```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import ttest_ind
from sklearn.model_selection import train_test_split,
RandomizedSearchCV
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.metrics import classification_report, roc_auc_score,
roc_curve, adjusted_rand_score, silhouette_score
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier
from imblearn.over_sampling import SMOTE
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans

# Set plot style
sns.set(style='whitegrid')
```

1. Load and Inspect the dataset

```python
# Load dataset
data = pd.read_csv("teen_phone_addiction_dataset.csv")

# View shape and first few rows
print(f"Dataset shape: {data.shape}")
data.head()
```

```
Dataset shape: (3000, 25)

   ID               Name  Age  Gender          Location
School_Grade  \
0   1    Shannon Francis   13  Female        Hansonfort          9th

1   2    Scott Rodriguez   17  Female      Theodorefort          7th

2   3         Adrian Knox   13   Other       Lindseystad         11th

3   4  Brittany Hamilton   18  Female     West Anthony          12th

4   5       Steven Smith   14   Other  Port Lindsaystad          9th


   Daily_Usage_Hours  Sleep_Hours  Academic_Performance
Social_Interactions  \
0                4.0          6.1                    78
5
```

```
1                 5.5          6.5                      70
5
2                 5.8          5.5                      93
8
3                 3.1          3.9                      78
8
4                 2.5          6.7                      56
4

   ...  Screen_Time_Before_Bed  Phone_Checks_Per_Day  Apps_Used_Daily
\
0  ...                     1.4                    86               19

1  ...                     0.9                    96                9

2  ...                     0.5                   137                8

3  ...                     1.4                   128                7

4  ...                     1.0                    96               20


   Time_on_Social_Media  Time_on_Gaming  Time_on_Education  \
0                   3.6             1.7                1.2
1                   1.1             4.0                1.8
2                   0.3             1.5                0.4
3                   3.1             1.6                0.8
4                   2.6             0.9                1.1

   Phone_Usage_Purpose  Family_Communication  Weekend_Usage_Hours  \
0             Browsing                     4                  8.7
1             Browsing                     2                  5.3
2            Education                     6                  5.7
3         Social Media                     8                  3.0
4               Gaming                    10                  3.7

   Addiction_Level
0             10.0
1             10.0
2              9.2
3              9.8
4              8.6

[5 rows x 25 columns]
```

2.1 Data cleaning

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

```
# Convert Addiction_Level into binary classification
# Addiction scores > 7.0 are labeled as 'High' (1), otherwise 'Low'
(0)

data["Addiction_Binary"] = data["Addiction_Level"].apply(lambda x: 1
if x > 7.0 else 0)
data.head()
```

```
   ID               Name  Age  Gender          Location
School_Grade  \
0   1    Shannon Francis   13  Female        Hansonfort          9th

1   2    Scott Rodriguez   17  Female      Theodorefort          7th

2   3        Adrian Knox   13   Other       Lindseystad         11th

3   4  Brittany Hamilton   18  Female      West Anthony         12th

4   5       Steven Smith   14   Other  Port Lindsaystad          9th


   Daily_Usage_Hours  Sleep_Hours  Academic_Performance
Social_Interactions  \
0                4.0          6.1                    78
5
1                5.5          6.5                    70
5
2                5.8          5.5                    93
8
3                3.1          3.9                    78
8
4                2.5          6.7                    56
4

   ...  Phone_Checks_Per_Day  Apps_Used_Daily  Time_on_Social_Media  \
0  ...                    86               19                   3.6
1  ...                    96                9                   1.1
2  ...                   137                8                   0.3
3  ...                   128                7                   3.1
4  ...                    96               20                   2.6

   Time_on_Gaming  Time_on_Education  Phone_Usage_Purpose  \
0             1.7                1.2             Browsing
1             4.0                1.8             Browsing
2             1.5                0.4            Education
3             1.6                0.8         Social Media
4             0.9                1.1               Gaming

   Family_Communication  Weekend_Usage_Hours  Addiction_Level  \
0                     4                  8.7             10.0
```

```
1                      2                    5.3               10.0
2                      6                    5.7                9.2
3                      8                    3.0                9.8
4                     10                    3.7                8.6

   Addiction_Binary
0                 1
1                 1
2                 1
3                 1
4                 1

[5 rows x 26 columns]
```

2.2. Descriptive Statistics

```
# Summary of numerical features
data.describe()
```

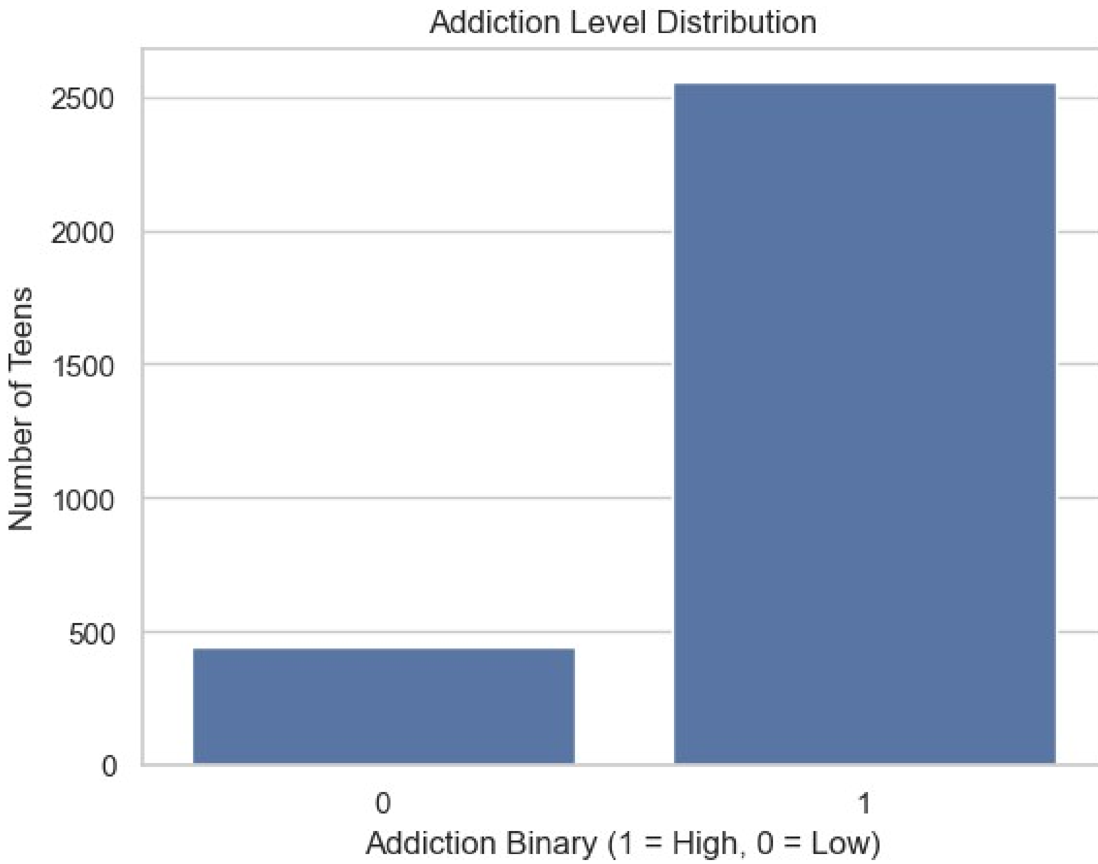
```
                ID          Age  Daily_Usage_Hours  Sleep_Hours  \
count  3000.000000  3000.000000        3000.000000  3000.000000
mean   1500.500000    15.969667           5.020667     6.489767
std     866.169729     1.989489           1.956501     1.490713
min       1.000000    13.000000           0.000000     3.000000
25%     750.750000    14.000000           3.700000     5.500000
50%    1500.500000    16.000000           5.000000     6.500000
75%    2250.250000    18.000000           6.400000     7.500000
max    3000.000000    19.000000          11.500000    10.000000

       Academic_Performance  Social_Interactions  Exercise_Hours  \
count           3000.000000          3000.000000     3000.000000
mean              74.947333             5.097667        1.040667
std               14.684156             3.139333        0.734620
min               50.000000             0.000000        0.000000
25%               62.000000             2.000000        0.500000
50%               75.000000             5.000000        1.000000
75%               88.000000             8.000000        1.500000
max              100.000000            10.000000        4.000000

       Anxiety_Level  Depression_Level  Self_Esteem  ...  \
count    3000.000000       3000.000000  3000.000000  ...
mean        5.590000          5.460333     5.546333  ...
std         2.890678          2.871557     2.860754  ...
min         1.000000          1.000000     1.000000  ...
25%         3.000000          3.000000     3.000000  ...
50%         6.000000          5.000000     6.000000  ...
75%         8.000000          8.000000     8.000000  ...
max        10.000000         10.000000    10.000000  ...

       Screen_Time_Before_Bed  Phone_Checks_Per_Day
```

```
Apps_Used_Daily  \
count            3000.000000          3000.000000      3000.000000

mean                1.006733            83.093000        12.609333

std                 0.492878            37.747044         4.611486

min                 0.000000            20.000000         5.000000

25%                 0.700000            51.000000         9.000000

50%                 1.000000            82.000000        13.000000

75%                 1.400000           115.250000        17.000000

max                 2.600000           150.000000        20.000000


       Time_on_Social_Media  Time_on_Gaming  Time_on_Education  \
count           3000.000000     3000.000000        3000.000000
mean               2.499233        1.525267           1.016333
std                0.988201        0.932701           0.648341
min                0.000000        0.000000           0.000000
25%                1.800000        0.800000           0.500000
50%                2.500000        1.500000           1.000000
75%                3.200000        2.200000           1.500000
max                5.000000        4.000000           3.000000

       Family_Communication  Weekend_Usage_Hours  Addiction_Level  \
count           3000.000000          3000.000000      3000.000000
mean               5.459667             6.015100         8.881900
std                2.864572             2.014776         1.609598
min                1.000000             0.000000         1.000000
25%                3.000000             4.700000         8.000000
50%                5.000000             6.000000        10.000000
75%                8.000000             7.400000        10.000000
max               10.000000            14.000000        10.000000

       Addiction_Binary
count       3000.000000
mean           0.851333
std            0.355819
min            0.000000
25%            1.000000
50%            1.000000
75%            1.000000
max            1.000000

[8 rows x 21 columns]
```

```python
# Check data types
data.dtypes
```

```
ID                              int64
Name                           object
Age                             int64
Gender                         object
Location                       object
School_Grade                   object
Daily_Usage_Hours             float64
Sleep_Hours                   float64
Academic_Performance            int64
Social_Interactions             int64
Exercise_Hours                float64
Anxiety_Level                   int64
Depression_Level                int64
Self_Esteem                     int64
Parental_Control                int64
Screen_Time_Before_Bed        float64
Phone_Checks_Per_Day            int64
Apps_Used_Daily                 int64
Time_on_Social_Media          float64
Time_on_Gaming                float64
Time_on_Education             float64
Phone_Usage_Purpose            object
Family_Communication            int64
Weekend_Usage_Hours           float64
Addiction_Level               float64
Addiction_Binary                int64
dtype: object
```

```python
# Check distribution of the target variable
sns.countplot(x="Addiction_Binary", data=data)
plt.title("Addiction Level Distribution")
plt.xlabel("Addiction Binary (1 = High, 0 = Low)")
plt.ylabel("Number of Teens")
plt.show()

# Display value counts
print(data["Addiction_Binary"].value_counts())
```

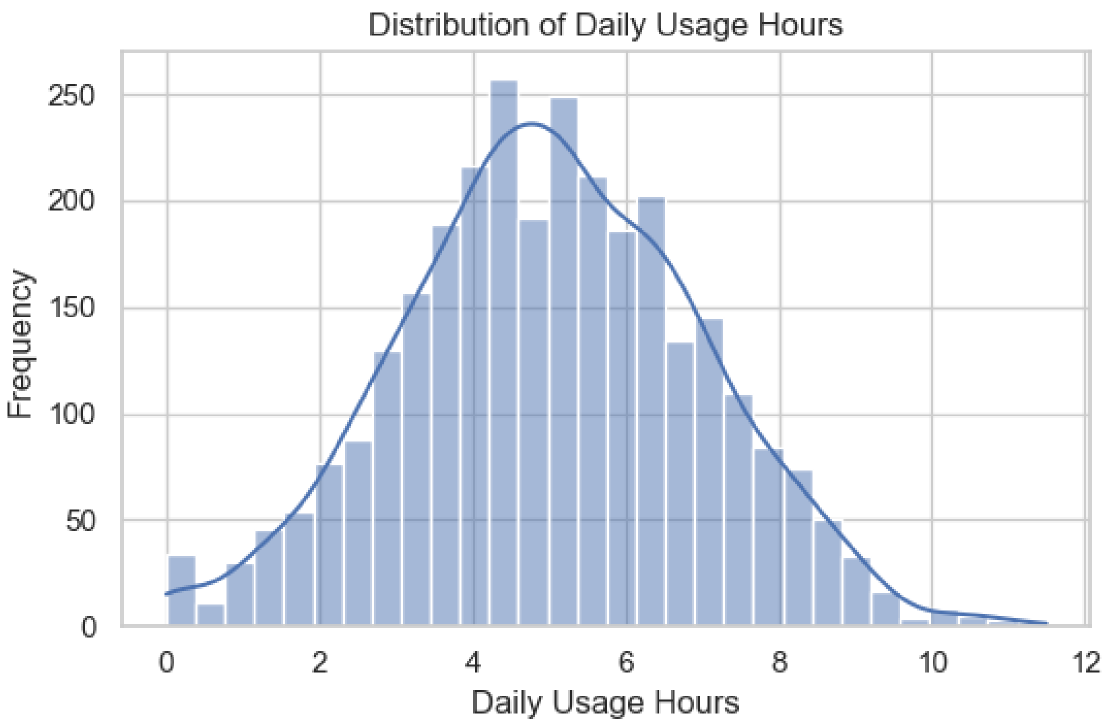


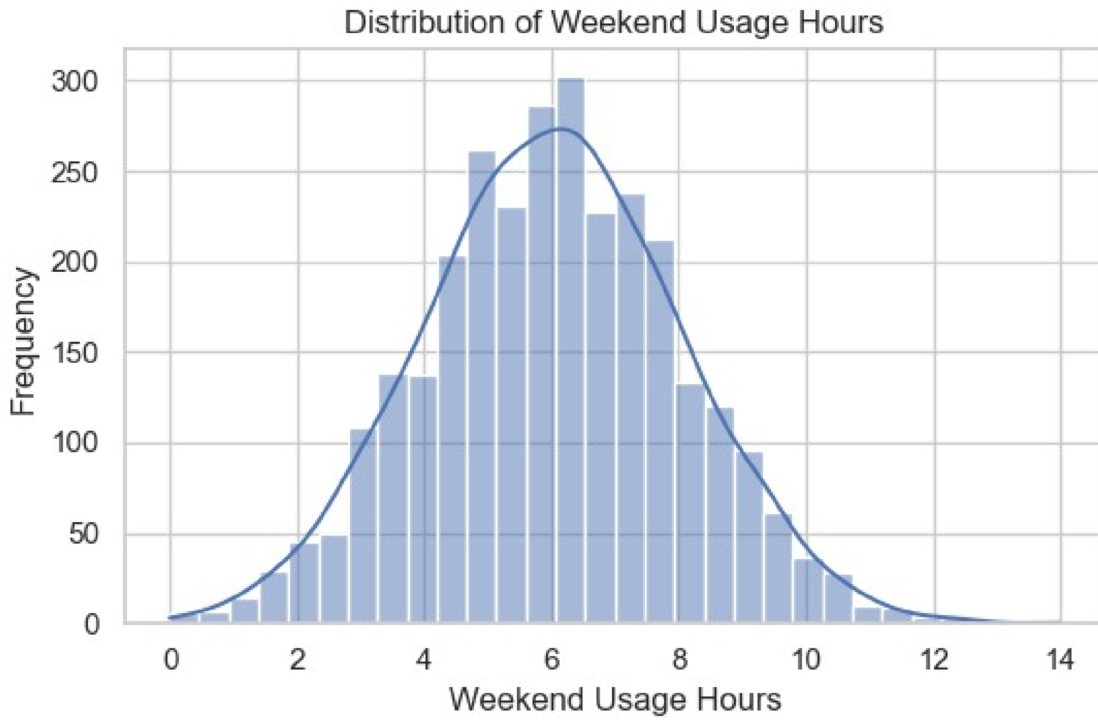

```
Addiction_Binary
1    2554
0     446
Name: count, dtype: int64
```

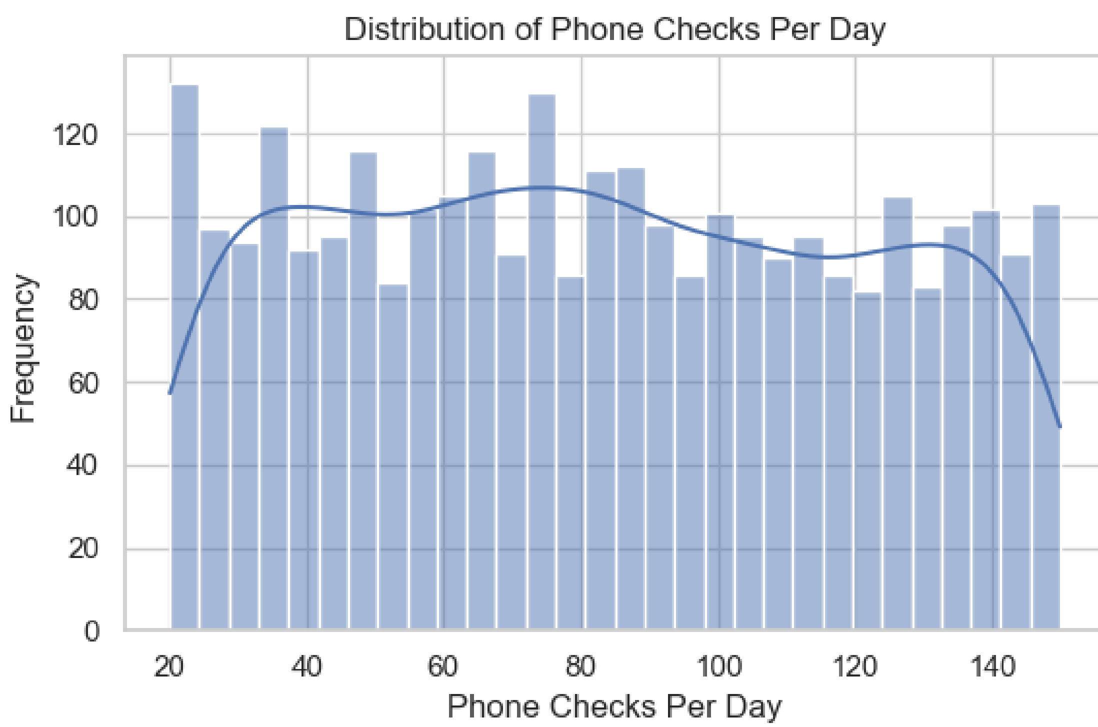
2.3 Univariate Visualizations

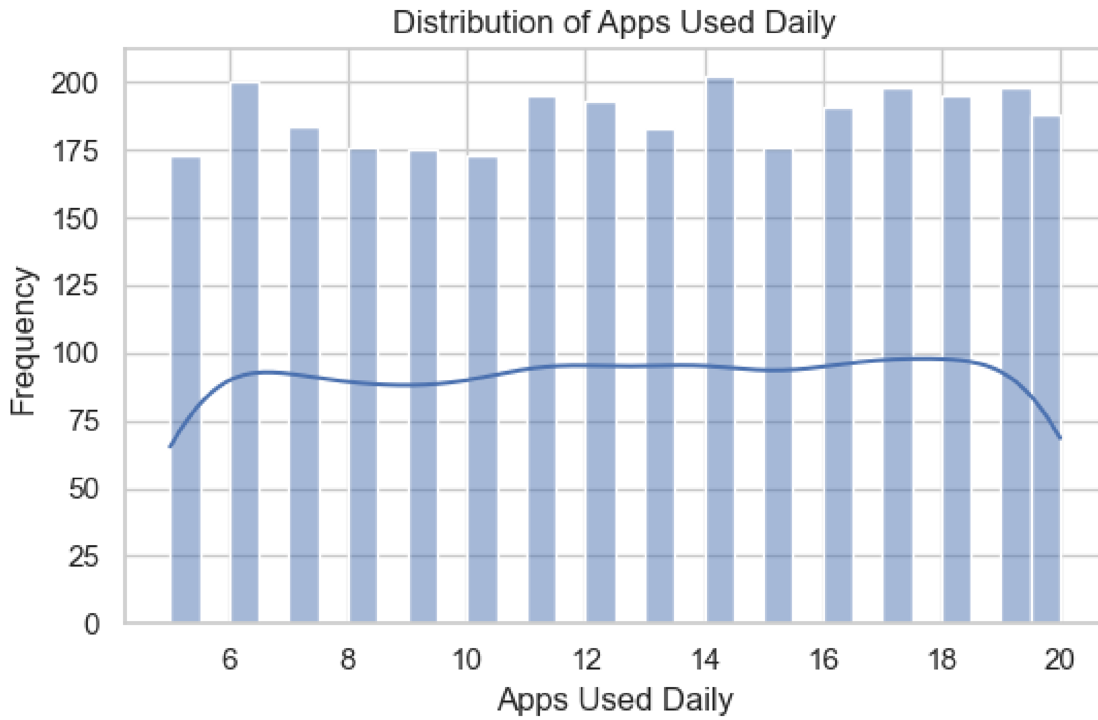
```
# List of features to plot
usage_features = [
    "Daily_Usage_Hours", "Weekend_Usage_Hours",
"Phone_Checks_Per_Day",
    "Apps_Used_Daily", "Screen_Time_Before_Bed",
"Time_on_Social_Media",
    "Time_on_Gaming", "Time_on_Education"
]

mental_health_features = ["Anxiety_Level", "Depression_Level",
"Self_Esteem"]
lifestyle_features = ["Sleep_Hours", "Exercise_Hours",
"Family_Communication"]
academic_feature = ["Academic_Performance"]

# Plot numeric feature distributions
```

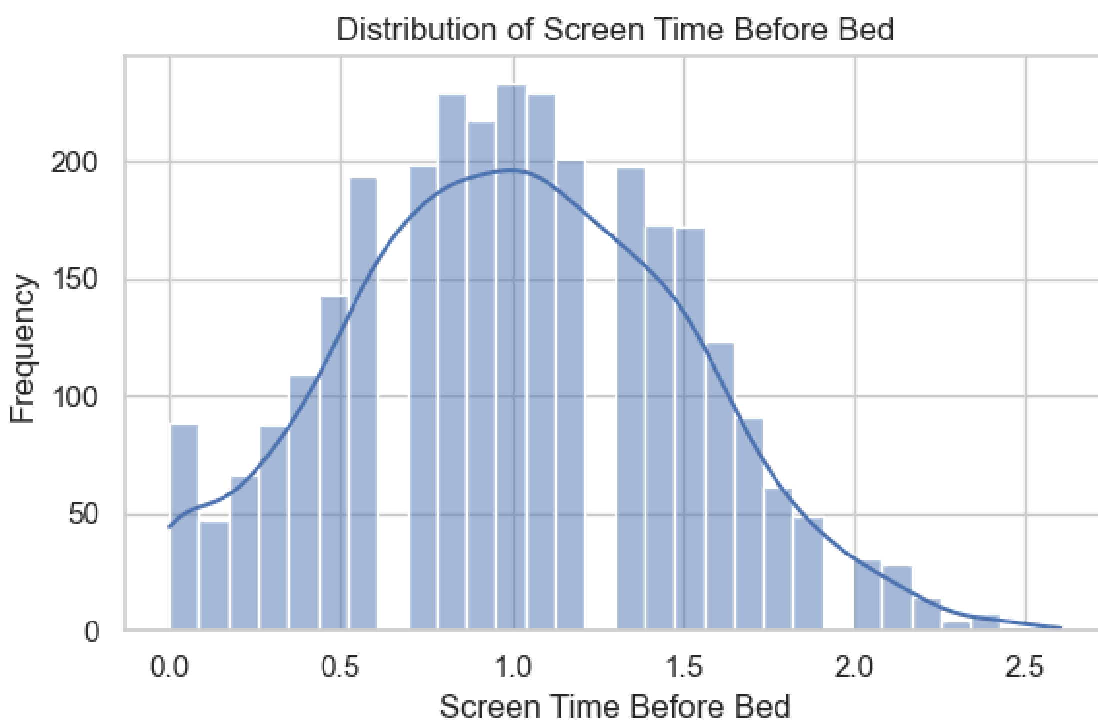
```
all_features = usage_features + mental_health_features +
lifestyle_features + academic_feature

for col in all_features:
    plt.figure(figsize=(6, 4))
    sns.histplot(data[col], bins=30, kde=True)
    plt.title(f"Distribution of {col.replace('_', ' ')}")
    plt.xlabel(col.replace('_', ' '))
    plt.ylabel("Frequency")
    plt.tight_layout()
    plt.show()
```

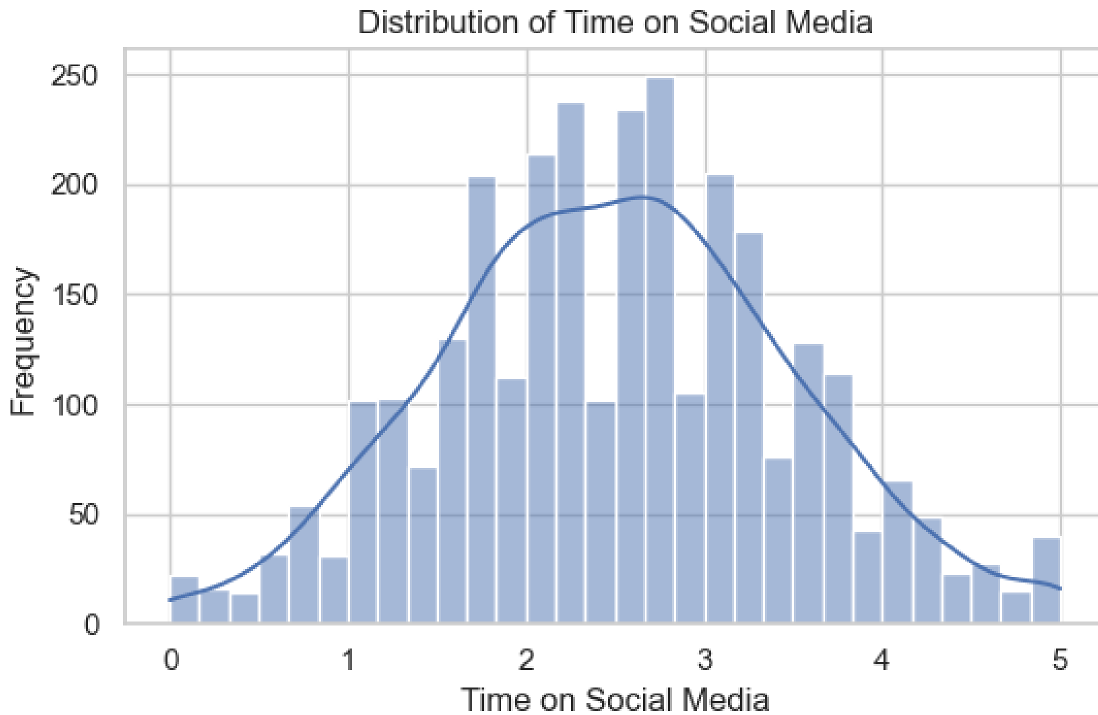


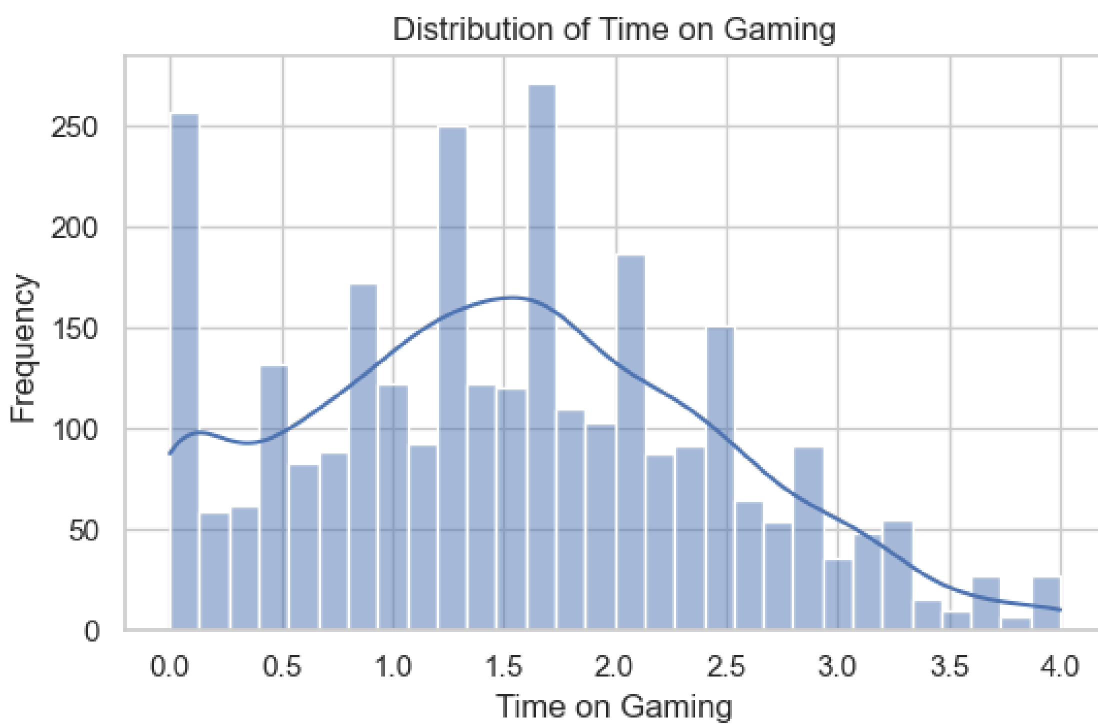

Distribution of Weekend Usage Hours
Frequency
300
250
200
150
100
50
0
0
2
4
6
8
10
12
14
Weekend Usage Hours

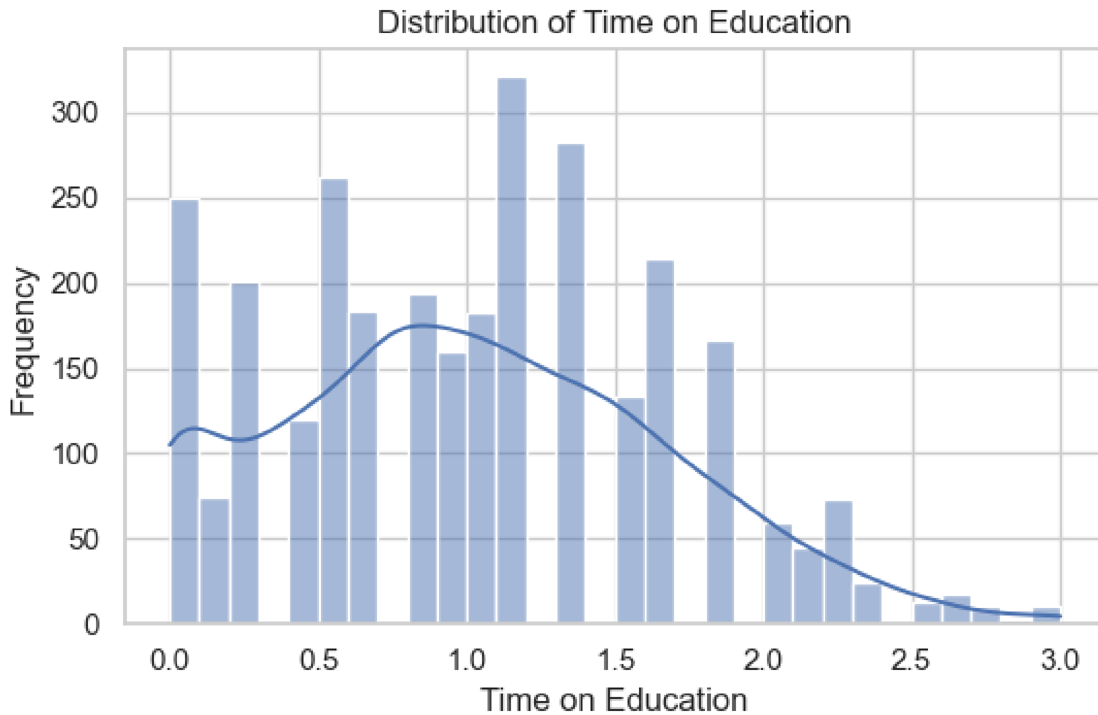

Distribution of Phone Checks Per Day
Frequency
120
100
80
60
40
20
0
20
40
60
80
100
120
140
Phone Checks Per Day

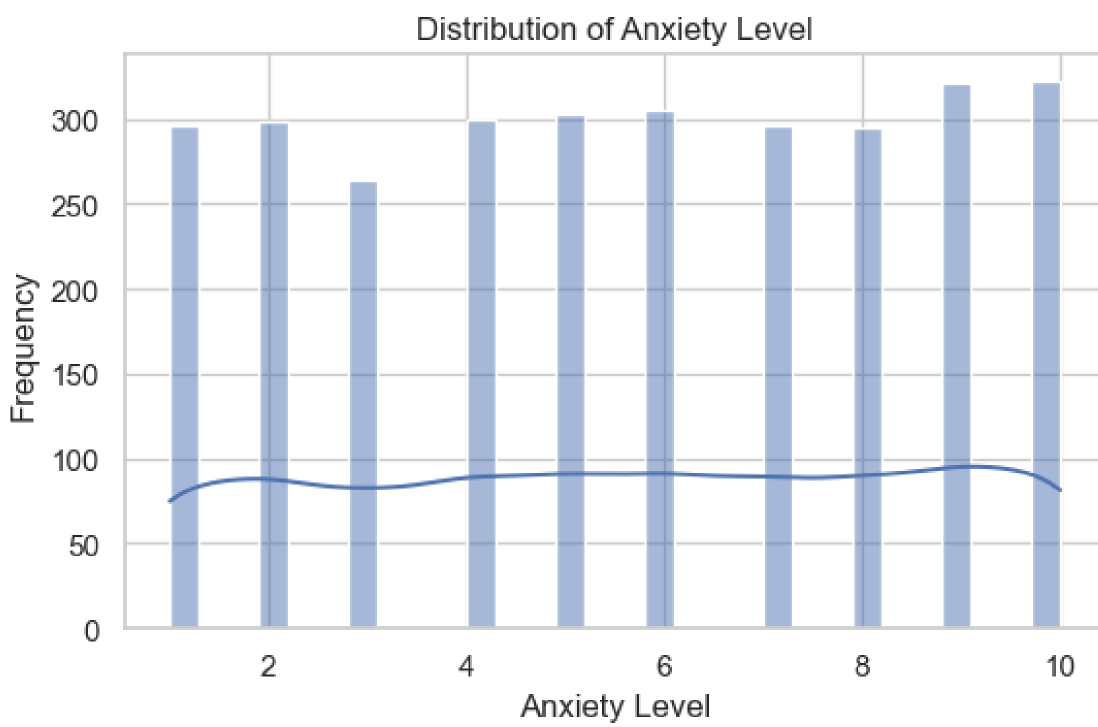

Distribution of Apps Used Daily
Frequency
0
25
50
75
100
125
150
175
200
6
8
10
12
14
16
18
20
Apps Used Daily

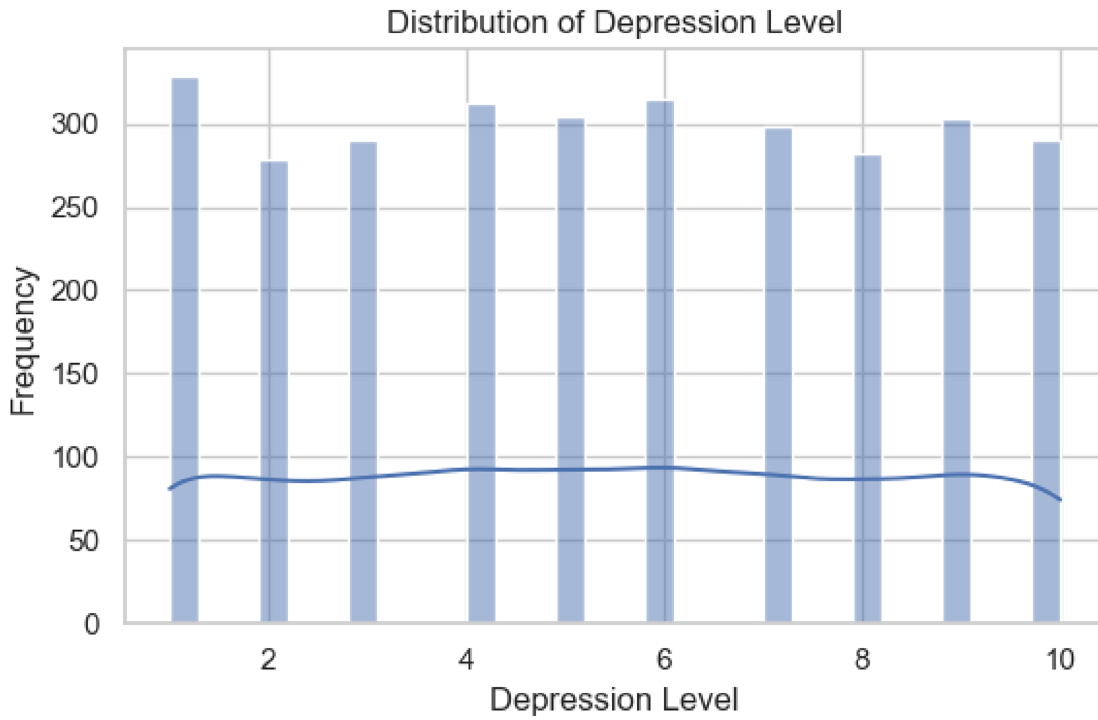

Distribution of Screen Time Before Bed
Frequency
0
50
100
150
200
0.0
0.5
1.0
1.5
2.0
2.5
Screen Time Before Bed

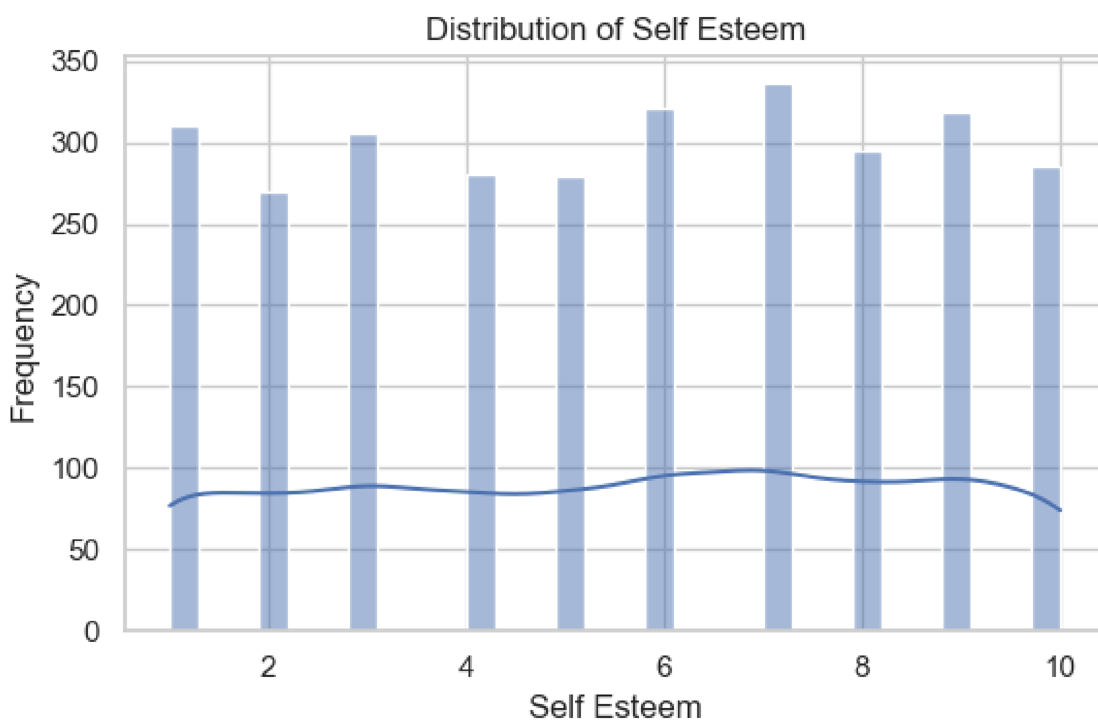

Distribution of Time on Social Media
Frequency
0
50
100
150
200
250
0
1
2
3
4
5
Time on Social Media

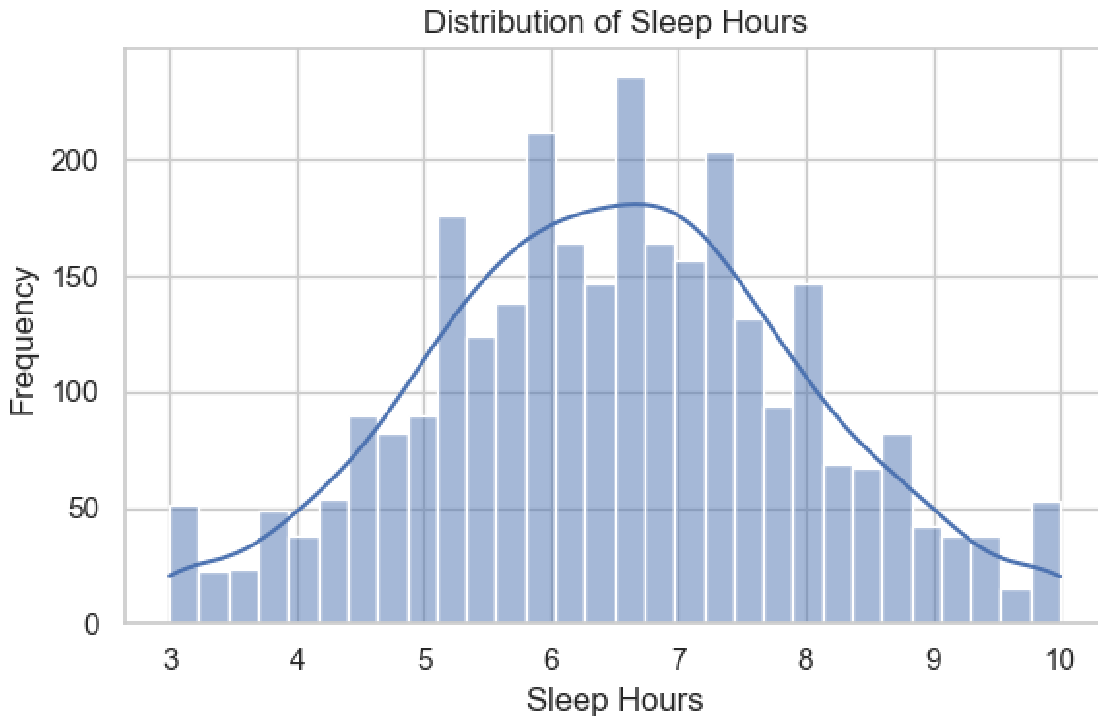

Distribution of Time on Gaming
Frequency
0
50
100
150
200
250
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Time on Gaming

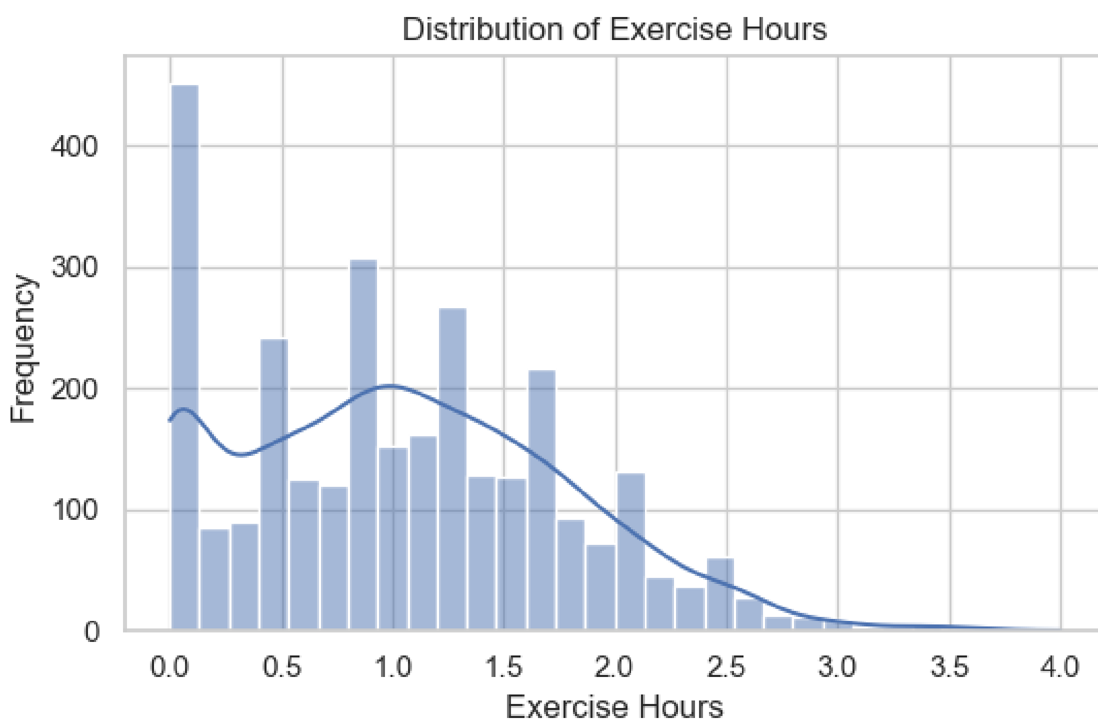

Distribution of Time on Education
Frequency
300
250
200
150
100
50
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Time on Education

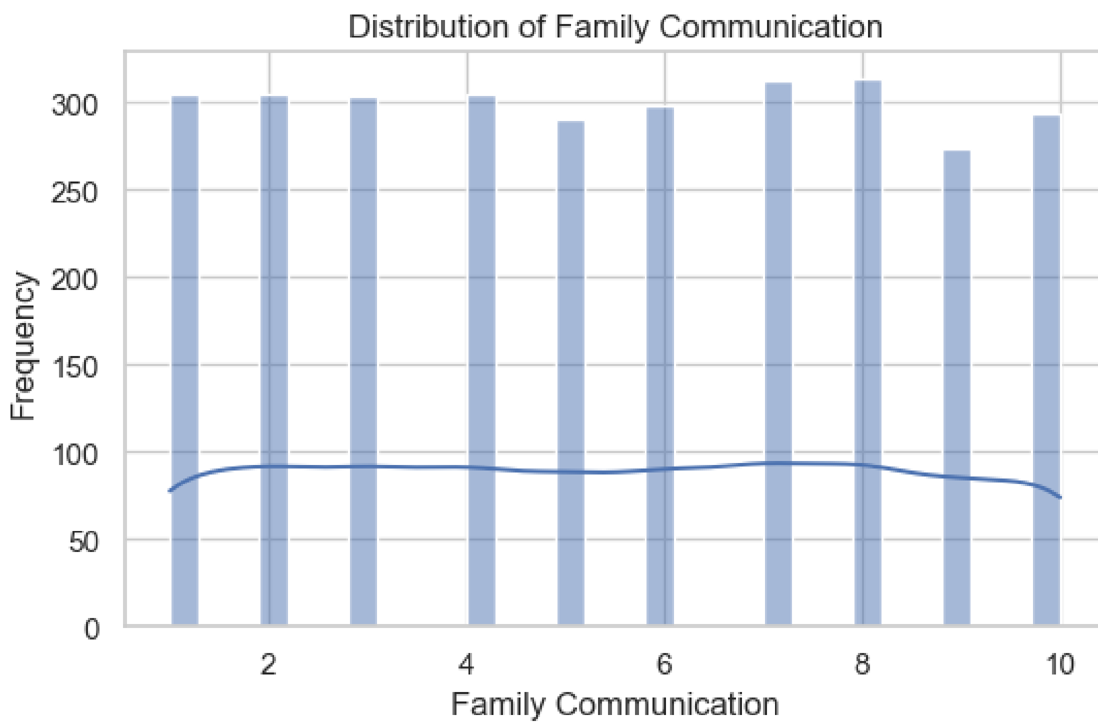

Distribution of Anxiety Level
Frequency
300
250
200
150
100
50
0
2
4
6
8
10
Anxiety Level

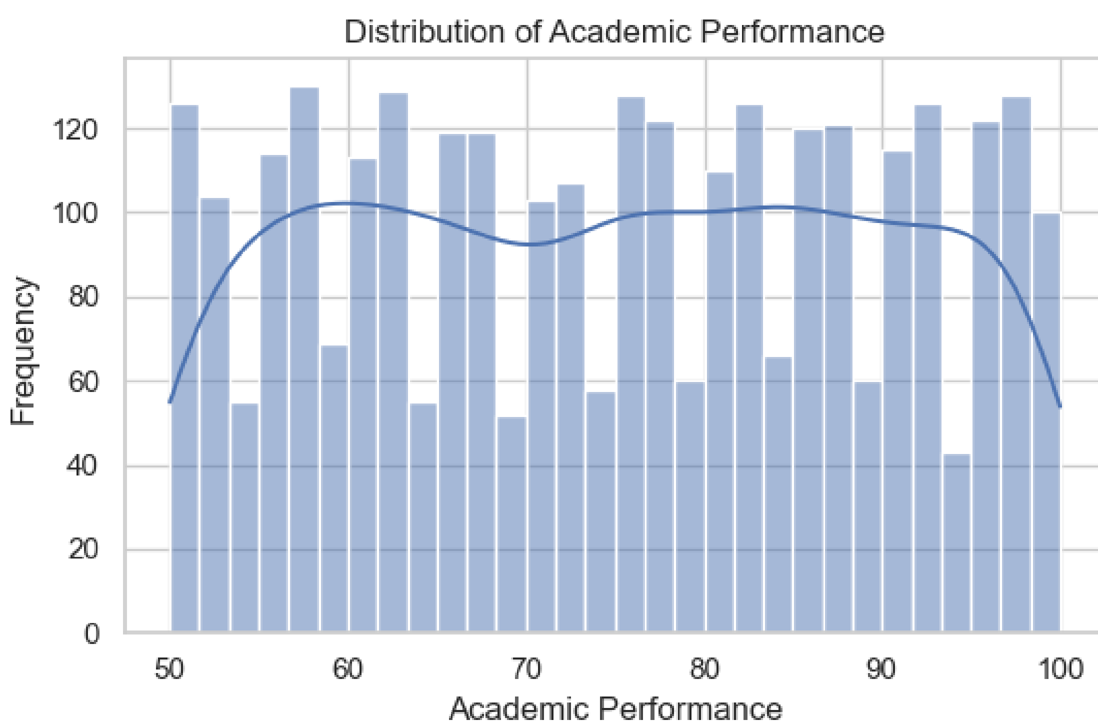

Distribution of Depression Level
Frequency
0
50
100
150
200
250
300
2
4
6
8
10
Depression Level


Distribution of Self Esteem
Frequency
0
50
100
150
200
250
300
350
2
4
6
8
10
Self Esteem


Distribution of Sleep Hours
Frequency
0
50
100
150
200
3
4
5
6
7
8
9
10
Sleep Hours


Distribution of Exercise Hours
Frequency
0
100
200
300
400
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Exercise Hours

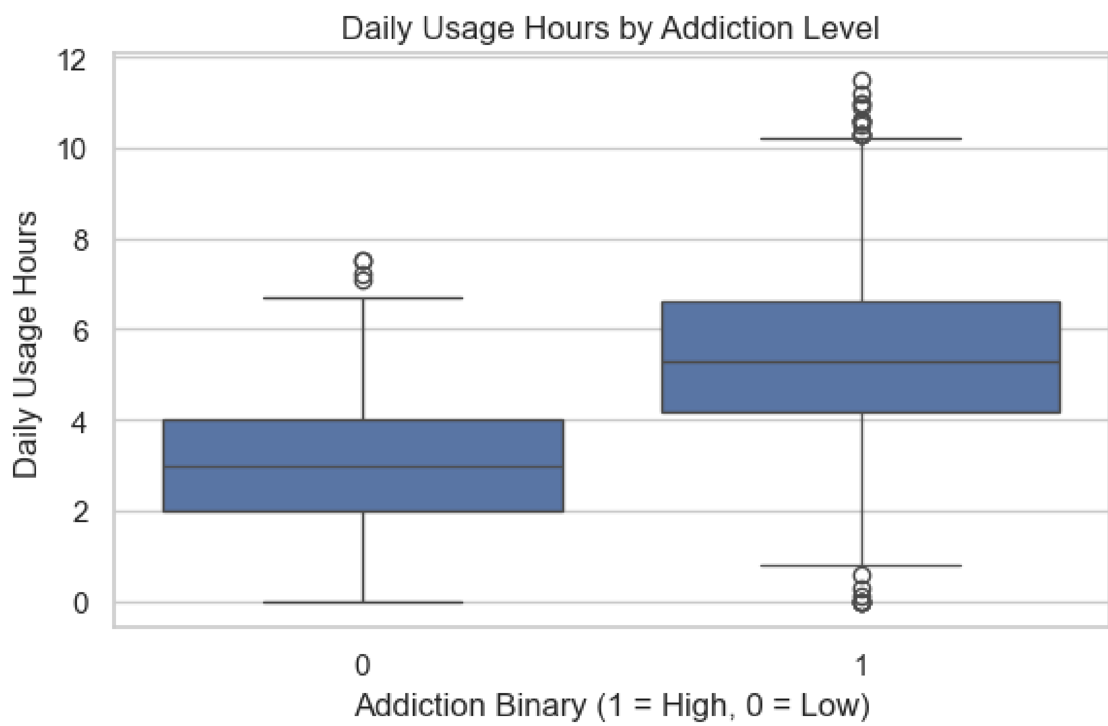


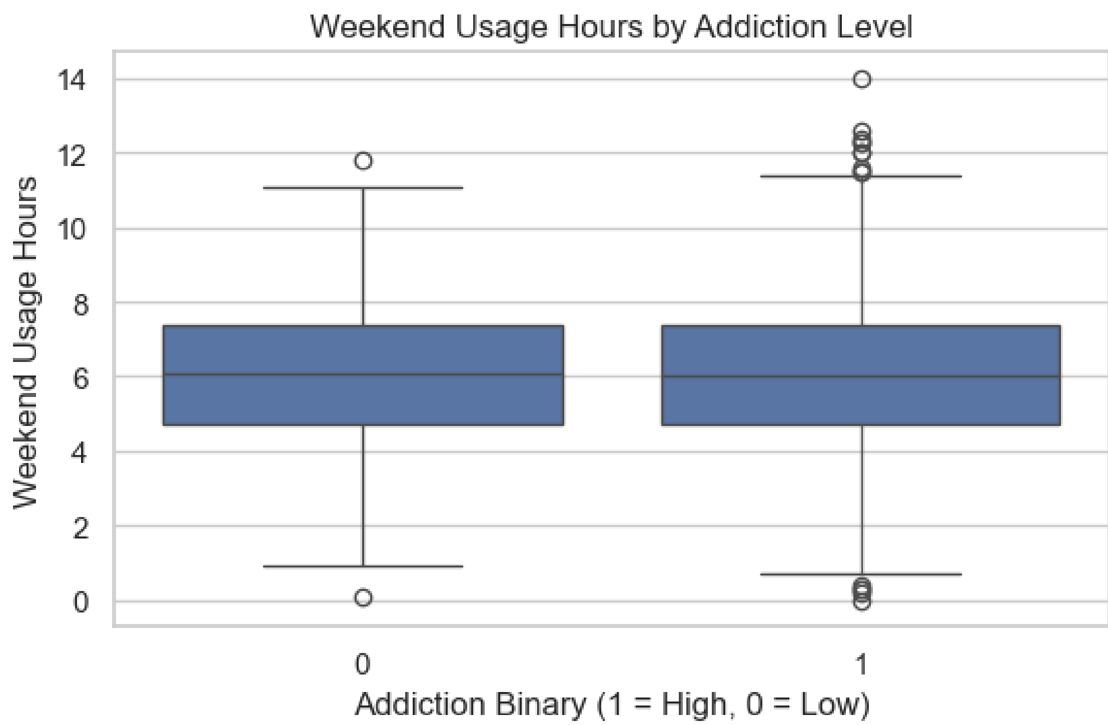


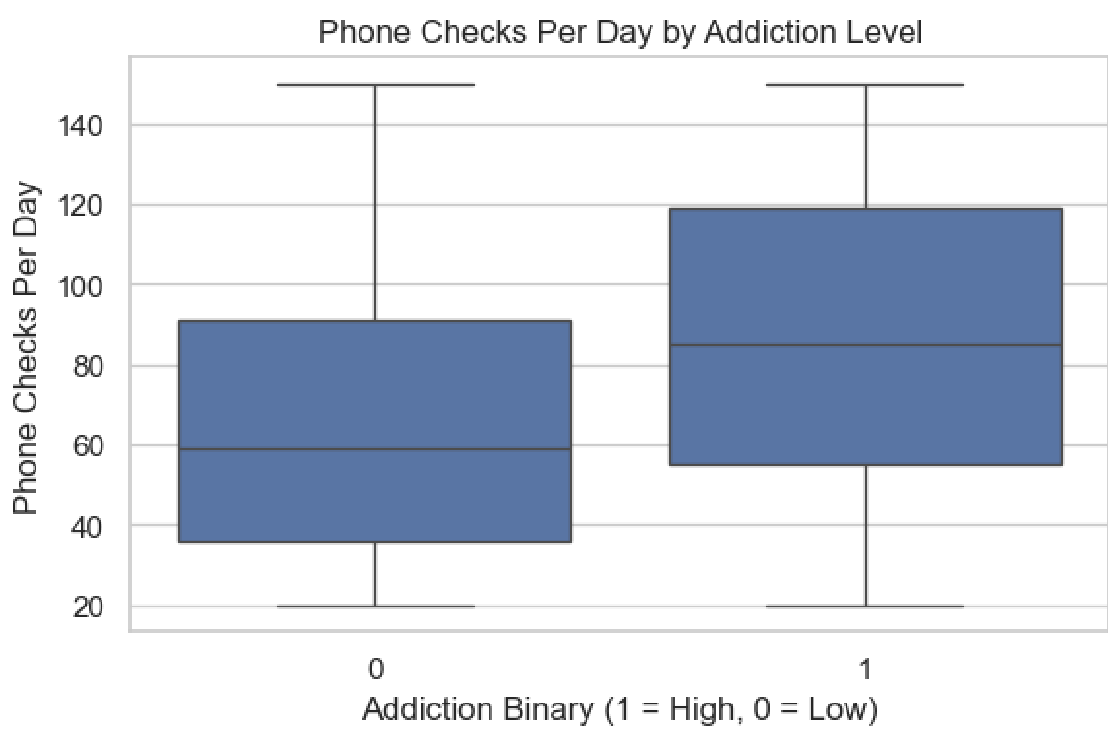
2.4 Bivariate Analysis & Statistical Testing

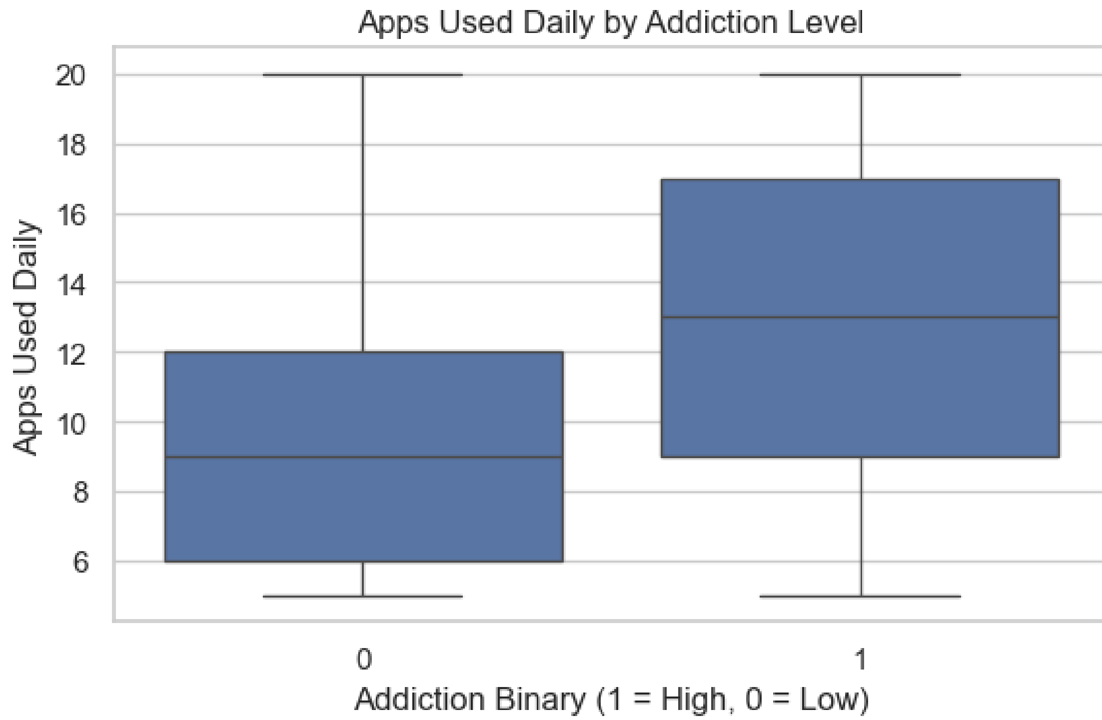
```
# Box plot by addiction Binary

for col in all_features:
```

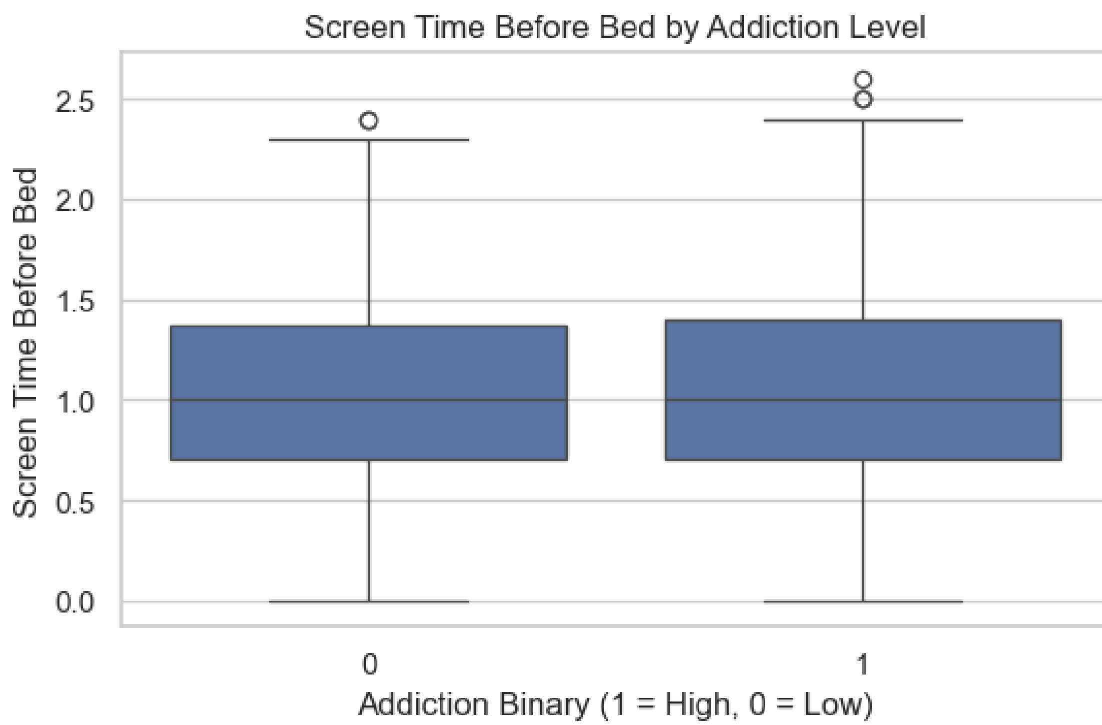
```
plt.figure(figsize=(6, 4))
sns.boxplot(x="Addiction_Binary", y=col, data=data)
plt.title(f"{col.replace('_', ' ')} by Addiction Level")
plt.xlabel("Addiction Binary (1 = High, 0 = Low)")
plt.ylabel(col.replace('_', ' '))
plt.tight_layout()
plt.show()
```

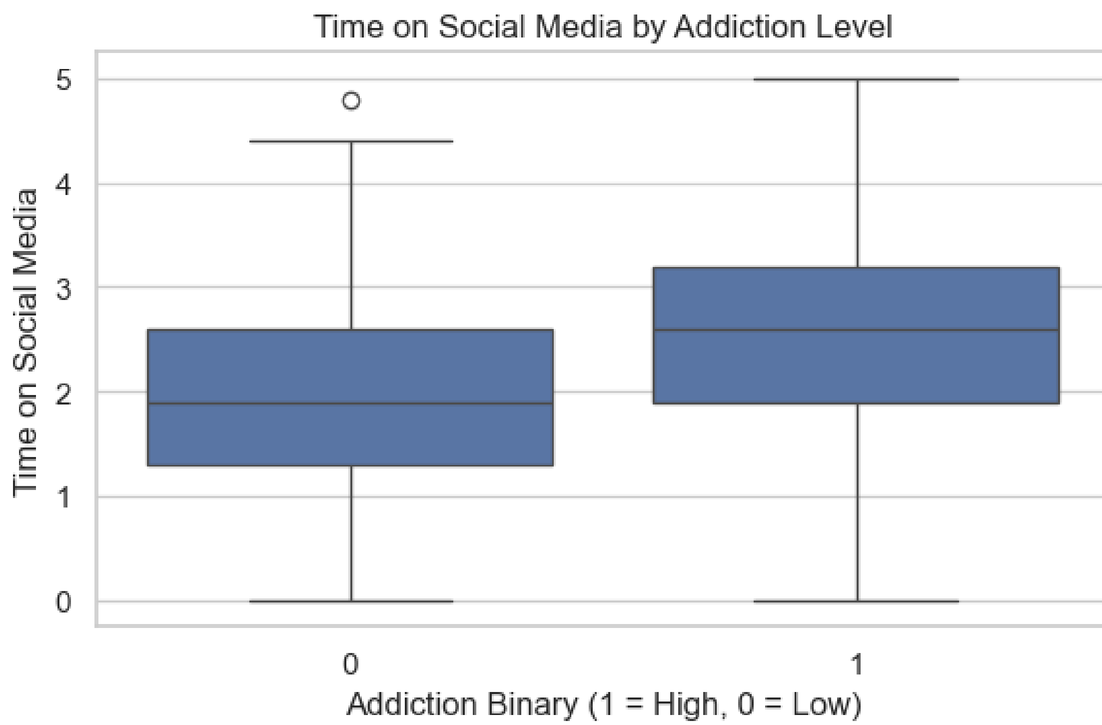


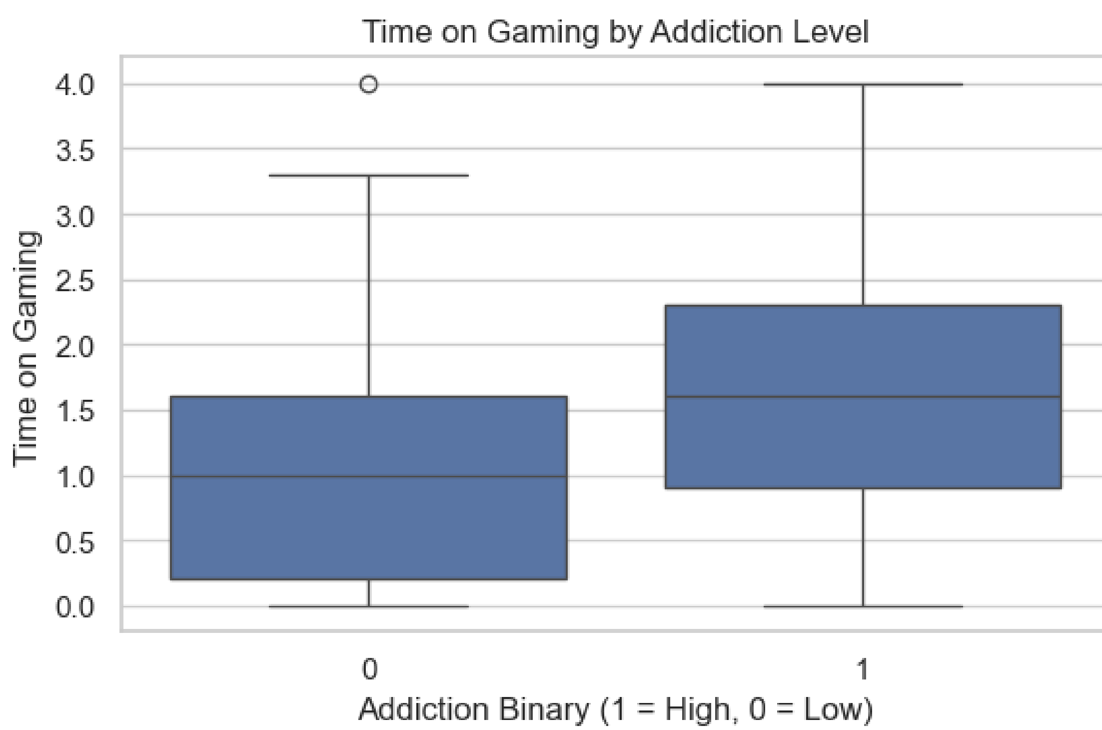

Weekend Usage Hours by Addiction Level
Weekend Usage Hours
14
12
10
8
6
4
2
0
0
1
Addiction Binary (1 = High, 0 = Low)

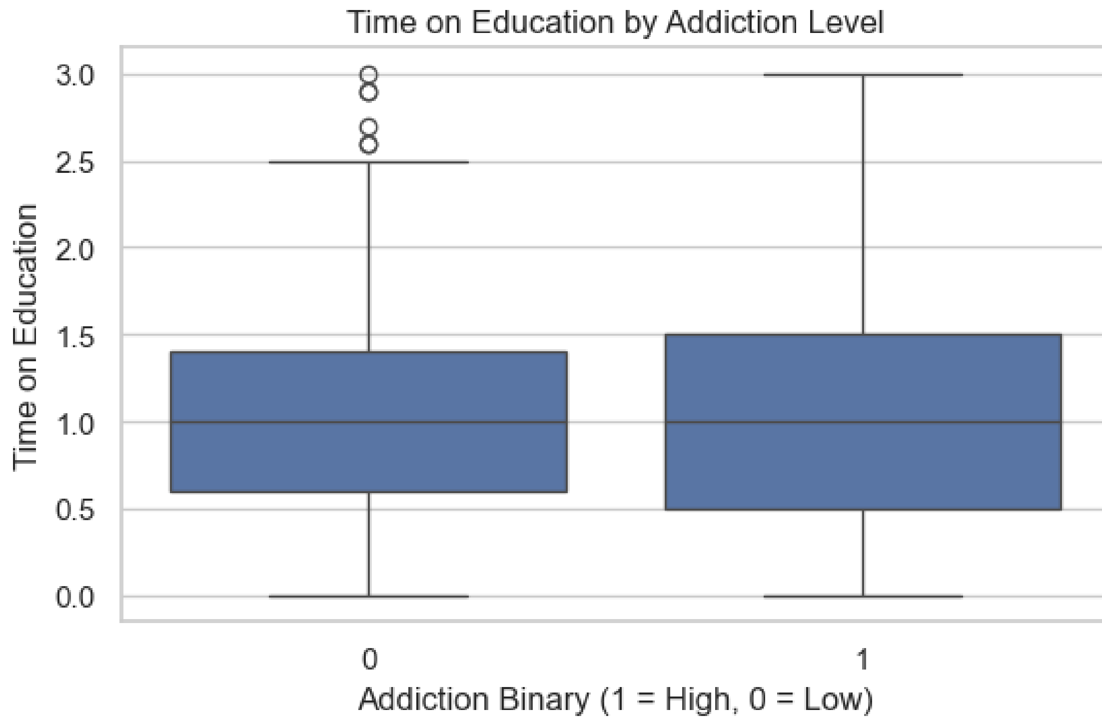

Phone Checks Per Day by Addiction Level
Phone Checks Per Day
140
120
100
80
60
40
20
0
1
Addiction Binary (1 = High, 0 = Low)

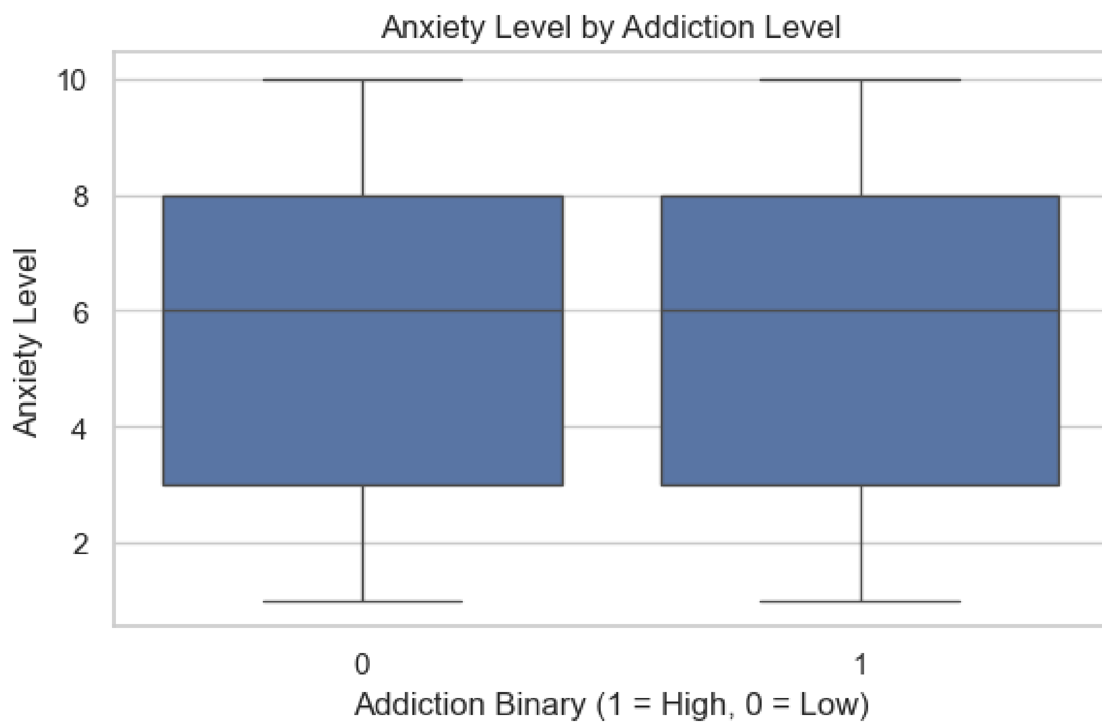

Apps Used Daily by Addiction Level
Apps Used Daily
20
18
16
14
12
10
8
6
0
1
Addiction Binary (1 = High, 0 = Low)

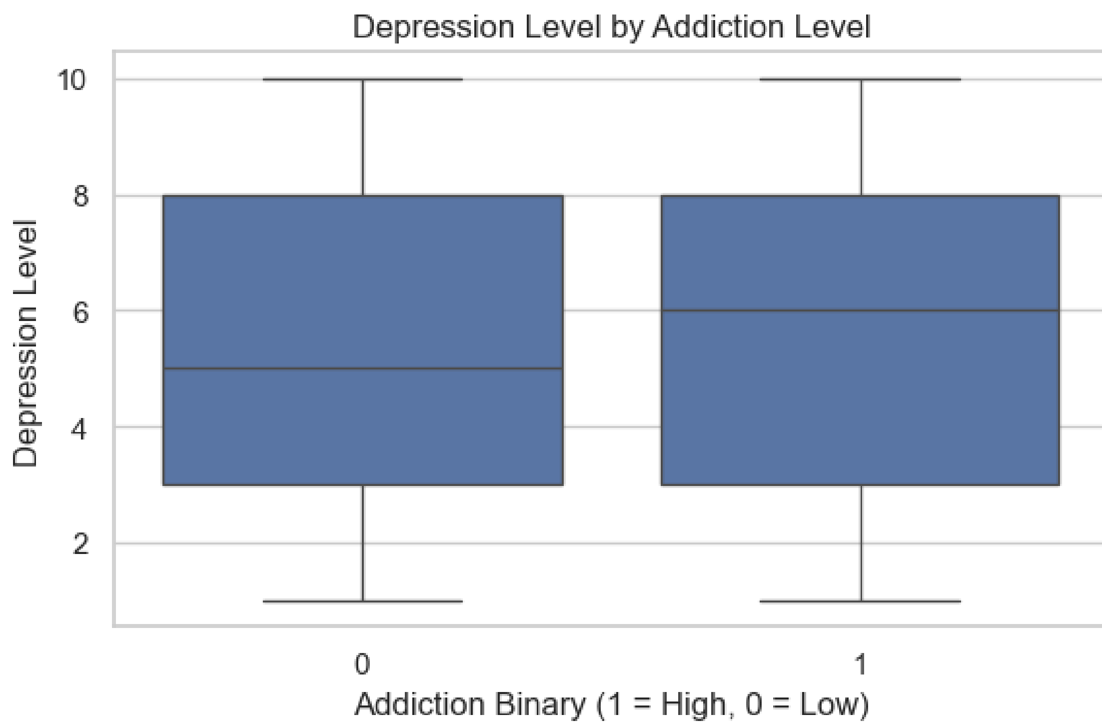

Screen Time Before Bed by Addiction Level
Screen Time Before Bed
2.5
2.0
1.5
1.0
0.5
0.0
0
1
Addiction Binary (1 = High, 0 = Low)

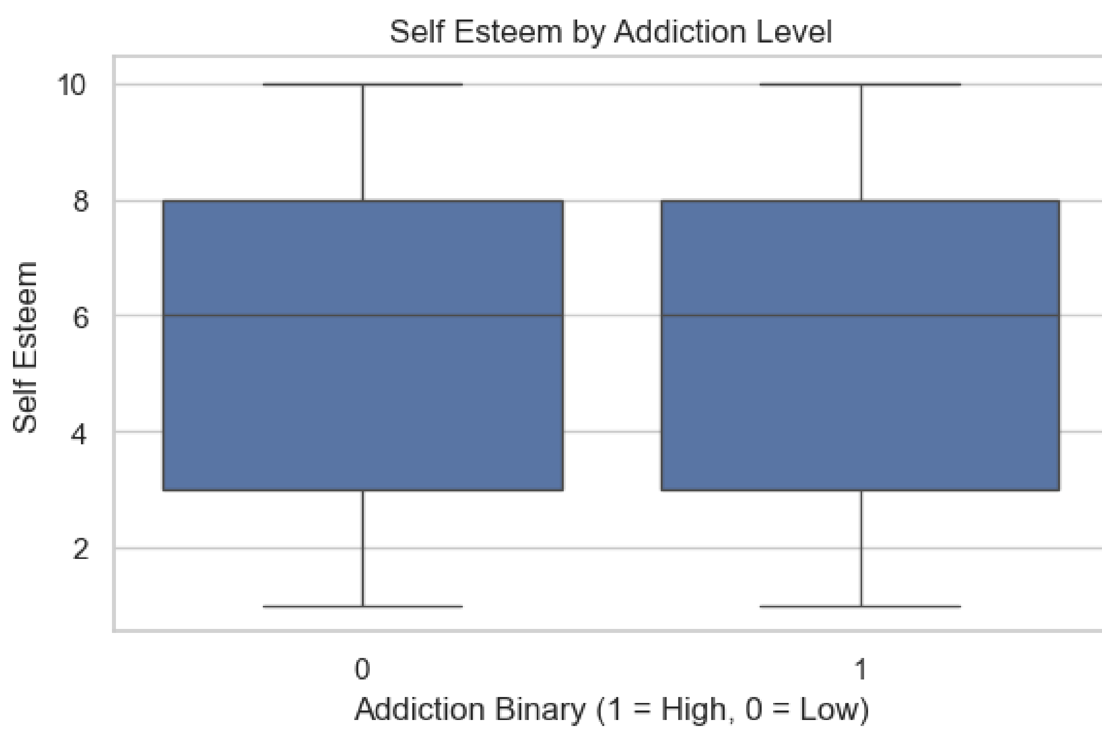

Time on Social Media by Addiction Level
Time on Social Media
0
1
2
3
4
5
0
1
Addiction Binary (1 = High, 0 = Low)

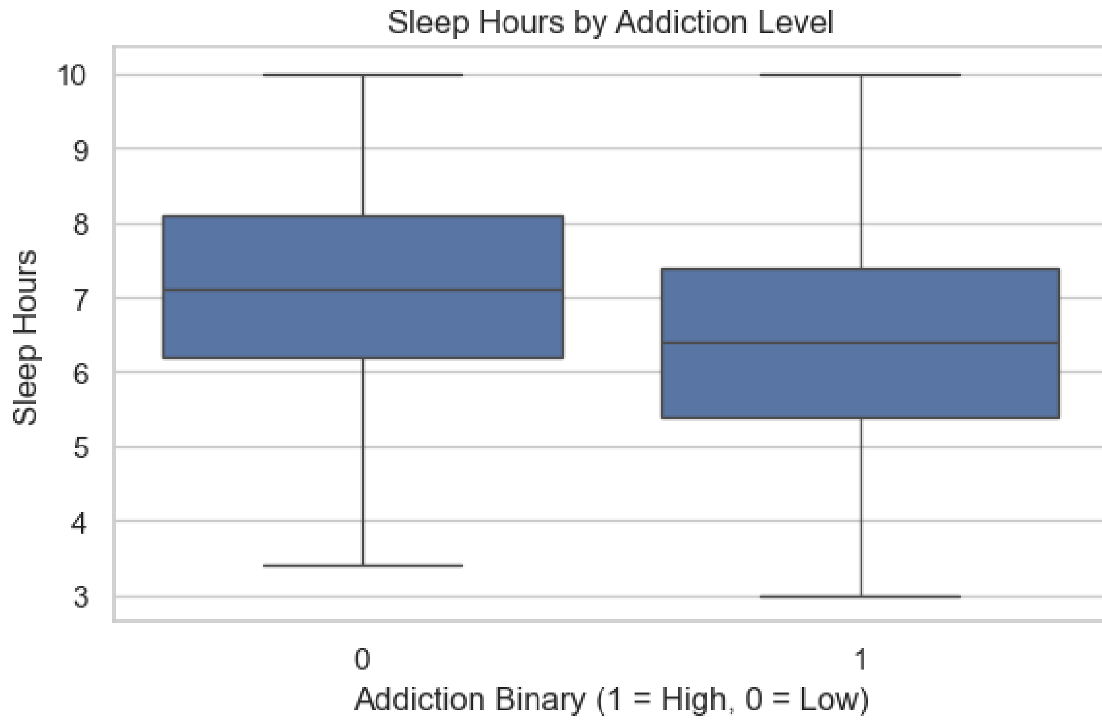

Time on Gaming by Addiction Level
Time on Gaming
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
0
1
Addiction Binary (1 = High, 0 = Low)

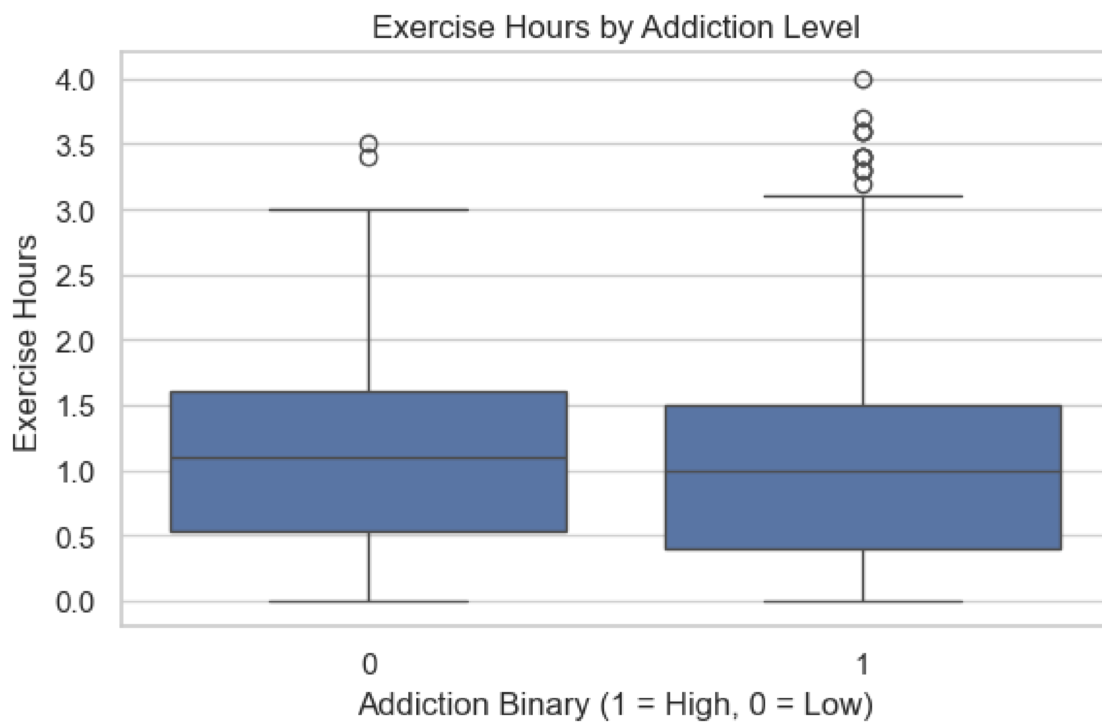

Time on Education by Addiction Level
Time on Education
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
1
Addiction Binary (1 = High, 0 = Low)

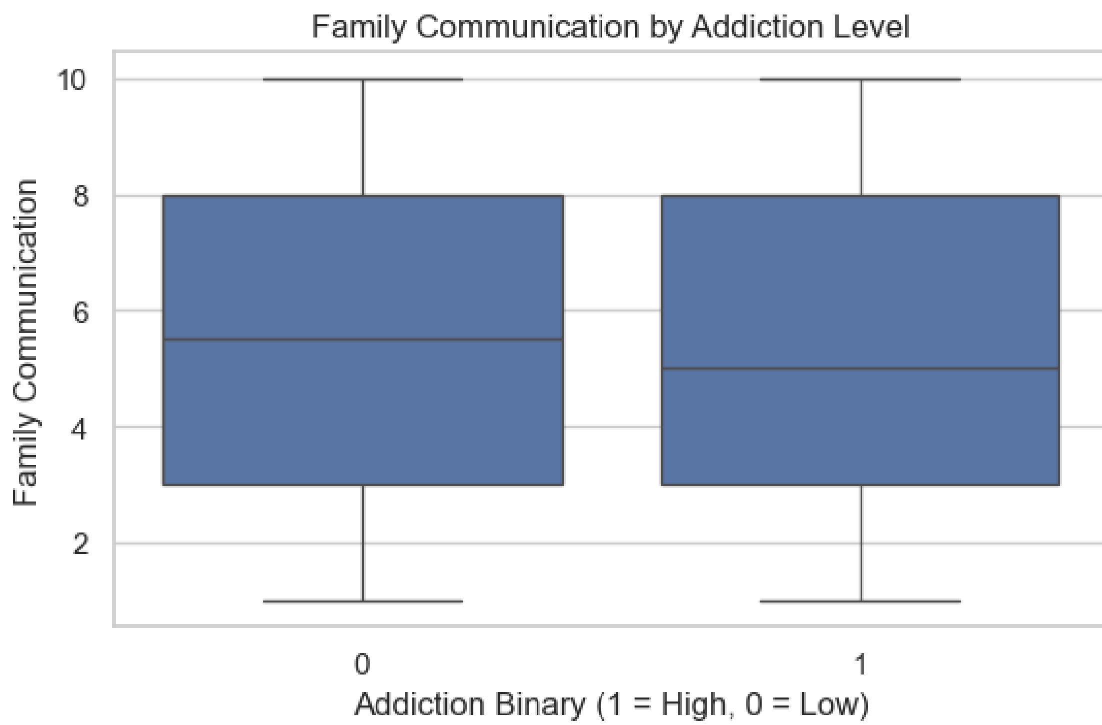

Anxiety Level by Addiction Level
Anxiety Level
10
8
6
4
2
0
1
Addiction Binary (1 = High, 0 = Low)

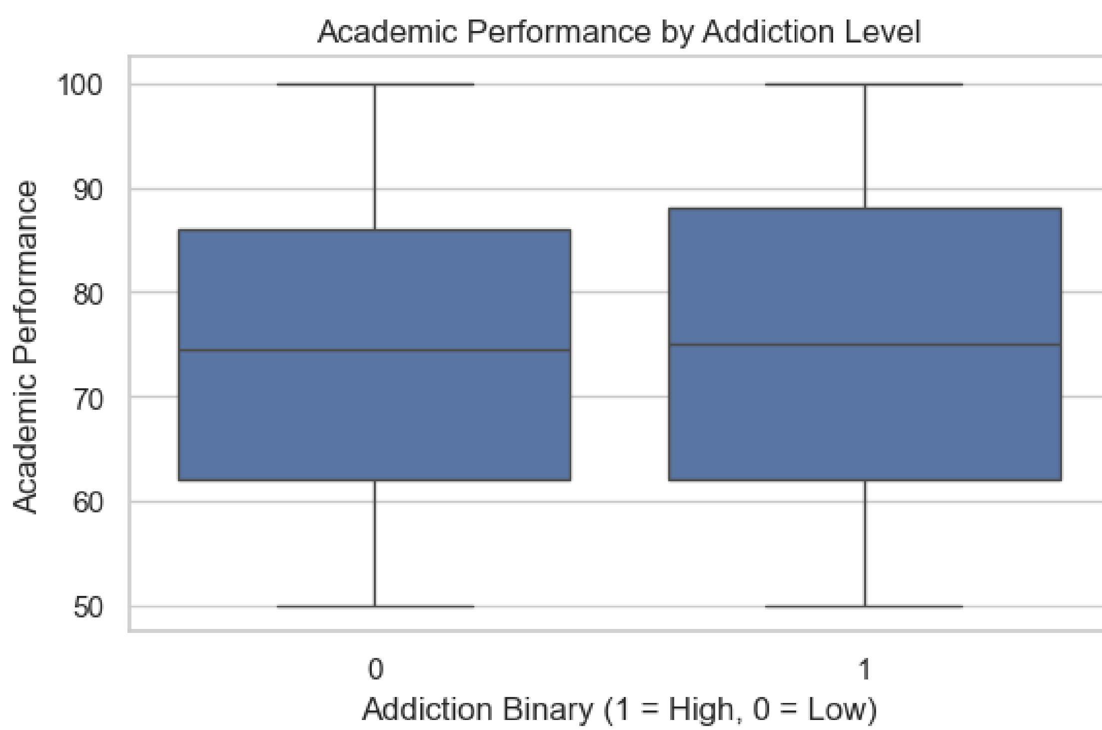

Depression Level by Addiction Level
10
8
6
4
2
Depression Level
0
1
Addiction Binary (1 = High, 0 = Low)


Self Esteem by Addiction Level
10
8
6
4
2
Self Esteem
0
1
Addiction Binary (1 = High, 0 = Low)


Sleep Hours by Addiction Level
Sleep Hours
10
9
8
7
6
5
4
3
0
1
Addiction Binary (1 = High, 0 = Low)


Exercise Hours by Addiction Level
Exercise Hours
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
1
Addiction Binary (1 = High, 0 = Low)





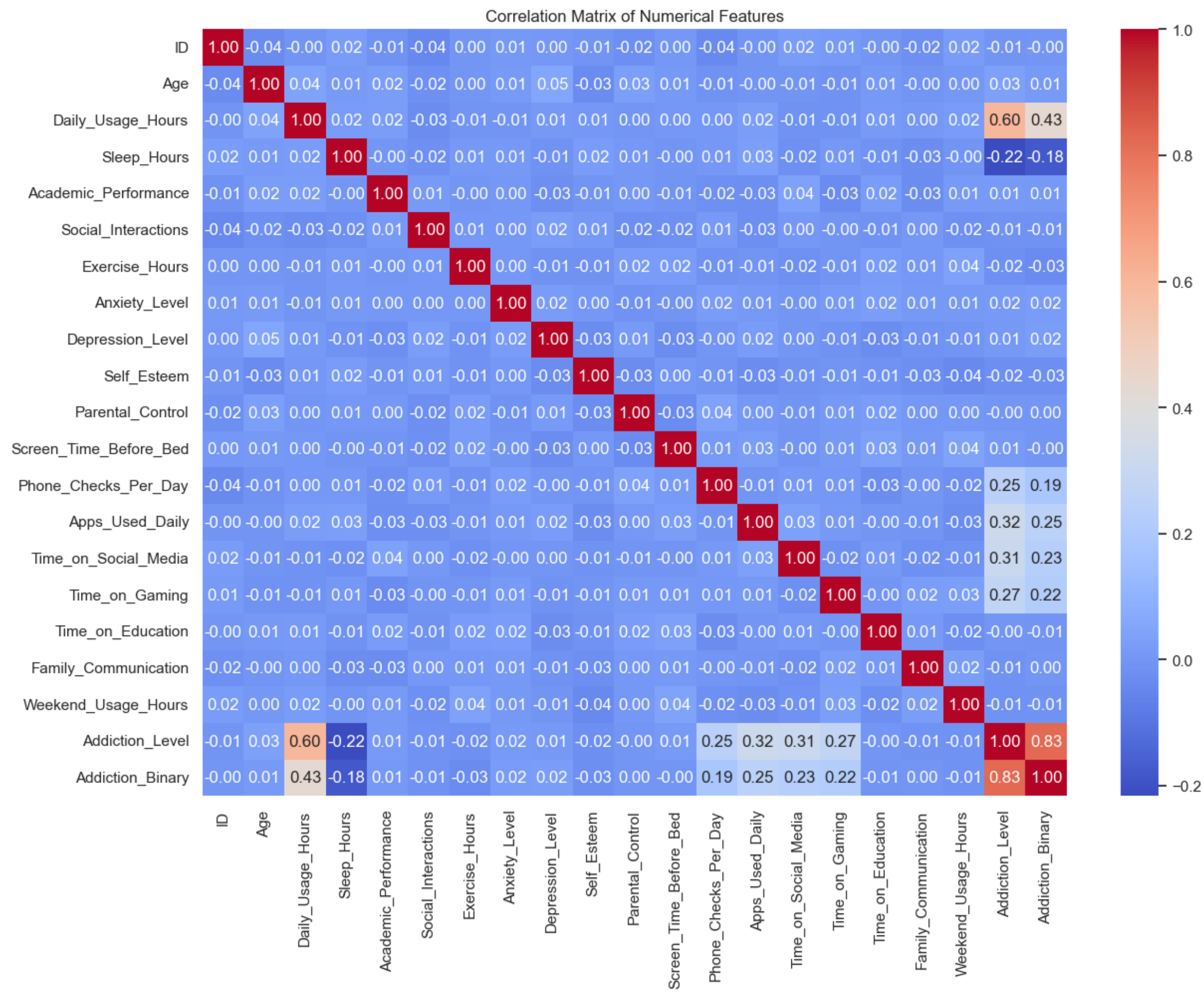

```
# T-Tests

# Split data by addiction level
high = data[data["Addiction_Binary"] == 1]
```

```
low = data[data["Addiction_Binary"] == 0]

# Run t-tests
from scipy.stats import ttest_ind

print("T-test Results:\n")
for col in all_features:
    t_stat, p_val = ttest_ind(high[col], low[col])
    print(f"{col}: t-stat = {t_stat:.3f}, p-value = {p_val:.5f}")
```

```
T-test Results:

Daily_Usage_Hours: t-stat = 26.349, p-value = 0.00000
Weekend_Usage_Hours: t-stat = -0.542, p-value = 0.58813
Phone_Checks_Per_Day: t-stat = 10.493, p-value = 0.00000
Apps_Used_Daily: t-stat = 14.144, p-value = 0.00000
Screen_Time_Before_Bed: t-stat = -0.083, p-value = 0.93389
Time_on_Social_Media: t-stat = 13.105, p-value = 0.00000
Time_on_Gaming: t-stat = 12.438, p-value = 0.00000
Time_on_Education: t-stat = -0.278, p-value = 0.78087
Anxiety_Level: t-stat = 0.961, p-value = 0.33655
Depression_Level: t-stat = 1.167, p-value = 0.24320
Self_Esteem: t-stat = -1.423, p-value = 0.15471
Sleep_Hours: t-stat = -10.017, p-value = 0.00000
Exercise_Hours: t-stat = -1.751, p-value = 0.07997
Family_Communication: t-stat = 0.072, p-value = 0.94272
Academic_Performance: t-stat = 0.606, p-value = 0.54434
```

2.5 Correlation Matrix

```
# Correlation heatmap
plt.figure(figsize=(14, 10))
sns.heatmap(data.corr(numeric_only=True), annot=True, fmt=".2f",
cmap="coolwarm")
plt.title("Correlation Matrix of Numerical Features")
plt.show()
```




```python
# Print correlation with target variable only
correlations = data.corr(numeric_only=True)
["Addiction_Binary"].sort_values(ascending=False)
print("Correlation with Addiction_Binary:\n", correlations)
```

```
Correlation with Addiction_Binary:
 Addiction_Binary          1.000000
Addiction_Level          0.827273
Daily_Usage_Hours        0.433626
Apps_Used_Daily          0.250108
Time_on_Social_Media     0.232770
Time_on_Gaming           0.221513
Phone_Checks_Per_Day     0.188220
Depression_Level         0.021313
Anxiety_Level            0.017551
Age                      0.013411
Academic_Performance     0.011073
Family_Communication     0.001312
Parental_Control         0.000507
```

```
Screen_Time_Before_Bed   -0.001515
ID                       -0.002694
Time_on_Education        -0.005081
Weekend_Usage_Hours      -0.009891
Social_Interactions      -0.009982
Self_Esteem              -0.025988
Exercise_Hours           -0.031971
Sleep_Hours              -0.179956
Name: Addiction_Binary, dtype: float64
```

Model Preperation

```
# Model Prep:
X = pd.get_dummies(data.drop(["ID", "Name", "Addiction_Level",
"Addiction_Binary"], axis=1), drop_first=True)
y = data["Addiction_Binary"]

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

smote = SMOTE(random_state=42)
X_train_balanced, y_train_balanced = smote.fit_resample(X_train,
y_train)

print(y_train_balanced.value_counts())

# Here we start with converting categorical variables to 1's and 0's
and storing them in x as features. This is one
# hot encoding, which allows models to better understand the data. The
ID and name column are dropped as they provide
# no predictive power. Addiction level is removed since we are using
low and high categories instead of the number
# ratings 1-10. Addiction binary is removed as this is the target
variable that we need to store in y not in x where
# the features are. Drop first is set to true to avoid dummy variable
trap. Then the data is split into train and test
# sets, 80% training, 20% testing. Stratify Y esnsures the split
maintains the same proportion of high and low
# addiction levels in both sets. Random state = 42 is for
reproducibility. Then SMOTE is applied to balance the training
# dataset. We then print the value counts of each addiction level to
be sure they are the same.
```

```
/Users/mostafazamaniturk/Library/Python/3.9/lib/python/site-packages/
sklearn/base.py:474: FutureWarning: `BaseEstimator._validate_data` is
deprecated in 1.6 and will be removed in 1.7. Use
`sklearn.utils.validation.validate_data` instead. This function
becomes public and is part of the scikit-learn developer API.
  warnings.warn(
```

```
Addiction_Binary
1    2043
0    2043
Name: count, dtype: int64
```

Logistic Regression Model

```
# Logistic Regression Model
log_reg = LogisticRegression(max_iter=2000)
log_reg.fit(X_train_balanced, y_train_balanced)
predictions_log_reg = log_reg.predict(X_test)

print("Logistic Regression Summary: \n")
print(classification_report(y_test, predictions_log_reg))
print("Adjusted Rand Index: ", round(adjusted_rand_score(y_test,
predictions_log_reg), 4))

# Here we initialize the logistic regression model and set max
iterations to 2000 to allow more iterations to converge
# in training. This helps with large datasets. Then model training is
done using the SMOTE balanced training data. Then the
# model is used to predict the addiction risk on the unseen test
dataset. Then the classification report of the model is
# outputted. Then the ARI is calculated and outputted.
```

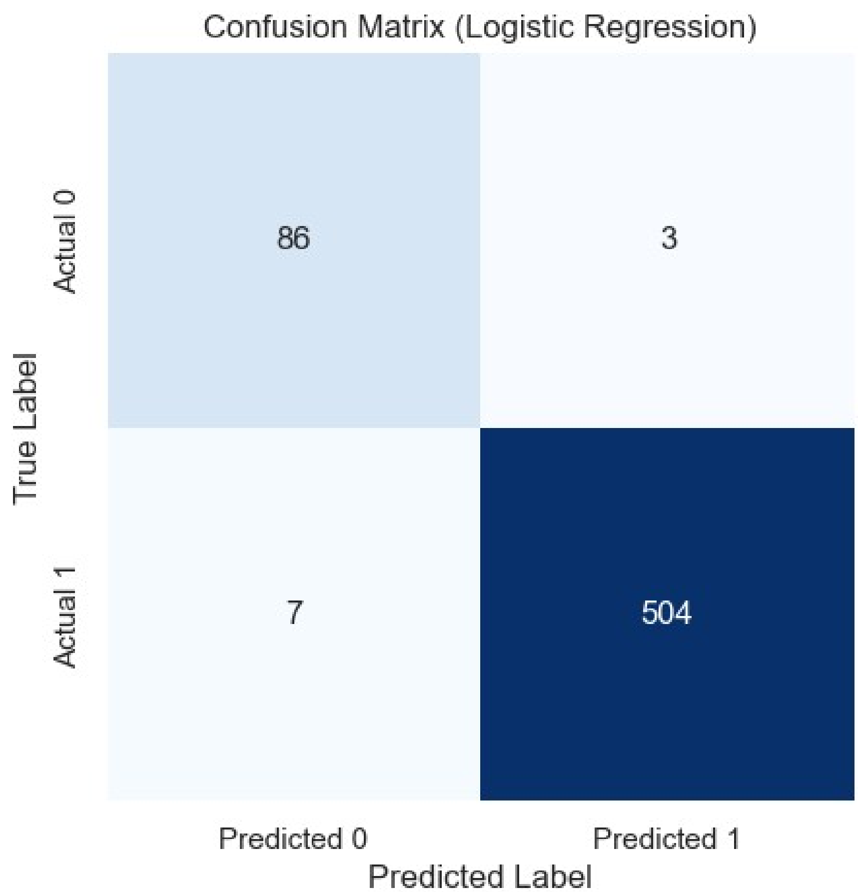
```
Logistic Regression Summary: 

              precision    recall  f1-score   support

           0       0.92      0.97      0.95        89
           1       0.99      0.99      0.99       511

    accuracy                           0.98       600
   macro avg       0.96      0.98      0.97       600
weighted avg       0.98      0.98      0.98       600

Adjusted Rand Index:  0.9142
```

```
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Compute the confusion matrix based on true labels and model
predictions.
cm = confusion_matrix(y_test, predictions_log_reg)
tn, fp, fn, tp = cm.ravel()

# Print each of the confusion matrix components to understand model
performance
print(f"True Negatives: {tn}")
```

```
print(f"False Positives: {fp}")
print(f"False Negatives: {fn}")
print(f"True Positives: {tp}")

# Define labels for axes and annotations (not directly used in heatmap
here)
group_names = [["True Neg", "False Pos"],
               ["False Neg", "True Pos"]]

# Set up the plot figure with specified size (width=6 inches, height=5
inches)
plt.figure(figsize=(6, 5))
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
xticklabels=["Predicted 0", "Predicted 1"],
            yticklabels=["Actual 0", "Actual 1"], cbar=False,
square=True)

# Add a title for the heatmap plot
plt.title("Confusion Matrix (Logistic Regression)")

# Label the x-axis as predicted class labels
plt.xlabel("Predicted Label")

# Label the y-axis as true class labels
plt.ylabel("True Label")

# Display the plot
plt.show()
```

```
True Negatives: 86
False Positives: 3
False Negatives: 7
True Positives: 504
```

```
<Figure size 600x500 with 0 Axes>
```



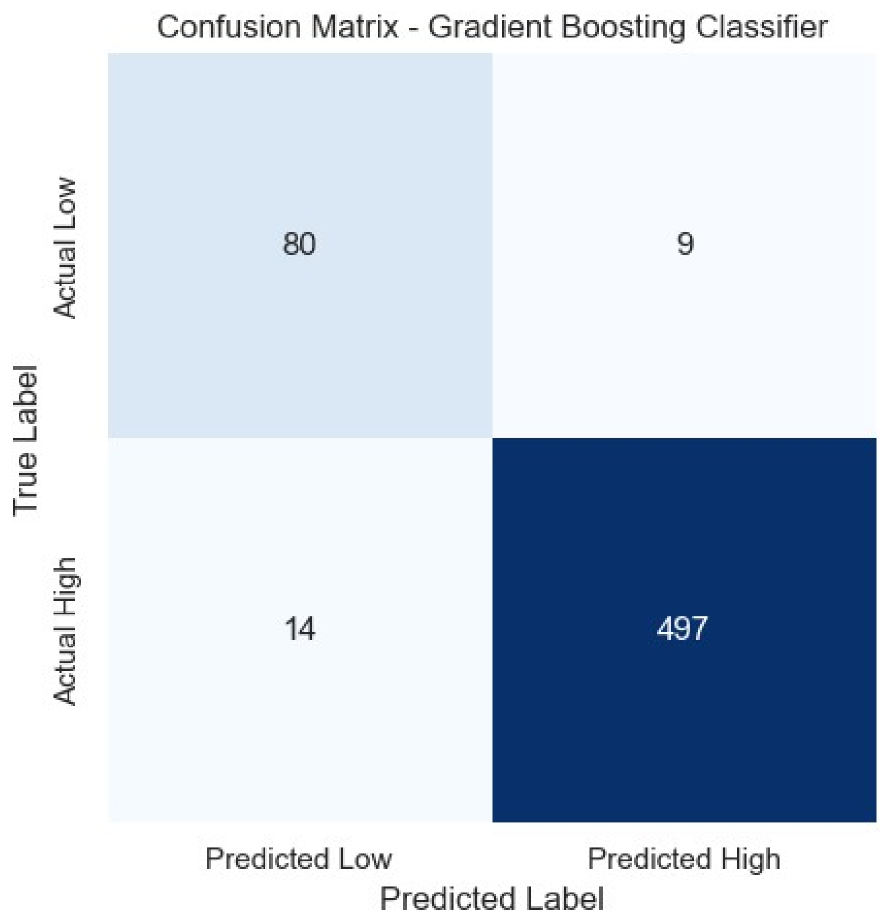
Gradient Boosting Model

```
# Gradient Boosting Model
gboost = GradientBoostingClassifier(random_state=42)
gboost.fit(X_train_balanced, y_train_balanced)
predictions_gboost = gboost.predict(X_test)

print("Gradient Boosting Summary: \n")
print(classification_report(y_test, predictions_gboost))
print("Adjusted Rand Index: ", round(adjusted_rand_score(y_test,
predictions_gboost), 4))

# Here we initialize the gradient boosting model. The random state is
42 for reproducibility. Then model training is
# done using the SMOTE balanced training data. Then the model is used
to predict the addiction risk on the unseen test
# dataset. Then the classification report of the model is outputted.
Then the ARI is calculated and outputted.

Gradient Boosting Summary:

              precision    recall  f1-score   support
```

```
           0       0.85      0.90      0.87        89
           1       0.98      0.97      0.98       511

    accuracy                           0.96       600
   macro avg       0.92      0.94      0.93       600
weighted avg       0.96      0.96      0.96       600

Adjusted Rand Index:  0.8076
```

```python
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# Generate confusion matrix
cm = confusion_matrix(y_test, predictions_gboost)
tn, fp, fn, tp = cm.ravel()

# Print values
print(f"True Negatives (TN): {tn}")
print(f"False Positives (FP): {fp}")
print(f"False Negatives (FN): {fn}")
print(f"True Positives (TP): {tp}")

# Plot confusion matrix heatmap
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted Low', 'Predicted High'],
            yticklabels=['Actual Low', 'Actual High'],
            square=True, cbar=False)

plt.title("Confusion Matrix - Gradient Boosting Classifier")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.tight_layout()
plt.show()
```

```
True Negatives (TN): 80
False Positives (FP): 9
False Negatives (FN): 14
True Positives (TP): 497
```

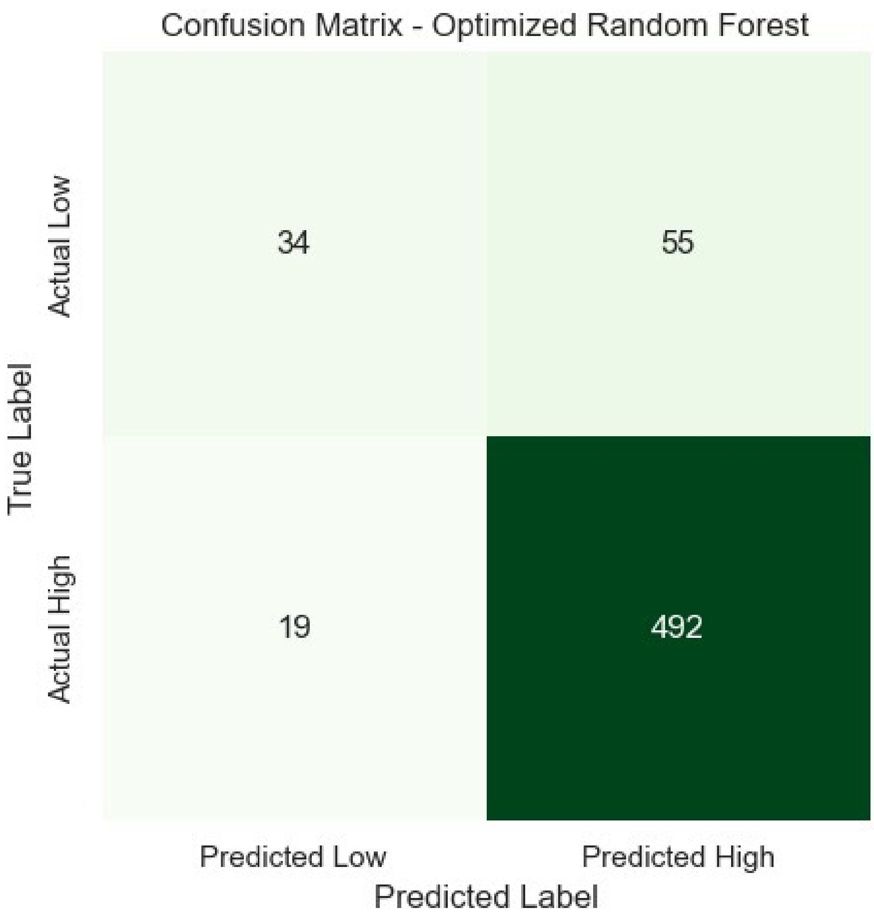


Random Forest Optimized Model

```
# Random Forest Optimized Model

rf = RandomForestClassifier(random_state=42)
parameters = {'n_estimators': [50, 100, 150], 'max_depth': [5, 10,
15]}
rf_optimized = RandomizedSearchCV(rf, parameters, n_iter=5, cv=3,
random_state=42)
rf_optimized.fit(X_train_balanced, y_train_balanced)
predictions_rf = rf_optimized.predict(X_test)

print("Random Forest Summary: \n")
print(classification_report(y_test, predictions_rf))
print("Adjusted Rand Index: ", round(adjusted_rand_score(y_test,
predictions_rf), 4))

# Here we initialize the random forest model. The random state is 42
for reproducibility. Then the parameters are set for optimization.
# The n_estimators allows us to run deifferent size trees to find the
optimal one, large tree can reduce variance. Max_depth allows
# us to control the depth of each tree, shallow trees can help avoid
```

```
overfitting. We then use randomized search to get best
hyperparameters.
# Here we feed the model, previous parameters for tree size/depth,
n_iter = 5 means 5 random combos are tried, cv = 3 performs 3 fold
# cross validation for each combo and random_state = 42 is for
reproducibility purposes. Then model training is
# done using the SMOTE balanced training data. Then the model is used
to predict the addiction risk on the unseen test
# dataset. Then the classification report of the model is outputted.
Then the ARI is calculated and outputted.

Random Forest Summary:

              precision    recall  f1-score   support

           0       0.64      0.38      0.48        89
           1       0.90      0.96      0.93       511

    accuracy                           0.88       600
   macro avg       0.77      0.67      0.70       600
weighted avg       0.86      0.88      0.86       600

Adjusted Rand Index:  0.3491

# Generate and print confusion matrix values
cm = confusion_matrix(y_test, predictions_rf)
tn, fp, fn, tp = cm.ravel()

print(f"\nConfusion Matrix Values:")
print(f"True Negatives (TN): {tn}")
print(f"False Positives (FP): {fp}")
print(f"False Negatives (FN): {fn}")
print(f"True Positives (TP): {tp}")

# Plot confusion matrix heatmap
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Greens',
            xticklabels=['Predicted Low', 'Predicted High'],
            yticklabels=['Actual Low', 'Actual High'],
            square=True, cbar=False)

plt.title("Confusion Matrix - Optimized Random Forest")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.tight_layout()
plt.show()


Confusion Matrix Values:
True Negatives (TN): 34
False Positives (FP): 55
```

```
False Negatives (FN): 19
True Positives (TP): 492
```



XGBoost Optimized Model

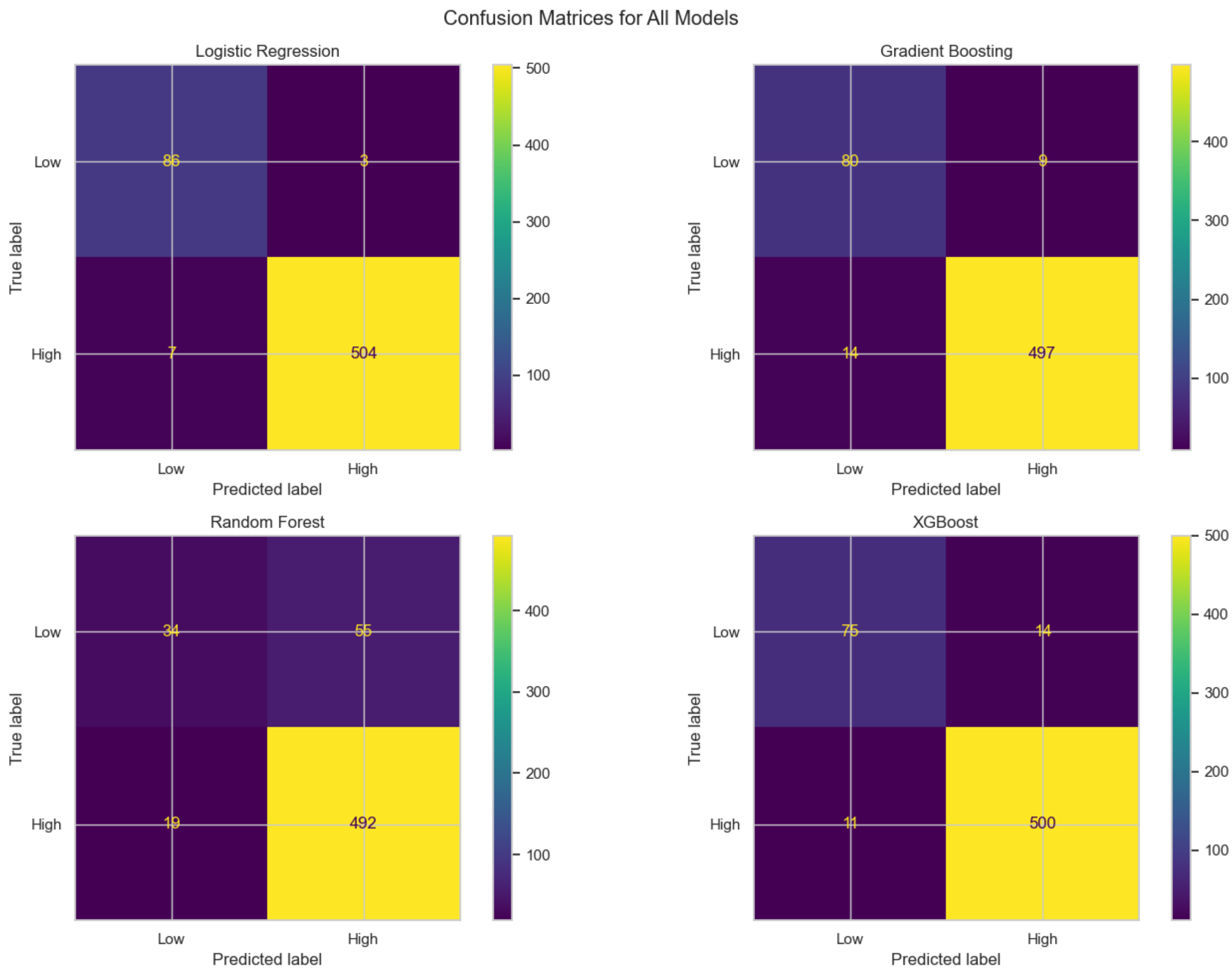
```
# XGBoost Optimized Model

xgboost = XGBClassifier(eval_metric='logloss', random_state=42)
parameters_xgb = {'n_estimators': [50, 100, 150], 'max_depth': [3, 5,
8], 'learning_rate': [0.05, 0.1, 0.2]}
xgb_optimized = RandomizedSearchCV(xgboost, parameters_xgb, n_iter=5,
cv=3, random_state=42)
xgb_optimized.fit(X_train_balanced, y_train_balanced)
predictions_xgb = xgb_optimized.predict(X_test)

print("XGBoost Summary: \n")
print(classification_report(y_test, predictions_xgb))
print("Adjusted Rand Index: ", round(adjusted_rand_score(y_test,
predictions_xgb), 4))

# Here we initialize the xgboost model. The eval_metric is logloss
```

```
because this is a case of binary classification,
# random state is 42 for reproducibility. Then the parameters are set for optimization.
# The n_estimators allows us to run different number of tree sizes, more means better accuracy usually. Max_depth allows
# us to control the depth of each tree, shallow trees can help avoid overfitting. Learning_rate controls how much each new tree
# affects the model, a smaller step size usually results in better accuracy. We then use randomized search to get best hyperparameters.
# Here we feed the model, previous parameters above, n_iter = 5 means 5 random combos are tried, cv = 3 performs 3 fold
# cross validation for each combo and random_state = 42 is for reproducibility purposes. Then model training is
# done using the SMOTE balanced training data. Then the model is used to predict the addiction risk on the unseen test
# dataset. Then the classification report of the model is outputted. Then the ARI is calculated and outputted.

XGBoost Summary:

              precision    recall  f1-score   support

           0       0.87      0.84      0.86        89
           1       0.97      0.98      0.98       511

    accuracy                           0.96       600
   macro avg       0.92      0.91      0.92       600
weighted avg       0.96      0.96      0.96       600

Adjusted Rand Index:  0.7864

from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

# Compute confusion matrix
cm = confusion_matrix(y_test, predictions_xgb)
labels = ['True Negative', 'False Positive', 'False Negative', 'True Positive']
grouped_labels = [f"{label}\nCount: {value}" for label, value in zip(labels, cm.ravel())]
grouped_labels = np.asarray(grouped_labels).reshape(2, 2)

# Unpack the confusion matrix values
tn, fp, fn, tp = cm.ravel()

# Print each value with its label
print(f"True Negative (TN): {tn}")
print(f"False Positive (FP): {fp}")
```

```
print(f"False Negative (FN): {fn}")
print(f"True Positive (TP): {tp}")

# Plot heatmap
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=grouped_labels, fmt='', cmap='Purples',
cbar=False,
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])

plt.title('Confusion Matrix - XGBoost Optimized')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.tight_layout()
plt.show()
```

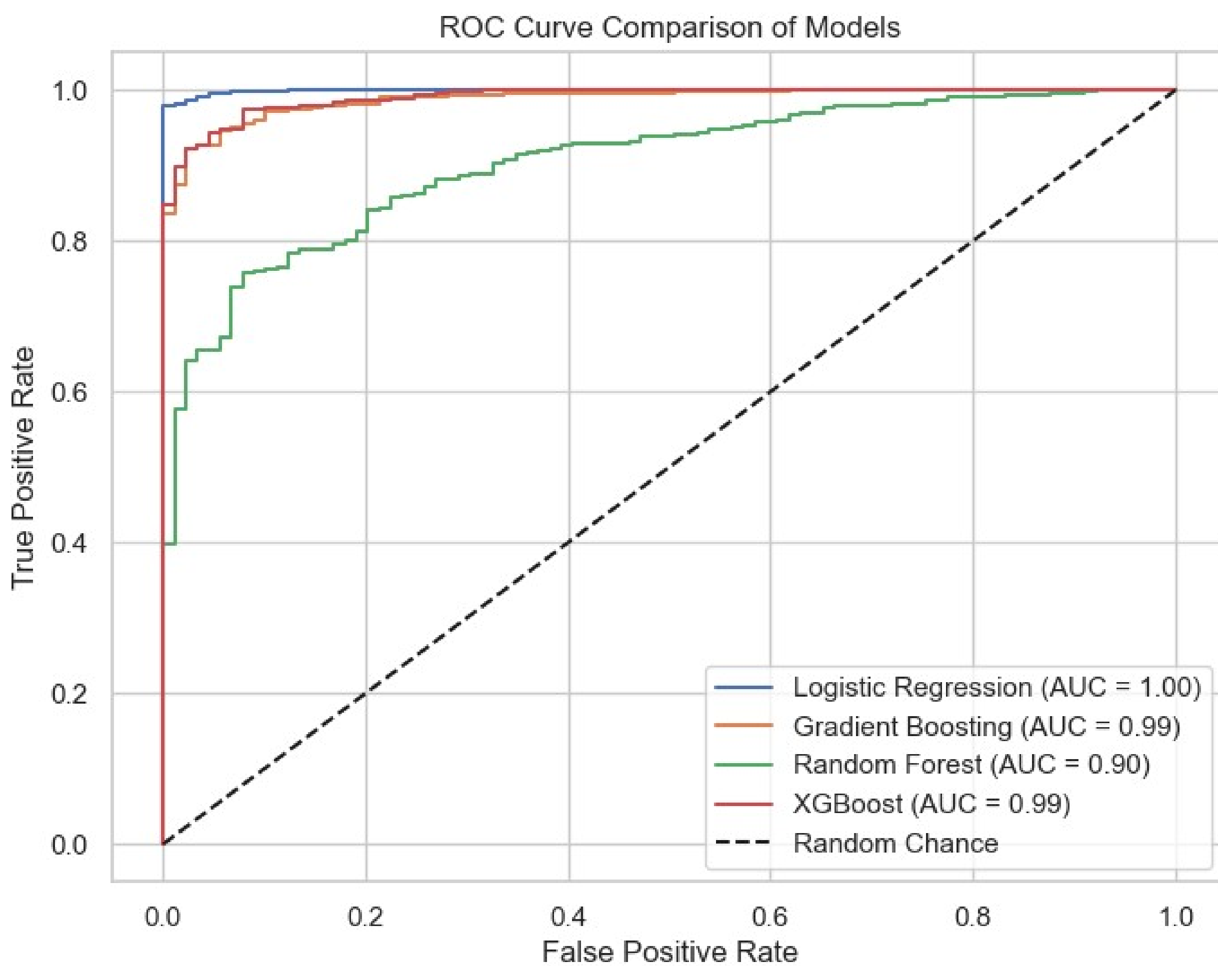
```
True Negative (TN): 75
False Positive (FP): 14
False Negative (FN): 11
True Positive (TP): 500
```

```python
# Confusion Matrices
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

# Initialize models
models = {
    "Logistic Regression": LogisticRegression(max_iter=2000),
    "Gradient Boosting": GradientBoostingClassifier(random_state=42),
    "Random Forest": RandomizedSearchCV(
        RandomForestClassifier(random_state=42),
        {'n_estimators': [50, 100, 150], 'max_depth': [5, 10, 15]},
        n_iter=5, cv=3, random_state=42
    ),
    "XGBoost": RandomizedSearchCV(
        XGBClassifier(eval_metric='logloss', random_state=42),
        {'n_estimators': [50, 100, 150], 'max_depth': [3, 5, 8],
'learning_rate': [0.05, 0.1, 0.2]},
        n_iter=5, cv=3, random_state=42
    )
}

# Fit models and get predictions
model_preds = {}
model_probs = {}
for name, model in models.items():
    model.fit(X_train_balanced, y_train_balanced)
    preds = model.predict(X_test)
    probs = model.predict_proba(X_test)[:, 1]
    model_preds[name] = preds
    model_probs[name] = probs

# Confusion Matrices
fig, axes = plt.subplots(2, 2, figsize=(14, 10))
axes = axes.ravel()
for i, (name, preds) in enumerate(model_preds.items()):
    cm = confusion_matrix(y_test, preds)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=["Low", "High"])
    disp.plot(ax=axes[i], values_format='d')
    axes[i].set_title(name)
plt.suptitle("Confusion Matrices for All Models")
plt.tight_layout()
plt.show()
```




```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc

plt.figure(figsize=(8, 6))

# Logistic Regression
probs_log_reg = log_reg.predict_proba(X_test)[:, 1]
fpr_log, tpr_log, _ = roc_curve(y_test, probs_log_reg)
roc_auc_log = auc(fpr_log, tpr_log)
plt.plot(fpr_log, tpr_log, label=f"Logistic Regression (AUC =
{roc_auc_log:.2f})")

# Gradient Boosting
probs_gboost = gboost.predict_proba(X_test)[:, 1]
fpr_gb, tpr_gb, _ = roc_curve(y_test, probs_gboost)
roc_auc_gb = auc(fpr_gb, tpr_gb)
plt.plot(fpr_gb, tpr_gb, label=f"Gradient Boosting (AUC =
{roc_auc_gb:.2f})")

# Random Forest Optimized
```

```
probs_rf = rf_optimized.predict_proba(X_test)[:, 1]
fpr_rf, tpr_rf, _ = roc_curve(y_test, probs_rf)
roc_auc_rf = auc(fpr_rf, tpr_rf)
plt.plot(fpr_rf, tpr_rf, label=f"Random Forest (AUC =
{roc_auc_rf:.2f})")

# XGBoost Optimized
probs_xgb = xgb_optimized.predict_proba(X_test)[:, 1]
fpr_xgb, tpr_xgb, _ = roc_curve(y_test, probs_xgb)
roc_auc_xgb = auc(fpr_xgb, tpr_xgb)
plt.plot(fpr_xgb, tpr_xgb, label=f"XGBoost (AUC = {roc_auc_xgb:.2f})")

# Plot formatting
plt.plot([0, 1], [0, 1], 'k--', label='Random Chance')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Comparison of Models')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```



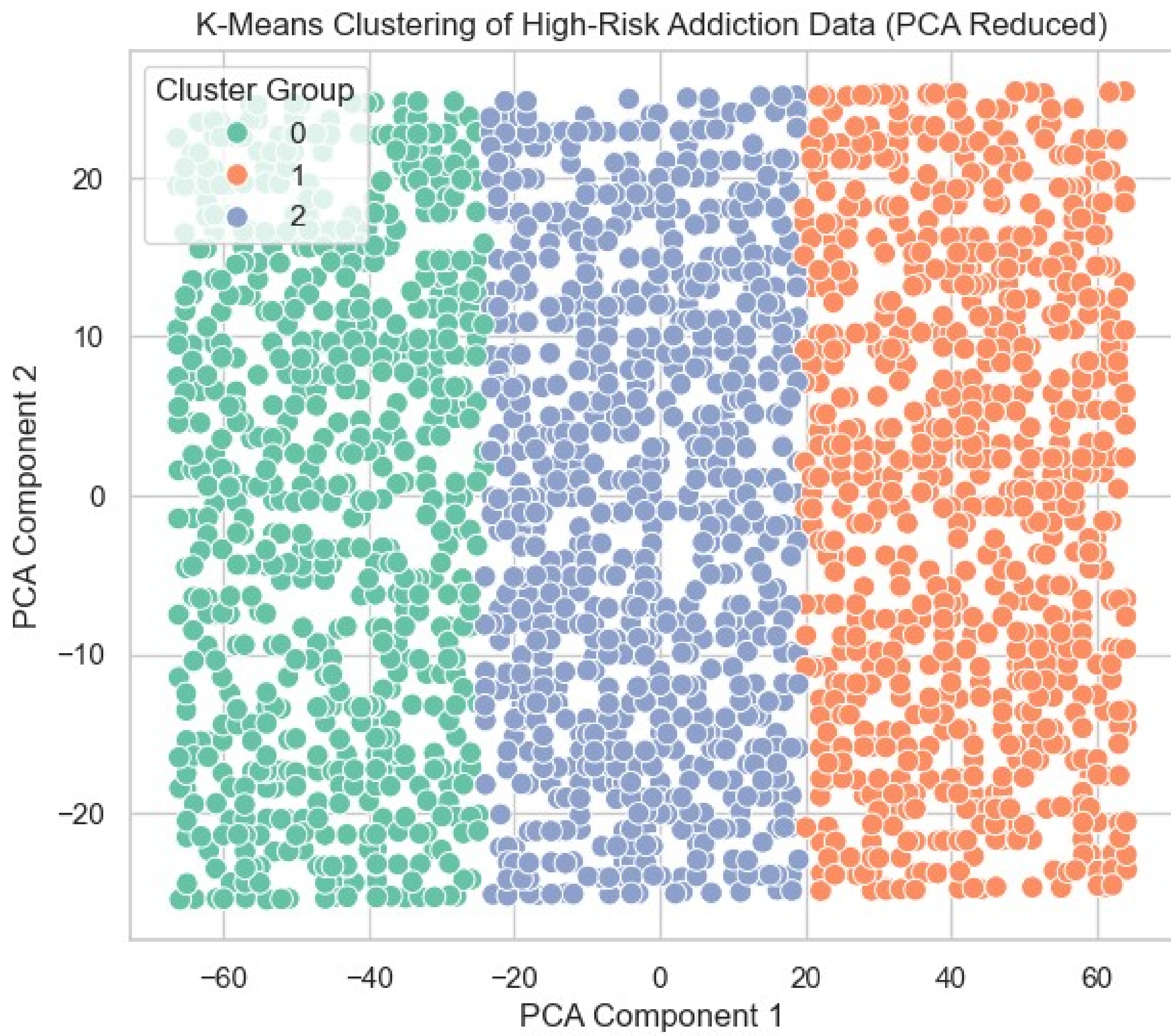
Unsupervised Learning (K-Means)

```
# Unsupervised Learning (K-Means):

high_risk_data = data[data['Addiction_Binary'] == 1].drop(["ID",
"Name", "Addiction_Level", "Addiction_Binary"], axis=1)
high_risk_enc = pd.get_dummies(high_risk_data, drop_first=True)

pca = PCA(n_components=2)
dim_reduced_data = pca.fit_transform(high_risk_enc)

kmeans = KMeans(n_clusters=3, random_state=42)
kmeans_predictions = kmeans.fit_predict(dim_reduced_data)

silhouette = silhouette_score(dim_reduced_data, kmeans_predictions)
print("Silhouette Score of K-Means Clustering: ", round(silhouette,
4))

# Here we begin with filtering for high risk individuals, these are
the people with the binary value of 1. We then drop useless
# columns, no identifiers, no original addiction ratings, no target
column. One hot encoding is then applied to swap categorical
# values to dummy variables 1's and 0's, which the model will
understand better. The drop first avoids multicollinearity by dropping
# one column from each set of dummy variables. Then pca is used to
reduce the feature space to 2 dimensions for vizualization and
# efficiency. We then apply KMeans clustering on the dimensionally
reduced data. 3 clusters are used and random_state = 42 allows for
# reproducibility. Then the silhouette score is calculated to evalute
the clustering quality and outputted.
```

```
Silhouette Score of K-Means Clustering:  0.4239
```

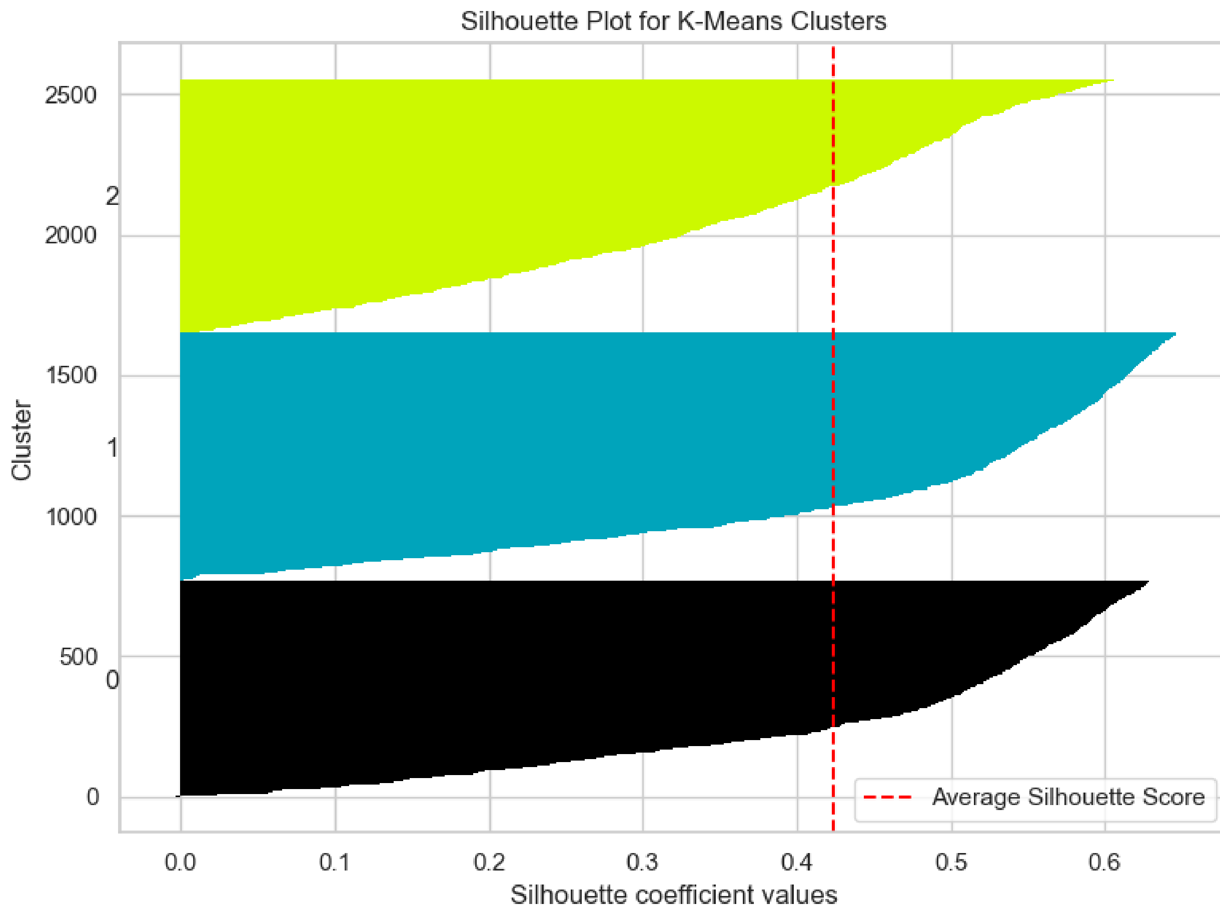
```
#cluster counts summary table (since all are high risk, no binary
label here)
cluster_counts =
pd.Series(kmeans_predictions).value_counts().sort_index()
print("\nCluster Counts:")
print(cluster_counts)

# Scatter plot of clusters
plt.figure(figsize=(7, 6))
sns.scatterplot(x=dim_reduced_data[:, 0], y=dim_reduced_data[:, 1],
hue=kmeans_predictions, palette="Set2", s=70)
plt.title("K-Means Clustering of High-Risk Addiction Data (PCA
Reduced)")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.legend(title="Cluster Group")
plt.grid(True)
plt.show()
```

```
Cluster Counts:
0    770
1    885
2    899
Name: count, dtype: int64
```




```
from sklearn.metrics import silhouette_samples
import matplotlib.cm as cm
import numpy as np
import matplotlib.pyplot as plt

silhouette_vals = silhouette_samples(dim_reduced_data,
kmeans_predictions)
y_lower = 0
plt.figure(figsize=(8, 6))
```

```python
for i in range(3):  # Assuming 3 clusters
    cluster_silhouette_vals = silhouette_vals[kmeans_predictions == i]
    cluster_silhouette_vals.sort()
    size_cluster_i = cluster_silhouette_vals.shape[0]
    y_upper = y_lower + size_cluster_i

    color = cm.nipy_spectral(float(i) / 3)
    plt.barh(range(y_lower, y_upper), cluster_silhouette_vals,
height=1.0, color=color, edgecolor='none')
    plt.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))

    y_lower = y_upper  # Move to the next cluster's bar

plt.axvline(np.mean(silhouette_vals), color="red", linestyle="--",
label="Average Silhouette Score")
plt.title("Silhouette Plot for K-Means Clusters")
plt.xlabel("Silhouette coefficient values")
plt.ylabel("Cluster")
plt.legend()
plt.tight_layout()
plt.show()
```




```
# Add the cluster labels (from K-Means predictions) back into the
original high_risk_data DataFrame.
# This allows us to link each individual's original numeric features
to their assigned cluster.
high_risk_data['Cluster_Label'] = kmeans_predictions

# Select only the numeric columns from high_risk_data for statistical
summarization.
# This ensures we calculate meaningful averages (not trying to average
categorical text).
numeric_columns =
high_risk_data.select_dtypes(include='number').columns


# Group the data by cluster label and compute the mean of each numeric
feature within each cluster.
# This gives a "profile" of the typical values for each cluster across
numeric variables.
cluster_summary = high_risk_data.groupby('Cluster_Label')
[numeric_columns].mean()

# Print a header to describe what the output table represents.
```

```python
print("Cluster Profiles (Average Behavioral Patterns):")

# Display the summary table with a background color gradient applied
to the numeric values.
display(cluster_summary.style.background_gradient())
```

```
Cluster Profiles (Average Behavioral Patterns):
```

```
<pandas.io.formats.style.Styler at 0x326858190>
```

```python
import matplotlib.pyplot as plt
import matplotlib.image as mpimg

img = mpimg.imread('cluster_profiles.png')
plt.figure(figsize=(20, 16))
plt.imshow(img)
plt.axis('off')
plt.show()
```

Cluster_Label	Age	Daily_Usage_Hours	Sleep_Hours	Academic_Performance	Social_Interactions	Exercise_Hours	Anxiety_Level	Depression_Level	Self_Esteem
	16.061039	5.521429	6.29974	75.549351	5.131169	1.036883	5.518182	5.546753	5.468831
1	15.950282	5.216045	6.460452	74.916384	5.233898	1.011864	5.630508	5.520904	5.540113
2	15.942158	5.406452	6.362959	74.655172	4.897664	1.044383	5.671858	5.399333	5.53059
continue									
Parental_Control	Screen_Time_Before_Bed	Phone_Checks_Per_Day	Apps_Used_Daily	Time_on_Social_Media	Time_on_Gaming	Time_on_Education	Family_Communication	Weekend_Usage_Hours	Cluster_Label
0.488312	1.005065	40.814286	13.325974	2.636234	1.641948	1.028312	5.45974	6.056104	0
0.510734	1.00678	128.322034	12.880226	2.603729	1.567119	1.001695	5.438418	5.928927	1
0.520578	1.00723	83.213571	13.097887	2.552058	1.629366	1.016574	5.484983	6.041157	2