

```

In [11]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import roc_curve, auc, classification_report, confusion_matrix
import joblib

# Load the saved logistic regression model
model = joblib.load('logreg_model.pkl') # Load pre-trained model

# Load the new dataset
df = pd.read_csv("Healthcare_Support_Occupations.csv")
print(df.head()) # Inspect the dataset structure

# Convert 'Automatability' into binary labels (1 if >= 0.5, else 0)
df['Automatability_Label'] = (df['Automatability'] >= 0.5).astype(int)
df.drop(columns=['Automatability'], inplace=True) # Drop original column

# Encode 'Task Type' (1 -> 0 for Core, 2 -> 1 for Supplemental)
df['Task Type'] = df['Task Type'] - 1

# Convert 'Scale Name' to numeric values using LabelEncoder
label_encoder = LabelEncoder()
df['Scale Name'] = label_encoder.fit_transform(df['Scale Name'])

# Drop non-relevant columns
columns_to_drop = ["O*NET-SOC Code", "Task ID", "Task_x", "Title", "Category"]
df.drop(columns=columns_to_drop, errors='ignore', inplace=True)

# Handle missing values by replacing them with column means
df.fillna(df.mean(), inplace=True)

# Split data into features (X) and target (y)
X = df.drop(columns=["Automatability_Label"])
y = df["Automatability_Label"]

# Train-test split with stratification to maintain class balance
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Scale features for consistency with training data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Use the trained model for predictions
y_pred = model.predict(X_test_scaled)
y_prob = model.predict_proba(X_test_scaled)[:, 1] # Get probabilities for the positive class

# Evaluate the model with classification metrics
print("\nClassification Report:")
print(classification_report(y_test, y_pred))

print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred))

# Calculate and plot ROC curve and AUC
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(10, 6))

```

```
plt.plot(fpr, tpr, color="darkorange", lw=2, label=f"ROC curve (AUC = {roc_auc:.4f})")
plt.plot([0, 1], [0, 1], color="navy", lw=2, linestyle="--")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend(loc="lower right")
plt.show()

print(f"AUC Score: {roc_auc:.4f}")
```

O*NET-SOC Code		Task ID	
x \			
0	31-1121.00	4240	Maintain records of patient care, condition, p...
1	31-1121.00	4240	Maintain records of patient care, condition, p...
2	31-1121.00	4240	Maintain records of patient care, condition, p...
3	31-1121.00	4240	Maintain records of patient care, condition, p...
4	31-1121.00	4240	Maintain records of patient care, condition, p...

	Scale Name	Data Value	Task_y	Task Type	Importance_x	Level_x \
0	1	0.00	8138	1	3.079512	2.972683
1	1	0.08	8138	1	3.079512	2.972683
2	1	2.50	8138	1	3.079512	2.972683
3	1	12.18	8138	1	3.079512	2.972683
4	1	66.48	8138	1	3.079512	2.972683

	Importance_y ...	Importance	Level	Tech Readiness	Tool Dependency
\					
0	2.370571 ...	2.509808	2.2675	0.666667	32.0
1	2.370571 ...	2.509808	2.2675	0.666667	32.0
2	2.370571 ...	2.509808	2.2675	0.666667	32.0
3	2.370571 ...	2.509808	2.2675	0.666667	32.0
4	2.370571 ...	2.509808	2.2675	0.666667	32.0

	Context	Context (Categories 1-3)	Context (Categories 1-5) \
0	2.559298	33.333333	19.999964
1	2.559298	33.333333	19.999964
2	2.559298	33.333333	19.999964
3	2.559298	33.333333	19.999964
4	2.559298	33.333333	19.999964

	Title	Automatability	Category
0	Home Health Aides	0.570689	Healthcare Support Occupations
1	Home Health Aides	0.570689	Healthcare Support Occupations
2	Home Health Aides	0.570689	Healthcare Support Occupations
3	Home Health Aides	0.570689	Healthcare Support Occupations
4	Home Health Aides	0.570689	Healthcare Support Occupations

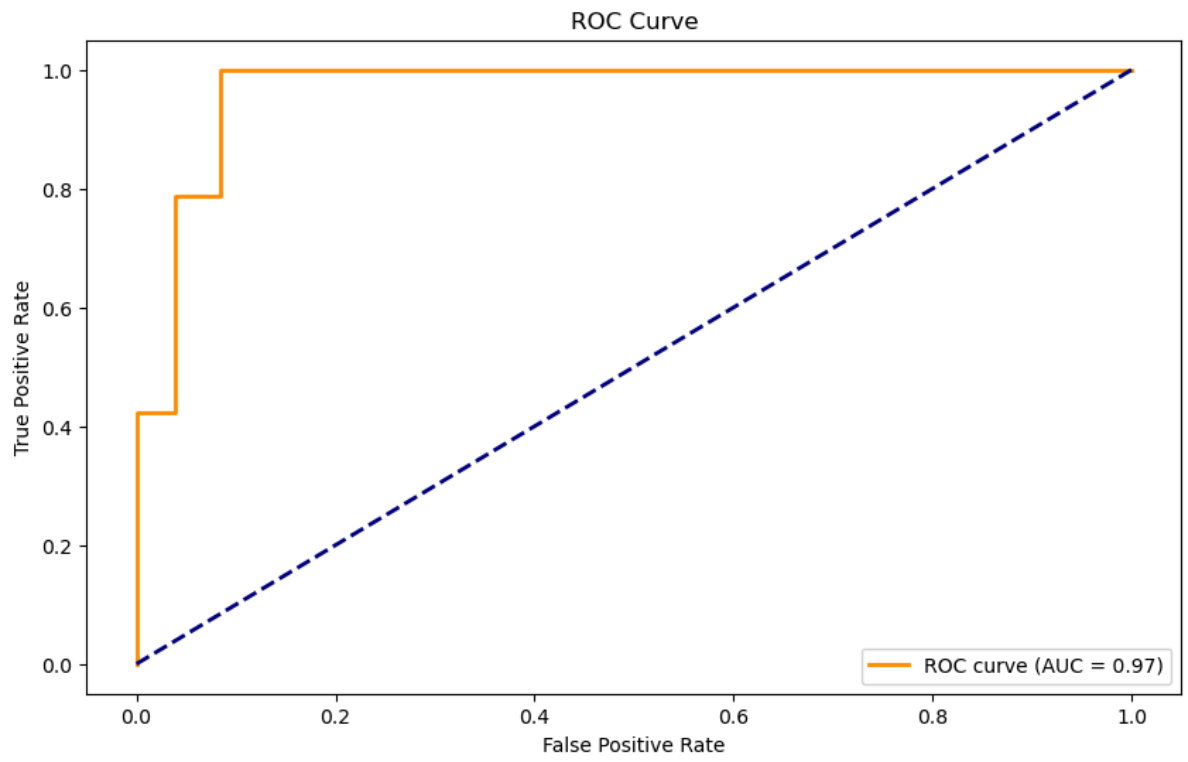
[5 rows x 21 columns]

Classification Report:

	precision	recall	f1-score	support
0	0.76	0.96	0.85	382
1	0.89	0.51	0.65	236
accuracy			0.79	618
macro avg	0.83	0.74	0.75	618
weighted avg	0.81	0.79	0.77	618

Confusion Matrix:

[[367 15]
[115 121]]



AUC Score: 0.9679