)
```

Out[24]:

```
▼ RandomForestClassifier
                                                              i ?
RandomForestClassifier(class_weight='balanced', max_depth=10,
                       min_samples_leaf=2, min_samples_split=10,
                       n_estimators=200, random_state=42)
```

In [25]:

```
# Predict on the test set
y_pred = best_rf_model.predict(X_test)
y_proba = best_rf_model.predict_proba(X_test)[:, 1]  # Probability estimates for ROC-AUC

# Classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))

# ROC-AUC score
roc_auc = roc_auc_score(y_test, y_proba)
print(f"ROC-AUC Score: {roc_auc}")
```

```
# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.83      0.82       156
           1       0.88      0.86      0.87       221

    accuracy                           0.85       377
   macro avg       0.84      0.85      0.84       377
weighted avg       0.85      0.85      0.85       377

ROC-AUC Score: 0.9150713539853811
Confusion Matrix:
[[130  26]
 [ 31 190]]
```

Support Vector Machine (Soft Margin)

- **Type: Kernel-based Model**
- **Best For:**
  - **High-dimensional data.**
  - **Non-linear decision boundaries (via kernel functions).**
  - **Problems where a soft margin (allowing some misclassifications) is beneficial.**
- **Pros:**
  - **Effective for high-dimensional spaces and small datasets.**
  - **Can model complex relationships using kernels (e.g., radial basis function, polynomial).**
  - **Well-suited for imbalanced datasets with proper tuning (e.g., class weights).**
- **Cons:**
  - **Computationally expensive for large datasets.**
  - **Sensitive to the choice of hyperparameters (e.g., kernel type, `C` parameter).**
  - **Less interpretable compared to Logistic Regression or Random Forest.**

In [26]:

```
import numpy as np
from sklearn.svm import SVC
from sklearn.model_selection import cross_val_score, GridSearchCV, train_test_split
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score
import matplotlib.pyplot as plt
```

In [27]:

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

# Train SVM with default hyperparameters
svm_model = SVC(C=1.0, kernel='rbf', gamma='scale', probability=True, random_state=42)
svm_model.fit(X_train, y_train)

# Cross-validation
scores = cross_val_score(svm_model, X_train, y_train, cv=5)
print("Cross-validation mean accuracy: {:.3f}".format(np.mean(scores)))
```

```
Cross-validation mean accuracy: 0.836
```

In [28]:

```
# Predict on the test set
y_pred = svm_model.predict(X_test)
y_proba = svm_model.decision_function(X_test)

# Classification report
print("Classification Report:")
```

```
print(classification_report(y_test, y_pred))

# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)

# ROC-AUC Score
roc_auc = roc_auc_score(y_test, y_proba)
print(f"ROC-AUC Score: {roc_auc}")
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.79      0.80       156
           1       0.86      0.86      0.86       221

    accuracy                           0.84       377
   macro avg       0.83      0.83      0.83       377
weighted avg       0.84      0.84      0.84       377

Confusion Matrix:
[[124  32]
 [ 30 191]]
ROC-AUC Score: 0.8974649031210117
```

In [29]:

```
kernels = ['linear', 'poly', 'rbf', 'sigmoid']

for kernel in kernels:
    svm = SVC(C=1.0, kernel=kernel, gamma='scale', random_state=42)
    scores = cross_val_score(svm, X_train, y_train, cv=5)
    print(f"kernel = {kernel}, cross-val mean-accuracy: {np.mean(scores):.3f}")
```

```
kernel = linear, cross-val mean-accuracy: 0.839
kernel = poly, cross-val mean-accuracy: 0.810
kernel = rbf, cross-val mean-accuracy: 0.836
kernel = sigmoid, cross-val mean-accuracy: 0.796
```

In [30]:

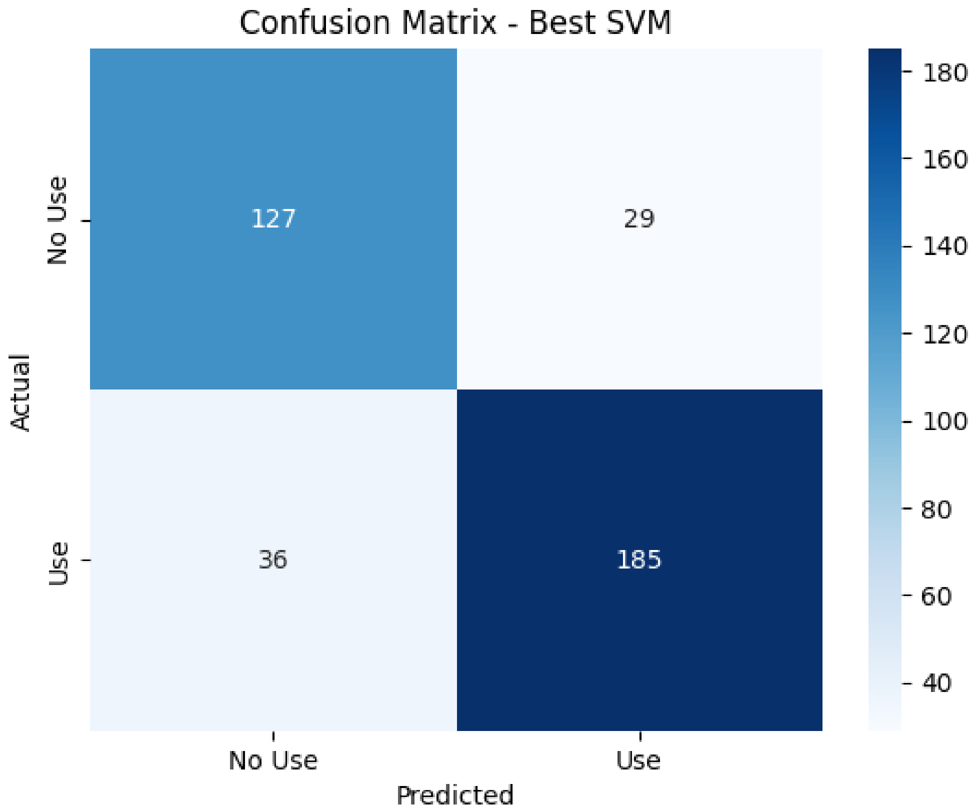
```
# Define the parameter grid
param_grid = {
    'C': np.logspace(-5, 5, num=11, base=2),  # C values: 2^-5 to 2^5
    'gamma': np.logspace(-5, 5, num=11, base=2)  # gamma values: 2^-5 to 2^5
}

# GridSearchCV for hyperparameter tuning
grid = GridSearchCV(
    estimator=SVC(kernel='linear', probability=True, random_state=42),
    param_grid=param_grid,
    cv=5,
    scoring='roc_auc',
    verbose=1
)

# Fit the grid search to the data
grid.fit(X_train, y_train)

# Print the best parameters and corresponding accuracy
print("Best parameters found: ", grid.best_params_)
print("Best cross-validation ROC-AUC: {:.3f}".format(grid.best_score_))

# Use the best model for predictions
best_model = grid.best_estimator_
y_pred_best = best_model.predict(X_test)
print("Test set accuracy of the best model: {:.3f}".format(best_model.score(X_test, y_tes
t)))
```

```
Fitting 5 folds for each of 121 candidates, totalling 605 fits
Best parameters found:  {'C': 2.0, 'gamma': 0.03125}
```

```
Best cross-validation ROC-AUC: 0.914
Test set accuracy of the best model: 0.828
```

In [31]:

```
# Confusion matrix for the best model
conf_matrix_best = confusion_matrix(y_test, y_pred_best)
sns.heatmap(conf_matrix_best, annot=True, fmt='d', cmap='Blues', xticklabels=['No Use',
'Use'], yticklabels=['No Use', 'Use'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - Best SVM')
plt.show()
```



k-Nearest Neighbors (kNN)

- **Type: Instance-based Learning**
- **Best For:**
  - **Simple datasets with clear clusters or patterns.**
  - **When interpretability isn't a priority but simplicity is.**
- **Pros:**
  - **Easy to implement.**
  - **Makes no assumptions about the data distribution.**
  - **Adapts naturally to non-linear decision boundaries.**
- **Cons:**
  - **Computationally expensive for large datasets.**
  - **Sensitive to irrelevant features and feature scaling.**
  - **Performance depends heavily on the choice of `k`.**

In [32]:

```
import numpy as np
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
import matplotlib.pyplot as plt
```

In [33]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
```

```
, stratify=y)

# Initialize KNN with K=3
knn = KNeighborsClassifier(n_neighbors=3)

# Train the model
knn.fit(X_train, y_train)

# Predict on the test set
y_pred = knn.predict(X_test)

# Evaluate the model
print("Classification Report for K=3:")
print(classification_report(y_test, y_pred))

# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix for K=3:")
print(conf_matrix)
```

```
Classification Report for K=3:
              precision    recall  f1-score   support

           0       0.76      0.77      0.76       156
           1       0.84      0.83      0.83       221

    accuracy                           0.80       377
   macro avg       0.80      0.80      0.80       377
weighted avg       0.80      0.80      0.80       377

Confusion Matrix for K=3:
[[120  36]
 [ 38 183]]
```

In [34]:

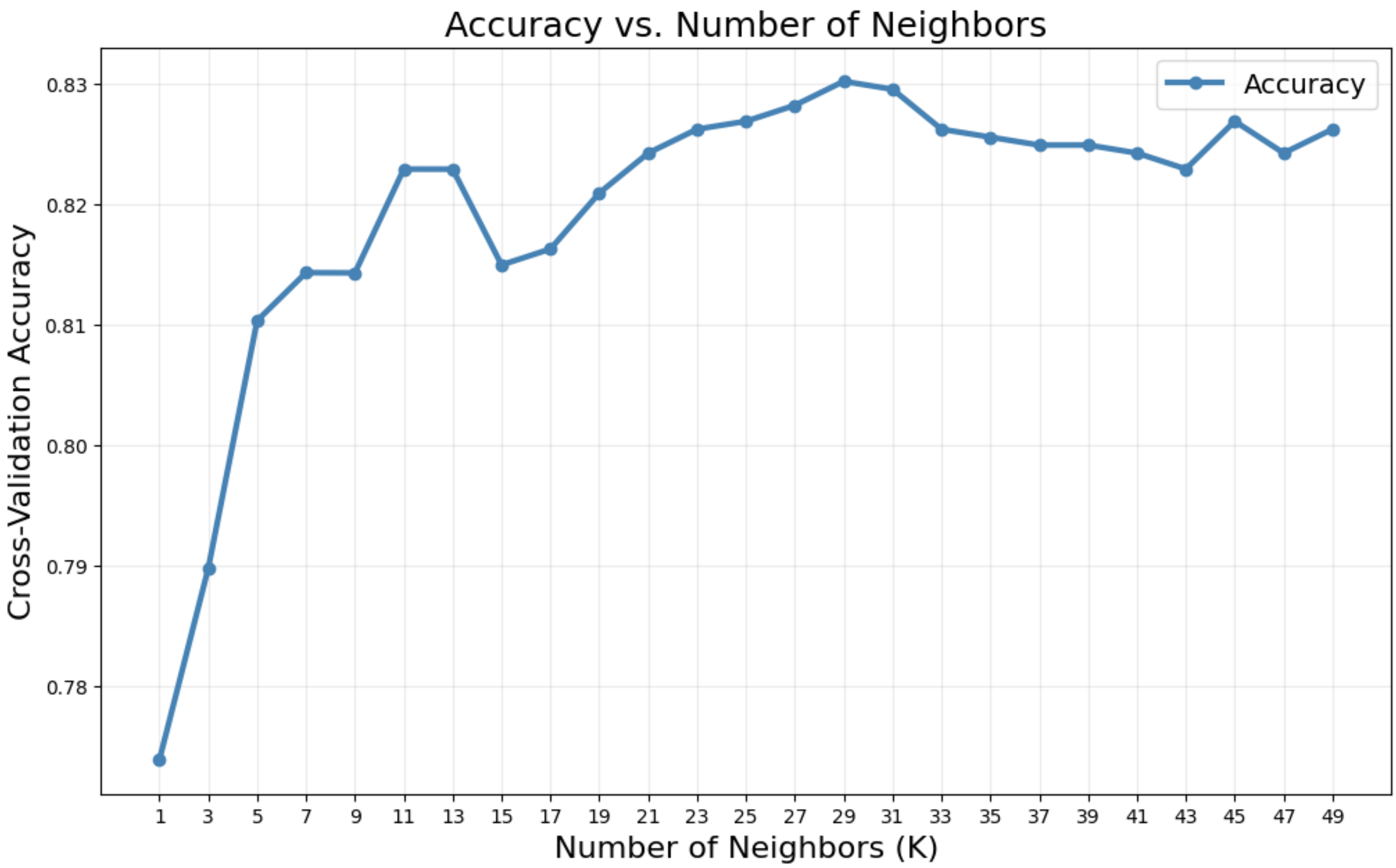
```
from sklearn.model_selection import cross_val_score

# Test different values of K
acc = []
allks = range(1, 50, 2)

for k in allks:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, X_train, y_train, cv=5, scoring='accuracy')
    acc.append(scores.mean())
    print(f"K = {k}, Cross-Validation Accuracy: {scores.mean():.3f}")
```

```
K = 1, Cross-Validation Accuracy: 0.774
K = 3, Cross-Validation Accuracy: 0.790
K = 5, Cross-Validation Accuracy: 0.810
K = 7, Cross-Validation Accuracy: 0.814
K = 9, Cross-Validation Accuracy: 0.814
K = 11, Cross-Validation Accuracy: 0.823
K = 13, Cross-Validation Accuracy: 0.823
K = 15, Cross-Validation Accuracy: 0.815
K = 17, Cross-Validation Accuracy: 0.816
K = 19, Cross-Validation Accuracy: 0.821
K = 21, Cross-Validation Accuracy: 0.824
K = 23, Cross-Validation Accuracy: 0.826
K = 25, Cross-Validation Accuracy: 0.827
K = 27, Cross-Validation Accuracy: 0.828
K = 29, Cross-Validation Accuracy: 0.830
K = 31, Cross-Validation Accuracy: 0.830
K = 33, Cross-Validation Accuracy: 0.826
K = 35, Cross-Validation Accuracy: 0.826
K = 37, Cross-Validation Accuracy: 0.825
K = 39, Cross-Validation Accuracy: 0.825
K = 41, Cross-Validation Accuracy: 0.824
K = 43, Cross-Validation Accuracy: 0.823
K = 45, Cross-Validation Accuracy: 0.827
K = 47, Cross-Validation Accuracy: 0.824
```

```
K = 49, Cross-Validation Accuracy: 0.826
```

In [35]:

```python
# Plot accuracy vs K
plt.figure(figsize=(12, 7))
plt.plot(allks, acc, marker="o", color="steelblue", lw=3, label="Accuracy")
plt.xlabel("Number of Neighbors (K)", fontsize=16)
plt.ylabel("Cross-Validation Accuracy", fontsize=16)
plt.title("Accuracy vs. Number of Neighbors", fontsize=18)
plt.xticks(range(1, 50, 2))
plt.grid(alpha=0.25)
plt.legend(fontsize=14)
plt.show()
```



In [36]:

```python
# Optimal K (max accuracy)
optimal_k = np.argmax(acc) + 1  # Adding 1 because index starts at 0
print(f"Optimal K: {optimal_k}")

# Train KNN with the optimal K
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k)
knn_optimal.fit(X_train, y_train)

# Predict on the test set
y_pred_optimal = knn_optimal.predict(X_test)

# Evaluate the optimal KNN model
print(f"Classification Report for K={optimal_k}:")
print(classification_report(y_test, y_pred_optimal))

# Confusion matrix for optimal K
conf_matrix_optimal = confusion_matrix(y_test, y_pred_optimal)
print(f"Confusion Matrix for K={optimal_k}:")
print(conf_matrix_optimal)
```

```
Optimal K: 15
Classification Report for K=15:
              precision    recall  f1-score   support

           0       0.78      0.82      0.80       156
```

```
           1       0.87      0.83      0.85       221

    accuracy                           0.83       377
   macro avg       0.82      0.83      0.82       377
weighted avg       0.83      0.83      0.83       377

Confusion Matrix for K=15:
[[128  28]
 [ 37 184]]
```

In [37]:

```python
import seaborn as sns

# Confusion matrix heatmap
sns.heatmap(conf_matrix_optimal, annot=True, fmt='d', cmap='Blues', xticklabels=['No Use'
, 'Use'], yticklabels=['No Use', 'Use'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title(f'Confusion Matrix for K={optimal_k}')
plt.show()
```