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Anxiety EDA & Model Analysis

In [16]:

```
# Basic Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
sb.set()
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, roc_curve, roc
import seaborn as sns
from scipy import stats
import warnings
warnings.filterwarnings('ignore')

df = pd.read_csv('MentalHealthSurvey.csv')
df.head()
```

Out[16]:

	gender	age	university	degree_level	degree_major	academic_year	cgpa	residential_status
0	Male	20	PU	Undergraduate	Data Science	2nd year	3.0-3.5	Off-Campus
1	Male	20	UET	Postgraduate	Computer Science	3rd year	3.0-3.5	Off-Campus
2	Male	20	FAST	Undergraduate	Computer Science	3rd year	2.5-3.0	Off-Campus
3	Male	20	UET	Undergraduate	Computer Science	3rd year	2.5-3.0	On-Campus
4	Female	20	UET	Undergraduate	Computer Science	3rd year	3.0-3.5	Off-Campus

5 rows × 21 columns

In [28]:

```
# Mental Health Survey - Exploratory Data Analysis

# Set visualization styles
plt.style.use('ggplot')
sns.set_palette("Set2")
sns.set_context("notebook", font_scale=1.2)

# 1. Basic Data Exploration
print("Dataset Shape:", df.shape)
print("\nFirst 5 rows of data:")
display(df.head())

print("\nActual column names in the dataset:")
print(df.columns.tolist())

print("\nData Info:")
df.info()
```

```
print("\nDescriptive Statistics:")
display(df.describe())

print("\nChecking for missing values:")
display(df.isnull().sum())

# 2. Data Cleaning and Preparation
# Check unique values in key columns
print("\nUnique values in categorical columns:")
categorical_cols = ['gender', 'university', 'degree_level', 'degree_major', 'reside
for col in categorical_cols:
    if col in df.columns:
        print(f"\n{col}: {df[col].unique()}")
    else:
        print(f"\n{col}: Column not found in dataset")

# 3. Univariate Analysis

# 3.1 Demographic Distribution
plt.figure(figsize=(18, 12))

# Gender distribution
if 'gender' in df.columns:
    plt.subplot(2, 3, 1)
    gender_counts = df['gender'].value_counts()
    sns.barplot(x=gender_counts.index, y=gender_counts.values)
    plt.title('Gender Distribution')
    plt.ylabel('Count')

# Age distribution
if 'age' in df.columns:
    plt.subplot(2, 3, 2)
    sns.histplot(df['age'], kde=True, bins=10)
    plt.title('Age Distribution')
    plt.xlabel('Age')

# University distribution
if 'university' in df.columns:
    plt.subplot(2, 3, 3)
    uni_counts = df['university'].value_counts()
    sns.barplot(x=uni_counts.index, y=uni_counts.values)
    plt.title('University Distribution')
    plt.ylabel('Count')

# Degree level distribution
if 'degree_level' in df.columns:
    plt.subplot(2, 3, 4)
    degree_level_counts = df['degree_level'].value_counts()
    sns.barplot(x=degree_level_counts.index, y=degree_level_counts.values)
    plt.title('Degree Level Distribution')
    plt.ylabel('Count')
    plt.xticks(rotation=45)

# Degree major distribution
if 'degree_major' in df.columns:
    plt.subplot(2, 3, 5)
    major_counts = df['degree_major'].value_counts()
    sns.barplot(x=major_counts.index, y=major_counts.values)
    plt.title('Degree Major Distribution')
    plt.ylabel('Count')
    plt.xticks(rotation=45)

# Academic CGPA distribution
```

```python
if 'cgpa' in df.columns:
    plt.subplot(2, 3, 6)
    sns.histplot(df['cgpa'], kde=True, bins=10)
    plt.title('Academic CGPA Distribution')
    plt.xlabel('CGPA')

plt.tight_layout()
plt.show()

# 3.2 Mental Health Metrics Distribution
# First, identify which mental health columns actually exist in the dataset
all_mental_health_cols = ['study_satisfaction', 'academic_pressure',
                          'financial_concerns', 'social_relationships', 'depression',
                          'anxiety', 'isolation', 'future_insecurity']

mental_health_cols = [col for col in all_mental_health_cols if col in df.columns]

if mental_health_cols:
    num_cols = len(mental_health_cols)
    rows = (num_cols + 2) // 3
    plt.figure(figsize=(20, 5 * rows))

    for i, col in enumerate(mental_health_cols, 1):
        plt.subplot(rows, 3, i)
        sns.countplot(x=df[col])
        plt.title(f'Distribution of {col.replace("_", " ").title()}')
        plt.xlabel(f'{col.replace("_", " ").title()} Level')
        plt.ylabel('Count')
        plt.xticks(rotation=45)

    plt.tight_layout()
    plt.show()

# 3.3 Residential Status and Campus Discrimination
if 'residential_status' in df.columns or 'campus_discrimination' in df.columns:
    plt.figure(figsize=(15, 6))

    subplot_count = 1
    if 'residential_status' in df.columns:
        plt.subplot(1, 2 if 'campus_discrimination' in df.columns else 1, subplot_c
        res_counts = df['residential_status'].value_counts()
        sns.barplot(x=res_counts.index, y=res_counts.values)
        plt.title('Residential Status Distribution')
        plt.ylabel('Count')
        plt.xticks(rotation=45)
        subplot_count += 1

    if 'campus_discrimination' in df.columns:
        plt.subplot(1, 2, subplot_count)
        campus_disc_counts = df['campus_discrimination'].value_counts()
        sns.barplot(x=campus_disc_counts.index, y=campus_disc_counts.values)
        plt.title('Campus Discrimination Distribution')
        plt.ylabel('Count')
        plt.xticks(rotation=45)

    plt.tight_layout()
    plt.show()

# 3.4 Sports Engagement and Average Sleep
if 'sports_engagement' in df.columns or 'average_sleep' in df.columns:
    plt.figure(figsize=(15, 6))

    subplot_count = 1
    if 'sports_engagement' in df.columns:
```

```python
        plt.subplot(1, 2 if 'average_sleep' in df.columns else 1, subplot_count)
        sports_counts = df['sports_engagement'].value_counts()
        sns.barplot(x=sports_counts.index, y=sports_counts.values)
        plt.title('Sports Engagement Distribution')
        plt.ylabel('Count')
        plt.xticks(rotation=45)
        subplot_count += 1

    if 'average_sleep' in df.columns:
        plt.subplot(1, 2, subplot_count)
        sleep_counts = df['average_sleep'].value_counts()
        sns.barplot(x=sleep_counts.index, y=sleep_counts.values)
        plt.title('Average Sleep Distribution')
        plt.ylabel('Count')
        plt.xticks(rotation=45)

    plt.tight_layout()
    plt.show()

# 4. Bivariate Analysis

# 4.1 Correlation Analysis

# Create a copy of the dataframe for correlation analysis
df_corr = df.copy()

# Function to convert categorical variables to numeric
def categorical_to_numeric(series):
    """Convert categorical variables to numeric using label encoding"""
    if series.dtype == 'object':
        unique_vals = series.unique()
        map_dict = {val: idx for idx, val in enumerate(unique_vals) if pd.notna(val
        return series.map(map_dict)
    return series

# Function to convert GPA ranges to numeric values
def convert_gpa_range(gpa_range):
    if isinstance(gpa_range, str) and '-' in gpa_range:
        low, high = map(float, gpa_range.split('-'))
        return (low + high) / 2
    return np.nan

# Function to convert sleep ranges to numeric values
def convert_sleep_range(sleep_range):
    if isinstance(sleep_range, str) and 'hrs' in sleep_range:
        import re
        numbers = re.findall(r'\d+\.?\d*', sleep_range)
        if len(numbers) >= 2:
            low, high = map(float, numbers[:2])
            return (low + high) / 2
    return np.nan

# Convert special columns
if 'cgpa' in df_corr.columns:
    df_corr['cgpa_numeric'] = df_corr['cgpa'].apply(convert_gpa_range)

if 'average_sleep' in df_corr.columns:
    df_corr['average_sleep_numeric'] = df_corr['average_sleep'].apply(convert_sleep

# Convert all categorical columns to numeric
categorical_cols = ['gender', 'university', 'degree_level', 'degree_major',
                    'residential_status', 'sports_engagement', 'campus_discriminati

for col in categorical_cols:
```

```
    if col in df_corr.columns:
        df_corr[f'{col}_numeric'] = categorical_to_numeric(df_corr[col])

# Prepare list of all variables for correlation with anxiety
all_variables = []

# Original numeric columns
base_numeric_cols = ['age', 'study_satisfaction', 'academic_pressure',
                     'financial_concerns', 'social_relationships', 'depression',
                     'isolation', 'future_insecurity']

# Check which columns exist and are numeric
for col in base_numeric_cols:
    if col in df_corr.columns and col != 'anxiety':  # Exclude anxiety itself
        try:
            if pd.api.types.is_numeric_dtype(df_corr[col]):
                all_variables.append(col)
            else:
                df_corr[col] = pd.to_numeric(df_corr[col], errors='coerce')
                if not df_corr[col].isna().all():
                    all_variables.append(col)
        except:
            pass

# Add converted numeric columns
converted_cols = ['cgpa_numeric', 'average_sleep_numeric'] + [f'{col}_numeric' for
for col in converted_cols:
    if col in df_corr.columns and not df_corr[col].isna().all():
        all_variables.append(col)

# Calculate correlations with anxiety
if 'anxiety' in df_corr.columns:
    anxiety_correlations = []
    correlations_dict = {}

    for variable in all_variables:
        # Get valid data pairs
        valid_data = df_corr[[variable, 'anxiety']].dropna()
        if len(valid_data) > 2:  # Need at least 3 data points for correlation
            corr, p_value = stats.pearsonr(valid_data[variable], valid_data['anxiet

            # Create readable variable name
            var_name = variable.replace('_numeric', '').replace('_', ' ').title()
            anxiety_correlations.append({
                'Variable': var_name,
                'Correlation': corr,
                'p_value': p_value
            })
            correlations_dict[var_name] = corr

    # Convert to DataFrame and sort by absolute correlation value
    correlations_df = pd.DataFrame(anxiety_correlations)
    correlations_df['abs_correlation'] = correlations_df['Correlation'].abs()
    correlations_df = correlations_df.sort_values('abs_correlation', ascending=Fals
    correlations_df = correlations_df.drop('abs_correlation', axis=1)

   # Create horizontal bar plot with better spacing
    plt.figure(figsize=(14, 10))

    # Create color mapping based on correlation value
    colors = []
    for corr in correlations_df['Correlation']:
        if corr > 0:
            colors.append(plt.cm.Reds(min(abs(corr) / 0.8, 1.0)))  # Red for positi
```

```
        else:
            colors.append(plt.cm.Blues(min(abs(corr) / 0.8, 1.0)))  # Blue for nega


    # Create a better traditional heatmap with improved layout
    plt.figure(figsize=(12, 10))

    # Create a single row DataFrame for heatmap
    heatmap_data = pd.DataFrame([correlations_dict]).T
    heatmap_data.columns = ['Correlation with Anxiety']

    # Create heatmap with improved display
    ax = plt.axes()
    sns.heatmap(heatmap_data, cmap='RdBu_r', center=0, annot=True, fmt='.3f',
                cbar_kws={'label': 'Correlation Coefficient', 'orientation': 'horiz
                         'pad': 0,  'anchor': (0.0, 0.1)}, vmin=-0.8, vmax=0.8, ax=

    # Rotate x-axis labels to prevent overlap
    plt.xticks(rotation=0)
    plt.yticks(rotation=0, fontsize=10)

    # Adjust title and layout
    plt.title('Correlation Heatmap: All Variables with Anxiety', fontsize=16, pad=2

    # Make sure all labels are visible
    plt.tight_layout()
    plt.show()



    # Display the correlation table
    print("\nCorrelation Table: All Variables with Anxiety")
    print("-" * 50)
    print(correlations_df.to_string(index=False, float_format='{:.3f}'.format))

else:
    print("Anxiety column not found in dataset")

# 4.2 Mental Health Metrics by Gender
mental_health_metrics = [col for col in ['depression', 'anxiety', 'isolation', 'fut
                         if col in df.columns]

if 'gender' in df.columns and mental_health_metrics:
    plt.figure(figsize=(20, 15))

    for i, metric in enumerate(mental_health_metrics, 1):
        plt.subplot(2, 2, i)
        sns.boxplot(x='gender', y=metric, data=df)
        plt.title(f'{metric.replace("_", " ").title()} by Gender')
        plt.xlabel('Gender')
        plt.ylabel(f'{metric.replace("_", " ").title()} Level')

    plt.tight_layout()
    plt.show()

# 4.3 Academic Performance and Mental Health
# Extract both numbers from the range and calculate the average
df['cgpa_numeric'] = df['cgpa'].apply(convert_gpa_range)

plt.figure(figsize=(18, 12))

for i, metric in enumerate(mental_health_metrics[:4], 1):
    plt.subplot(2, 2, i)
    sns.boxplot(x=metric, y='cgpa_numeric', data=df)
```

```python
    plt.title(f'CGPA vs {metric.replace("_", " ").title()} Level')
    plt.xlabel(f'{metric.replace("_", " ").title()} Level')
    plt.ylabel('CGPA')

plt.tight_layout()
plt.show()

# 4.4 Sports Engagement and Mental Health
if 'sports_engagement' in df.columns and mental_health_metrics:
    plt.figure(figsize=(18, 12))

    for i, metric in enumerate(mental_health_metrics[:4], 1):  # Limit to 4 plots
        plt.subplot(2, 2, i)
        sns.boxplot(x='sports_engagement', y=metric, data=df)
        plt.title(f'{metric.replace("_", " ").title()} by Sports Engagement')
        plt.xlabel('Sports Engagement')
        plt.ylabel(f'{metric.replace("_", " ").title()} Level')
        plt.xticks(rotation=45)

    plt.tight_layout()
    plt.show()

# 4.5 Residential Status and Mental Health
if 'residential_status' in df.columns and mental_health_metrics:
    plt.figure(figsize=(18, 12))

    for i, metric in enumerate(mental_health_metrics[:4], 1):  # Limit to 4 plots
        plt.subplot(2, 2, i)
        sns.boxplot(x='residential_status', y=metric, data=df)
        plt.title(f'{metric.replace("_", " ").title()} by Residential Status')
        plt.xlabel('Residential Status')
        plt.ylabel(f'{metric.replace("_", " ").title()} Level')
        plt.xticks(rotation=45)

    plt.tight_layout()
    plt.show()

# 5. Stress Relief Activities Analysis
if 'stress_relief_activities' in df.columns:
    # Check if the column has string values that can be split
    if df['stress_relief_activities'].dtype == 'object':
        # Create a new Series with all activities split and stacked
        stress_activities = df['stress_relief_activities'].astype(str).str.split(',
        unique_activities = stress_activities.unique()

        print("\nUnique Stress Relief Activities:")
        print(unique_activities)

        # Count the frequency of each activity
        activity_counts = {}
        for activity in unique_activities:
            if pd.notna(activity) and activity.lower() != 'nan':  # Check if the ac
                count = df['stress_relief_activities'].astype(str).str.contains(act
                activity_counts[activity] = count

        # Sort activities by frequency
        sorted_activities = sorted(activity_counts.items(), key=lambda x: x[1], rev

        if sorted_activities:  # Check if we have any activities to plot
            # Plot the distribution of stress relief activities
            plt.figure(figsize=(14, 8))
            activities, counts = zip(*sorted_activities)
            sns.barplot(x=list(counts), y=list(activities))
            plt.title('Frequency of Different Stress Relief Activities')
```

```python
            plt.xlabel('Count')
            plt.ylabel('Activity')
            plt.tight_layout()
            plt.show()
    else:
        print("Stress relief activities column is not in string format for splittir

# 6. Multivariate Analysis

# 6.1 Mental Health Relationships
if all(col in df.columns for col in ['depression', 'anxiety']):
    plt.figure(figsize=(12, 10))

    hue_col = next((col for col in ['academic_pressure', 'study_satisfaction', 'fir
                    if col in df.columns), None)
    size_col = next((col for col in ['cgpa_numeric', 'isolation', 'future_insecurit
                     if col in df.columns), None)

    if hue_col and size_col:
        sns.scatterplot(x='depression', y='anxiety', hue=hue_col, size=size_col,
                        palette='viridis', sizes=(50, 200), data=df)
        plt.title(f'Depression vs Anxiety colored by {hue_col.replace("_", " ").tit
        plt.xlabel('Depression Level')
        plt.ylabel('Anxiety Level')
        plt.legend(title=hue_col.replace("_", " ").title(), bbox_to_anchor=(1.05, 1
        plt.tight_layout()
        plt.show()

# 6.2 Sleep, Study Satisfaction, and Academic Pressure
if 'average_sleep' in df.columns:
    plt.figure(figsize=(12, 8))

    # If average_sleep is in hours-range format like "6-8 hrs"
    if df['average_sleep'].dtype == object and df['average_sleep'].str.contains('-'
        # Try to extract numeric values from sleep range
        try:
            avg_sleep_hours = df['average_sleep'].str.extract(r'(\d+\.?\d*)-(\d+\.?
            df['min_sleep_hours'] = pd.to_numeric(avg_sleep_hours[0], errors='coerc
            df['max_sleep_hours'] = pd.to_numeric(avg_sleep_hours[1], errors='coerc
            df['avg_sleep_hours_value'] = (df['min_sleep_hours'] + df['max_sleep_hc

            y_col = next((col for col in ['study_satisfaction', 'depression', 'anxi
                          if col in df.columns), None)
            hue_col = next((col for col in ['academic_pressure', 'financial_concern
                            if col in df.columns), None)

            if y_col and hue_col:
                sns.scatterplot(x='avg_sleep_hours_value', y=y_col,
                                hue=hue_col, palette='viridis', data=df)
                plt.title(f'Sleep Hours vs {y_col.replace("_", " ").title()} by {hu
                plt.xlabel('Average Sleep Hours')
                plt.ylabel(f'{y_col.replace("_", " ").title()} Level')
                plt.legend(title=hue_col.replace("_", " ").title(), bbox_to_anchor=
        except:
            print("Could not parse sleep hours from the average_sleep column.")
    else:
        # If average_sleep is already numeric or different format
        y_col = next((col for col in ['study_satisfaction', 'depression', 'anxiety'
                      if col in df.columns), None)
        hue_col = next((col for col in ['academic_pressure', 'financial_concerns']
                        if col in df.columns), None)

        if y_col and hue_col:
            sns.boxplot(x='average_sleep', y=y_col, hue=hue_col, data=df)
```

```
            plt.title(f'{y_col.replace("_", " ").title()} by Sleep and {hue_col.rep
            plt.xlabel('Average Sleep')
            plt.ylabel(f'{y_col.replace("_", " ").title()} Level')
            plt.legend(title=hue_col.replace("_", " ").title())

    plt.tight_layout()
    plt.show()

# 7. Statistical Tests

# 7.1 T-test: Depression levels between different residential statuses
if all(col in df.columns for col in ['residential_status', 'depression']):
    res_types = df['residential_status'].unique()
    if len(res_types) >= 2:  # Need at least 2 groups for comparison
        group1 = df[df['residential_status'] == res_types[0]]['depression']
        group2 = df[df['residential_status'] == res_types[1]]['depression']
        if not group1.empty and not group2.empty:
            t_stat, p_value = stats.ttest_ind(group1, group2, nan_policy='omit')
            print(f"\nT-test for Depression Levels between {res_types[0]} and {res_
            print(f"t-statistic: {t_stat:.4f}")
            print(f"p-value: {p_value:.4f}")
            print(f"Significant difference: {p_value < 0.05}")

# 7.2 ANOVA: Anxiety levels across universities
if all(col in df.columns for col in ['university', 'anxiety']):
    universities = df['university'].unique()
    if len(universities) >= 2:  # Need at least 2 groups for ANOVA
        anxiety_by_uni = [df[df['university'] == uni]['anxiety'].dropna() for uni i
        # Filter out empty groups
        anxiety_by_uni = [group for group in anxiety_by_uni if len(group) > 0]
        if len(anxiety_by_uni) >= 2:  # Still need at least 2 non-empty groups
            f_stat, p_value = stats.f_oneway(*anxiety_by_uni)
            print(f"\nANOVA for Anxiety Levels across Universities:")
            print(f"F-statistic: {f_stat:.4f}")
            print(f"p-value: {p_value:.4f}")
            print(f"Significant difference: {p_value < 0.05}")

# 7.3 Chi-square test: Association between gender and sports engagement
if all(col in df.columns for col in ['gender', 'sports_engagement']):
    contingency_table = pd.crosstab(df['gender'], df['sports_engagement'])
    if contingency_table.shape[0] > 1 and contingency_table.shape[1] > 1:
        chi2, p, dof, expected = stats.chi2_contingency(contingency_table)
        print(f"\nChi-square test for Gender and Sports Engagement:")
        print(f"Chi2: {chi2:.4f}")
        print(f"p-value: {p:.4f}")
        print(f"Significant association: {p < 0.05}")

# 8. Key Findings Summary
print("\n=== SUMMARY OF KEY FINDINGS ===")
print(f"1. Dataset contains information on {df.shape[0]} students.")

if 'gender' in df.columns:
    print(f"2. Gender distribution: {df['gender'].value_counts(normalize=True).mul(

if 'age' in df.columns:
    print(f"3. Age range: {df['age'].min()} to {df['age'].max()} years, with mean {

if 'university' in df.columns:
    print(f"4. Top university representation: {df['university'].value_counts().inde

if 'stress_relief_activities' in df.columns and 'sorted_activities' in locals() and
    print(f"5. Most common stress relief activity: {sorted_activities[0][0]}")

# Calculate average depression and anxiety scores
```

```python
if 'depression' in df.columns:
    print(f"6. Average depression level: {df['depression'].mean():.2f}")

if 'anxiety' in df.columns:
    print(f"7. Average anxiety level: {df['anxiety'].mean():.2f}")

# Correlation between CGPA and mental health metrics
if all(col in df.columns for col in ['cgpa_numeric', 'depression']):
    cgpa_depression_corr = df['cgpa_numeric'].corr(df['depression'])
    print(f"8. Correlation between CGPA and depression: {cgpa_depression_corr:.3f}'

if all(col in df.columns for col in ['cgpa_numeric', 'anxiety']):
    cgpa_anxiety_corr = df['cgpa_numeric'].corr(df['anxiety'])
    print(f"9. Correlation between CGPA and anxiety: {cgpa_anxiety_corr:.3f}")
```

```
Dataset Shape: (87, 25)

First 5 rows of data:
```

	gender	age	university	degree_level	degree_major	academic_year	cgpa	residential_status
0	Male	20	PU	Undergraduate	Data Science	2nd year	3.0-3.5	Off-Campus
1	Male	20	UET	Postgraduate	Computer Science	3rd year	3.0-3.5	Off-Campus
2	Male	20	FAST	Undergraduate	Computer Science	3rd year	2.5-3.0	Off-Campus
3	Male	20	UET	Undergraduate	Computer Science	3rd year	2.5-3.0	On-Campus
4	Female	20	UET	Undergraduate	Computer Science	3rd year	3.0-3.5	Off-Campus

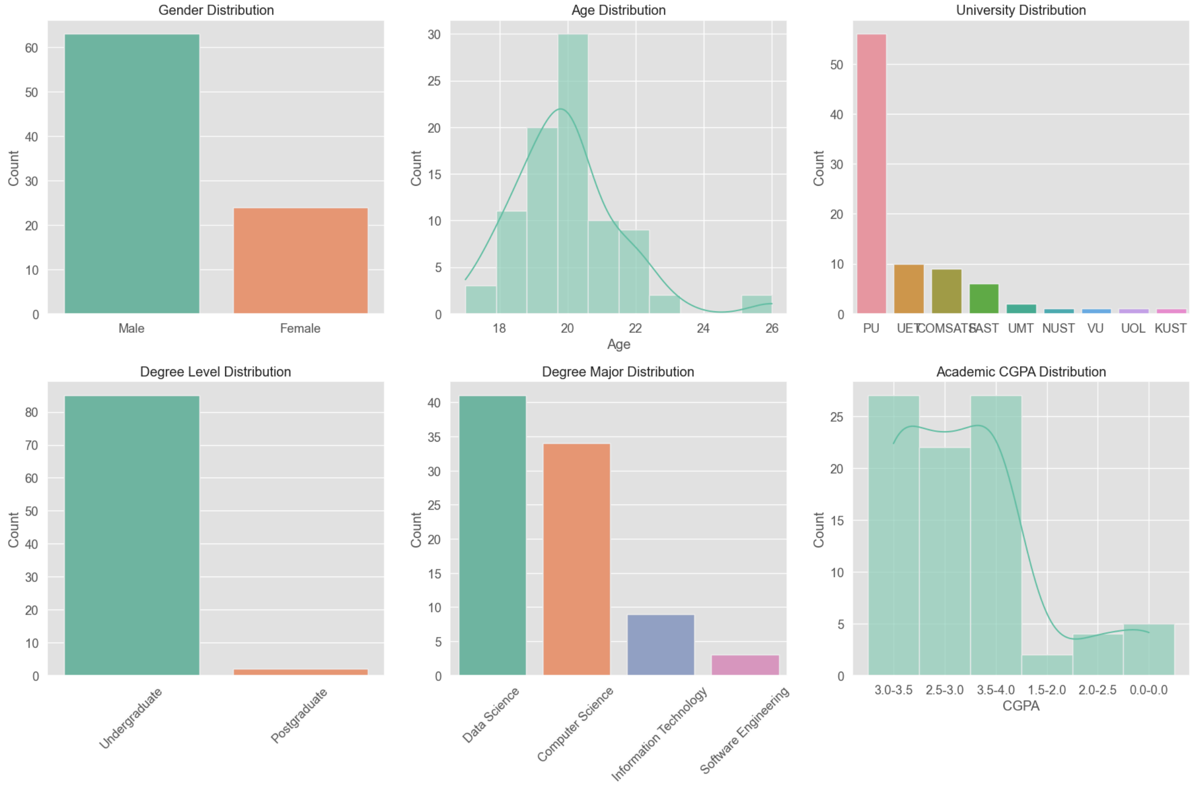
5 rows × 25 columns

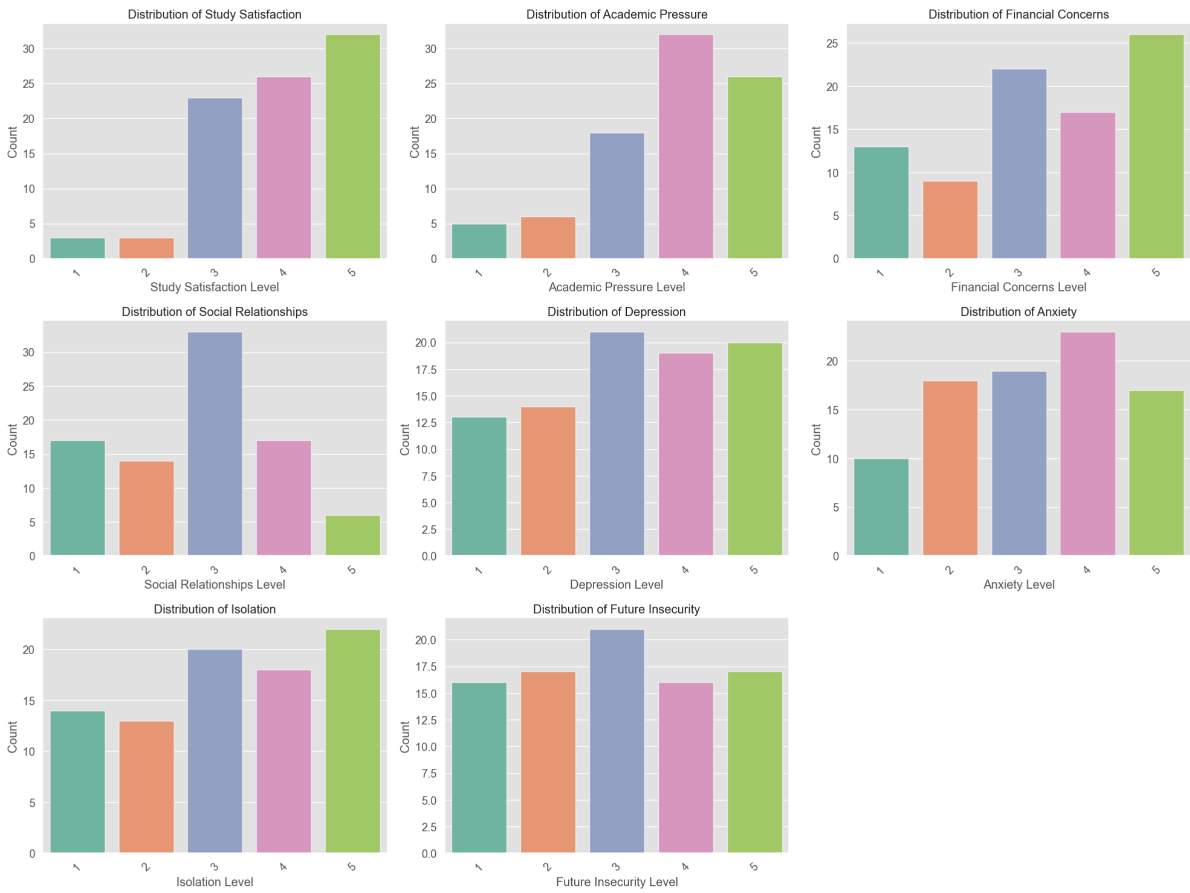
```
Actual column names in the dataset:
['gender', 'age', 'university', 'degree_level', 'degree_major', 'academic_year',
'cgpa', 'residential_status', 'campus_discrimination', 'sports_engagement', 'avera
ge_sleep', 'study_satisfaction', 'academic_workload ', 'academic_pressure', 'finan
cial_concerns', 'social_relationships', 'depression', 'anxiety', 'isolation', 'fut
ure_insecurity', 'stress_relief_activities', 'cgpa_numeric', 'min_sleep_hours', 'm
ax_sleep_hours', 'avg_sleep_hours_value']

Data Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 87 entries, 0 to 86
Data columns (total 25 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   gender                    87 non-null     object 
 1   age                       87 non-null     int64  
 2   university                87 non-null     object 
 3   degree_level              87 non-null     object 
 4   degree_major              87 non-null     object 
 5   academic_year             87 non-null     object 
 6   cgpa                      87 non-null     object 
 7   residential_status        87 non-null     object 
 8   campus_discrimination     87 non-null     object 
 9   sports_engagement         87 non-null     object 
 10  average_sleep             87 non-null     object 
 11  study_satisfaction        87 non-null     int64  
 12  academic_workload         87 non-null     int64  
 13  academic_pressure         87 non-null     int64  
 14  financial_concerns        87 non-null     int64  
 15  social_relationships      87 non-null     int64  
 16  depression                87 non-null     int64  
 17  anxiety                   87 non-null     int64  
 18  isolation                 87 non-null     int64  
 19  future_insecurity         87 non-null     int64  
 20  stress_relief_activities  87 non-null     object 
 21  cgpa_numeric              87 non-null     float64
 22  min_sleep_hours           87 non-null     int64  
 23  max_sleep_hours           87 non-null     int64  
 24  avg_sleep_hours_value     87 non-null     float64
dtypes: float64(2), int64(12), object(11)
memory usage: 17.1+ KB

Descriptive Statistics:
```

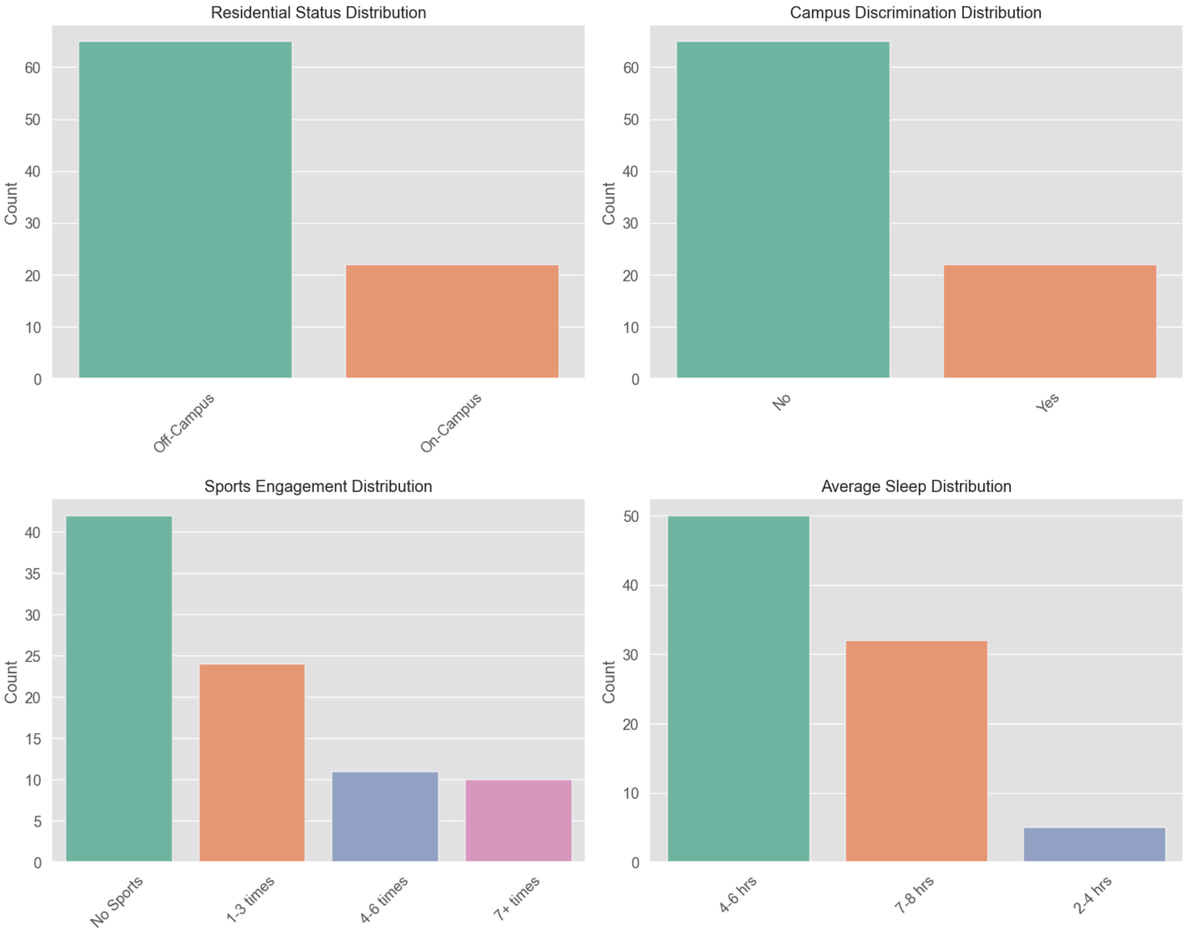
	age	study_satisfaction	academic_workload	academic_pressure	financial_concerns	so
count	87.000000	87.000000	87.000000	87.000000	87.000000	
mean	19.942529	3.931034	3.885057	3.781609	3.390805	
std	1.623636	1.043174	0.854880	1.125035	1.400634	
min	17.000000	1.000000	2.000000	1.000000	1.000000	
25%	19.000000	3.000000	3.000000	3.000000	2.500000	
50%	20.000000	4.000000	4.000000	4.000000	3.000000	
75%	21.000000	5.000000	4.500000	5.000000	5.000000	
max	26.000000	5.000000	5.000000	5.000000	5.000000	

```
Checking for missing values:
```

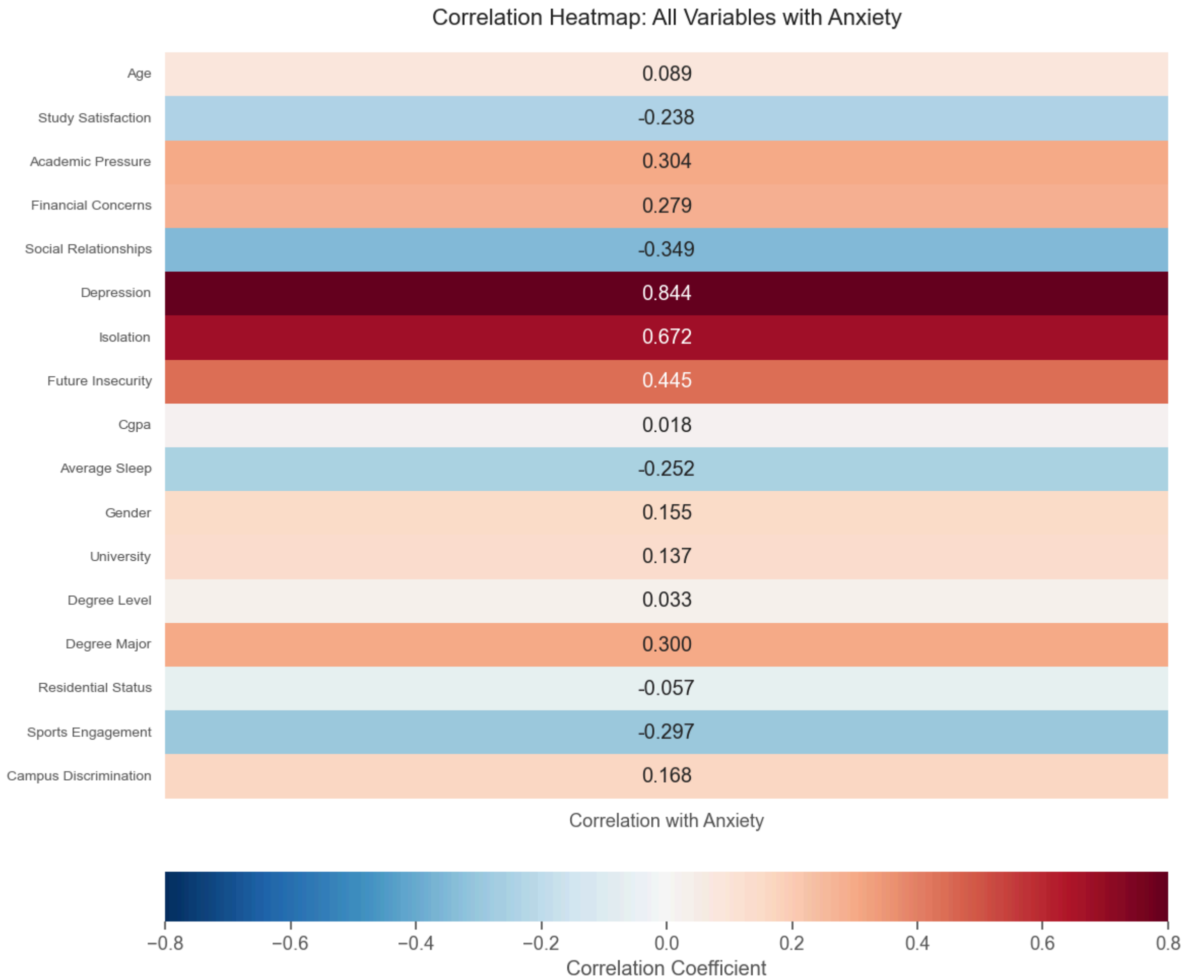
```
gender                      0
age                         0
university                  0
degree_level                0
degree_major                0
academic_year               0
cgpa                        0
residential_status          0
campus_discrimination       0
sports_engagement           0
average_sleep               0
study_satisfaction          0
academic_workload           0
academic_pressure           0
financial_concerns          0
social_relationships        0
depression                  0
anxiety                     0
isolation                   0
future_insecurity           0
stress_relief_activities    0
cgpa_numeric                0
min_sleep_hours             0
max_sleep_hours             0
avg_sleep_hours_value       0
dtype: int64
Unique values in categorical columns:

gender: ['Male' 'Female']

university: ['PU' 'UET' 'FAST' 'COMSATS' 'NUST' 'VU' 'UMT' 'UOL' 'KUST']

degree_level: ['Undergraduate' 'Postgraduate']

degree_major: ['Data Science' 'Computer Science' 'Software Engineering'
 'Information Technology']

residential_status: ['Off-Campus' 'On-Campus']

sports_engagement: ['No Sports' '1-3 times' '7+ times' '4-6 times']
```


Gender Distribution
Count
Male
Female
Age Distribution
Age
University Distribution
PU
UET
COMSATS
FAST
UMT
NUST
VU
UOL
KUST
Degree Level Distribution
Undergraduate
Postgraduate
Degree Major Distribution
Data Science
Computer Science
Information Technology
Software Engineering
Academic CGPA Distribution
3.0-3.5
2.5-3.0
3.5-4.0
1.5-2.0
2.0-2.5
0.0-0.0
CGPA


Distribution of Study Satisfaction
Count
Study Satisfaction Level
Distribution of Academic Pressure
Academic Pressure Level
Distribution of Financial Concerns
Financial Concerns Level
Distribution of Social Relationships
Social Relationships Level
Distribution of Depression
Depression Level
Distribution of Anxiety
Anxiety Level
Distribution of Isolation
Isolation Level
Distribution of Future Insecurity
Future Insecurity Level

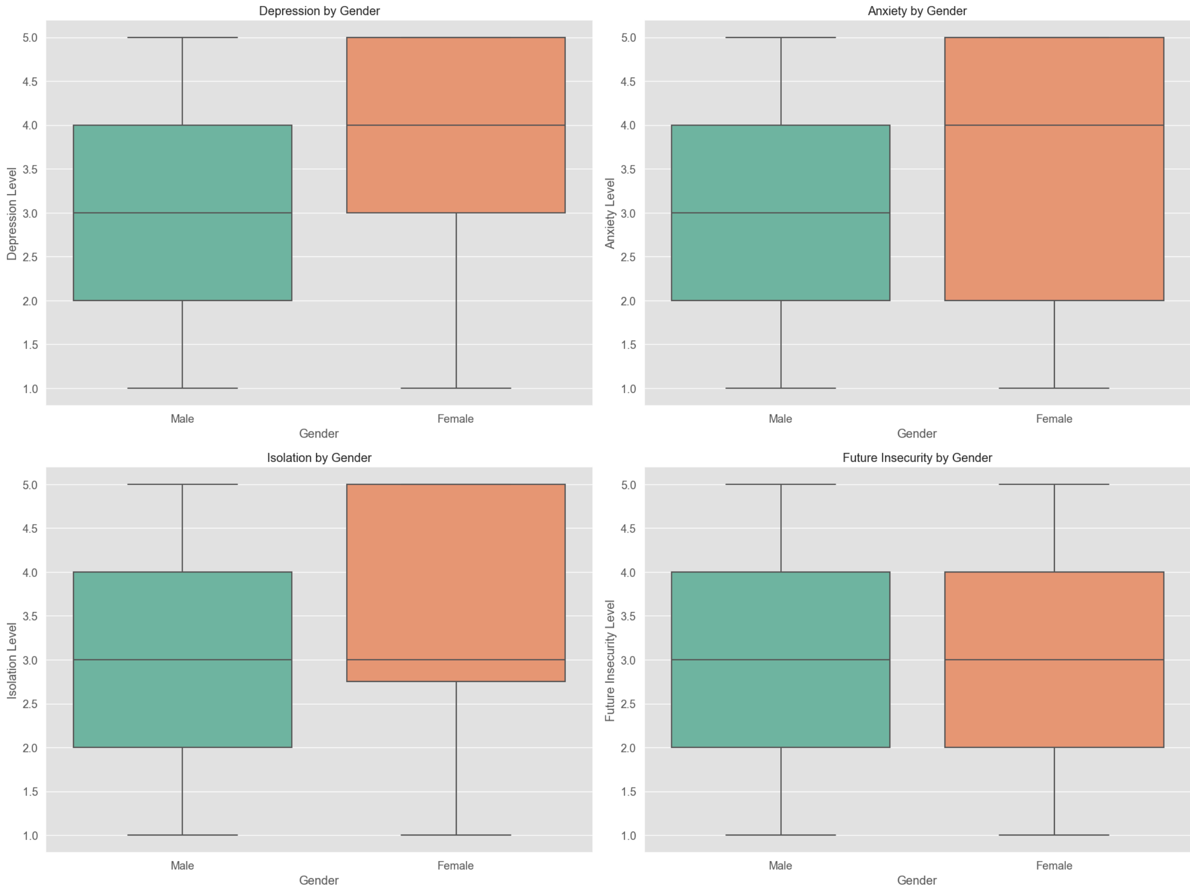


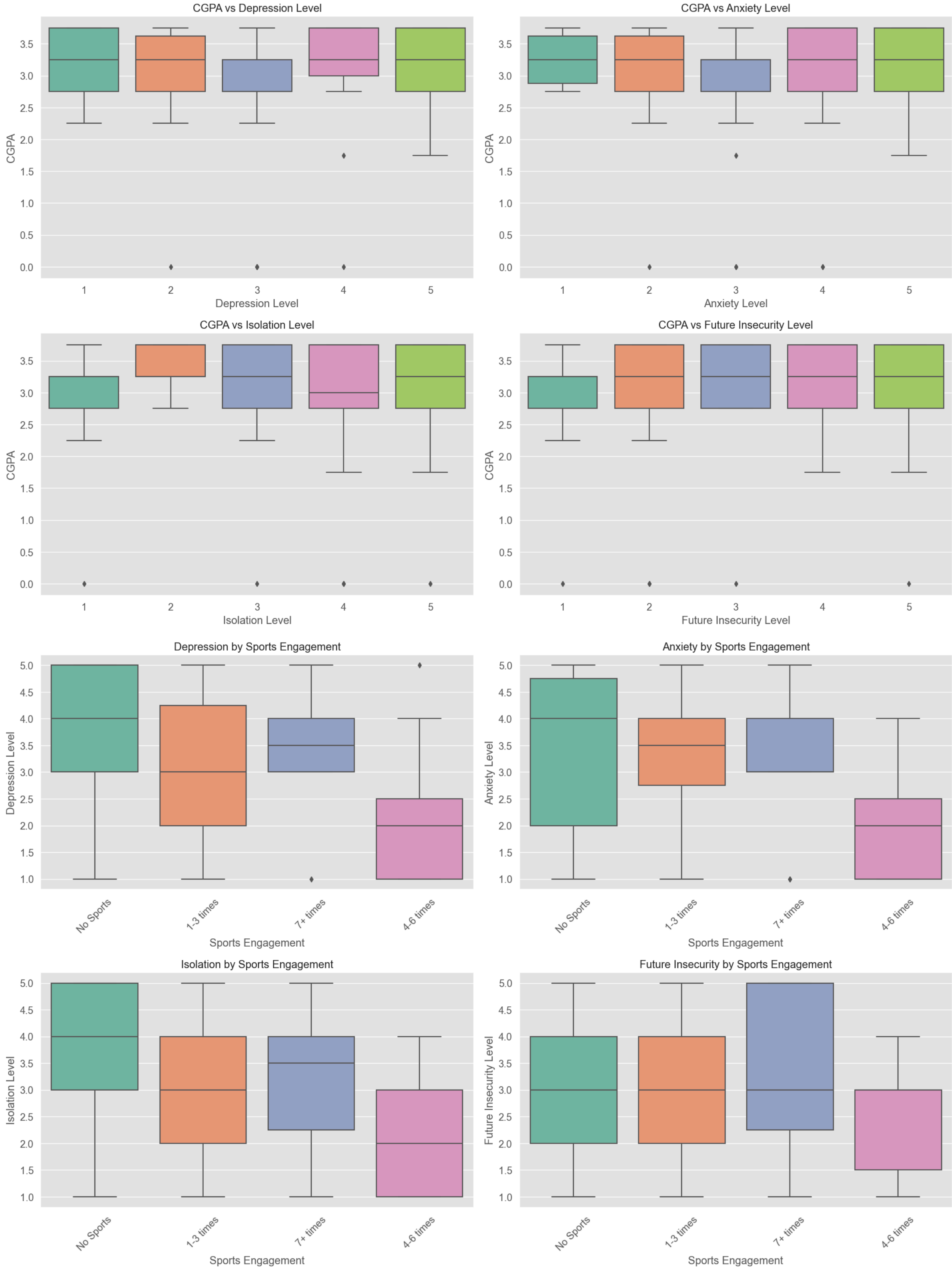
<Figure size 1400x1000 with 0 Axes>

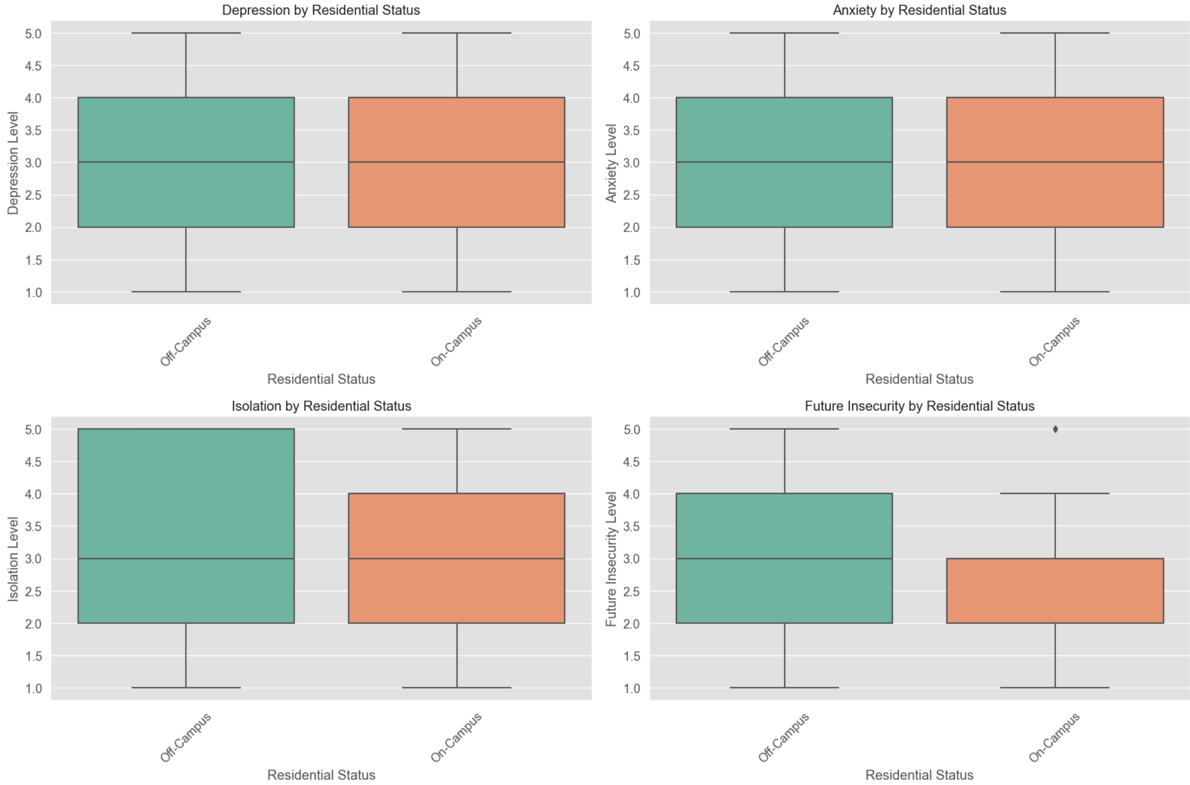


Correlation Table: All Variables with Anxiety

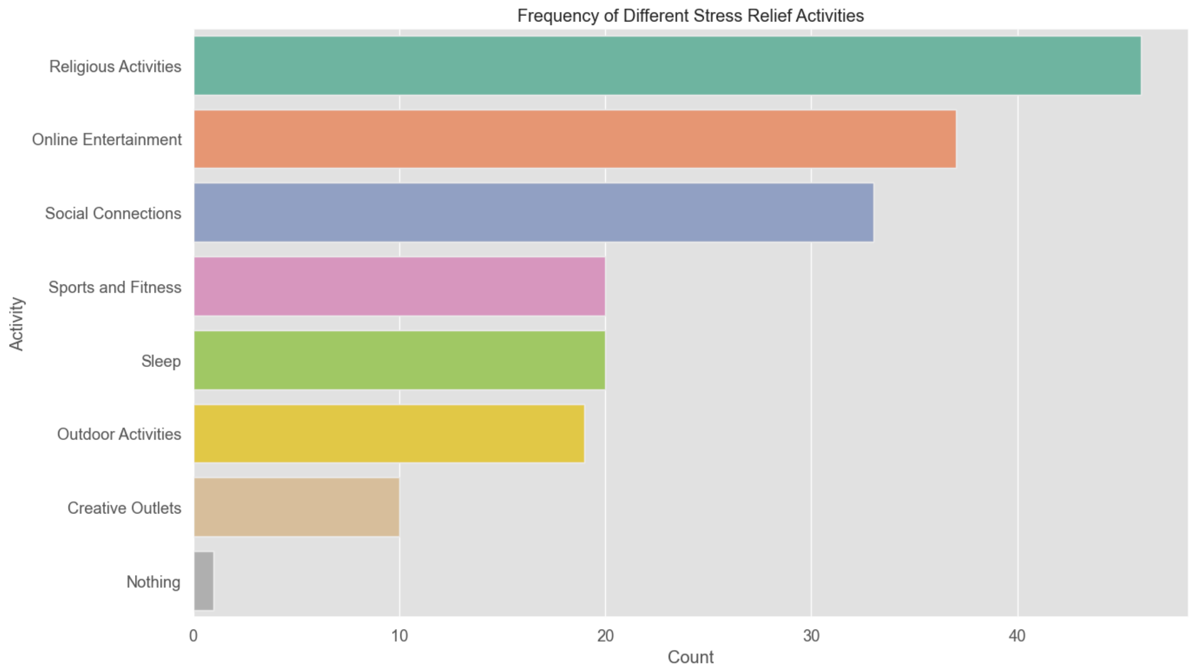
Variable	Correlation	p_value
Depression	0.844	0.000
Isolation	0.672	0.000
Future Insecurity	0.445	0.000
Social Relationships	-0.349	0.001
Academic Pressure	0.304	0.004
Degree Major	0.300	0.005
Sports Engagement	-0.297	0.005
Financial Concerns	0.279	0.009
Average Sleep	-0.252	0.019
Study Satisfaction	-0.238	0.027
Campus Discrimination	0.168	0.120
Gender	0.155	0.153
University	0.137	0.207
Age	0.089	0.413
Residential Status	-0.057	0.597
Degree Level	0.033	0.758
Cgpa	0.018	0.870

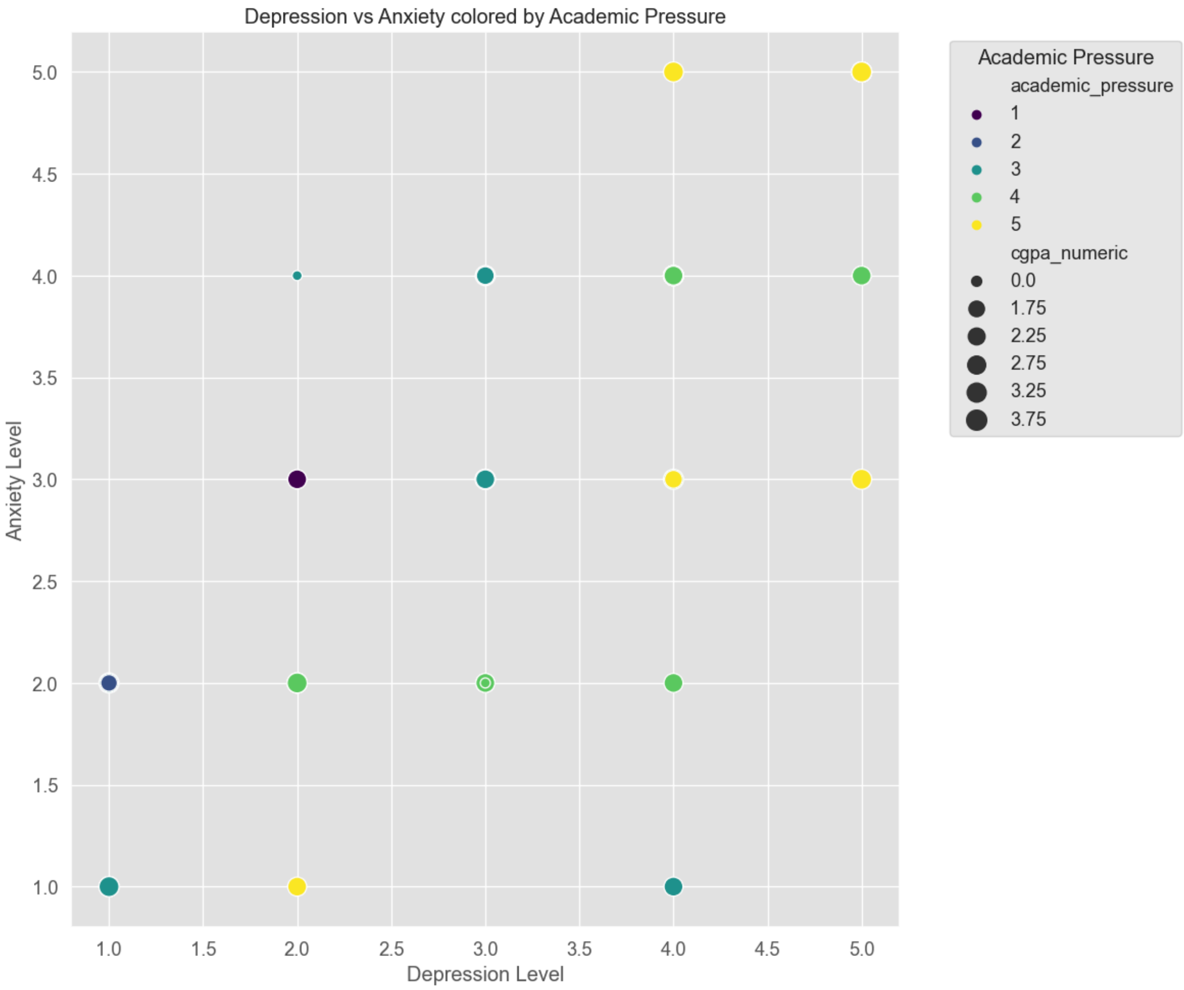



CGPA vs Depression Level
CGPA
Depression Level
CGPA vs Anxiety Level
CGPA
Anxiety Level
CGPA vs Isolation Level
CGPA
Isolation Level
CGPA vs Future Insecurity Level
CGPA
Future Insecurity Level
Depression by Sports Engagement
Depression Level
Sports Engagement
No Sports
1-3 times
7+ times
4-6 times
Anxiety by Sports Engagement
Anxiety Level
Sports Engagement
No Sports
1-3 times
7+ times
4-6 times
Isolation by Sports Engagement
Isolation Level
Sports Engagement
No Sports
1-3 times
7+ times
4-6 times
Future Insecurity by Sports Engagement
Future Insecurity Level
Sports Engagement
No Sports
1-3 times
7+ times
4-6 times

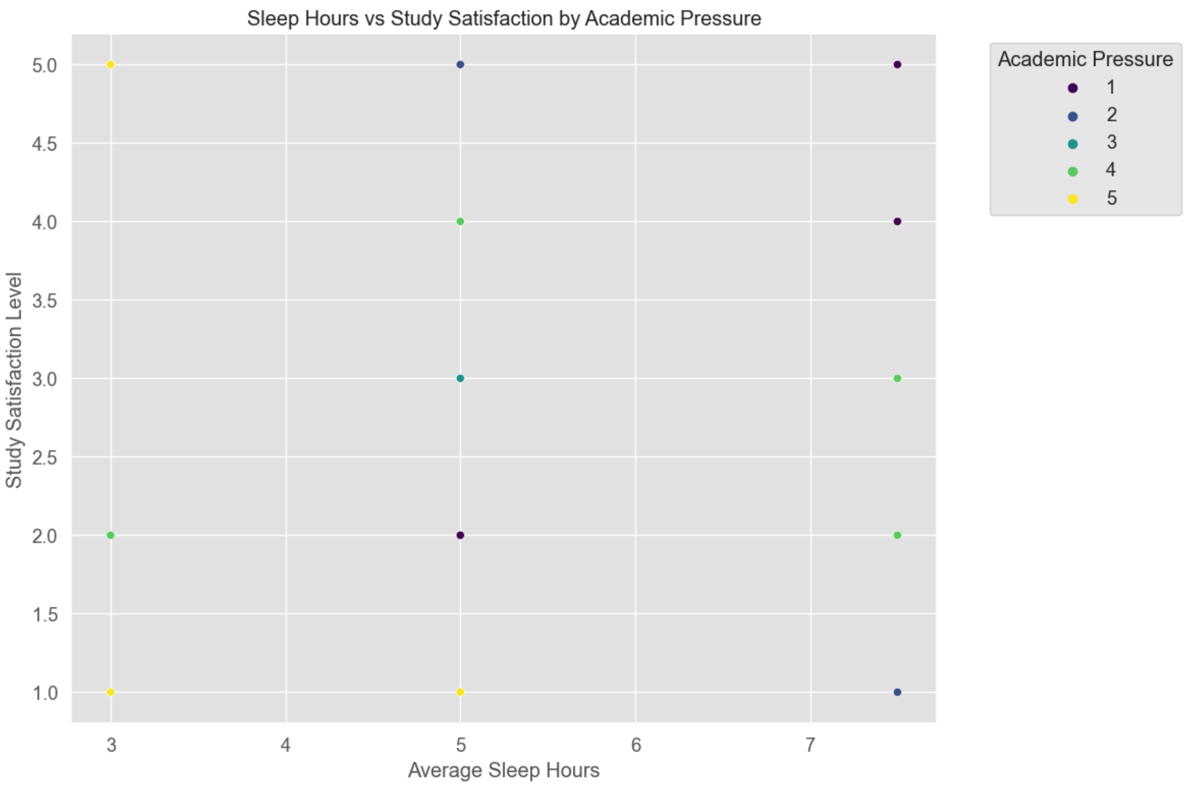



```
Unique Stress Relief Activities:
['Religious Activities' 'Social Connections' 'Online Entertainment'
 'Sports and Fitness' 'Outdoor Activities' 'Nothing' 'Creative Outlets'
 'Sleep']
```





Depression vs Anxiety colored by Academic Pressure
Anxiety Level
Depression Level
Academic Pressure
academic_pressure
1
2
3
4
5
cgpa_numeric
0.0
1.75
2.25
2.75
3.25
3.75



Sleep Hours vs Study Satisfaction by Academic Pressure
Study Satisfaction Level
Average Sleep Hours
Academic Pressure
1
2
3
4
5

```
T-test for Depression Levels between Off-Campus and On-Campus Students:
t-statistic: 0.1443
p-value: 0.8856
Significant difference: False

ANOVA for Anxiety Levels across Universities:
F-statistic: 2.6657
p-value: 0.0122
Significant difference: True

Chi-square test for Gender and Sports Engagement:
Chi2: 10.6321
p-value: 0.0139
Significant association: True

=== SUMMARY OF KEY FINDINGS ===
1. Dataset contains information on 87 students.
2. Gender distribution: {'Male': 72.4, 'Female': 27.6}
3. Age range: 17 to 26 years, with mean 19.9 years.
4. Top university representation: PU with 56 students.
5. Most common stress relief activity: Religious Activities
6. Average depression level: 3.22
7. Average anxiety level: 3.22
8. Correlation between CGPA and depression: 0.072
```

In [58]:

```python
# Model Analysis
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix, roc_curve, roc
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier
from sklearn.utils import resample

# Set random seed for reproducibility
np.random.seed(42)

# Load the dataset
df = pd.read_csv('MentalHealthSurvey.csv')

# Display correlation between anxiety and predictors
print("Correlation with anxiety:")
correlations = df[['social_relationships', 'future_insecurity', 'isolation', 'anxie
print(correlations)
print("\n")

# Try different thresholds for defining high anxiety
thresholds = [3, 4]

# Prepare data for plotting
labels = []
counts_0 = []
counts_1 = []

for threshold in thresholds:
    col_name = f'high_anxiety_{threshold}'
    df[col_name] = (df['anxiety'] >= threshold).astype(int)
    class_counts = df[col_name].value_counts().sort_index()
```

```python
    labels.append(f'Threshold {threshold}')
    counts_0.append(class_counts.get(0, 0))
    counts_1.append(class_counts.get(1, 0))

# Bar plot
x = range(len(thresholds))
width = 0.35

plt.figure(figsize=(8, 5))
plt.bar(x, counts_0, width=width, label='Class 0 (Low Anxiety)', color='skyblue')
plt.bar([i + width for i in x], counts_1, width=width, label='Class 1 (High Anxiety

# Labels & legend
plt.xticks([i + width / 2 for i in x], labels)
plt.xlabel('Anxiety Threshold')
plt.ylabel('Number of Samples')
plt.title('Class Distribution at Different Anxiety Thresholds')
plt.legend()
plt.tight_layout()
plt.show()

# Choose threshold 4 for our analysis
anxiety_threshold = 4
anxiety_col = f'high_anxiety_{anxiety_threshold}'

# Select predictors and target
X = df[['social_relationships', 'future_insecurity', 'isolation']]
y = df[anxiety_col]

# Split data into training and testing sets with stratification
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y
)

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

# Upsample minority class
X_majority = X_train_scaled[y_train==0]
y_majority = y_train[y_train==0]
X_minority = X_train_scaled[y_train==1]
y_minority = y_train[y_train==1]

if len(y_minority) < len(y_majority):
    X_minority_upsampled, y_minority_upsampled = resample(
        X_minority, y_minority,
        replace=True,
        n_samples=len(y_train[y_train==0]),
        random_state=42
    )

    # Combine with majority class
    X_train_resampled = np.vstack([X_majority, X_minority_upsampled])
    y_train_resampled = np.hstack([y_majority, y_minority_upsampled])
else:
    X_train_resampled = X_train_scaled
    y_train_resampled = y_train

# Before resampling
fig, axs = plt.subplots(1, 2, figsize=(10, 4))
```

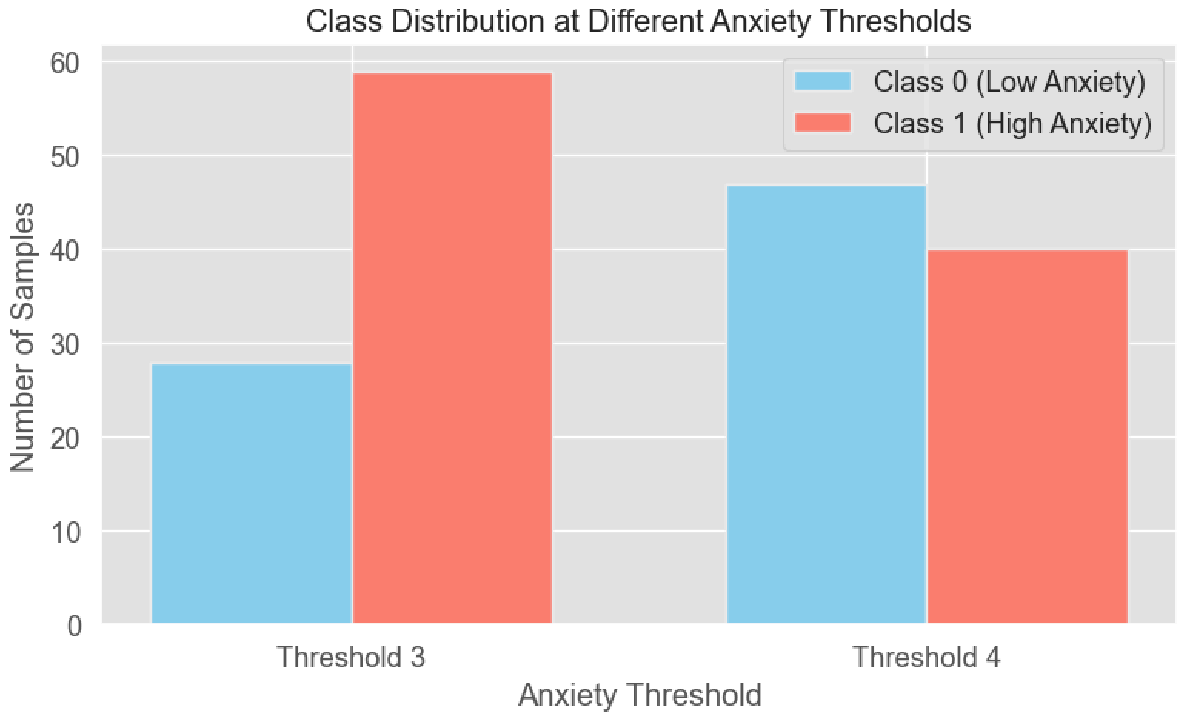
```
sns.countplot(x=y_train, ax=axs[0])
axs[0].set_title("Before Resampling")
axs[0].set_xlabel("Class")
axs[0].set_ylabel("Count")

# After resampling
sns.countplot(x=y_train_resampled, ax=axs[1])
axs[1].set_title("After Resampling")
axs[1].set_xlabel("Class")
axs[1].set_ylabel("Count")

plt.tight_layout()
plt.show()

# Hyperparameter tuning with GridSearchCV
param_grid = {
    'C': [0.01, 0.1, 1, 10, 100],
    'penalty': ['l1', 'l2'],
    'solver': ['liblinear', 'saga'],
    'class_weight': [None, 'balanced'],
    'max_iter': [3000],
    'tol': [1e-4]
}

grid_search = GridSearchCV(
    LogisticRegression(random_state=42),
    param_grid,
    cv=5,
    scoring='precision',
    return_train_score=True
)

grid_search.fit(X_train_resampled, y_train_resampled)
best_model = grid_search.best_estimator_
print(f"\nBest Parameters: {grid_search.best_params_}")

# Dictionary to store optimal thresholds for each model
model_thresholds = {}

# Compare different algorithms
models = {
    "Logistic Regression (Optimized)": best_model,
    "Random Forest": RandomForestClassifier(n_estimators=100, random_state=42, clas
    "SVM": SVC(probability=True, kernel='rbf', random_state=42, class_weight='balar
    "XGBoost": XGBClassifier(random_state=42, scale_pos_weight=sum(y_train == 0)/su
}

# Train and evaluate each model
for name, model in models.items():
    print(f"\n--- {name} ---")
    model.fit(X_train_resampled, y_train_resampled)

    # Get predictions
    y_pred_prob = model.predict_proba(X_test_scaled)[:, 1]

    # Find optimal threshold
    precision, recall, thresholds = precision_recall_curve(y_test, y_pred_prob)
    # Fix for division by zero warning - add small epsilon
    f1_scores = 2 * (precision[:-1] * recall[:-1]) / (precision[:-1] + recall[:-1]
    optimal_idx = np.argmax(f1_scores)
    optimal_threshold = thresholds[optimal_idx] if len(thresholds) > optimal_idx el

    # Store the threshold for this model
    model_thresholds[name] = optimal_threshold
```

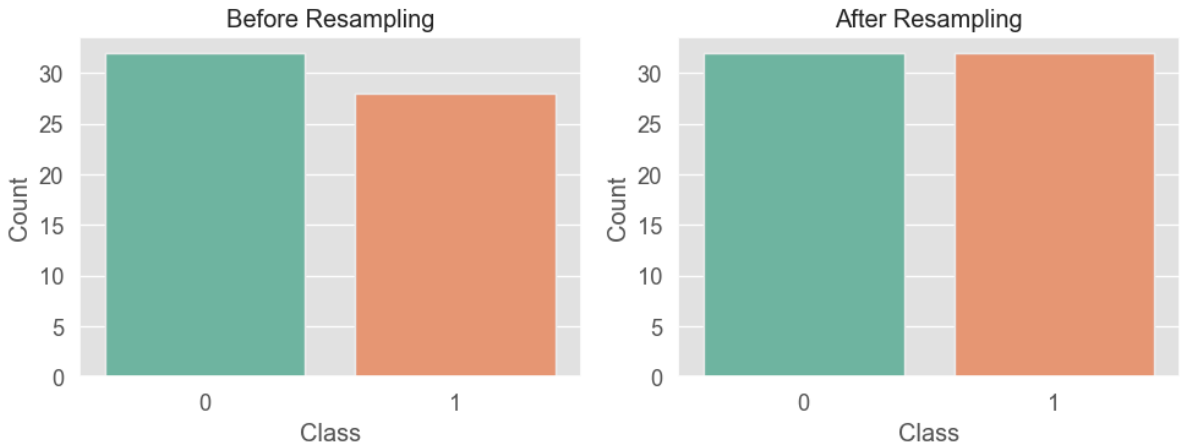
```python
    print(f"Optimal threshold: {optimal_threshold:.3f}")

    # Apply threshold
    y_pred = (y_pred_prob >= optimal_threshold).astype(int)

    # Fix for precision warnings - use zero_division parameter
    print("Classification Report:")
    print(classification_report(y_test, y_pred, zero_division=0))

    # Confusion Matrix
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(6, 5))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=['Low Anxiety', 'High Anxiety'],
                yticklabels=['Low Anxiety', 'High Anxiety'])
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title(f'Confusion Matrix - {name}')
    plt.tight_layout()
    plt.show()

    # ROC curve
    fpr, tpr, _ = roc_curve(y_test, y_pred_prob)
    auc = roc_auc_score(y_test, y_pred_prob)

    plt.figure(figsize=(6, 5))
    plt.plot(fpr, tpr, label=f'AUC = {auc:.3f}')
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'ROC Curve - {name}')
    plt.legend(loc='lower right')
    plt.grid(True, alpha=0.3)
    plt.tight_layout()
    plt.show()

# Choose the best performing model based on analysis
# For this example, let's choose SVM as it had the best balance of precision and re
best_model_name = "SVM"  # You can change this based on your analysis
final_model = models[best_model_name]
final_threshold = model_thresholds[best_model_name]

# Create function to predict anxiety probability for new cases
def predict_anxiety_probability(social_relationships, future_insecurity, isolation,
    """
    Predicts the probability of high anxiety based on input factors.

    Parameters:
    - social_relationships: Score on social relationships (1-5)
    - future_insecurity: Score on future insecurity (1-5)
    - isolation: Score on isolation (1-5)
    - model: Trained model
    - threshold: Classification threshold

    Returns:
    - Probability of high anxiety (0-1)
    - Binary prediction (0 or 1)
    """
    # Create a DataFrame with the input values
    new_data = pd.DataFrame({
        'social_relationships': [social_relationships],
        'future_insecurity': [future_insecurity],
        'isolation': [isolation]
```

```
    })

    # Scale the data
    new_data_scaled = scaler.transform(new_data)

    # Predict probability
    probability = model.predict_proba(new_data_scaled)[0, 1]

    # Binary prediction based on threshold
    prediction = 1 if probability >= threshold else 0

    return probability, prediction

# Example usage
example_cases = [
    {"social": 5, "future": 1, "isolation": 1, "label": "High social, Low future ir
    {"social": 1, "future": 5, "isolation": 5, "label": "Low social, High future ir
    {"social": 3, "future": 3, "isolation": 3, "label": "Average on all factors"}
]

print(f"\n--- Example Predictions (using {best_model_name} with threshold {final_th
for case in example_cases:
    prob, pred = predict_anxiety_probability(
        social_relationships=case["social"],
        future_insecurity=case["future"],
        isolation=case["isolation"],
        model=final_model,
        threshold=final_threshold
    )
    print(f"{case['label']}:")
    print(f"  - Probability of high anxiety: {prob:.2f} ({prob*100:.1f}%)")
    print(f"  - Prediction: {'High Anxiety' if pred == 1 else 'Low Anxiety'}")

# Visualize how each factor affects anxiety probability
plt.figure(figsize=(15, 5))

# For social_relationships
plt.subplot(1, 3, 1)
social_values = np.linspace(1, 5, 100)
probabilities = []

for val in social_values:
    # Keep other variables at their median values
    prob, _ = predict_anxiety_probability(
        social_relationships=val,
        future_insecurity=df['future_insecurity'].median(),
        isolation=df['isolation'].median(),
        model=final_model,
        threshold=final_threshold
    )
    probabilities.append(prob)

plt.plot(social_values, probabilities)
plt.axhline(y=final_threshold, color='r', linestyle='--', alpha=0.7, label=f'Thresh
plt.xlabel('Social Relationships Score')
plt.ylabel('Probability of High Anxiety')
plt.title('Effect of Social Relationships')
plt.legend()
plt.grid(True, alpha=0.3)

# For future_insecurity
plt.subplot(1, 3, 2)
future_values = np.linspace(1, 5, 100)
probabilities = []
```

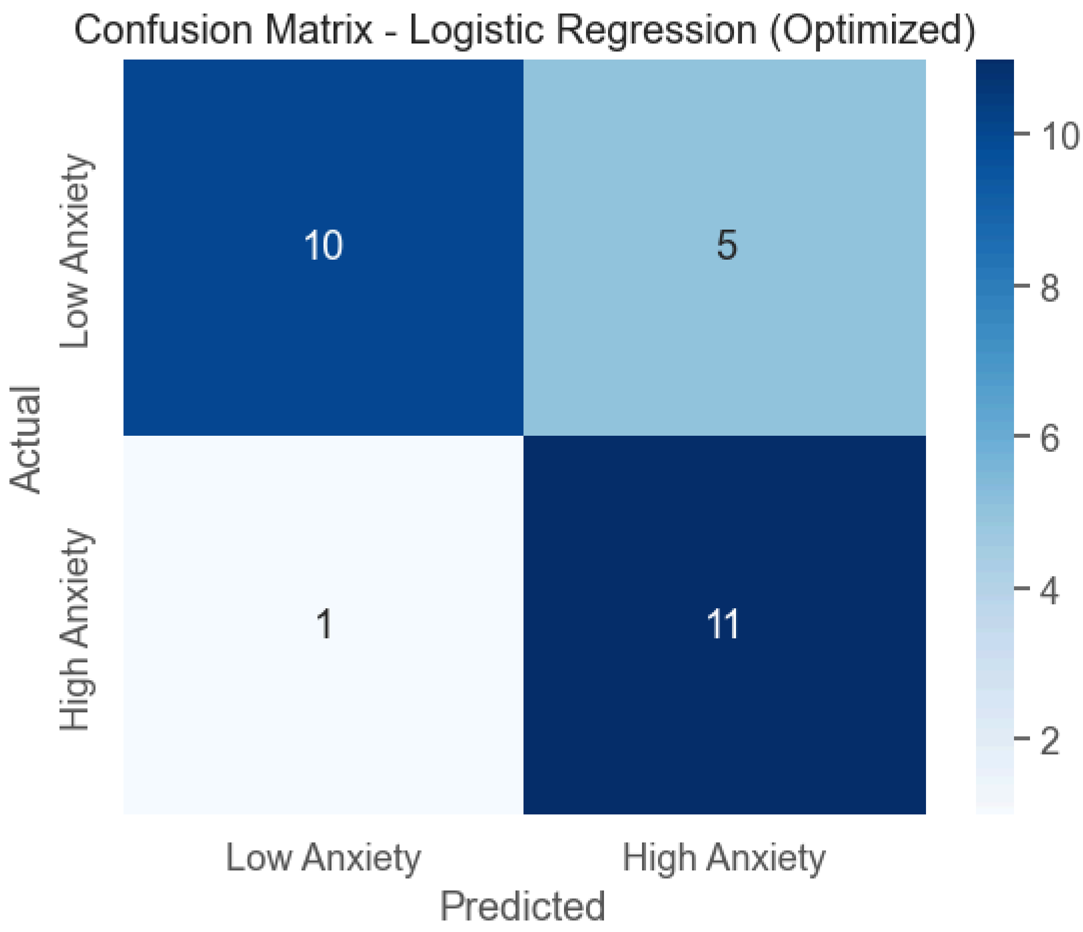
```python
for val in future_values:
    prob, _ = predict_anxiety_probability(
        social_relationships=df['social_relationships'].median(),
        future_insecurity=val,
        isolation=df['isolation'].median(),
        model=final_model,
        threshold=final_threshold
    )
    probabilities.append(prob)

plt.plot(future_values, probabilities)
plt.axhline(y=final_threshold, color='r', linestyle='--', alpha=0.7, label=f'Thresh
plt.xlabel('Future Insecurity Score')
plt.ylabel('Probability of High Anxiety')
plt.title('Effect of Future Insecurity')
plt.legend()
plt.grid(True, alpha=0.3)

# For isolation
plt.subplot(1, 3, 3)
isolation_values = np.linspace(1, 5, 100)
probabilities = []

for val in isolation_values:
    prob, _ = predict_anxiety_probability(
        social_relationships=df['social_relationships'].median(),
        future_insecurity=df['future_insecurity'].median(),
        isolation=val,
        model=final_model,
        threshold=final_threshold
    )
    probabilities.append(prob)

plt.plot(isolation_values, probabilities)
plt.axhline(y=final_threshold, color='r', linestyle='--', alpha=0.7, label=f'Thresh
plt.xlabel('Isolation Score')
plt.ylabel('Probability of High Anxiety')
plt.title('Effect of Isolation')
plt.legend()
plt.grid(True, alpha=0.3)

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

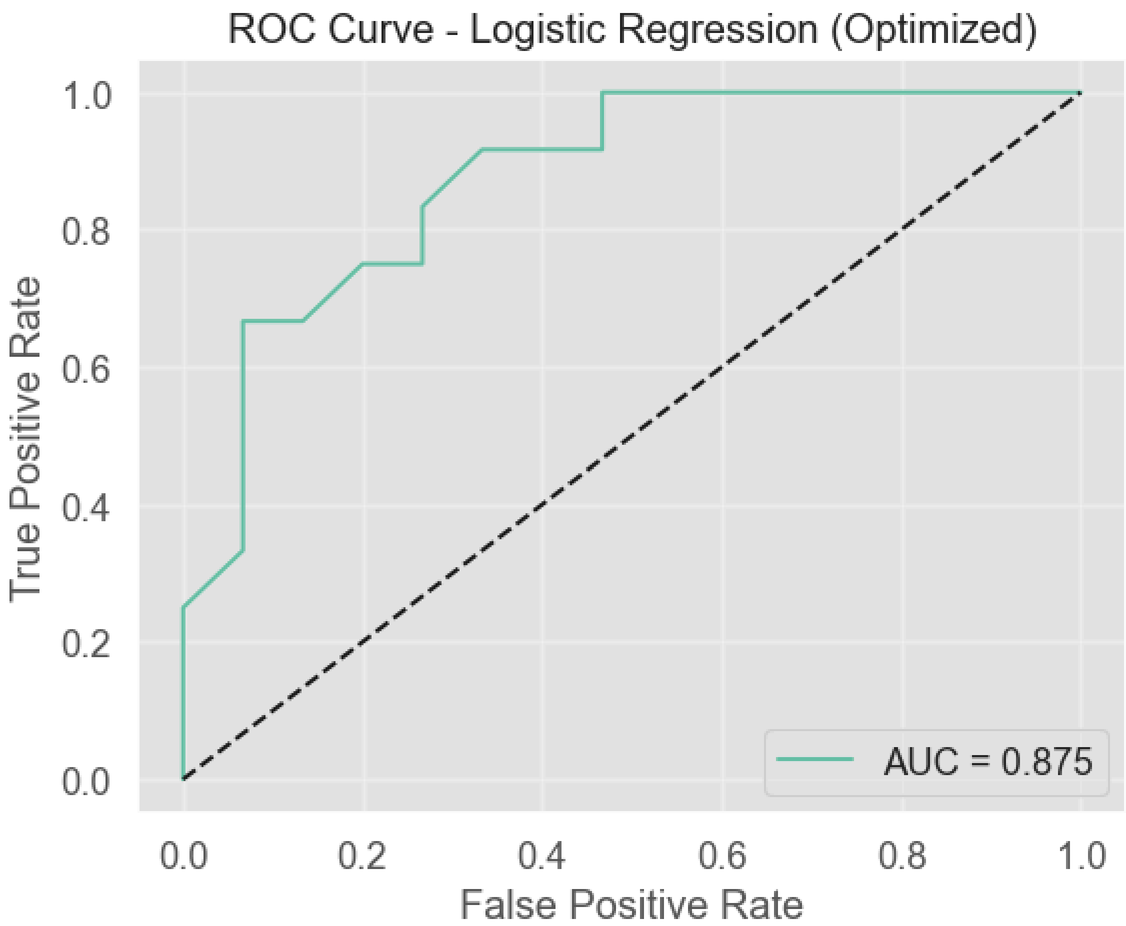
```
Correlation with anxiety:
anxiety                 1.000000
isolation               0.671894
future_insecurity       0.444924
social_relationships   -0.349449
Name: anxiety, dtype: float64
```



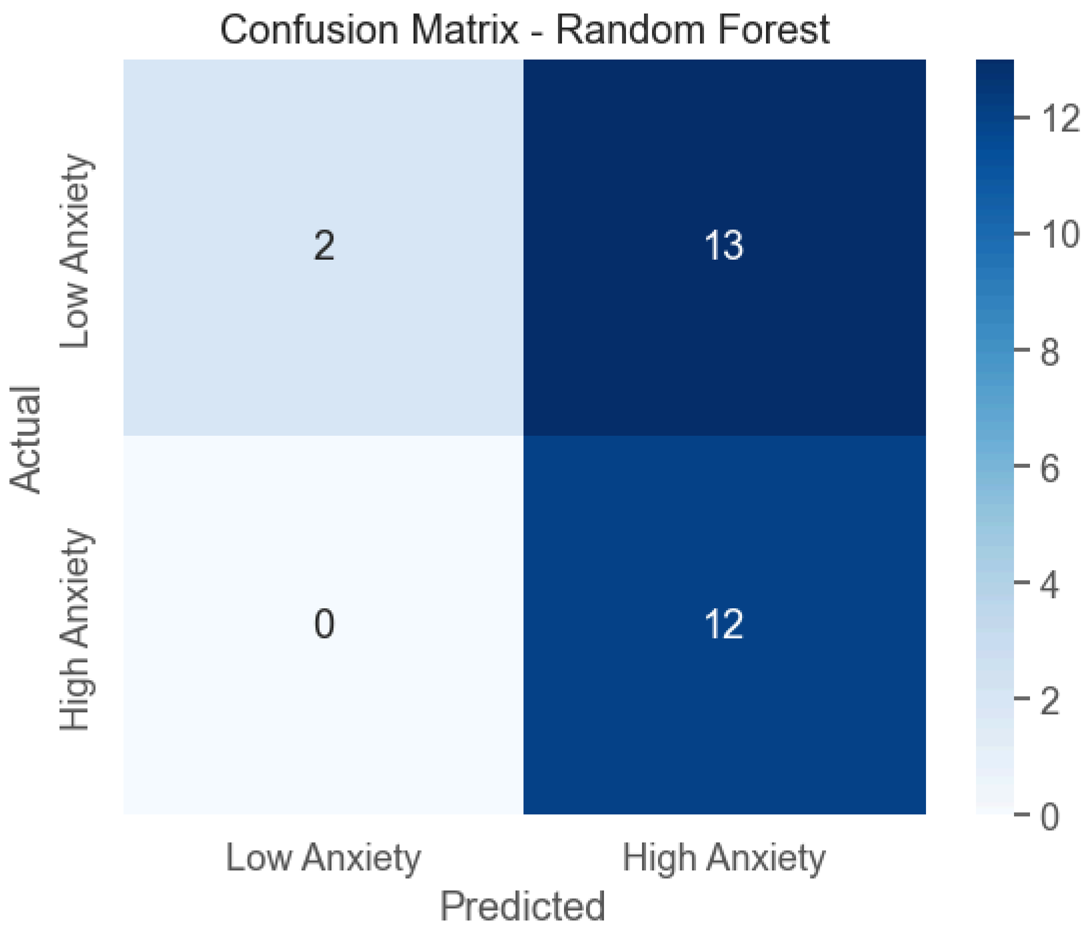


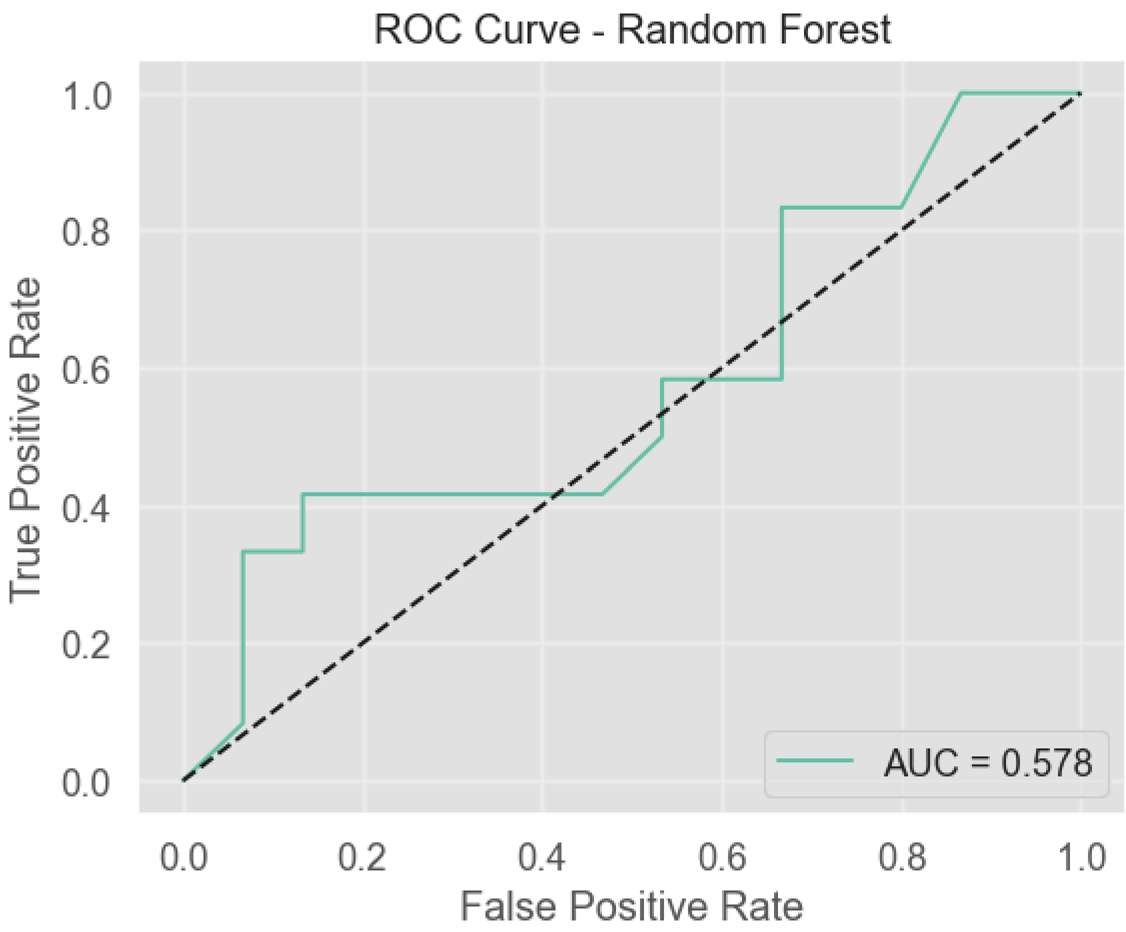

```
Best Parameters: {'C': 1, 'class_weight': None, 'max_iter': 3000, 'penalty': 'l2',
'solver': 'liblinear', 'tol': 0.0001}

--- Logistic Regression (Optimized) ---
Optimal threshold: 0.434
Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.67      0.77        15
           1       0.69      0.92      0.79        12

    accuracy                           0.78        27
   macro avg       0.80      0.79      0.78        27
weighted avg       0.81      0.78      0.78        27
```


Confusion Matrix - Logistic Regression (Optimized)
Actual
Low Anxiety
High Anxiety
10
5
1
11
Low Anxiety
High Anxiety
Predicted
10
8
6
4
2

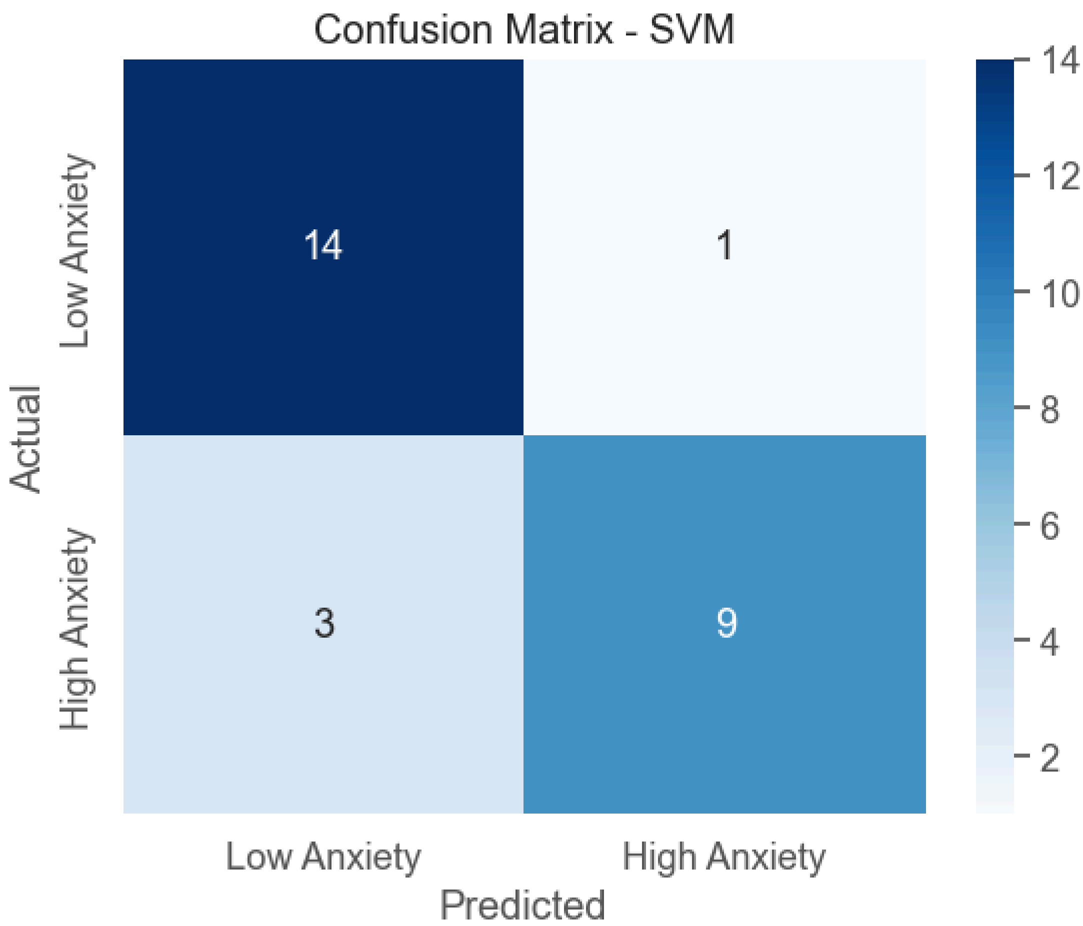

ROC Curve - Logistic Regression (Optimized)
True Positive Rate
False Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
AUC = 0.875

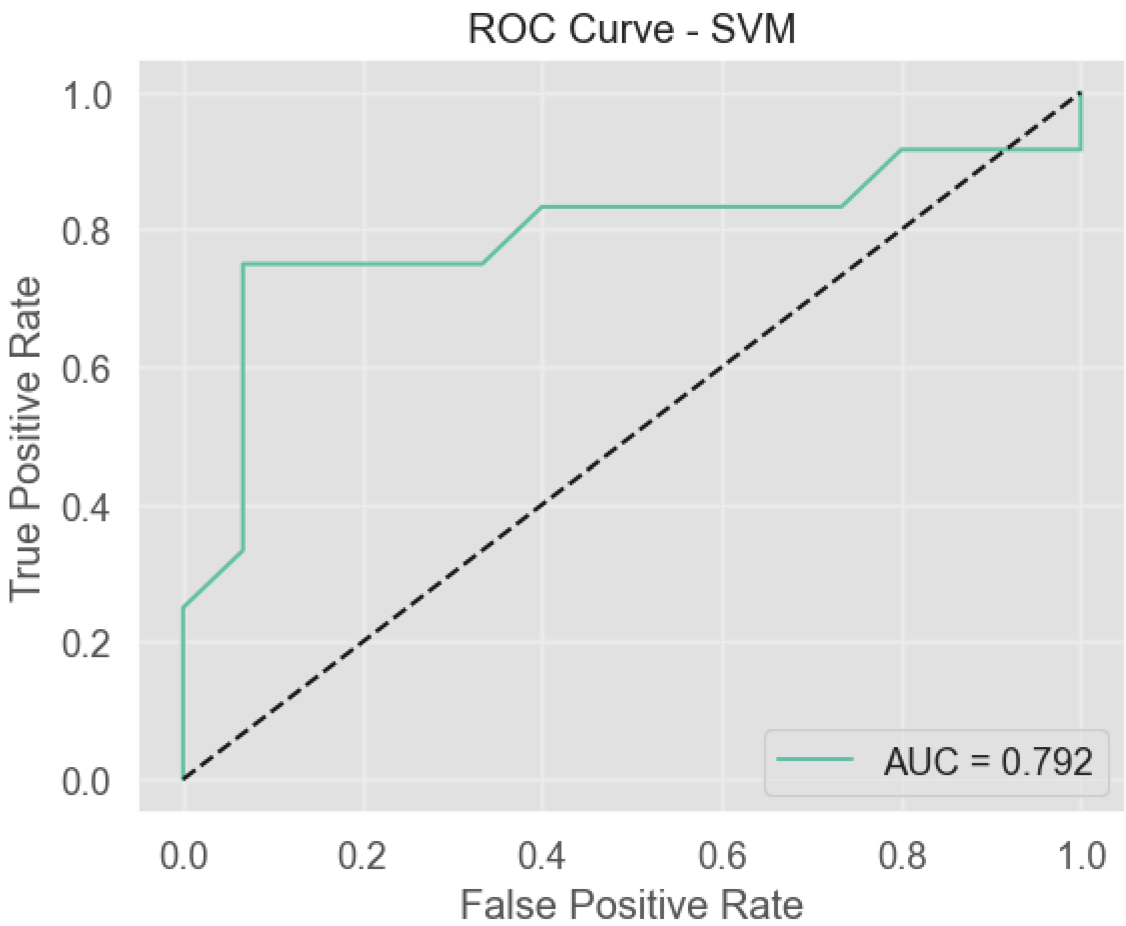
```
--- Random Forest ---
Optimal threshold: 0.020
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.13      0.24        15
           1       0.48      1.00      0.65        12

    accuracy                           0.52        27
   macro avg       0.74      0.57      0.44        27
weighted avg       0.77      0.52      0.42        27
```



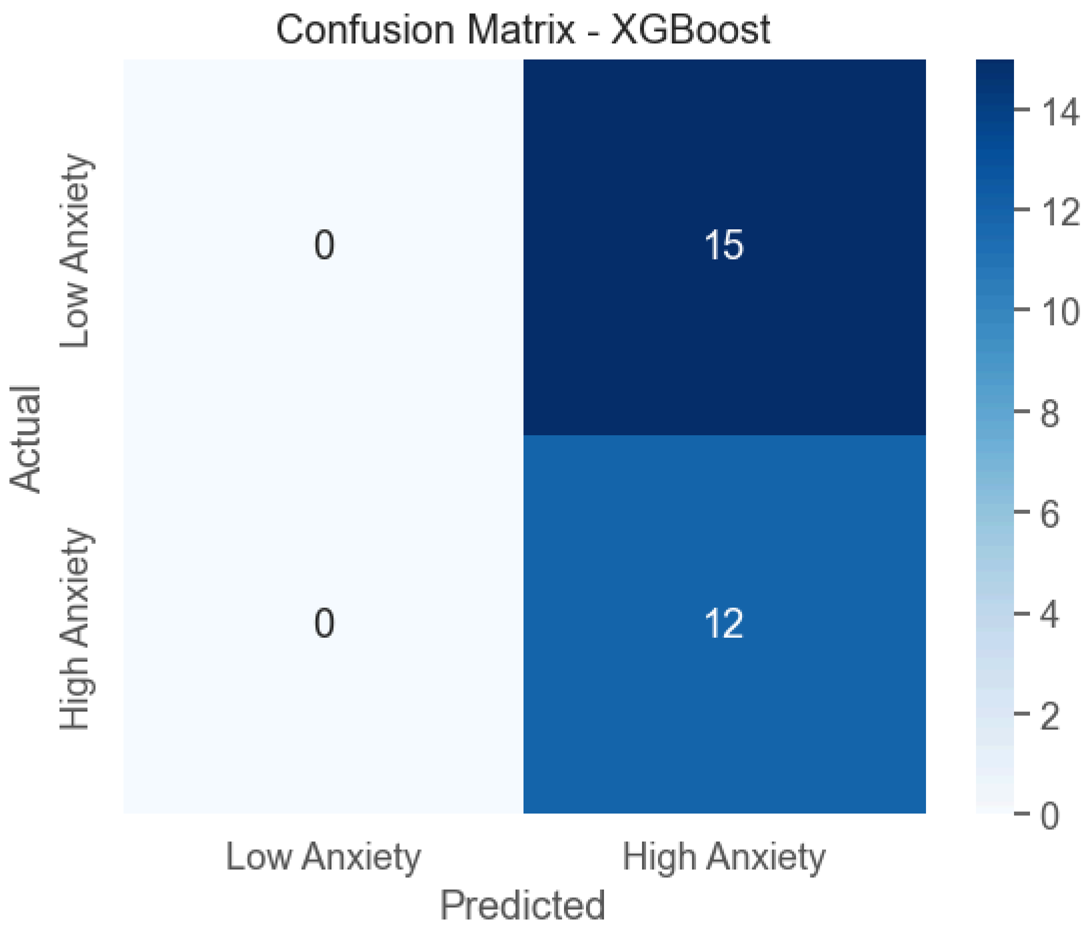


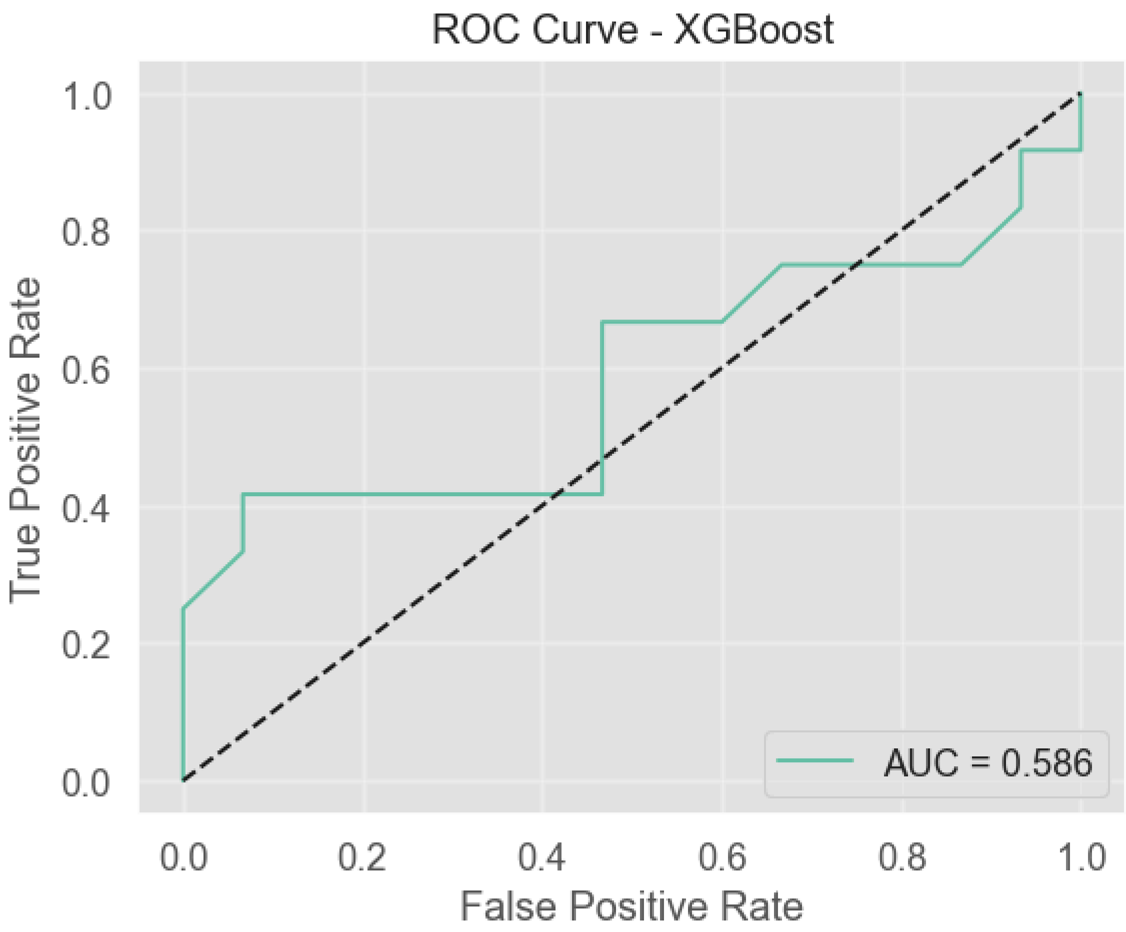

```
--- SVM ---
Optimal threshold: 0.382
Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.93      0.88        15
           1       0.90      0.75      0.82        12

    accuracy                           0.85        27
   macro avg       0.86      0.84      0.85        27
weighted avg       0.86      0.85      0.85        27
```


Confusion Matrix - SVM
Low Anxiety
High Anxiety
Actual
14
1
3
9
Low Anxiety
High Anxiety
Predicted
14
12
10
8
6
4
2

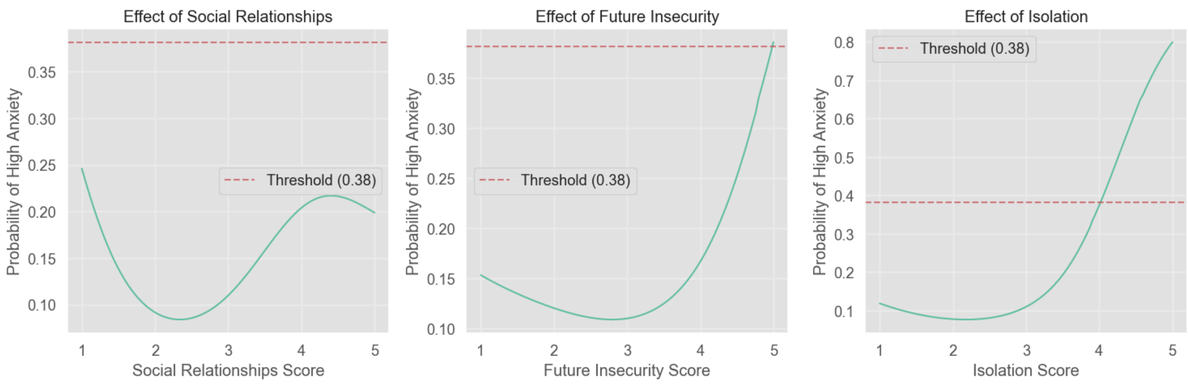

ROC Curve - SVM
True Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
AUC = 0.792

```
--- XGBoost ---
Optimal threshold: 0.000
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        15
           1       0.44      1.00      0.62        12

    accuracy                           0.44        27
   macro avg       0.22      0.50      0.31        27
weighted avg       0.20      0.44      0.27        27
```





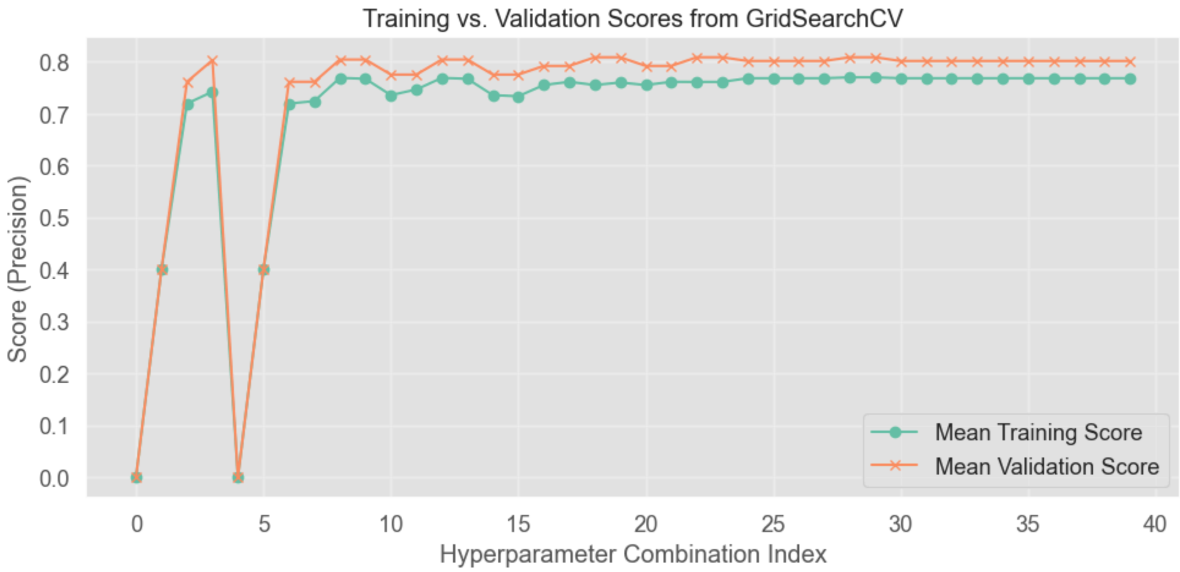

```
--- Example Predictions (using SVM with threshold 0.382) ---
High social, Low future insecurity, Low isolation:
  - Probability of high anxiety: 0.19 (19.3%)
  - Prediction: Low Anxiety
Low social, High future insecurity, High isolation:
  - Probability of high anxiety: 0.95 (94.5%)
  - Prediction: High Anxiety
Average on all factors:
  - Probability of high anxiety: 0.11 (11.0%)
  - Prediction: Low Anxiety
```



In [59]:

```python
# Extract mean train and validation scores
train_scores = grid_search.cv_results_['mean_train_score'] if 'mean_train_score' in
val_scores = grid_search.cv_results_['mean_test_score']

if train_scores is not None:
    # Plot train and validation mean scores
    plt.figure(figsize=(10, 5))
    plt.plot(train_scores, label='Mean Training Score', marker='o')
    plt.plot(val_scores, label='Mean Validation Score', marker='x')
    plt.xlabel('Hyperparameter Combination Index')
    plt.ylabel('Score (Precision)')
```

```
    plt.title('Training vs. Validation Scores from GridSearchCV')
    plt.legend()
    plt.grid(True, alpha=0.3)
    plt.tight_layout()
    plt.show()
else:
    print("Train scores were not recorded. Set `return_train_score=True` in GridSea
```



In [53]:

```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

# Set random seed for reproducibility
np.random.seed(42)

# Load the dataset - update this path
df = pd.read_csv('MentalHealthSurvey.csv')

# Define high anxiety threshold
anxiety_threshold = 4
anxiety_col = f'high_anxiety_{anxiety_threshold}'
df[anxiety_col] = (df['anxiety'] >= anxiety_threshold).astype(int)

# Select predictors and target
X = df[['social_relationships', 'future_insecurity', 'isolation']]
y = df[anxiety_col]

# Split data into training and testing sets with stratification
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y
)

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

from sklearn.svm import SVC
final_model = models[best_model_name]
final_threshold = model_thresholds[best_model_name]

# Function to create 2D visualizations of the SVM decision boundaries
```

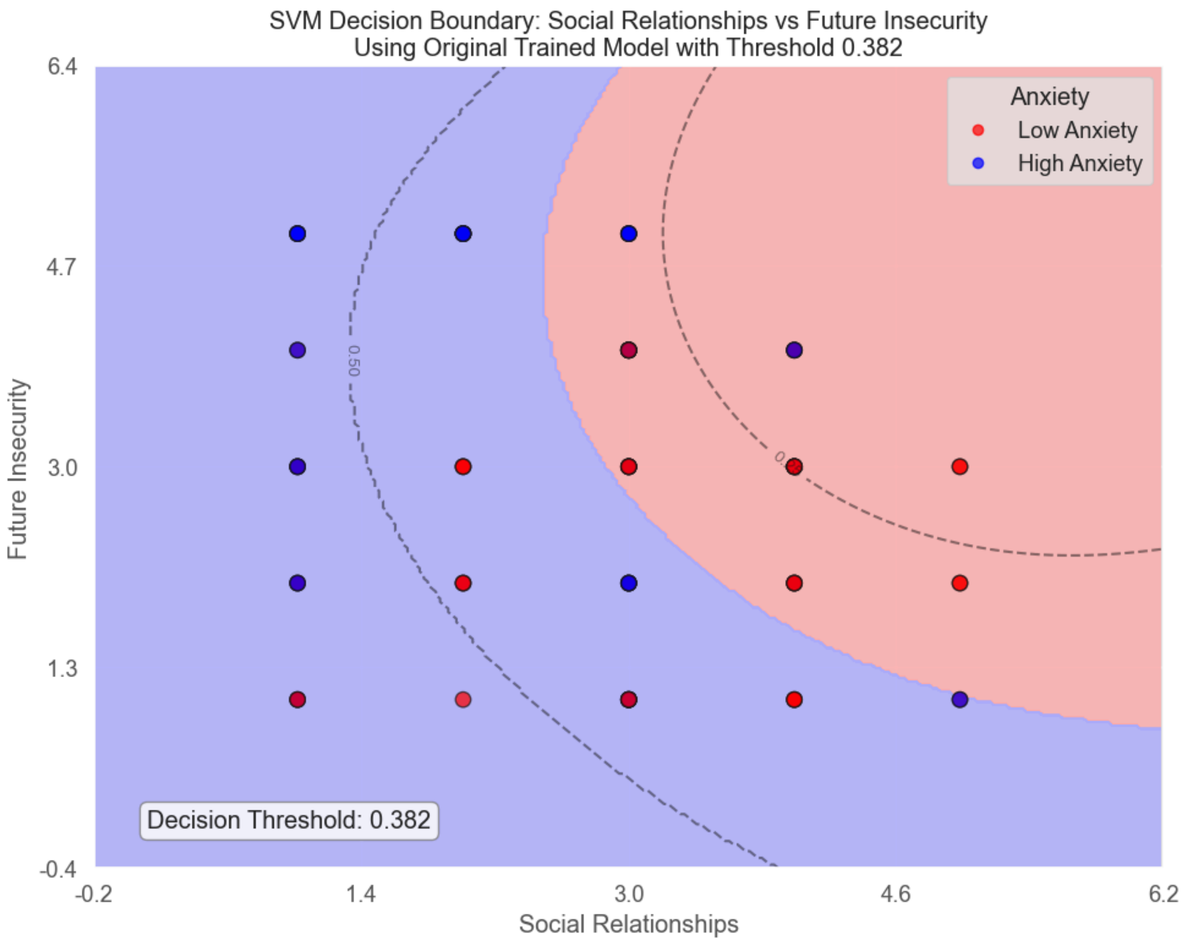
```python
def plot_svm_2d_with_existing_model(X, y, feature_indices, feature_names, model, sc

    # Extract the two features we want to visualize
    X_2d = X.iloc[:, feature_indices].values
    # Create a temporary array with all 3 features
    X_temp = np.zeros((X_2d.shape[0], 3))
    X_temp[:, feature_indices] = X_2d  # Set the 2 features we're using
    # For the remaining feature, fill with median value
    remaining_feature = list(set(range(3)) - set(feature_indices))[0]
    X_temp[:, remaining_feature] = X.iloc[:, remaining_feature].median()
    # Now transform all 3 features
    X_2d_scaled = scaler.transform(X_temp)[:, feature_indices]  # Only keep the 2 w

    # Create color maps
    cmap_light = ListedColormap(['#FFAAAA', '#AAAAFF'])
    cmap_bold = ListedColormap(['#FF0000', '#0000FF'])

    # Create mesh grid
    x_min, x_max = X_2d_scaled[:, 0].min() - 1, X_2d_scaled[:, 0].max() + 1
    y_min, y_max = X_2d_scaled[:, 1].min() - 1, X_2d_scaled[:, 1].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.02),
                         np.arange(y_min, y_max, 0.02))

    # Create grid for full feature space with default values
    grid_shape = xx.shape
    n_features = X.shape[1]  # Total number of features
    grid = np.zeros((grid_shape[0], grid_shape[1], n_features))

    # Fill in the two features we're plotting
    grid[:, :, feature_indices[0]] = xx
    grid[:, :, feature_indices[1]] = yy

    # Fill in median values for other features
    for i in range(n_features):
        if i not in feature_indices:
            grid[:, :, i] = X.iloc[:, i].median()

    # Reshape grid for prediction and scale it
    grid_reshaped = grid.reshape(-1, n_features)
    grid_scaled = scaler.transform(grid_reshaped)

    # Predict probabilities using the existing model
    Z_prob = model.predict_proba(grid_scaled)[:, 1]  # Probability of high anxiety

    # Apply threshold
    Z = (Z_prob >= threshold).astype(int)
    Z = Z.reshape(xx.shape)

    # Plot decision boundary
    plt.figure(figsize=(10, 8))
    plt.contourf(xx, yy, Z, cmap=cmap_light, alpha=0.8)

    # Plot contour lines for probability
    contour_levels = np.linspace(0, 1, 5)
    Z_prob = Z_prob.reshape(xx.shape)
    CS = plt.contour(xx, yy, Z_prob, contour_levels, colors='k', linestyles='dashed
    plt.clabel(CS, inline=True, fontsize=10, fmt='%.2f')

    # Plot training points
    scatter = plt.scatter(X_2d_scaled[:, 0], X_2d_scaled[:, 1], c=y,
                          cmap=cmap_bold, edgecolors='k', s=80, alpha=0.7)

    # Convert scaled axes back to original values for better interpretability
    def scale_back(val, feature_idx):
```

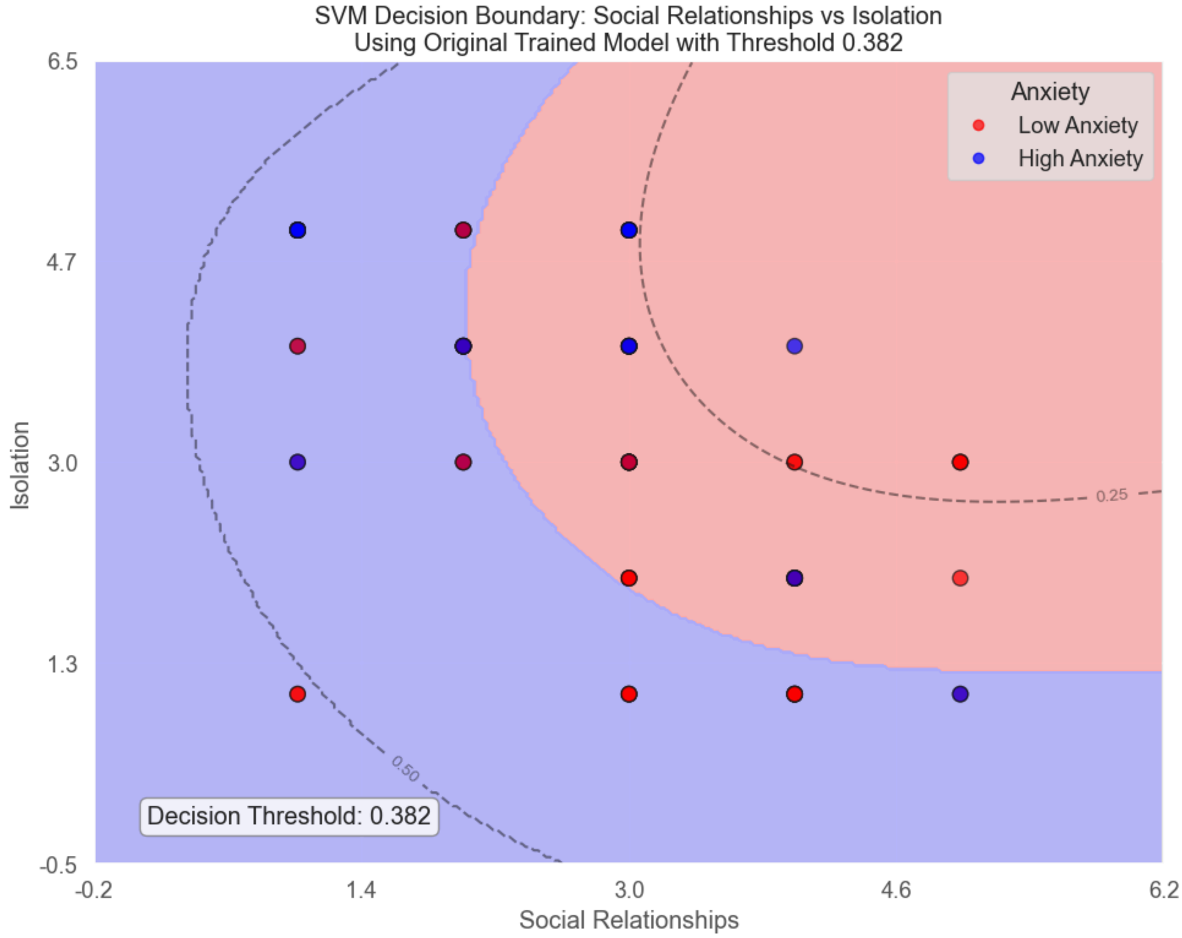
```
        # Convert from standardized to original scale
        return val * scaler.scale_[feature_indices[feature_idx]] + scaler.mean_[fea

    # Create new tick positions and labels
    x_ticks = np.linspace(x_min, x_max, 5)
    y_ticks = np.linspace(y_min, y_max, 5)

    x_tick_labels = [f'{scale_back(x, 0):.1f}' for x in x_ticks]
    y_tick_labels = [f'{scale_back(y, 1):.1f}' for y in y_ticks]

    plt.xticks(x_ticks, x_tick_labels)
    plt.yticks(y_ticks, y_tick_labels)

    plt.xlabel(feature_names[0])
    plt.ylabel(feature_names[1])
    plt.title(f'SVM Decision Boundary: {feature_names[0]} vs {feature_names[1]}\nUs

    # Add legend
    legend1 = plt.legend(*scatter.legend_elements(),
                    loc="upper right", title="Anxiety")
    labels = ['Low Anxiety', 'High Anxiety']
    legend1.get_texts()[0].set_text(labels[0])
    legend1.get_texts()[1].set_text(labels[1])

    # Add threshold annotation
    plt.annotate(f'Decision Threshold: {threshold:.3f}',
                xy=(0.05, 0.05), xycoords='axes fraction',
                bbox=dict(boxstyle="round,pad=0.3", fc="white", ec="gray", alpha=0.

    plt.tight_layout()
    plt.grid(True, alpha=0.3)
    return plt

# Plot all three possible 2D visualizations using your original trained model
feature_names = ['Social Relationships', 'Future Insecurity', 'Isolation']

# Social Relationships vs Future Insecurity
plot1 = plot_svm_2d_with_existing_model(X, y, [0, 1], [feature_names[0], feature_na
                                        final_model, scaler, final_threshold)
plot1.savefig('svm_social_vs_future_original_model.png')
plot1.show()

# Social Relationships vs Isolation
plot2 = plot_svm_2d_with_existing_model(X, y, [0, 2], [feature_names[0], feature_na
                                       final_model, scaler, final_threshold)
plot2.savefig('svm_social_vs_isolation_original_model.png')
plot2.show()

# Future Insecurity vs Isolation
plot3 = plot_svm_2d_with_existing_model(X, y, [1, 2], [feature_names[1], feature_na
                                       final_model, scaler, final_threshold)
plot3.savefig('svm_future_vs_isolation_original_model.png')
plot3.show()

# 3D Visualization with your original model
try:
    from mpl_toolkits.mplot3d import Axes3D

    # Create a 3D figure
    fig = plt.figure(figsize=(12, 10))
    ax = fig.add_subplot(111, projection='3d')

    # Get probability predictions using your trained model
    y_prob = final_model.predict_proba(X_test_scaled)[:, 1]
```

```
    # Apply your optimal threshold
    y_pred = (y_prob >= final_threshold).astype(int)

    # Plot points colored by true class and marked by prediction correctness
    colors = ['red' if label == 1 else 'blue' for label in y_test]
    markers = ['o' if pred == actual else 'x' for pred, actual in zip(y_pred, y_tes
    sizes = [40 if pred == actual else 80 for pred, actual in zip(y_pred, y_test)]

    # Scatter plot
    for i in range(len(X_test_scaled)):
        ax.scatter(
            X_test_scaled[i, 0],
            X_test_scaled[i, 1],
            X_test_scaled[i, 2],
            c=colors[i],
            marker=markers[i],
            s=sizes[i],
            alpha=0.7
        )

    # Set labels for the axes (scaled values)
    ax.set_xlabel('Social Relationships (Scaled)')
    ax.set_ylabel('Future Insecurity (Scaled)')
    ax.set_zlabel('Isolation (Scaled)')

    # Add a title
    ax.set_title(f'3D Visualization of Original SVM Model Predictions\nUsing Thresh

    # Add legend
    from matplotlib.lines import Line2D
    legend_elements = [
        Line2D([0], [0], marker='o', color='w', markerfacecolor='blue', markersize=
        Line2D([0], [0], marker='o', color='w', markerfacecolor='red', markersize=1
        Line2D([0], [0], marker='x', color='black', markersize=10, label='Misclassi
    ]
    ax.legend(handles=legend_elements, loc='upper right')

    plt.tight_layout()
    plt.savefig('svm_3d_visualization_original_model.png')
    plt.show()

except ImportError:
    print("3D visualization requires mplot3d. Install with: pip install matplotlib>

# Create a probability heatmap for each 2D combination using your original model
plt.figure(figsize=(18, 6))

# Function to plot probability heatmap with original model
def plot_probability_heatmap_original_model(feature_idx1, feature_idx2, ax, feature
    # Create a mesh grid for the two features
    x_min, x_max = X.iloc[:, feature_idx1].min() - 0.5, X.iloc[:, feature_idx1].max
    y_min, y_max = X.iloc[:, feature_idx2].min() - 0.5, X.iloc[:, feature_idx2].max

    xx, yy = np.meshgrid(np.linspace(x_min, x_max, 100), np.linspace(y_min, y_max,

    # Create grid points for all features
    n_features = X.shape[1]
    grid = np.zeros((xx.shape[0], xx.shape[1], n_features))

    # Fill in the features we're visualizing
    grid[:, :, feature_idx1] = xx
    grid[:, :, feature_idx2] = yy

    # Fill in median values for other features
```

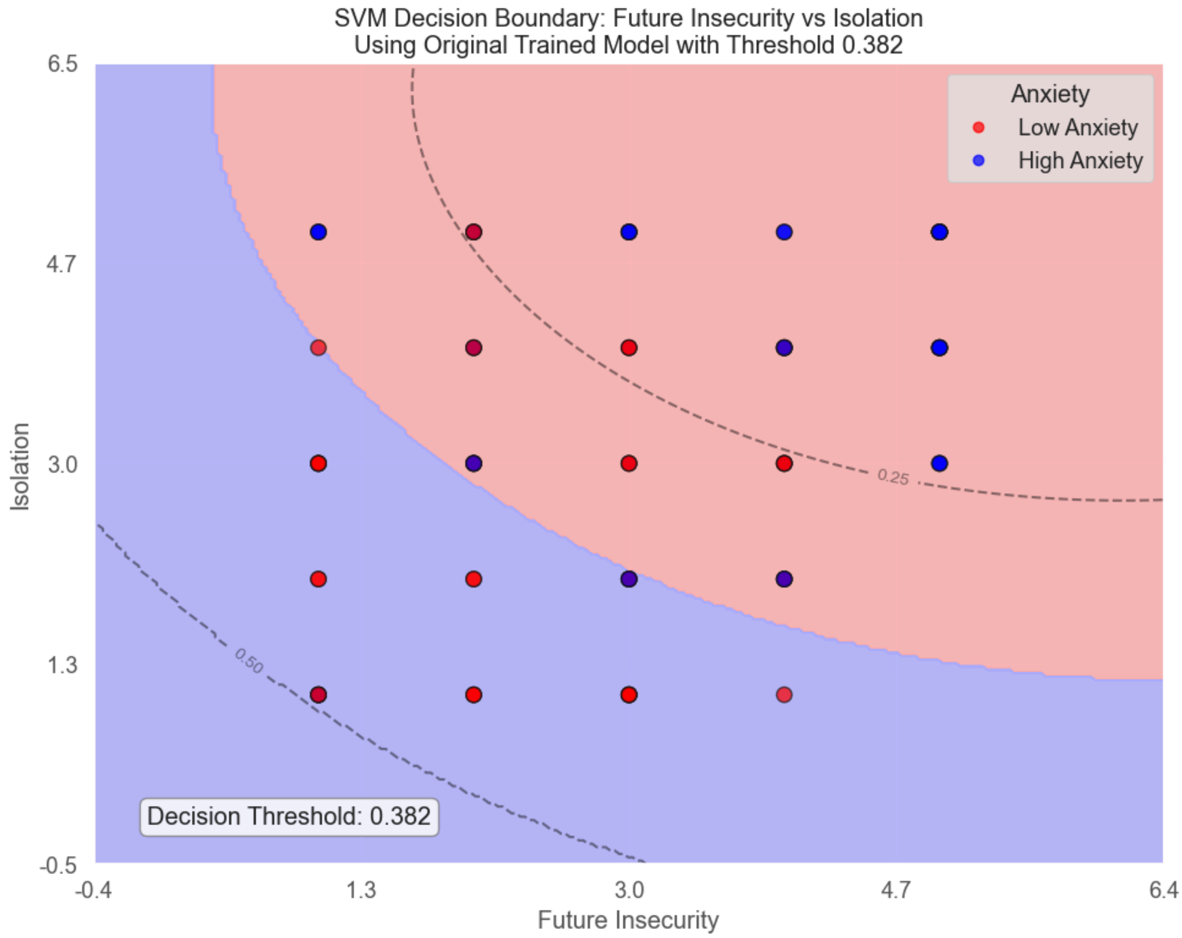
```
    for i in range(n_features):
        if i not in [feature_idx1, feature_idx2]:
            grid[:, :, i] = X.iloc[:, i].median()

    # Reshape grid for prediction
    grid_reshaped = grid.reshape(-1, n_features)

    # Scale the grid points
    grid_scaled = scaler.transform(grid_reshaped)

    # Get probabilities from your original model
    probabilities = model.predict_proba(grid_scaled)[:, 1]  # Probability of high a

    # Reshape probabilities back to grid
    prob_grid = probabilities.reshape(xx.shape)

    # Plot heatmap
    im = ax.imshow(prob_grid, cmap='coolwarm', origin='lower',
             extent=[x_min, x_max, y_min, y_max], aspect='auto', alpha=0.8,
             vmin=0, vmax=1)

    # Draw contour at decision threshold
    ax.contour(xx, yy, prob_grid, levels=[threshold], colors='k', linestyles='--',

    # Plot training points
    ax.scatter(X.iloc[:, feature_idx1], X.iloc[:, feature_idx2], c=y,
               cmap=ListedColormap(['blue', 'red']), edgecolors='k', s=50, alpha=0.

    # Labels
    ax.set_xlabel(feature_names[feature_idx1])
    ax.set_ylabel(feature_names[feature_idx2])
    ax.set_title(f'Probability Heatmap: {feature_names[feature_idx1]} vs {feature_n

    return im

# Plot all combinations
fig, axes = plt.subplots(1, 3, figsize=(18, 6))

im1 = plot_probability_heatmap_original_model(0, 1, axes[0], feature_names, final_m
im2 = plot_probability_heatmap_original_model(0, 2, axes[1], feature_names, final_m
im3 = plot_probability_heatmap_original_model(1, 2, axes[2], feature_names, final_m

# Add colorbar
cbar_ax = fig.add_axes([0.92, 0.15, 0.02, 0.7])
cbar = fig.colorbar(im3, cax=cbar_ax)
cbar.set_label('Probability of High Anxiety')

# Add decision threshold annotation to colorbar
cbar.ax.axhline(y=final_threshold, color='k', linestyle='--', linewidth=2)
cbar.ax.text(0.5, final_threshold + 0.05, f'Threshold: {final_threshold:.3f}',
             ha='center', va='bottom', transform=cbar.ax.transAxes)

plt.tight_layout(rect=[0, 0, 0.9, 1])
plt.savefig('svm_probability_heatmaps_original_model.png')
plt.show()

# Feature importance visualization based on SVM coefficients (if using linear kerne
# For RBF kernel, we use a different approach
if hasattr(final_model, 'coef_'):
    # For linear SVM
    coefficients = final_model.coef_[0]
    plt.figure(figsize=(10, 6))
    plt.bar(feature_names, coefficients)
    plt.title('SVM Feature Importance (Linear Kernel)')
```

```python
    plt.xlabel('Features')
    plt.ylabel('Coefficient Value')
    plt.grid(alpha=0.3)
    plt.tight_layout()
    plt.savefig('svm_feature_importance.png')
    plt.show()
else:
    # For non-linear kernels like RBF
    # We can analyze feature importance using permutation importance
    from sklearn.inspection import permutation_importance

    # Calculate permutation importance
    result = permutation_importance(final_model, X_test_scaled, y_test,
                                    n_repeats=10, random_state=42, n_jobs=-1)

    # Plot permutation importance
    plt.figure(figsize=(10, 6))
    sorted_idx = result.importances_mean.argsort()
    plt.barh([feature_names[i] for i in sorted_idx], result.importances_mean[sorted
    plt.xlabel('Permutation Importance')
    plt.title('SVM Feature Importance (Non-linear Kernel)')
    plt.grid(alpha=0.3)
    plt.tight_layout()
    plt.savefig('svm_permutation_importance.png')
    plt.show()
```

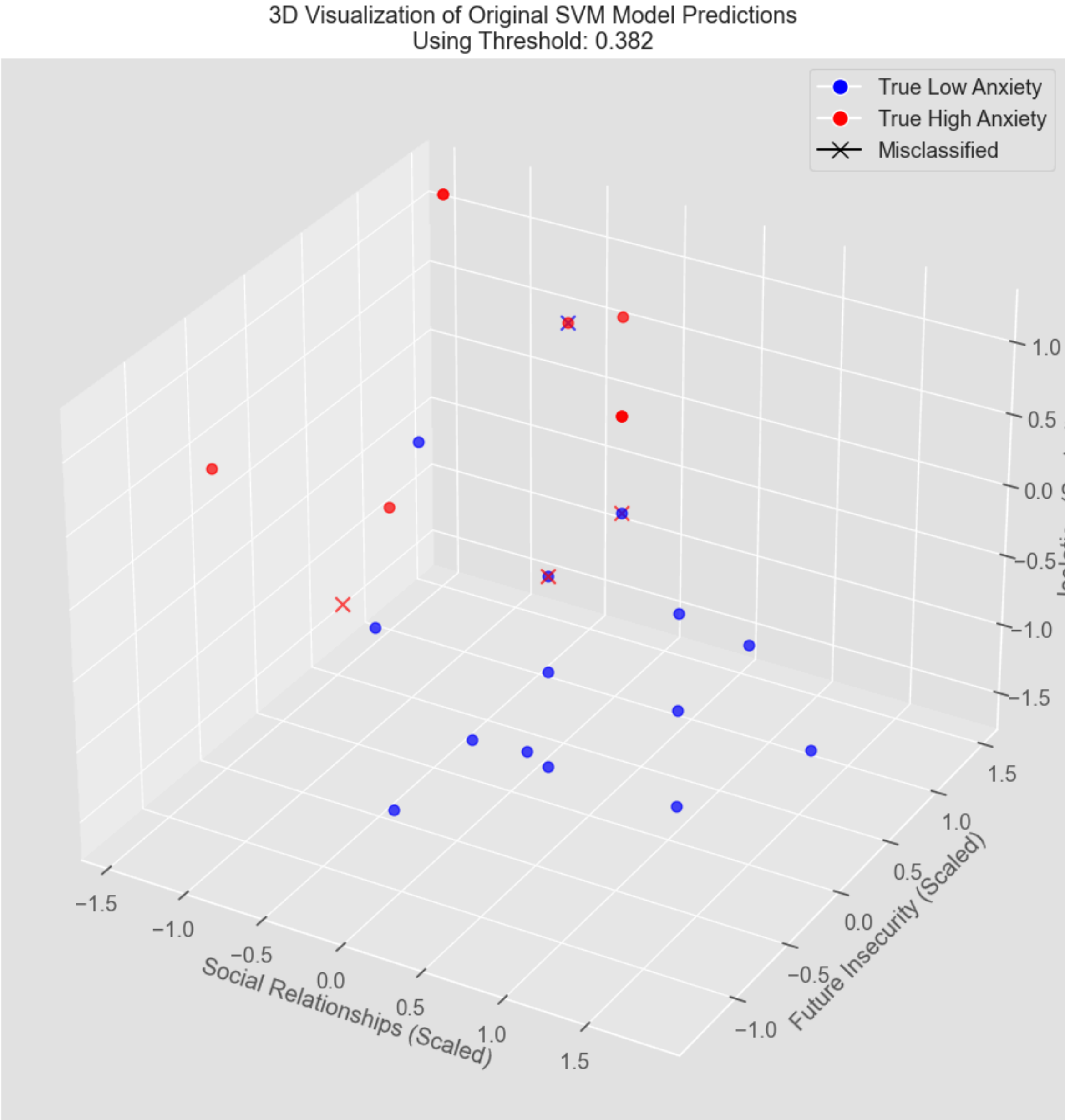




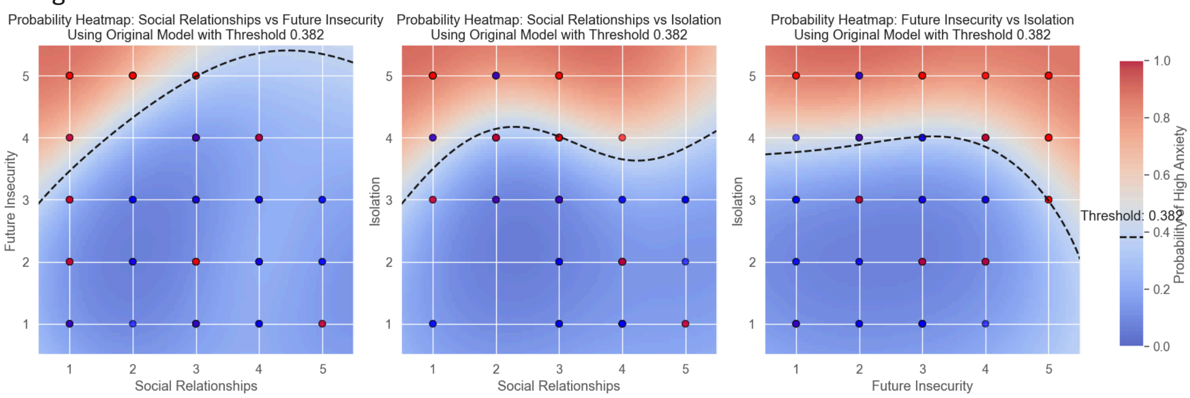
SVM Decision Boundary: Social Relationships vs Isolation
Using Original Trained Model with Threshold 0.382
Anxiety
Low Anxiety
High Anxiety
0.25
0.50
Decision Threshold: 0.382
Isolation
Social Relationships
6.5
4.7
3.0
1.3
-0.5
-0.2
1.4
3.0
4.6
6.2

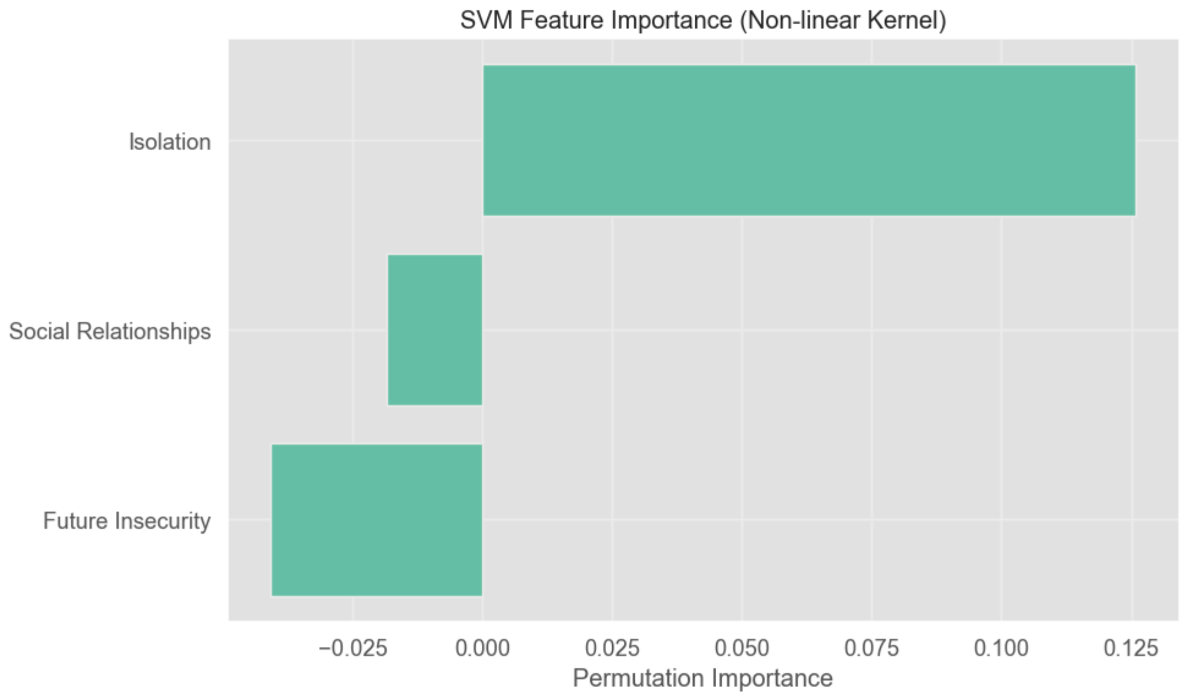


SVM Decision Boundary: Future Insecurity vs Isolation
Using Original Trained Model with Threshold 0.382
Anxiety
Low Anxiety
High Anxiety
0.25
0.50
Decision Threshold: 0.382
Isolation
Future Insecurity
6.5
4.7
3.0
1.3
-0.5
-0.4
1.3
3.0
4.7
6.4



<Figure size 1800x600 with 0 Axes>




SVM Feature Importance (Non-linear Kernel)
Isolation
Social Relationships
Future Insecurity
−0.025
0.000
0.025
0.050
0.075
0.100
0.125
Permutation Importance