Heart Attack Risk Prediction

This project aims to predict the risk of heart attacks based on various health and lifestyle factors using machine learning techniques. We preprocess the data, explore patterns, and build predictive models to analyze and identify key contributors to heart health.

Data Loading and Exploration

In this section, we load the dataset and explore its structure, including the size, sample records, and overall statistics.

In [2]:
```python
# Import all the tools we need
# Regular EDA (Exploratory data analysis) and plotting libaries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
# This will make all plots appear inside the notebook
#%matplotlib inline
# Data Preprocessing
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder, LabelEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.pipeline import Pipeline
# Models from Scikit-Learn
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
# Model Evaluations
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import precision_score, accuracy_score, recall_score, f1_score
from sklearn.metrics import RocCurveDisplay, roc_curve, roc_auc_score, auc
heart_risk_load_df = pd.read_csv(r'heart_attack_prediction_dataset.csv')
heart_risk_load_df.shape
heart_risk_load_df.sample(5)
# Let us find out how many of each class is present
heart_risk_load_df['Heart Attack Risk'].value_counts()
heart_risk_load_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8763 entries, 0 to 8762
Data columns (total 26 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   Patient ID                       8763 non-null   object 
 1   Age                              8763 non-null   int64  
 2   Sex                              8763 non-null   object 
 3   Cholesterol                      8763 non-null   int64  
 4   Blood Pressure                   8763 non-null   object 
 5   Heart Rate                       8763 non-null   int64  
 6   Diabetes                         8763 non-null   int64  
 7   Family History                   8763 non-null   int64  
 8   Smoking                          8763 non-null   int64  
 9   Obesity                          8763 non-null   int64  
 10  Alcohol Consumption              8763 non-null   int64  
 11  Exercise Hours Per Week          8763 non-null   float64
 12  Diet                             8763 non-null   object 
 13  Previous Heart Problems          8763 non-null   int64  
 14  Medication Use                   8763 non-null   int64  
 15  Stress Level                     8763 non-null   int64  
 16  Sedentary Hours Per Day          8763 non-null   float64
 17  Income                           8763 non-null   int64  
 18  BMI                              8763 non-null   float64
 19  Triglycerides                    8763 non-null   int64  
 20  Physical Activity Days Per Week  8763 non-null   int64  
 21  Sleep Hours Per Day              8763 non-null   int64  
 22  Country                          8763 non-null   object 
 23  Continent                        8763 non-null   object 
 24  Hemisphere                       8763 non-null   object 
 25  Heart Attack Risk                8763 non-null   int64  
dtypes: float64(3), int64(16), object(7)
memory usage: 1.7+ MB
```

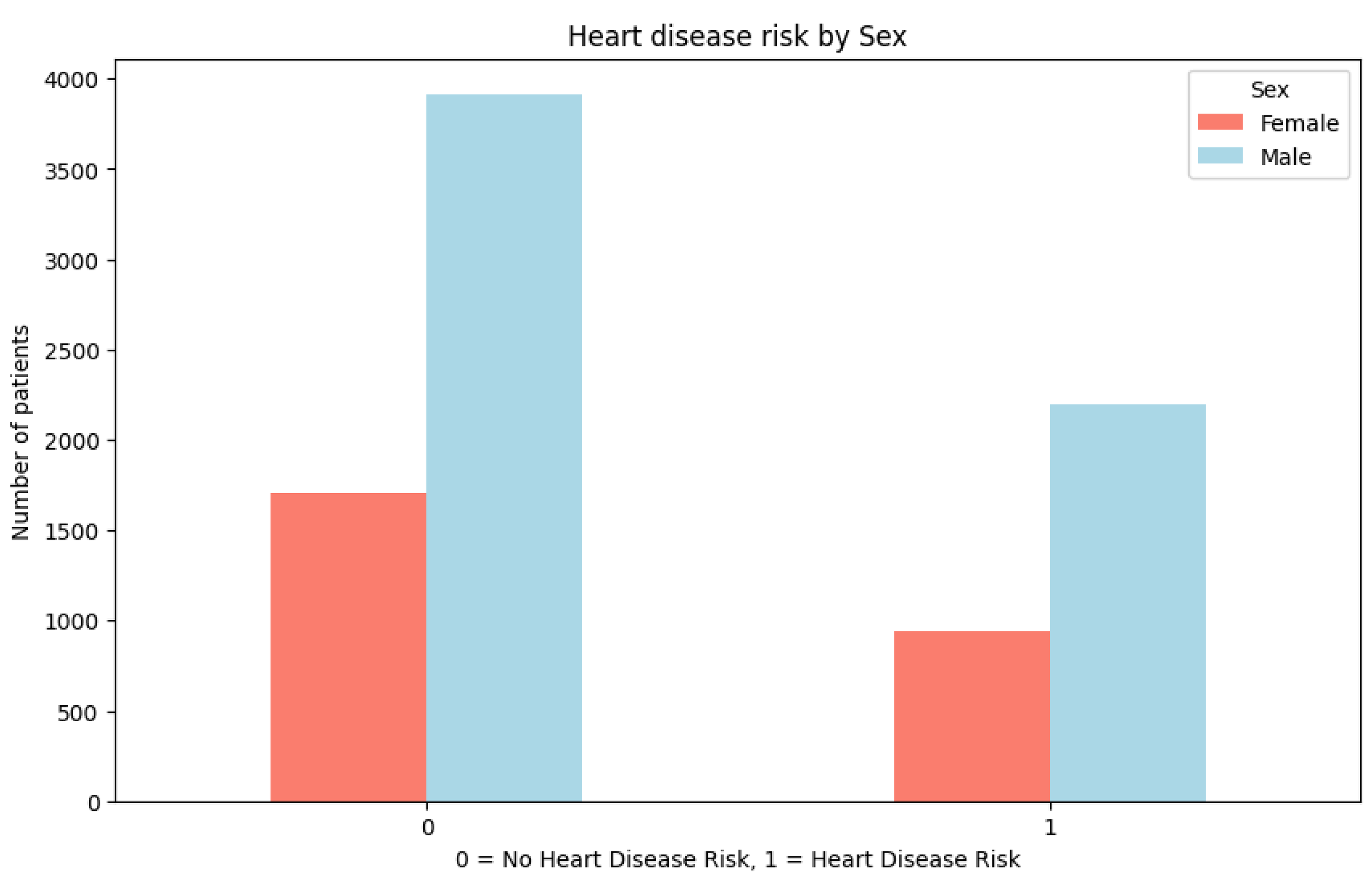
Exploratory Data Analysis (EDA)

Here, we perform visual and statistical analysis to understand the data distribution and relationships between features, including:

- Distribution of age groups
- Heart disease risk by gender
- Country-wise and continent-wise risk distribution

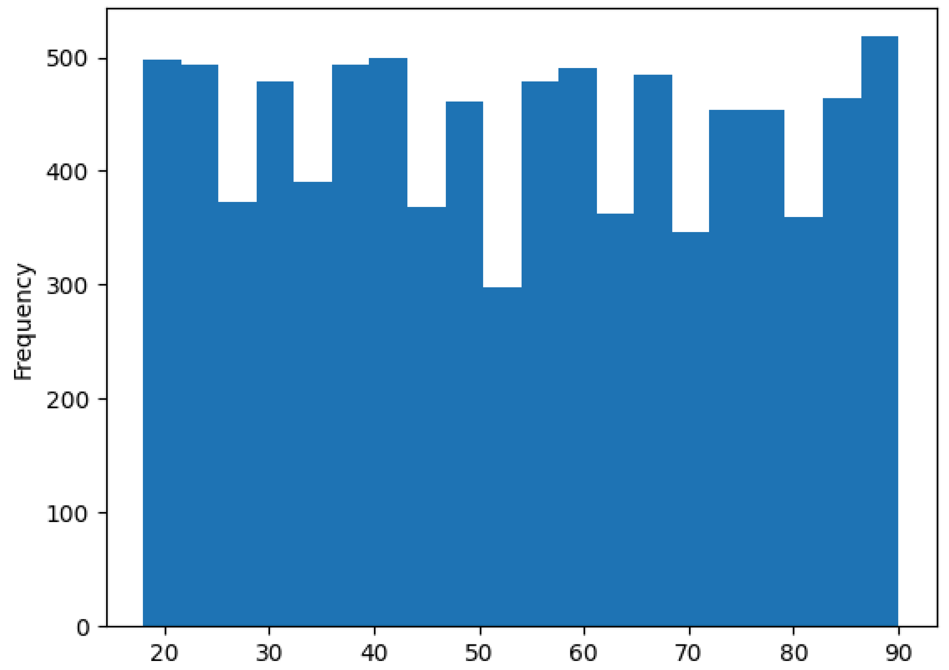
In [3]:
```python
# Create a plot of crosstab
pd.crosstab(heart_risk_load_df['Heart Attack Risk'], heart_risk_load_df['Sex']).plot(kind='bar',
figsize=(10, 6),
color=['salmon', 'lightblue'])
plt.title('Heart disease risk by Sex')
plt.xlabel('0 = No Heart Disease Risk, 1 = Heart Disease Risk')
plt.ylabel('Number of patients')
plt.xticks(rotation=0)
```

Out[3]:
```
(array([0, 1]), [Text(0, 0, '0'), Text(1, 0, '1')])
```



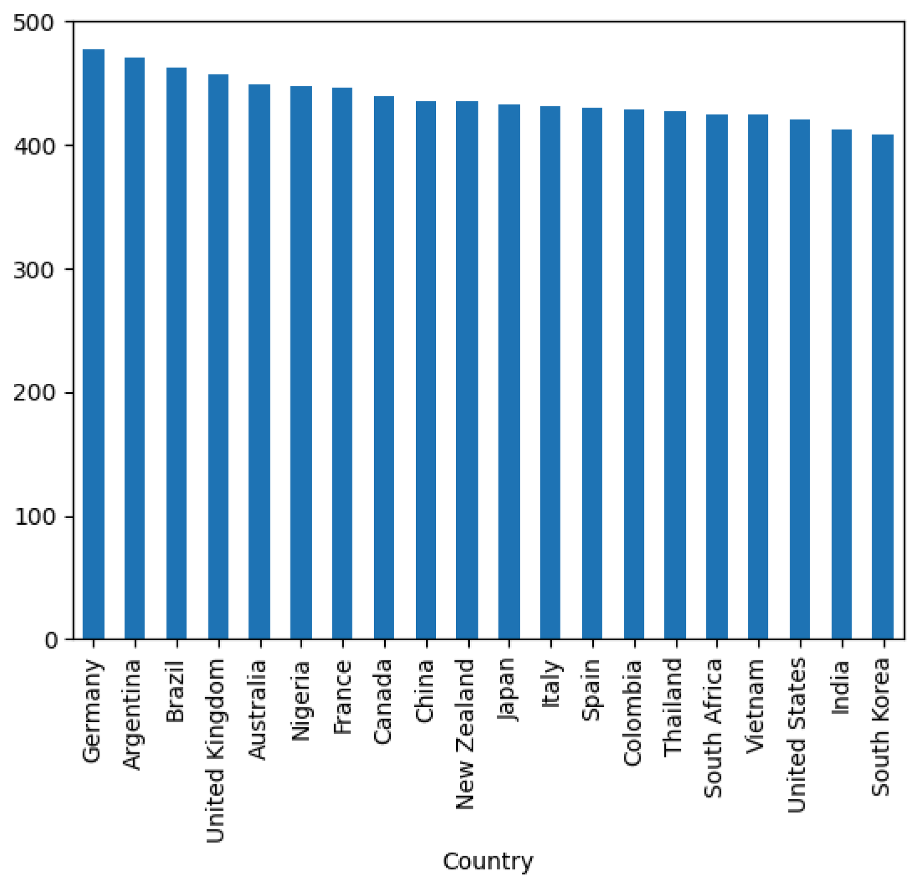
In [4]:
```python
heart_risk_load_df['Age'].plot.hist(bins=20)
```

Out[4]: `<Axes: ylabel='Frequency'>`

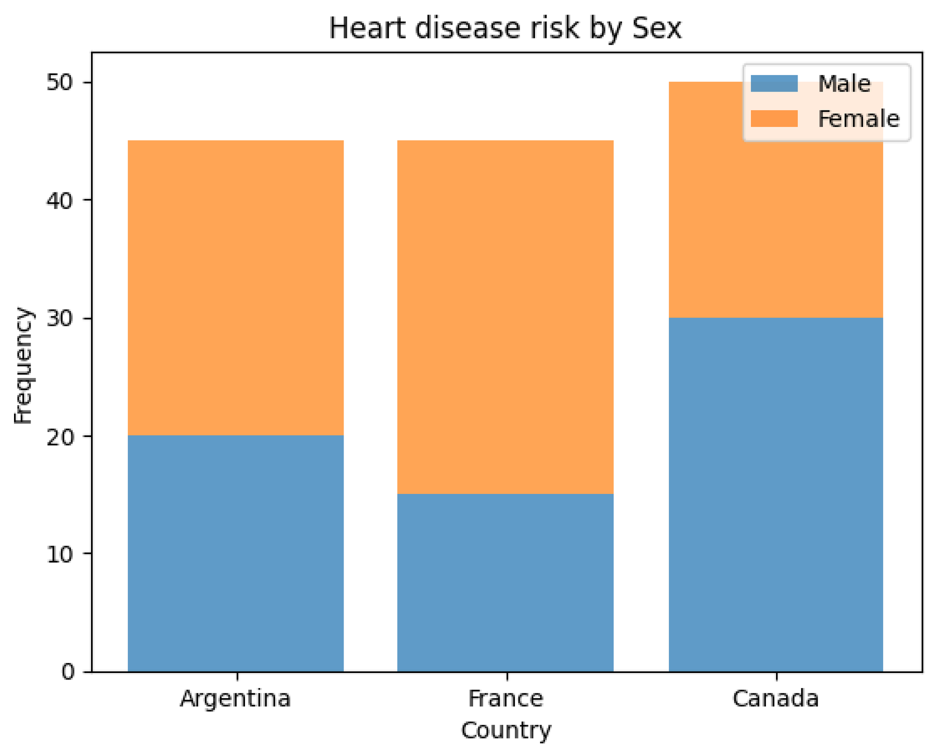


In [5]:
```python
heart_risk_load_df['Country'].value_counts().plot.bar()
```

Out[5]: `<Axes: xlabel='Country'>`

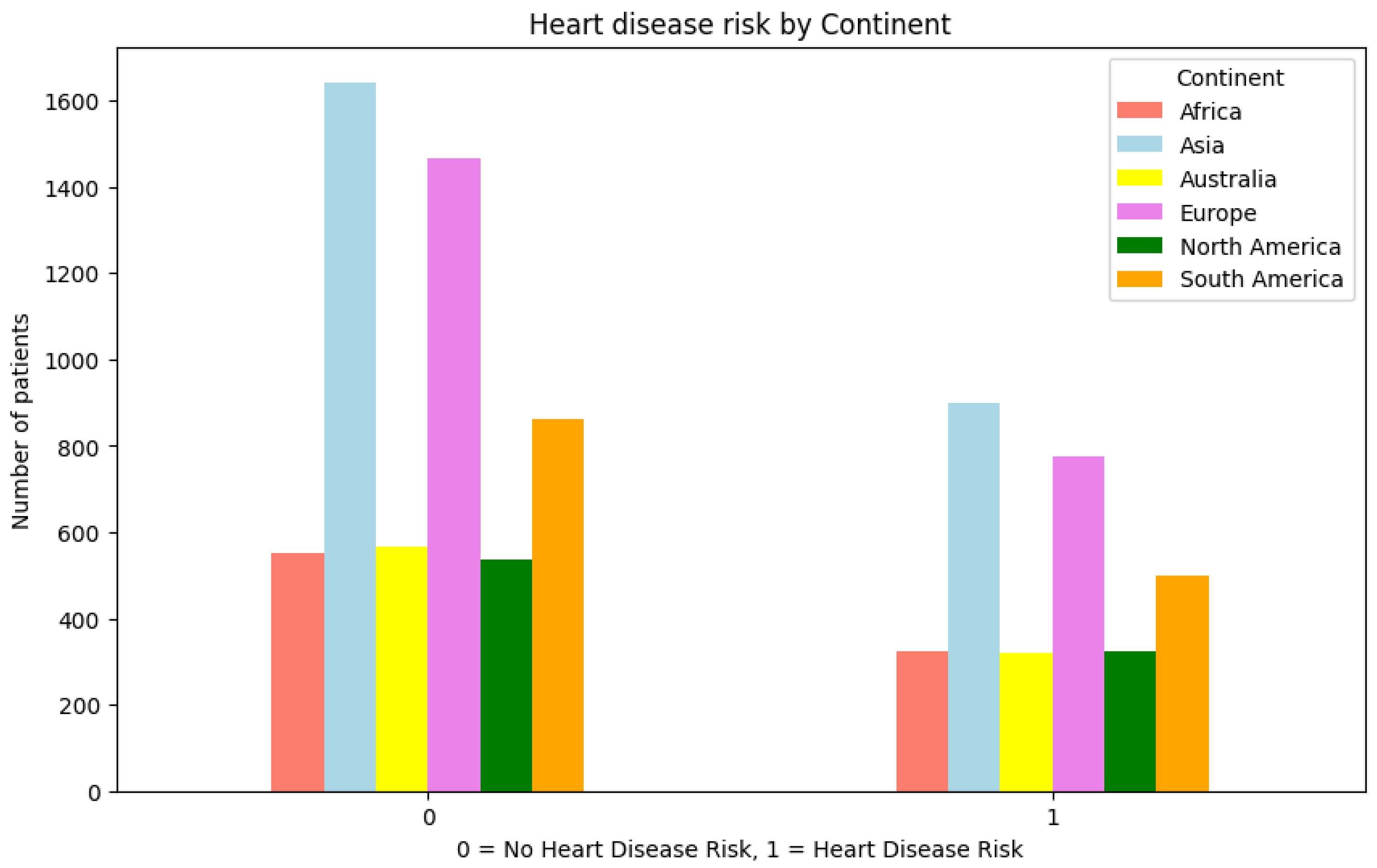


In [7]:
```python
import matplotlib.pyplot as plt

# بيانات تخيلية
countries = ['Argentina', 'France', 'Canada']
male = [20, 15, 30]
female = [25, 30, 20]

# إنشاء الشكل
fig, ax = plt.subplots()
ax.bar(countries, male, label='Male', alpha=0.7)
ax.bar(countries, female, label='Female', alpha=0.7, bottom=male)

# تسمية المحاور والعنوان
ax.set_title('Heart disease risk by Sex')
ax.set_xlabel('Country')
ax.set_ylabel('Frequency')

# إضافة وسيلة إيضاح
ax.legend()

# عرض الرسم البياني
plt.show()
```



In [8]:
```python
# Create a plot of crosstab for continent
pd.crosstab(heart_risk_load_df['Heart Attack Risk'], heart_risk_load_df['Continent']).plot(kind='bar',
figsize=(10, 6),
color=['salmon', 'lightblue', 'Yellow', 'Violet', 'Green', 'Orange'])
plt.title('Heart disease risk by Continent')
plt.xlabel('0 = No Heart Disease Risk, 1 = Heart Disease Risk')
plt.ylabel('Number of patients')
plt.xticks(rotation=0)
```

Out[8]: `(array([0, 1]), [Text(0, 0, '0'), Text(1, 0, '1')])`



Data Preprocessing

We clean the data and transform categorical and numerical features. This includes:

- Grouping age into meaningful categories.
- Categorizing physical activity levels.
- Encoding income levels and other categorical features.

In [10]:
```
heart_risk_load_analyzed_df = pd.read_csv(r'heart_attack_prediction_dataset.csv')

def group_age(age):
  '''
  This function will group people with in a range into groups.
  age - age of the person, integer
  returns below groups
  Babies - 0-2
  Young Adult - 3-39
  Middle-aged Adult 40-59
  Senior - 60-99
  '''
  if age <= 2:
    return 'Baby'
  if age > 2 and age < 40:
    return 'Young Adult'
  if age >= 40 and age < 60:
    return 'Middle-aged Adult'
  if age >= 60:
    return 'Senior'

heart_risk_load_analyzed_df['Age Group'] = heart_risk_load_analyzed_df['Age'].apply(group_age)
heart_risk_load_analyzed_df.drop(columns=['Age'], inplace=True)
heart_risk_load_analyzed_df
```

Out[10]:

	Patient ID	Sex	Cholesterol	Blood Pressure	Heart Rate	Diabetes	Family History	Smoking	Obesity	Alcohol Consumption	...	Income	BMI	Triglycerides	Physical Activity Days Per Week	Sleep Hours Per Day	Country	Continent	Hemisphere	Heart Attack Risk	Age Group
0	BMW7812	Male	208	158/88	72	0	0	1	0	0	...	261404	31.251233	286	0	6	Argentina	South America	Southern Hemisphere	0	Senior
1	CZE1114	Male	389	165/93	98	1	1	1	1	1	...	285768	27.194973	235	1	7	Canada	North America	Northern Hemisphere	0	Young Adult
2	BNI9906	Female	324	174/99	72	1	0	0	0	0	...	235282	28.176571	587	4	4	France	Europe	Northern Hemisphere	0	Young Adult
3	JLN3497	Male	383	163/100	73	1	1	1	0	1	...	125640	36.464704	378	3	4	Canada	North America	Northern Hemisphere	0	Senior
4	GFO8847	Male	318	91/88	93	1	1	1	1	0	...	160555	21.809144	231	1	5	Thailand	Asia	Northern Hemisphere	0	Senior
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
8758	MSV9918	Male	121	94/76	61	1	1	1	0	1	...	235420	19.655895	67	7	7	Thailand	Asia	Northern Hemisphere	0	Senior
8759	QSV6764	Female	120	157/102	73	1	0	0	1	0	...	217881	23.993866	617	4	9	Canada	North America	Northern Hemisphere	0	Young Adult
8760	XKA5925	Male	250	161/75	105	0	1	1	1	1	...	36998	35.406146	527	4	4	Brazil	South America	Southern Hemisphere	1	Middle-aged Adult
8761	EPE6801	Male	178	119/67	60	1	0	1	0	0	...	209943	27.294020	114	2	8	Brazil	South America	Southern Hemisphere	0	Young Adult
8762	ZWN9666	Female	356	138/67	75	1	1	0	0	1	...	247338	32.914151	180	7	4	United Kingdom	Europe	Northern Hemisphere	1	Young Adult

8763 rows × 26 columns

In [11]:
```
def physical_activity_group(exercisehoursperweek):
  '''
  This function groups people by number of hours or exercise per week
  Input: exercisehoursperweek - float
  Physical activity group.
  Low activity <2hours
  Normal activity 2-3
  High activity > 3
  '''
  if exercisehoursperweek < 2.0:
    return 'Low activity'
  if exercisehoursperweek >= 2.0 and exercisehoursperweek <= 3.0:
    return 'Normal activity'
  if exercisehoursperweek > 3.0:
    return 'High activity'

heart_risk_load_analyzed_df['Physical Activity Group'] = heart_risk_load_analyzed_df['Exercise Hours Per Week'].apply(physical_activity_group)
heart_risk_load_analyzed_df.drop(columns=['Exercise Hours Per Week'], inplace=True)
heart_risk_load_analyzed_df
```

Out[11]:

	Patient ID	Sex	Cholesterol	Blood Pressure	Heart Rate	Diabetes	Family History	Smoking	Obesity	Alcohol Consumption	...	BMI	Triglycerides	Physical Activity Days Per Week	Sleep Hours Per Day	Country	Continent	Hemisphere	Heart Attack Risk	Age Group	Physical Activity Group
0	BMW7812	Male	208	158/88	72	0	0	1	0	0	...	31.251233	286	0	6	Argentina	South America	Southern Hemisphere	0	Senior	High activity
1	CZE1114	Male	389	165/93	98	1	1	1	1	1	...	27.194973	235	1	7	Canada	North America	Northern Hemisphere	0	Young Adult	Low activity
2	BNI9906	Female	324	174/99	72	1	0	0	0	0	...	28.176571	587	4	4	France	Europe	Northern Hemisphere	0	Young Adult	Normal activity
3	JLN3497	Male	383	163/100	73	1	1	1	0	1	...	36.464704	378	3	4	Canada	North America	Northern Hemisphere	0	Senior	High activity
4	GFO8847	Male	318	91/88	93	1	1	1	1	0	...	21.809144	231	1	5	Thailand	Asia	Northern Hemisphere	0	Senior	High activity
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
8758	MSV9918	Male	121	94/76	61	1	1	1	0	1	...	19.655895	67	7	7	Thailand	Asia	Northern Hemisphere	0	Senior	High activity
8759	QSV6764	Female	120	157/102	73	1	0	0	1	0	...	23.993866	617	4	9	Canada	North America	Northern Hemisphere	0	Young Adult	High activity
8760	XKA5925	Male	250	161/75	105	0	1	1	1	1	...	35.406146	527	4	4	Brazil	South America	Southern Hemisphere	1	Middle-aged Adult	High activity
8761	EPE6801	Male	178	119/67	60	1	0	1	0	0	...	27.294020	114	2	8	Brazil	South America	Southern Hemisphere	0	Young Adult	High activity
8762	ZWN9666	Female	356	138/67	75	1	1	0	0	1	...	32.914151	180	7	4	United Kingdom	Europe	Northern Hemisphere	1	Young Adult	High activity

8763 rows × 26 columns

In [12]:

```python
def income_group(income):
  '''
  This function breaks income into groups
  Break them into groups.
  Low-income ❤5K
  Mid-income <105K
  High-income > 105K
  '''
  if income < 35000:
    return 'Low-income'
  if income >= 35000 and income < 105000:
    return 'Mid-income'
  if income > 105000:
    return 'High-income'

heart_risk_load_analyzed_df['Income Group'] = heart_risk_load_analyzed_df['Income'].apply(income_group)
heart_risk_load_analyzed_df.drop(columns=['Income'], inplace=True)
heart_risk_load_analyzed_df
```

Out[12]:

	Patient ID	Sex	Cholesterol	Blood Pressure	Heart Rate	Diabetes	Family History	Smoking	Obesity	Alcohol Consumption	...	Triglycerides	Physical Activity Days Per Week	Sleep Hours Per Day	Country	Continent	Hemisphere	Heart Attack Risk	Age Group	Physical Activity Group	Income Group
0	BMW7812	Male	208	158/88	72	0	0	1	0	0	...	286	0	6	Argentina	South America	Southern Hemisphere	0	Senior	High activity	High-income
1	CZE1114	Male	389	165/93	98	1	1	1	1	1	...	235	1	7	Canada	North America	Northern Hemisphere	0	Young Adult	Low activity	High-income
2	BNI9906	Female	324	174/99	72	1	0	0	0	0	...	587	4	4	France	Europe	Northern Hemisphere	0	Young Adult	Normal activity	High-income
3	JLN3497	Male	383	163/100	73	1	1	1	0	1	...	378	3	4	Canada	North America	Northern Hemisphere	0	Senior	High activity	High-income
4	GFO8847	Male	318	91/88	93	1	1	1	1	0	...	231	1	5	Thailand	Asia	Northern Hemisphere	0	Senior	High activity	High-income
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
8758	MSV9918	Male	121	94/76	61	1	1	1	0	1	...	67	7	7	Thailand	Asia	Northern Hemisphere	0	Senior	High activity	High-income
8759	QSV6764	Female	120	157/102	73	1	0	0	1	0	...	617	4	9	Canada	North America	Northern Hemisphere	0	Young Adult	High activity	High-income
8760	XKA5925	Male	250	161/75	105	0	1	1	1	1	...	527	4	4	Brazil	South America	Southern Hemisphere	1	Middle-aged Adult	High activity	Mid-income
8761	EPE6801	Male	178	119/67	60	1	0	1	0	0	...	114	2	8	Brazil	South America	Southern Hemisphere	0	Young Adult	High activity	High-income
8762	ZWN9666	Female	356	138/67	75	1	1	0	0	1	...	180	7	4	United Kingdom	Europe	Northern Hemisphere	1	Young Adult	High activity	High-income

8763 rows × 26 columns

In [13]:

```python
def bmi_group(bmi):
  '''
  This function will group the patients based on the BMI
  Break into groups.
  Underweight < 18.5
  Normal 18.5-25
  Overweight 25-30
  Obese >30
  '''
  if bmi < 18.5:
    return 'Underweight'
  if bmi >= 18.5 and bmi < 25:
    return 'Normal'
  if bmi >= 25 and bmi < 30:
    return 'Overweight'
  if bmi > 30:
    return 'Obese'

heart_risk_load_analyzed_df['BMI Group'] = heart_risk_load_analyzed_df['BMI'].apply(income_group)
heart_risk_load_analyzed_df.drop(columns=['BMI'], inplace=True)
heart_risk_load_analyzed_df
```

Out[13]:

	Patient ID	Sex	Cholesterol	Blood Pressure	Heart Rate	Diabetes	Family History	Smoking	Obesity	Alcohol Consumption	...	Physical Activity Days Per Week	Sleep Hours Per Day	Country	Continent	Hemisphere	Heart Attack Risk	Age Group	Physical Activity Group	Income Group	BMI Group
0	BMW7812	Male	208	158/88	72	0	0	1	0	0	...	0	6	Argentina	South America	Southern Hemisphere	0	Senior	High activity	High-income	Low-income
1	CZE1114	Male	389	165/93	98	1	1	1	1	1	...	1	7	Canada	North America	Northern Hemisphere	0	Young Adult	Low activity	High-income	Low-income
2	BNI9906	Female	324	174/99	72	1	0	0	0	0	...	4	4	France	Europe	Northern Hemisphere	0	Young Adult	Normal activity	High-income	Low-income
3	JLN3497	Male	383	163/100	73	1	1	1	0	1	...	3	4	Canada	North America	Northern Hemisphere	0	Senior	High activity	High-income	Low-income
4	GFO8847	Male	318	91/88	93	1	1	1	1	0	...	1	5	Thailand	Asia	Northern Hemisphere	0	Senior	High activity	High-income	Low-income
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
8758	MSV9918	Male	121	94/76	61	1	1	1	0	1	...	7	7	Thailand	Asia	Northern Hemisphere	0	Senior	High activity	High-income	Low-income
8759	QSV6764	Female	120	157/102	73	1	0	0	1	0	...	4	9	Canada	North America	Northern Hemisphere	0	Young Adult	High activity	High-income	Low-income
8760	XKA5925	Male	250	161/75	105	0	1	1	1	1	...	4	4	Brazil	South America	Southern Hemisphere	1	Middle-aged Adult	High activity	Mid-income	Low-income
8761	EPE6801	Male	178	119/67	60	1	0	1	0	0	...	2	8	Brazil	South America	Southern Hemisphere	0	Young Adult	High activity	High-income	Low-income
8762	ZWN9666	Female	356	138/67	75	1	1	0	0	1	...	7	4	United Kingdom	Europe	Northern Hemisphere	1	Young Adult	High activity	High-income	Low-income

8763 rows × 26 columns

In [14]:

```python
# Instantiate OrdinalEncoder
diet_ordinal_encoder = OrdinalEncoder()
# Fit the encoder
diet_ordinal_encoder.fit(np.asarray(heart_risk_load_analyzed_df['Diet']).reshape(-1,1))
#Transform the dataset
heart_risk_load_analyzed_df['Diet Encoded'] = diet_ordinal_encoder.transform(np.asarray(heart_risk_load_analyzed_df['Diet']).reshape(-1,1))
heart_risk_load_analyzed_df.drop(columns=['Diet'], inplace=True)
heart_risk_load_analyzed_df
```

Out[14]:

	Patient ID	Sex	Cholesterol	Blood Pressure	Heart Rate	Diabetes	Family History	Smoking	Obesity	Alcohol Consumption	...	Sleep Hours Per Day	Country	Continent	Hemisphere	Heart Attack Risk	Age Group	Physical Activity Group	Income Group	BMI Group	Diet Encoded
0	BMW7812	Male	208	158/88	72	0	0	1	0	0	...	6	Argentina	South America	Southern Hemisphere	0	Senior	High activity	High-income	Low-income	0.0
1	CZE1114	Male	389	165/93	98	1	1	1	1	1	...	7	Canada	North America	Northern Hemisphere	0	Young Adult	Low activity	High-income	Low-income	2.0
2	BNI9906	Female	324	174/99	72	1	0	0	0	0	...	4	France	Europe	Northern Hemisphere	0	Young Adult	Normal activity	High-income	Low-income	1.0
3	JLN3497	Male	383	163/100	73	1	1	1	0	1	...	4	Canada	North America	Northern Hemisphere	0	Senior	High activity	High-income	Low-income	0.0
4	GFO8847	Male	318	91/88	93	1	1	1	1	0	...	5	Thailand	Asia	Northern Hemisphere	0	Senior	High activity	High-income	Low-income	2.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
8758	MSV9918	Male	121	94/76	61	1	1	1	0	1	...	7	Thailand	Asia	Northern Hemisphere	0	Senior	High activity	High-income	Low-income	1.0
8759	QSV6764	Female	120	157/102	73	1	0	0	1	0	...	9	Canada	North America	Northern Hemisphere	0	Young Adult	High activity	High-income	Low-income	1.0
8760	XKA5925	Male	250	161/75	105	0	1	1	1	1	...	4	Brazil	South America	Southern Hemisphere	1	Middle-aged Adult	High activity	Mid-income	Low-income	0.0
8761	EPE6801	Male	178	119/67	60	1	0	1	0	0	...	8	Brazil	South America	Southern Hemisphere	0	Young Adult	High activity	High-income	Low-income	2.0
8762	ZWN9666	Female	356	138/67	75	1	1	0	0	1	...	4	United Kingdom	Europe	Northern Hemisphere	1	Young Adult	High activity	High-income	Low-income	1.0

8763 rows × 26 columns

In [15]:

```
# We can apply label encoder on the dataframe itself like below
# Define categorical columns and apply label encoder using pipeline
cat_columns = ['Sex', 'Hemisphere', 'Age Group', 'Physical Activity Group', 'Income Group', 'BMI Group']
#cat_columns = ['Sex', 'Hemisphere']
heart_risk_load_analyzed_df[cat_columns] = heart_risk_load_analyzed_df[cat_columns].apply(LabelEncoder().fit_transform)
# Create a categorical transformer for either label encoder or onehot encoder
# We will try label encoder
#cat_transformer = Pipeline(steps=[('lbl_encode', LabelEncoder())])
heart_risk_load_analyzed_df
```

Out[15]:

	Patient ID	Sex	Cholesterol	Blood Pressure	Heart Rate	Diabetes	Family History	Smoking	Obesity	Alcohol Consumption	...	Sleep Hours Per Day	Country	Continent	Hemisphere	Heart Attack Risk	Age Group	Physical Activity Group	Income Group	BMI Group	Diet Encoded
0	BMW7812	1	208	158/88	72	0	0	1	0	0	...	6	Argentina	South America	1	0	1	0	0	0	0.0
1	CZE1114	1	389	165/93	98	1	1	1	1	1	...	7	Canada	North America	0	0	2	1	0	0	2.0
2	BNI9906	0	324	174/99	72	1	0	0	0	0	...	4	France	Europe	0	0	2	2	0	0	1.0
3	JLN3497	1	383	163/100	73	1	1	1	0	1	...	4	Canada	North America	0	0	1	0	0	0	0.0
4	GFO8847	1	318	91/88	93	1	1	1	1	0	...	5	Thailand	Asia	0	0	1	0	0	0	2.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
8758	MSV9918	1	121	94/76	61	1	1	1	0	1	...	7	Thailand	Asia	0	0	1	0	0	0	1.0
8759	QSV6764	0	120	157/102	73	1	0	0	1	0	...	9	Canada	North America	0	0	2	0	0	0	1.0
8760	XKA5925	1	250	161/75	105	0	1	1	1	1	...	4	Brazil	South America	1	1	0	0	2	0	0.0
8761	EPE6801	1	178	119/67	60	1	0	1	0	0	...	8	Brazil	South America	1	0	2	0	0	0	2.0
8762	ZWN9666	0	356	138/67	75	1	1	0	0	1	...	4	United Kingdom	Europe	0	1	2	0	0	0	1.0

8763 rows × 26 columns

Feature Transformation

We apply transformations, such as encoding and scaling, to make the data suitable for machine learning algorithms.

In [16]:

```
# set random seed
np.random.seed(50)
# Create X and y
X = heart_risk_load_analyzed_df.drop('Heart Attack Risk', axis=1)
y = heart_risk_load_analyzed_df['Heart Attack Risk']
# Split the data
X_train, X_test, y_train, y_test = train_test_split(X,
y,
test_size=0.2)
len(X), len(X_train), len(X_test)
# Let us scale the data since every in different scale
# Use MinMaxScaler() and we can do that using pipeline or directly
# scaler = MinMaxScaler()
# X_train_scaled = scaler.fit_transform(X_train)
# X_test_scaled = scaler.transform(X_test) # we dont for for X_test, just only do transform
# Build logistic regression classifier using pipeline
log_reg_model = Pipeline(steps=[
('minmaxscaler', MinMaxScaler()),
('logisticregression', LogisticRegression())], verbose=True)
# Build logistic regression classifier using pipeline
ran_for_model = Pipeline(steps=[
('minmaxscaler', MinMaxScaler()),
('randomrorestclassifier', RandomForestClassifier())], verbose=True)
# Build Kneighbor classifier using pipeline
knn_model = Pipeline(steps=[
('minmaxscaler', MinMaxScaler()),
('kneighborsclassifier', KNeighborsClassifier())], verbose=True)
```

In [17]:

```
# Create a function to fit and score models
def get_metrics(model, X_train, X_test, y_train, y_test):
  """
  Fits and evaluates given machine learning model.
  model : Scikit-Learn machine learning model
  X_train : training data
  X_test : testing data
  y_train : training labels
  y_test : test labels
  """
  # Set random seed
  np.random.seed(42)
  # Fit the model to the data
  model.fit(X_train, y_train)
  # Get Predictions
  y_preds = model.predict(X_test)
  # Evaluate the model and append its score to model_scores
  #return model.score(X_test, y_test)
  metric_dict = {
  'accuracy_score' : accuracy_score(y_test, y_preds),
  'precision_score' : precision_score(y_test, y_preds, average='weighted', labels=np.unique(y_preds)),
  'recall_score' : recall_score(y_test, y_preds),
  'f1_score' : f1_score(y_test, y_preds),
  'roc_auc_score' : roc_auc_score(y_test, y_preds),
  }
  return metric_dict
```

Model Building and Training && Model Evaluation

Several machine learning models are built and trained using the transformed dataset, including:

- Logistic Regression
- Random Forest
- K-Nearest Neighbors

Then we evaluate the performance of the models using metrics such as accuracy, precision, recall, and F1 score. The results are compared to identify the best-performing model.

In [18]:
```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.preprocessing import LabelEncoder

# دالة لحساب المقاييس
def get_metrics(model, X_train, X_test, y_train, y_test):
    """
    تقوم بتدريب النموذج على بيانات التدريب
    وتقييمه باستخدام بيانات الاختبار.
    """
    model.fit(X_train, y_train)
    y_preds = model.predict(X_test)
    metrics = {
        "Accuracy": accuracy_score(y_test, y_preds),
        "Precision": precision_score(y_test, y_preds, average='weighted'),
        "Recall": recall_score(y_test, y_preds, average='weighted'),
        "F1 Score": f1_score(y_test, y_preds, average='weighted')
    }
    return metrics

# تحميل البيانات (تأكد من تخصيص المتغير X و y حسب بياناتك)
# X: ميزات (Features)
# y: القيم المستهدفة (Target)
# ملاحظة: هذا مجرد مثال لبيانات وهمية
X = pd.read_csv(r'heart_attack_prediction_dataset.csv')  # عدّل المسار حسب بياناتك
y = X["Heart Attack Risk"]  # عدّل العمود حسب بياناتك
X = X.drop(columns=["Heart Attack Risk", "Patient ID", "Blood Pressure", "Country"])  # إسقاط الأعمدة غير المهمة

# تحويل الأعمدة غير العددية إلى تنسيق رقمي
categorical_columns = X.select_dtypes(include=['object']).columns
X = pd.get_dummies(X, columns=categorical_columns, drop_first=True)

# تقسيم البيانات إلى تدريب واختبار
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# التعامل مع القيم المفقودة (إن وجدت)
X_train = X_train.fillna(0)
X_test = X_test.fillna(0)

# تحويل القيم المستهدفة إلى تنسيق رقمي
le = LabelEncoder()
y_train = le.fit_transform(y_train)
y_test = le.transform(y_test)

# تدريب النماذج
log_reg_model = LogisticRegression()
ran_for_model = RandomForestClassifier(random_state=42)
knn_model = KNeighborsClassifier()

# حساب الدرجات
log_reg_scores = get_metrics(log_reg_model, X_train, X_test, y_train, y_test)
print("Logistic Regression Scores:", log_reg_scores)

ran_for_scores = get_metrics(ran_for_model, X_train, X_test, y_train, y_test)
print("Random Forest Scores:", ran_for_scores)

knn_scores = get_metrics(knn_model, X_train, X_test, y_train, y_test)
print("K-Nearest Neighbors Scores:", knn_scores)
```

```
C:\Users\myarn\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p0\LocalCache\local-packages\Python311\site-packages\sklearn\linear_model\_logistic.py:465: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
C:\Users\myarn\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p0\LocalCache\local-packages\Python311\site-packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
Logistic Regression Scores: {'Accuracy': 0.6417569880205363, 'Precision': 0.41185203167319073, 'Recall': 0.6417569880205363, 'F1 Score': 0.5017210642968056}
Random Forest Scores: {'Accuracy': 0.6349115801483172, 'Precision': 0.5341793778017578, 'Recall': 0.6349115801483172, 'F1 Score': 0.511121157875615}
K-Nearest Neighbors Scores: {'Accuracy': 0.5641756988020536, 'Precision': 0.5369982654681719, 'Recall': 0.5641756988020536, 'F1 Score': 0.5459615185126817}
```

In [19]:
```python
ran_for_model.get_params()
```

Out[19]:
```
{'bootstrap': True,
 'ccp_alpha': 0.0,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': None,
 'max_features': 'sqrt',
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'monotonic_cst': None,
 'n_estimators': 100,
 'n_jobs': None,
 'oob_score': False,
 'random_state': 42,
 'verbose': 0,
 'warm_start': False}
```

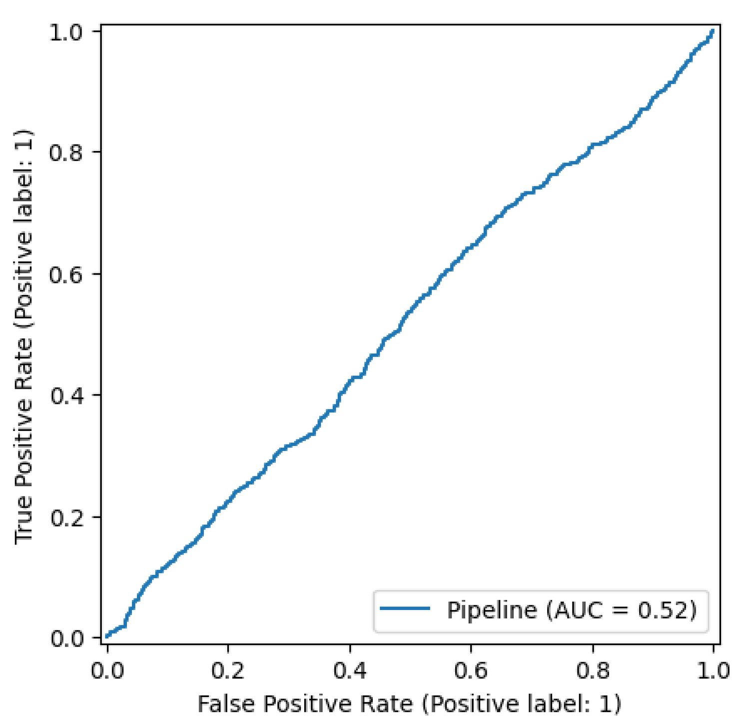
Hyperparameter Tuning

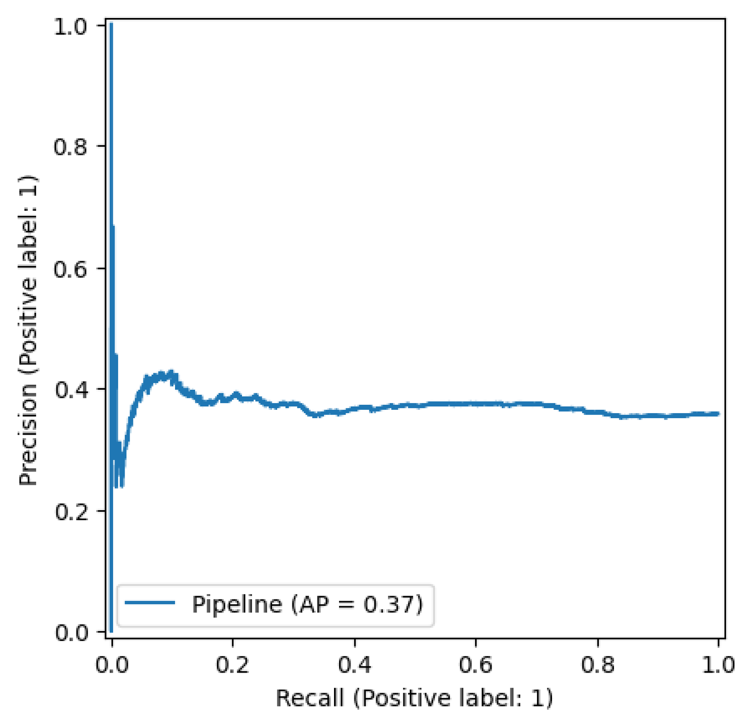
Using RandomizedSearchCV, we fine-tune the hyperparameters of the Random Forest model to improve performance.

In [24]:
```python
from sklearn.model_selection import RandomizedSearchCV
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.ensemble import RandomForestClassifier, IsolationForest
from sklearn.cluster import KMeans
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, RocCurveDisplay, PrecisionRecallDisplay
from sklearn.decomposition import PCA
import joblib

# تحميل البيانات
data = pd.read_csv('heart_attack_prediction_dataset.csv')
y = data["Heart Attack Risk"]
X = data.drop(columns=["Heart Attack Risk", "Patient ID", "Country"])

# معالجة البيانات (تعبئة القيم المفقودة وترميز النصوص)
categorical_columns = ['Blood Pressure', 'Continent']
numeric_columns = X.select_dtypes(include=['int64', 'float64']).columns.tolist()
```

```python
preprocessor = ColumnTransformer(
    transformers=[
        ('num', SimpleImputer(strategy='mean'), numeric_columns),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_columns)
    ]
)

# تقسيم البيانات
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# نموذج الغابة العشوائية مع RandomizedSearchCV
ran_for_model = RandomForestClassifier(random_state=42)
param_grid = {
    'n_estimators': [50, 100],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 4],
    'min_samples_leaf': [1, 2]
}
random_search = RandomizedSearchCV(
    estimator=ran_for_model,
    param_distributions=param_grid,
    n_iter=5,
    cv=3,
    verbose=2,
    random_state=42,
    scoring='accuracy'
)

# بناء Pipeline
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('pca', PCA(n_components=10)),
    ('randomforestclassifier', random_search)
])

# تدريب النموذج
# تدريب النموذج
pipeline.fit(X_train, y_train)

# استخدام الـ Pipeline مباشرة لتقييم الأداء بدلاً من التعامل مع النموذج
y_preds = pipeline.predict(X_test)
print("Model Performance:")
print(f"Accuracy: {accuracy_score(y_test, y_preds)}")
print(f"Precision: {precision_score(y_test, y_preds, average='weighted')}")
print(f"Recall: {recall_score(y_test, y_preds, average='weighted')}")
print(f"F1 Score: {f1_score(y_test, y_preds, average='weighted')}")

# تصورات الأداء
RocCurveDisplay.from_estimator(pipeline, X_test, y_test)
plt.show()

PrecisionRecallDisplay.from_estimator(pipeline, X_test, y_test)
plt.show()



# استخراج أفضل نموذج
best_model = pipeline.named_steps['randomforestclassifier'].best_estimator_

# تحويل البيانات باستخدام المعالج المسبق
X_test_transformed = pipeline.named_steps['preprocessor'].transform(X_test)



# طباعة أفضل المعلمات والنتيجة
print("Best Parameters:", random_search.best_params_)
print("Best Score:", random_search.best_score_)
```

```
Fitting 3 folds for each of 5 candidates, totalling 15 fits
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=2, n_estimators=50; total time=   1.9s
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=2, n_estimators=50; total time=   2.0s
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=2, n_estimators=50; total time=   2.0s
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=2, n_estimators=50; total time=   2.9s
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=2, n_estimators=50; total time=   3.0s
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=2, n_estimators=50; total time=   3.0s
[CV] END max_depth=None, min_samples_leaf=1, min_samples_split=2, n_estimators=50; total time=   3.0s
[CV] END max_depth=None, min_samples_leaf=1, min_samples_split=2, n_estimators=50; total time=   3.3s
[CV] END max_depth=None, min_samples_leaf=1, min_samples_split=2, n_estimators=50; total time=   3.1s
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=4, n_estimators=50; total time=   3.0s
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=4, n_estimators=50; total time=   2.9s
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=4, n_estimators=50; total time=   3.0s
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=4, n_estimators=100; total time=   4.1s
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=4, n_estimators=100; total time=   4.3s
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=4, n_estimators=100; total time=   3.9s
Model Performance:
Accuracy: 0.6400456360524814
Precision: 0.5311838726447105
Recall: 0.6400456360524814
F1 Score: 0.503985059734092
```






```
Best Parameters: {'n_estimators': 50, 'min_samples_split': 2, 'min_samples_leaf': 1, 'max_depth': 10}
Best Score: 0.638944269084003
```

In [21]:
```
print(X_train.dtypes)
```

```
Age                               int64
Cholesterol                       int64
Heart Rate                        int64
Diabetes                          int64
Family History                    int64
Smoking                           int64
Obesity                           int64
Alcohol Consumption               int64
Exercise Hours Per Week         float64
Previous Heart Problems           int64
Medication Use                    int64
Stress Level                      int64
Sedentary Hours Per Day         float64
Income                            int64
BMI                             float64
Triglycerides                     int64
Physical Activity Days Per Week   int64
Sleep Hours Per Day               int64
Sex_Male                           bool
Diet_Healthy                       bool
Diet_Unhealthy                     bool
Continent_Asia                     bool
Continent_Australia                bool
Continent_Europe                   bool
Continent_North America            bool
Continent_South America            bool
Hemisphere_Southern Hemisphere     bool
dtype: object
```

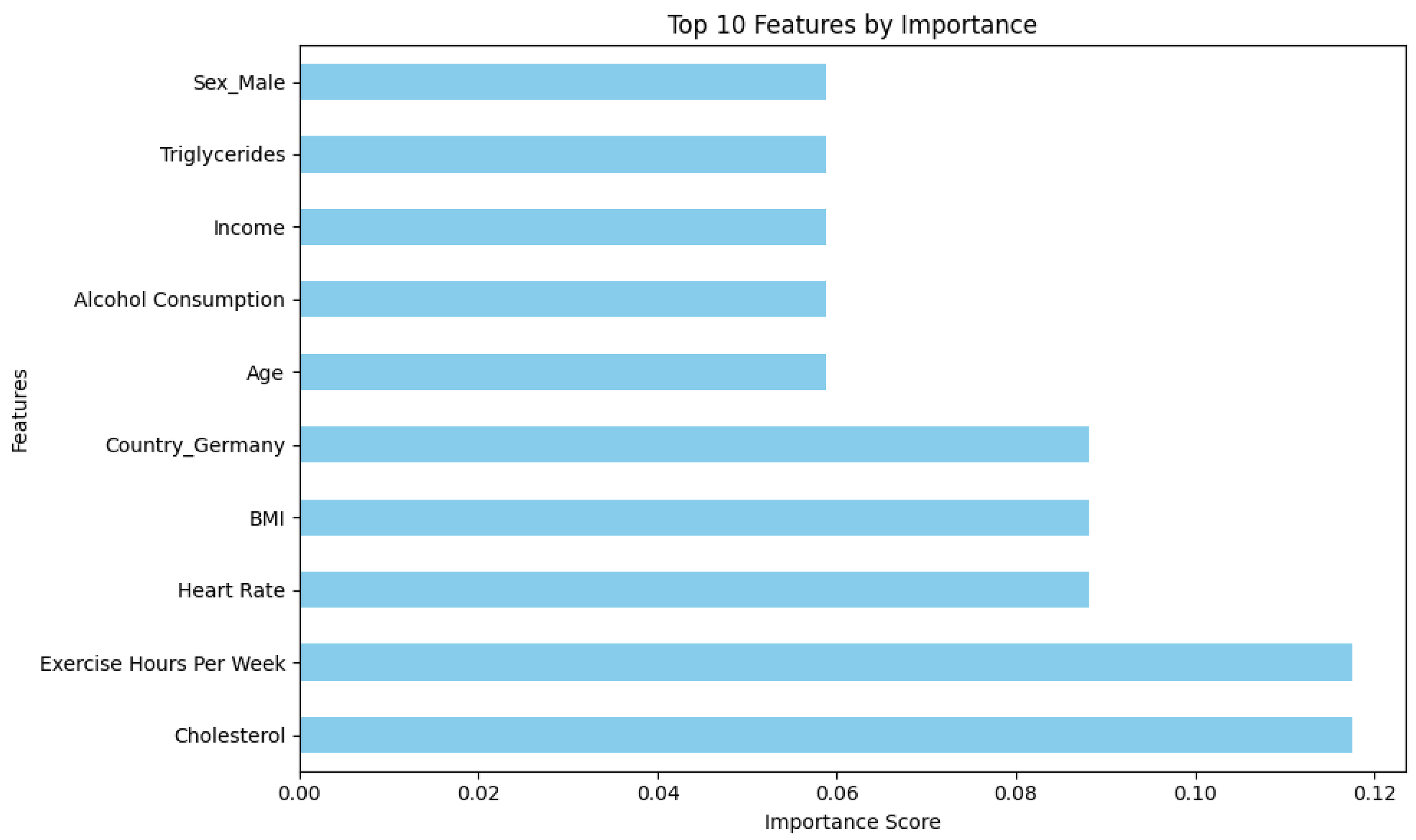
Feature Importance

The Random Forest model's feature importance is visualized to identify the most influential factors contributing to heart attack risk.

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split

# قراءة البيانات
data = {
    "Patient ID": ["BMW7812", "CZE1114", "BNI9906", "JLN3497", "GFO8847", "ZOO7941"],
    "Age": [67, 21, 21, 84, 66, 54],
    "Sex": ["Male", "Male", "Female", "Male", "Male", "Female"],
    "Cholesterol": [208, 389, 324, 383, 318, 297],
    "Blood Pressure": ["158/88", "165/93", "174/99", "163/100", "91/88", "172/86"],
    "Heart Rate": [72, 98, 72, 73, 93, 48],
    "Diabetes": [0, 1, 1, 1, 1, 1],
    "Family History": [0, 1, 0, 1, 1, 1],
    "Smoking": [1, 1, 0, 1, 1, 1],
    "Obesity": [0, 1, 0, 0, 1, 0],
    "Alcohol Consumption": [0, 1, 0, 1, 0, 1],
    "Exercise Hours Per Week": [4.17, 1.81, 2.08, 9.83, 5.80, 0.62],
    "Diet": ["Average", "Unhealthy", "Healthy", "Average", "Unhealthy", "Unhealthy"],
    "Previous Heart Problems": [0, 1, 1, 1, 1, 1],
    "Medication Use": [0, 0, 1, 0, 0, 1],
    "Stress Level": [9, 1, 9, 9, 6, 2],
    "Sedentary Hours Per Day": [6.62, 4.96, 9.46, 7.65, 1.51, 7.80],
    "Income": [261404, 285768, 235282, 125640, 160555, 241339],
    "BMI": [31.25, 27.19, 28.18, 36.46, 21.81, 20.15],
    "Triglycerides": [286, 235, 587, 378, 231, 795],
    "Physical Activity Days Per Week": [0, 1, 4, 3, 1, 5],
    "Sleep Hours Per Day": [6, 7, 4, 4, 5, 10],
    "Country": ["Argentina", "Canada", "France", "Canada", "Thailand", "Germany"],
    "Continent": ["South America", "North America", "Europe", "North America", "Asia", "Europe"],
    "Hemisphere": ["Southern Hemisphere", "Northern Hemisphere", "Northern Hemisphere", "Northern Hemisphere", "Northern Hemisphere", "Northern Hemisphere"],
    "Heart Attack Risk": [0, 0, 0, 0, 0, 1],
}

df = pd.DataFrame(data)

# فصل البيانات
X = df.drop(columns=["Patient ID", "Heart Attack Risk"])
y = df["Heart Attack Risk"]

# تحديد الأعمدة النصية والرقمية
categorical_columns = ["Blood Pressure", "Sex", "Diet", "Country", "Continent", "Hemisphere"]
numeric_columns = [
    "Age", "Cholesterol", "Heart Rate", "Diabetes", "Family History", "Smoking",
    "Obesity", "Alcohol Consumption", "Exercise Hours Per Week",
    "Previous Heart Problems", "Medication Use", "Stress Level",
    "Sedentary Hours Per Day", "Income", "BMI", "Triglycerides",
    "Physical Activity Days Per Week", "Sleep Hours Per Day",
]

# تقسيم البيانات إلى تدريب واختبار
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# معالجة البيانات
preprocessor = ColumnTransformer(
    transformers=[
        ("num", SimpleImputer(strategy="mean"), numeric_columns),
        ("cat", OneHotEncoder(handle_unknown="ignore"), categorical_columns),
    ]
)
```

```python
# إنشاء نموذج Random Forest
pipeline = Pipeline(steps=[
    ("preprocessor", preprocessor),
    ("classifier", RandomForestClassifier(n_estimators=50, random_state=42)),
])

# تدريب النموذج
pipeline.fit(X_train, y_train)

# التنبؤ وحساب الدقة
y_pred = pipeline.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")

# استخراج أهمية الميزات
feature_importances = pipeline.named_steps["classifier"].feature_importances_
encoded_columns = numeric_columns + list(
    pipeline.named_steps["preprocessor"]
    .named_transformers_["cat"]
    .get_feature_names_out(categorical_columns)
)

# إنشاء مخطط لأهم الميزات
imp_feature_score = pd.Series(feature_importances, index=encoded_columns)
top_features = imp_feature_score.nlargest(10)

top_features.plot(kind="barh", title="Top 10 Features by Importance", figsize=(10, 6), color="skyblue")
plt.xlabel("Importance Score")
plt.ylabel("Features")
plt.tight_layout()
plt.show()
```

```
Accuracy: 1.00
```




```
Accuracy:  1.00
```

In [26]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
import tkinter as tk
from tkinter import ttk, messagebox
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer

# 1. تحميل البيانات
data = pd.read_csv('heart_attack_prediction_dataset.csv')

# 2. تقسيم البيانات إلى مدخلات ومخرجات
y = data["Heart Attack Risk"]
X = data.drop(columns=["Heart Attack Risk", "Patient ID", "Country"])

# 3. تحديد الأعمدة النصية والرقمية
categorical_columns = X.select_dtypes(include=['object']).columns
numeric_columns = X.select_dtypes(include=['int64', 'float64']).columns

# 4. معالجة الأعمدة النصية باستخدام OneHotEncoder
preprocessor = ColumnTransformer(
    transformers=[
        ('num', 'passthrough', numeric_columns),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_columns)
    ]
)

# 5. تحويل البيانات
X_transformed = preprocessor.fit_transform(X)

# 6. تقسيم البيانات
X_train, X_test, y_train, y_test = train_test_split(X_transformed, y, test_size=0.2, random_state=42)

# 7. تدريب نموذج الغابة العشوائية
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)

# 8. التنبؤ بالمخاطر
y_preds = model.predict(X_test)
print("Model Performance:")
print(classification_report(y_test, y_preds))

# 9. تجميع المرضى باستخدام KMeans إلى مجموعات (عالية ومنخفضة المخاطر)
kmeans = KMeans(n_clusters=2, random_state=42)
risk_groups = kmeans.fit_predict(X_test)

print(f"Shape of X_test: {X_test.shape}")
print(f"Expected number of columns: {len(preprocessor.get_feature_names_out())}")


# إعداد DataFrame للنتائج
#results = pd.DataFrame(X_test, columns=preprocessor.get_feature_names_out())
#results['Risk Group'] = risk_groups
#results['Predicted Risk'] = y_preds
#results['Risk Level'] = results['Risk Group'].map({0: 'Low Risk', 1: 'High Risk'})

# طباعة الأشكال للتحقق
```

```python
print(f"Shape of X_test: {X_test.shape}")
print(f"Expected columns from preprocessor: {len(preprocessor.get_feature_names_out())}")
```

```
Model Performance:
              precision    recall  f1-score   support

           0       0.64      1.00      0.78      1125
           1       0.44      0.01      0.01       628

    accuracy                           0.64      1753
   macro avg       0.54      0.50      0.40      1753
weighted avg       0.57      0.64      0.51      1753

Shape of X_test: (1753, 3946)
Expected number of columns: 3946
Shape of X_test: (1753, 3946)
Expected columns from preprocessor: 3946
```

In [27]:
```python
print("X_test Transformed Preview:")
print(X_test[:5])  # عرض أول 5 صفوف
```

```
X_test Transformed Preview:
<Compressed Sparse Row sparse matrix of dtype 'float64'
	with 98 stored elements and shape (5, 3946)>
  Coords	Values
  (0, 0)	65.0
  (0, 1)	340.0
  (0, 2)	75.0
  (0, 5)	1.0
  (0, 6)	1.0
  (0, 7)	1.0
  (0, 8)	9.870784085657094
  (0, 9)	1.0
  (0, 10)	1.0
  (0, 11)	7.0
  (0, 12)	5.56736308745687
  (0, 13)	216664.0
  (0, 14)	35.56128348361503
  (0, 15)	315.0
  (0, 17)	4.0
  (0, 19)	1.0
  (0, 1074)	1.0
  (0, 3936)	1.0
  (0, 3943)	1.0
  (0, 3945)	1.0
  (1, 0)	77.0
  (1, 1)	361.0
  (1, 2)	46.0
  (1, 3)	1.0
  (1, 5)	1.0
  :	:
  (3, 17)	9.0
  (3, 19)	1.0
  (3, 2386)	1.0
  (3, 3935)	1.0
  (3, 3939)	1.0
  (3, 3944)	1.0
  (4, 0)	63.0
  (4, 1)	173.0
  (4, 2)	98.0
  (4, 5)	1.0
  (4, 7)	1.0
  (4, 8)	3.6814717164946265
  (4, 10)	1.0
  (4, 11)	1.0
  (4, 12)	8.841575331400762
  (4, 13)	148437.0
  (4, 14)	21.11004423235903
  (4, 15)	638.0
  (4, 16)	2.0
  (4, 17)	7.0
  (4, 19)	1.0
  (4, 168)	1.0
  (4, 3937)	1.0
  (4, 3941)	1.0
  (4, 3944)	1.0
```

Summary and Recommendations

The project highlights the key factors influencing heart health and provides a predictive framework to assess heart attack risk. Further improvements can be achieved by gathering more data and exploring advanced models.

In [28]:
```python
import pandas as pd

# تحويل مصفوفة sparse إلى مصفوفة كثيفة
X_test_dense = X_test.toarray()

# التحقق من تطابق الأبعاد
if X_test_dense.shape[1] == len(preprocessor.get_feature_names_out()):
    # إنشاء DataFrame مع أسماء الأعمدة
    results = pd.DataFrame(X_test_dense, columns=preprocessor.get_feature_names_out())
    results['Risk Group'] = risk_groups
    results['Predicted Risk'] = y_preds
    results['Risk Level'] = results['Risk Group'].map({0: 'Low Risk', 1: 'High Risk'})
    print(results.head())  # عرض أول 5 صفوف
else:
    print(f"Shape mismatch detected: X_test has shape {X_test_dense.shape}, but expected {len(preprocessor.get_feature_names_out())} columns.")



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

```
   num__Age  num__Cholesterol  num__Heart Rate  num__Diabetes  \
0      65.0             340.0             75.0            0.0   
1      77.0             361.0             46.0            1.0   
2      70.0             341.0             73.0            1.0   
3      47.0             392.0             72.0            0.0   
4      63.0             173.0             98.0            0.0   

   num__Family History  num__Smoking  num__Obesity  num__Alcohol Consumption  \
0                  0.0           1.0           1.0                       1.0   
1                  0.0           1.0           0.0                       0.0   
2                  1.0           1.0           1.0                       1.0   
3                  1.0           1.0           1.0                       0.0   
4                  0.0           1.0           0.0                       1.0   

   num__Exercise Hours Per Week  num__Previous Heart Problems  ...  \
0                      9.870784                           1.0  ...   
1                      2.763339                           0.0  ...   
2                     16.325463                           1.0  ...   
3                      5.161941                           0.0  ...   
4                      3.681472                           0.0  ...   

   cat__Continent_Asia  cat__Continent_Australia  cat__Continent_Europe  \
0                  0.0                       0.0                    0.0   
1                  1.0                       0.0                    0.0   
2                  0.0                       0.0                    0.0   
3                  1.0                       0.0                    0.0   
4                  0.0                       0.0                    1.0   

   cat__Continent_North America  cat__Continent_South America  \
0                           0.0                           1.0   
1                           0.0                           0.0   
2                           0.0                           0.0   
3                           0.0                           0.0   
4                           0.0                           0.0   

   cat__Hemisphere_Northern Hemisphere  cat__Hemisphere_Southern Hemisphere  \
0                                  0.0                                  1.0   
1                                  1.0                                  0.0   
2                                  0.0                                  1.0   
3                                  1.0                                  0.0   
4                                  1.0                                  0.0   

   Risk Group  Predicted Risk  Risk Level  
0           1               0   High Risk  
1           1               0   High Risk  
2           1               0   High Risk  
3           0               0    Low Risk  
4           0               0    Low Risk  

[5 rows x 3949 columns]
```

In [29]:

```python
import pandas as pd
import tkinter as tk
from tkinter import ttk, messagebox
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.cluster import KMeans
import numpy as np

# 1. إنشاء DataFrame من البيانات (مثالك)
data = {
    'Age': [25, 27, 30, 24, 28, 65, 70, 68, 72, 66],
    'Blood_Pressure': [120, 115, 130, 110, 125, 160, 170, 165, 175, 158],
    'Cholesterol': [180, 175, 200, 190, 185, 240, 250, 245, 260, 238],
    'Sex': ['Male', 'Female', 'Male', 'Female', 'Male', 'Male', 'Female', 'Male', 'Female', 'Male'],
    'Heart_Attack_Risk': [0, 0, 0, 0, 0, 1, 1, 1, 1, 1]
}
df = pd.DataFrame(data)

# 2. إعداد المدخلات (X) والمخرجات (y)
X = df.drop(columns=['Heart_Attack_Risk'])
y = df['Heart_Attack_Risk']

# 3. تعريف الأعمدة النصية والرقمية
categorical_columns = ['Sex']
numeric_columns = ['Age', 'Blood_Pressure', 'Cholesterol']

# 4. تجهيز المحول مع OneHotEncoder للأعمدة النصية
preprocessor = ColumnTransformer(
    transformers=[
        ('num', 'passthrough', numeric_columns),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_columns)
    ]
)

# 5. تطبيق التحويل على البيانات
X_transformed = preprocessor.fit_transform(X)

# 6. تدريب نموذج KMeans على البيانات المحولة (لتصنيف المخاطر)
kmeans = KMeans(n_clusters=2, random_state=42)
kmeans.fit(X_transformed)

# 7. بناء واجهة المستخدم

def predict_risk():
    try:
        user_input = []
        for idx, col in enumerate(numeric_columns + categorical_columns):
            val = user_entries[idx].get()
            if col in numeric_columns:
                user_input.append(float(val))
            else:
                # تحويل الإدخال من 0 و 1 إلى 'Male' و 'Female'
                if val == '0':
                    user_input.append('Male')
                elif val == '1':
                    user_input.append('Female')
                else:
                    raise ValueError("Sex must be 0 (Male) or 1 (Female)")

        # تحويل القائمة إلى DataFrame بنفس تنسيق الأعمدة الأصلية
        user_input_df = pd.DataFrame([user_input], columns=numeric_columns + categorical_columns)

        # تطبيق المحول على DataFrame
        user_transformed = preprocessor.transform(user_input_df)

        # التنبؤ بالمجموعة
        risk_group = kmeans.predict(user_transformed)[0]
        risk_level = 'High Risk' if risk_group == 1 else 'Low Risk'

        messagebox.showinfo("Prediction", f"The predicted risk level is: {risk_level}")
    except Exception as e:
        messagebox.showerror("Error", f"Invalid input: {str(e)}")



root = tk.Tk()
root.title("Heart Attack Risk Prediction")

# إنشاء واجهة إدخال بيانات المستخدم
labels = numeric_columns + categorical_columns
user_entries = []
```

```
for idx, col in enumerate(labels):
    ttk.Label(root, text=col).grid(row=idx, column=0, padx=5, pady=5)
    entry = ttk.Entry(root)
    entry.grid(row=idx, column=1, padx=5, pady=5)
    user_entries.append(entry)

# زر التنبؤ
ttk.Button(root, text="Predict Risk", command=predict_risk).grid(row=len(labels), column=0, columnspan=2, pady=10)

root.mainloop()
```