DSC680_PredictingAppUsageNotebook_LincolnBrown

February 2, 2025

[1]:
```
# Import libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from scipy.stats import ttest_ind, mannwhitneyu
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from xgboost import XGBRegressor
```

[2]:
```
f = "user_behavior_dataset.csv"
df = pd.read_csv(f, low_memory=False)
```

[3]:
```
df.describe()
```

[3]:
```
          User ID  App Usage Time (min/day)  Screen On Time (hours/day)  \
count   700.00000                700.000000                  700.000000
mean    350.50000                271.128571                    5.272714
std     202.21688                177.199484                    3.068584
min       1.00000                 30.000000                    1.000000
25%     175.75000                113.250000                    2.500000
50%     350.50000                227.500000                    4.900000
75%     525.25000                434.250000                    7.400000
max     700.00000                598.000000                   12.000000

       Battery Drain (mAh/day)  Number of Apps Installed  Data Usage (MB/day)  \
count               700.000000                700.000000           700.000000
mean               1525.158571                 50.681429           929.742857
std                 819.136414                 26.943324           640.451729
min                 302.000000                 10.000000           102.000000
25%                 722.250000                 26.000000           373.000000
50%                1502.500000                 49.000000           823.500000
75%                2229.500000                 74.000000          1341.000000
```

```
max                 2993.000000                     99.000000           2497.000000

              Age  User Behavior Class
count  700.000000           700.000000
mean    38.482857             2.990000
std     12.012916             1.401476
min     18.000000             1.000000
25%     28.000000             2.000000
50%     38.000000             3.000000
75%     49.000000             4.000000
max     59.000000             5.000000
```

[4]:
```python
df.columns
```

[4]:
```
Index(['User ID', 'Device Model', 'Operating System',
       'App Usage Time (min/day)', 'Screen On Time (hours/day)',
       'Battery Drain (mAh/day)', 'Number of Apps Installed',
       'Data Usage (MB/day)', 'Age', 'Gender', 'User Behavior Class'],
      dtype='object')
```

0.1 Exploratory Data Analysis

[5]:
```python
# Check for missing values
df.isna().sum()
```

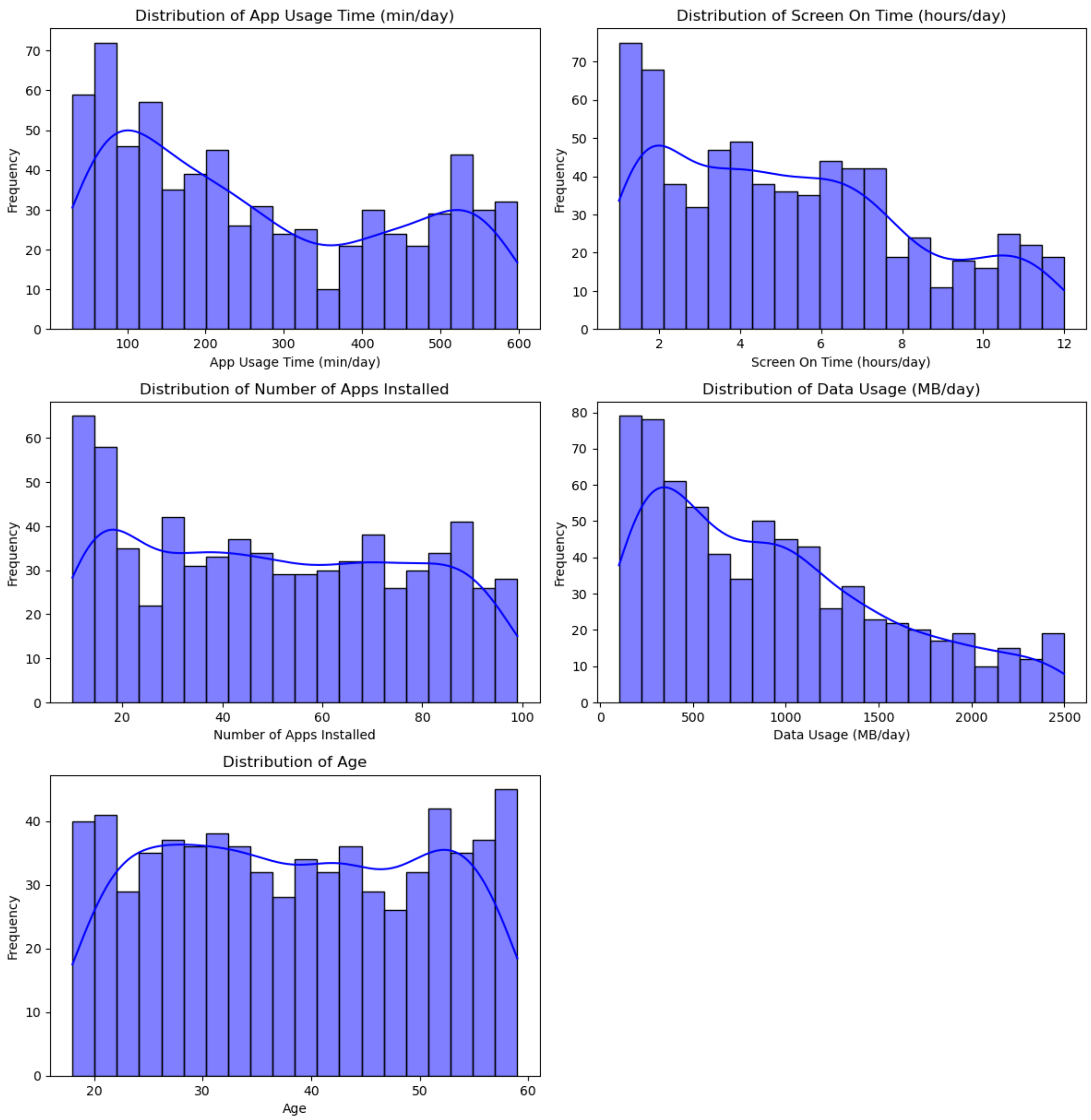
[5]:
```
User ID                       0
Device Model                  0
Operating System              0
App Usage Time (min/day)      0
Screen On Time (hours/day)    0
Battery Drain (mAh/day)       0
Number of Apps Installed      0
Data Usage (MB/day)           0
Age                           0
Gender                        0
User Behavior Class           0
dtype: int64
```

[6]:
```python
# Drop rows containing the missing values for age
df.dropna(inplace=True)
```

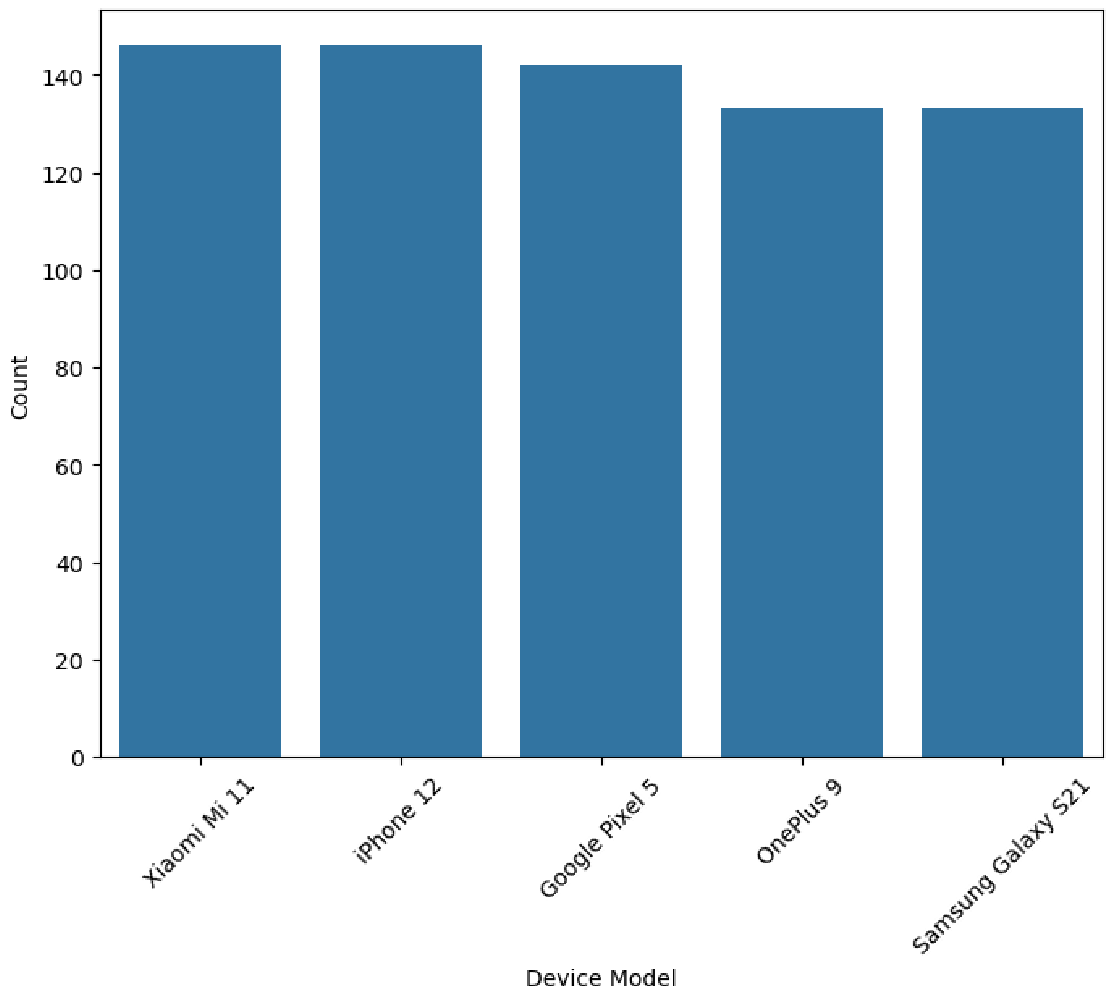
[7]:
```python
# Group the features
numerical_features = ['App Usage Time (min/day)', 'Screen On Time (hours/day)',␣
 ↪'Number of Apps Installed', 'Data Usage (MB/day)', 'Age']
categorical_features = ['Device Model', 'Operating System', 'Gender']
```

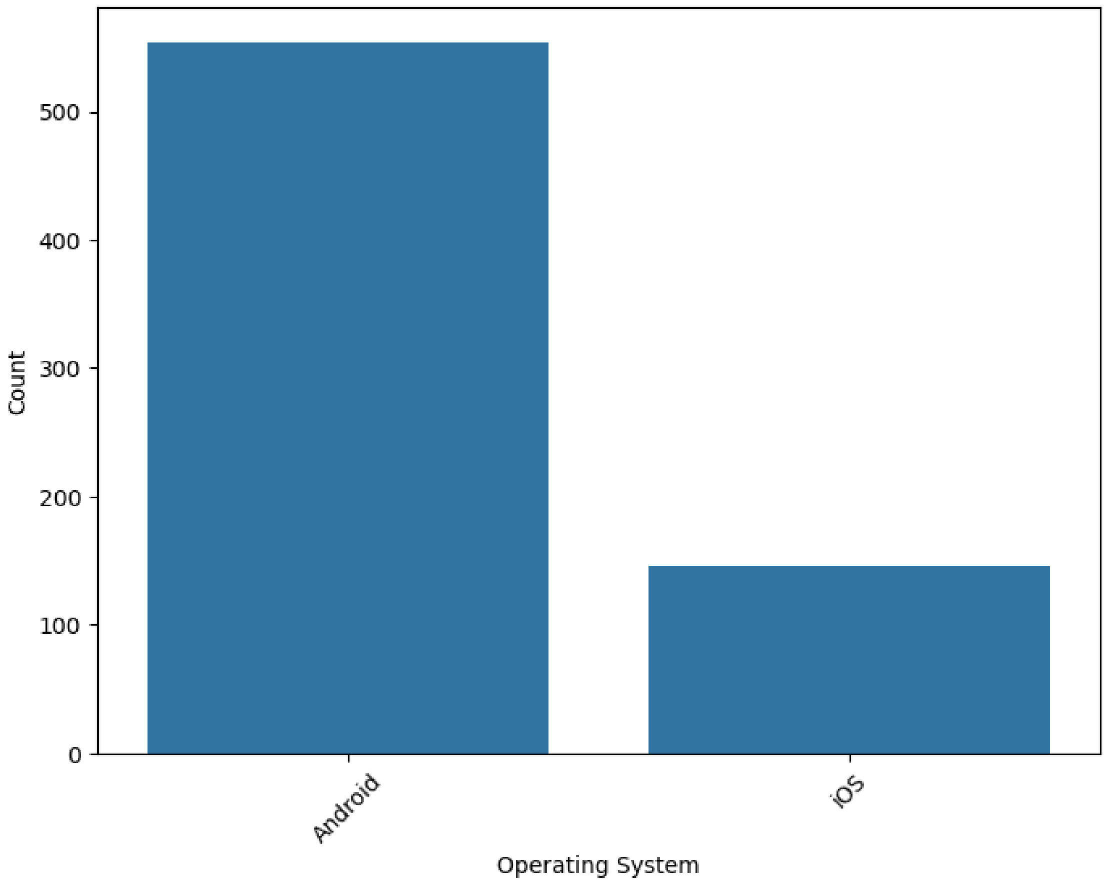
[8]:

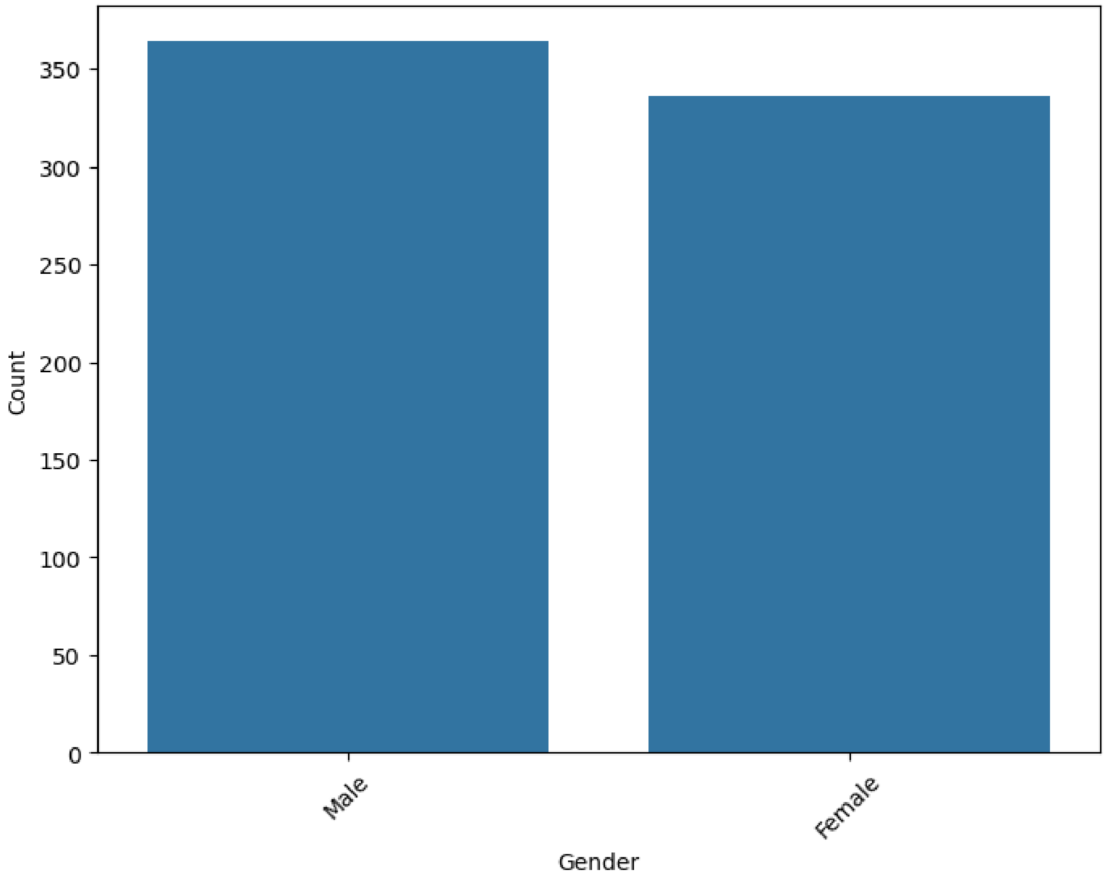
```
# Let's start looking at the distribution of numerical features
# Num of numerical features
num_features = len(numerical_features)

# Get the dimensions of the grid w/ 2 cols
n_cols = 2
n_rows = (num_features + n_cols -1)

# Create subplots
fig, axes = plt.subplots(n_rows, n_cols, figsize=(12, 4 * n_rows))

# Flatten the axes
axes = axes.flatten()

for i, feature in enumerate(numerical_features):
    sns.histplot(data=df, x=feature, kde=True, bins=20, color='blue',␣
 ↪ax=axes[i])
    axes[i].set_title(f'Distribution of {feature}')
    axes[i].set_xlabel(feature)
    axes[i].set_ylabel('Frequency')

# Remove unused subplots
for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

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



[9]:
```
# Now the categorical features
for feature in categorical_features:
    plt.figure(figsize=(8,6))
    sns.countplot(data=df, x=feature, order=df[feature].value_counts().index,␣
 ↪legend=False)
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.xticks(rotation=45)
    plt.show()
```

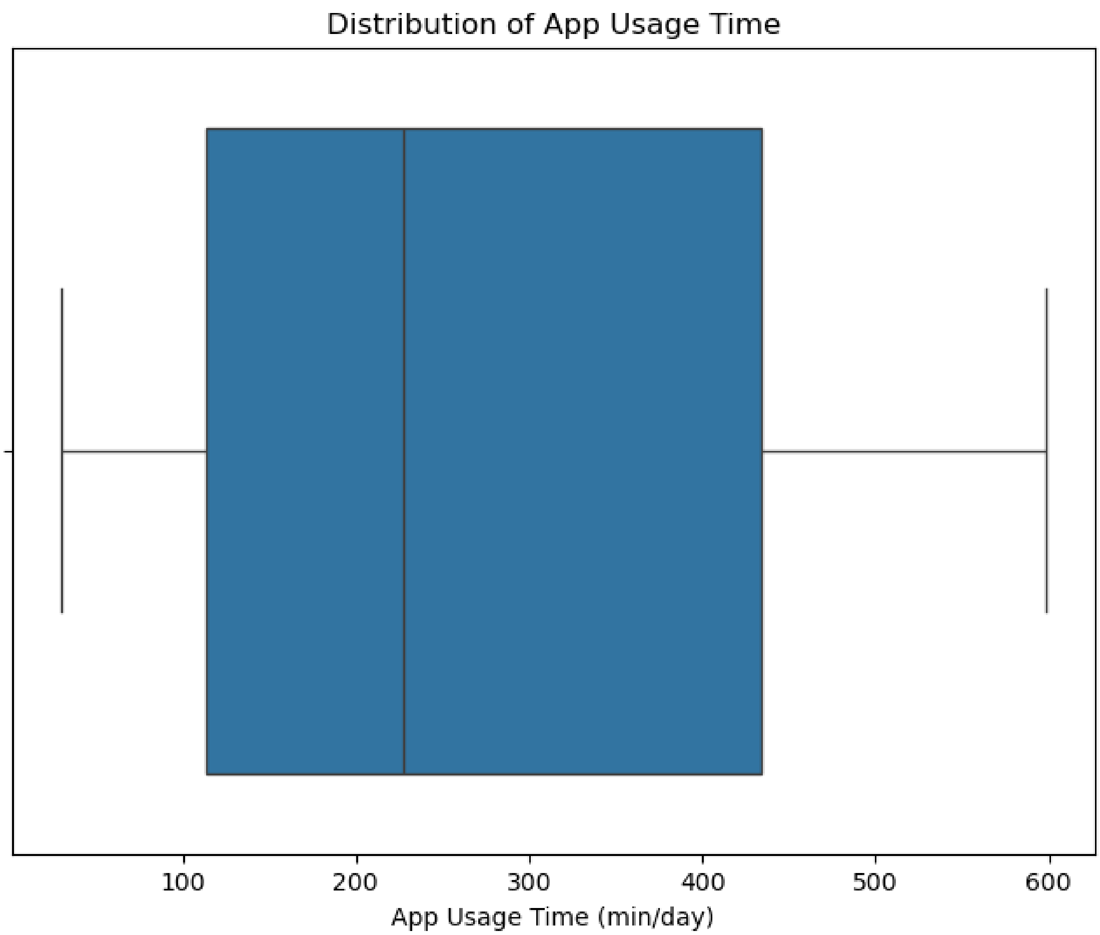

140
120
100
80
60
40
20
0
Count
Xiaomi Mi 11
iPhone 12
Google Pixel 5
OnePlus 9
Samsung Galaxy S21
Device Model


500
400
300
200
100
0
Count
Android
iOS
Operating System



[10]:

```
# Boxplot of App Usage Time
plt.figure(figsize=(8,6))
sns.boxplot(data=df, x='App Usage Time (min/day)')
plt.title('Distribution of App Usage Time')
plt.xlabel('App Usage Time (min/day)')
plt.show()
```



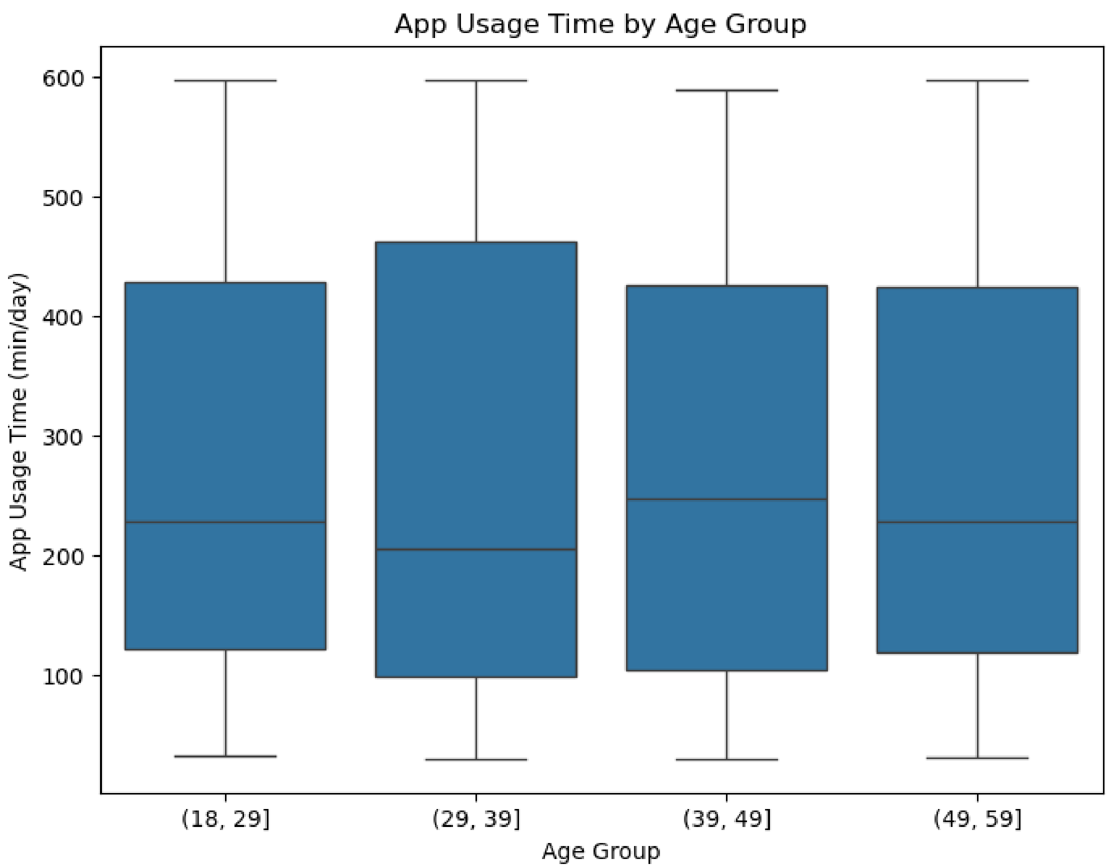
[11]:
```python
# Bins for the Age column
bins = [18, 29, 39, 49, 59]
df['Age Group'] = pd.cut(df['Age'], bins=bins)
df
```

[11]:
```
     User ID        Device Model Operating System  App Usage Time (min/day)  \
0          1      Google Pixel 5          Android                       393
1          2           OnePlus 9          Android                       268
2          3        Xiaomi Mi 11          Android                       154
3          4      Google Pixel 5          Android                       239
4          5           iPhone 12              iOS                       187
..       …                   …                …                        …
695      696           iPhone 12              iOS                        92
696      697        Xiaomi Mi 11          Android                       316
697      698      Google Pixel 5          Android                        99
698      699  Samsung Galaxy S21          Android                        62
699      700           OnePlus 9          Android                       212
```

```
     Screen On Time (hours/day)  Battery Drain (mAh/day)  \
0                           6.4                     1872
1                           4.7                     1331
2                           4.0                      761
3                           4.8                     1676
4                           4.3                     1367
..                          …                       …
695                         3.9                     1082
696                         6.8                     1965
697                         3.1                      942
698                         1.7                      431
699                         5.4                     1306

     Number of Apps Installed  Data Usage (MB/day)  Age  Gender  \
0                          67                 1122   40    Male
1                          42                  944   47  Female
2                          32                  322   42    Male
3                          56                  871   20    Male
4                          58                  988   31  Female
..                        …                  …   …     …
695                        26                  381   22    Male
696                        68                 1201   59    Male
697                        22                  457   50  Female
698                        13                  224   44    Male
699                        49                  828   23  Female

     User Behavior Class Age Group
0                      4  (39, 49]
1                      3  (39, 49]
2                      2  (39, 49]
3                      3  (18, 29]
4                      3  (29, 39]
..                   …       …
695                    2  (18, 29]
696                    4  (49, 59]
697                    2  (49, 59]
698                    1  (39, 49]
699                    3  (18, 29]

[700 rows x 12 columns]
```

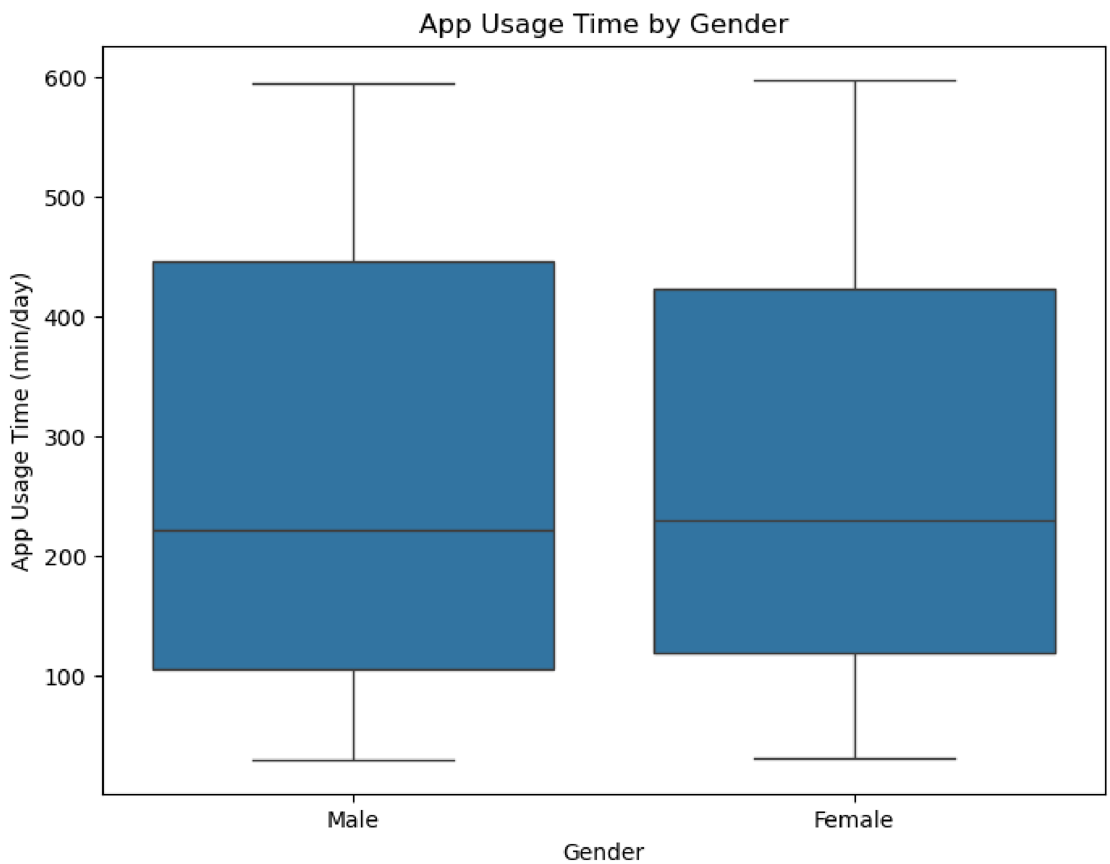
0.2 Which Age Group Has the Highest App Usage Time?

[12]:
```python
# App Usage Time by Age

plt.figure(figsize=(8,6))
sns.boxplot(data=df, x='Age Group', y='App Usage Time (min/day)')
plt.title('App Usage Time by Age Group')
plt.xlabel('Age Group')
plt.ylabel('App Usage Time (min/day)')
plt.show()
```



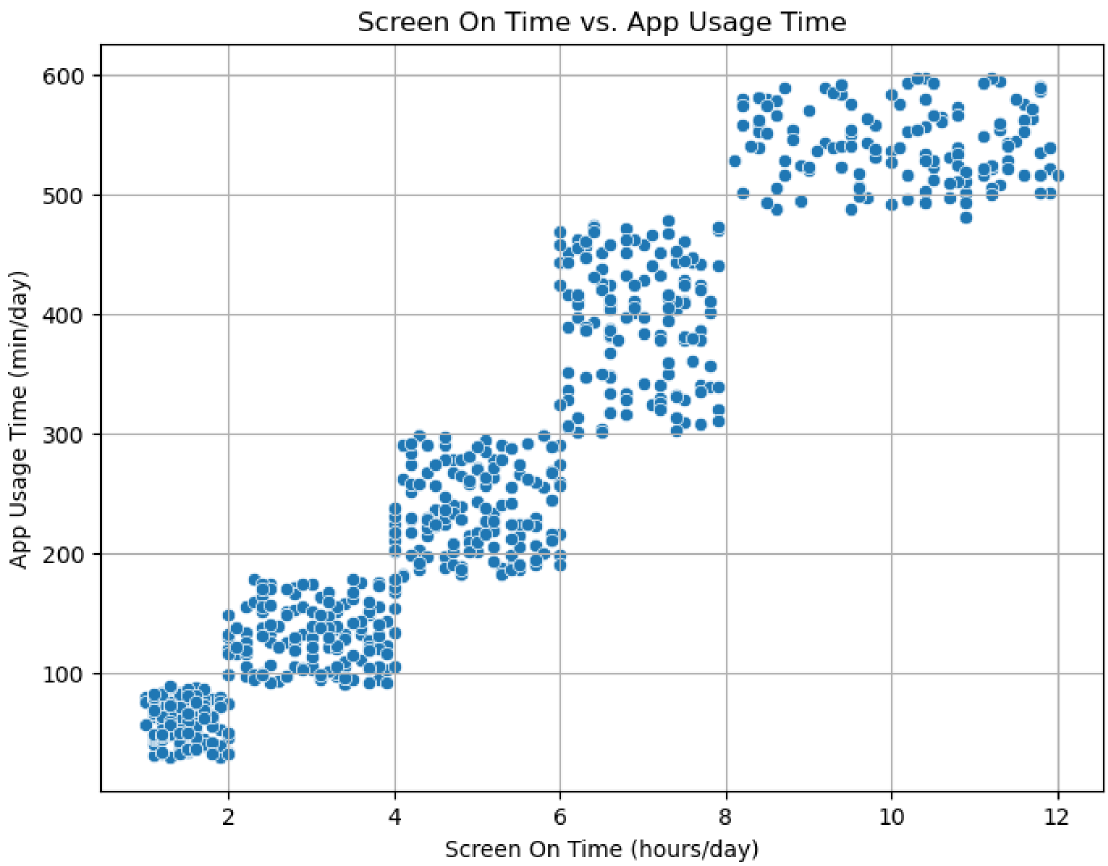
0.3 Are there any differences in app usage time between genders?

[13]:
```
# App Usage Time by Gender
plt.figure(figsize=(8, 6))
sns.boxplot(data=df, x='Gender', y='App Usage Time (min/day)')
plt.title('App Usage Time by Gender')
plt.xlabel('Gender')
plt.ylabel('App Usage Time (min/day)')
plt.show()
```



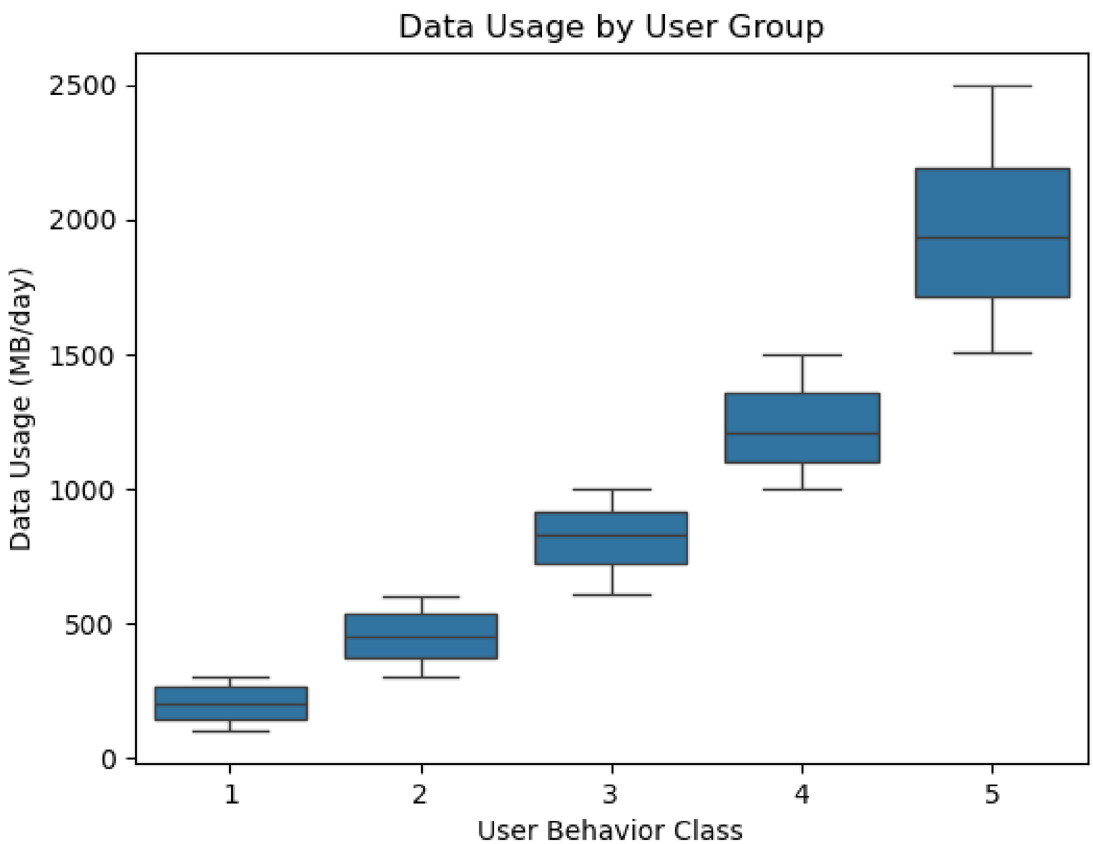
0.4 How does daily screen time correlate with app usage time?

[14]:
```
# Scatterplot of daily screen time vs app usage time
plt.figure(figsize=(8,6))
sns.scatterplot(x='Screen On Time (hours/day)', y='App Usage Time (min/day)',␣
↪data=df)
plt.title('Screen On Time vs. App Usage Time')
plt.xlabel('Screen On Time (hours/day)')
plt.ylabel('App Usage Time (min/day)')
plt.grid(True)
plt.show()
```



0.5 Do heavier app users use significantly more data?

[15]:
```
# Boxplot of Data Usage by User Group
sns.boxplot(x='User Behavior Class', y='Data Usage (MB/day)', data=df)
plt.title('Data Usage by User Group')
plt.show()
```

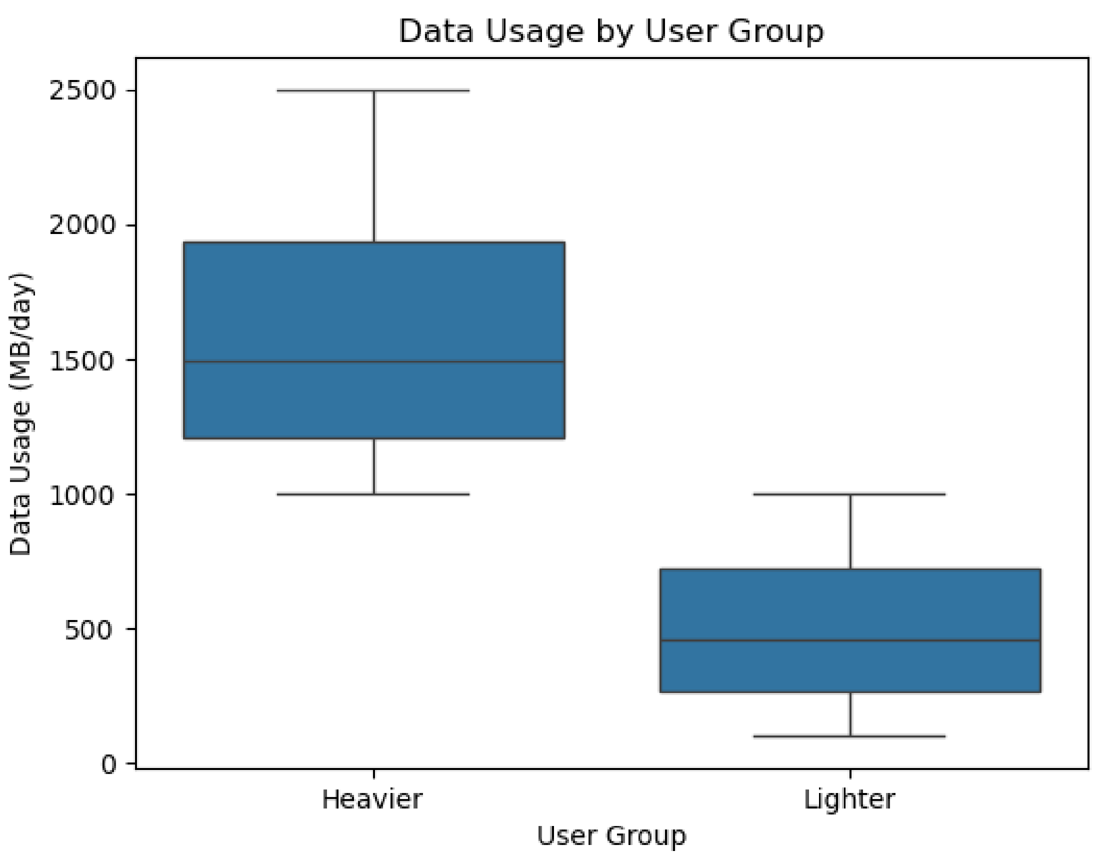


[16]:
```
# Group users into heavier and lighter data usage groups
df['User Group'] = df['User Behavior Class'].apply(lambda x: 'Heavier' if x >=␣
↪4 else 'Lighter')

# Group Data
heavier_users = df[df['User Group'] == 'Heavier']['Data Usage (MB/day)']
lighter_users = df[df['User Group'] == 'Lighter']['Data Usage (MB/day)']

# Summary Statistics
print(f'Heavier Usage Group Data Consumption: \n{heavier_users.describe()}')
print(f'Lighter Usage Group Data Consumption: \n{lighter_users.describe()}')
```

```
Heavier Usage Group Data Consumption:
count     275.000000
mean     1599.450909
std       438.960967
min      1002.000000
25%      1209.000000
50%      1493.000000
75%      1931.500000
```

```
max      2497.000000
Name: Data Usage (MB/day), dtype: float64
Lighter Usage Group Data Consumption:
count    425.000000
mean     496.402353
std      269.391401
min      102.000000
25%      266.000000
50%      457.000000
75%      723.000000
max      997.000000
Name: Data Usage (MB/day), dtype: float64
```

[17]:
```
# User Group Boxplot
sns.boxplot(x='User Group', y='Data Usage (MB/day)', data=df)
plt.title('Data Usage by User Group')
plt.show()
```

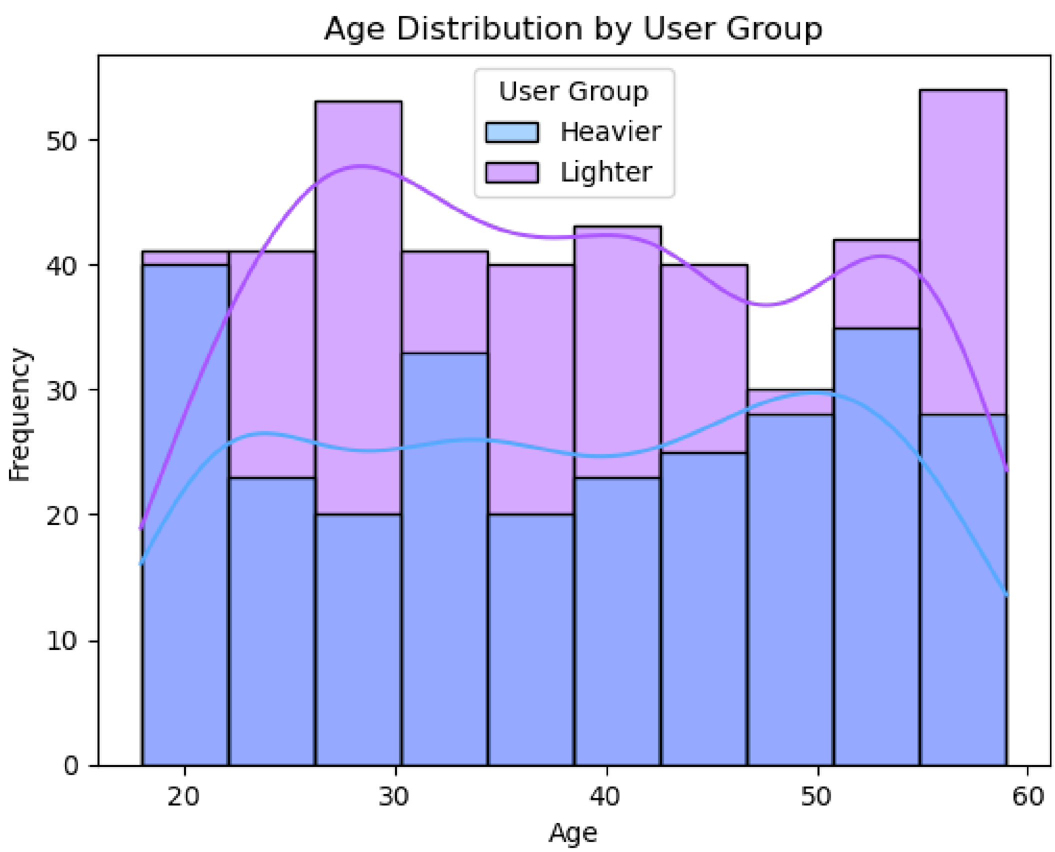


[18]:
```
t_stat, p_value = ttest_ind(heavier_users, lighter_users, equal_var=False)
print(f'T-Test: t-statistic = {t_stat}, p-value = {p_value}')
```

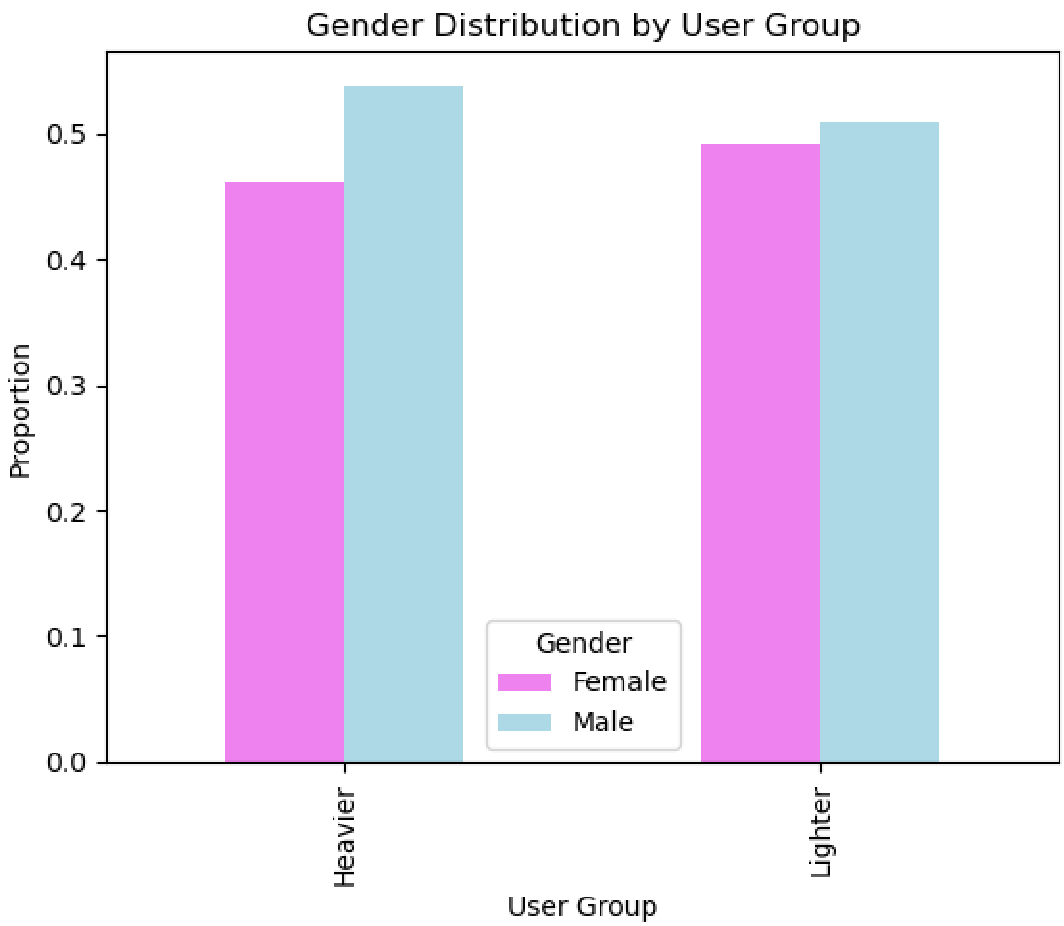
```python
if p_value < 0.05:
    print('Conclusion: Heavier app users consume significantly more data␣
 ↪compared to lighter app users.')
else:
    print('Conclusion: There is no significant difference in data consumption␣
 ↪between heavier and lighter app users.')
```

```
T-Test: t-statistic = 37.36602293628329, p-value = 8.29848208005354e-134
Conclusion: Heavier app users consume significantly more data compared to
lighter app users.
```

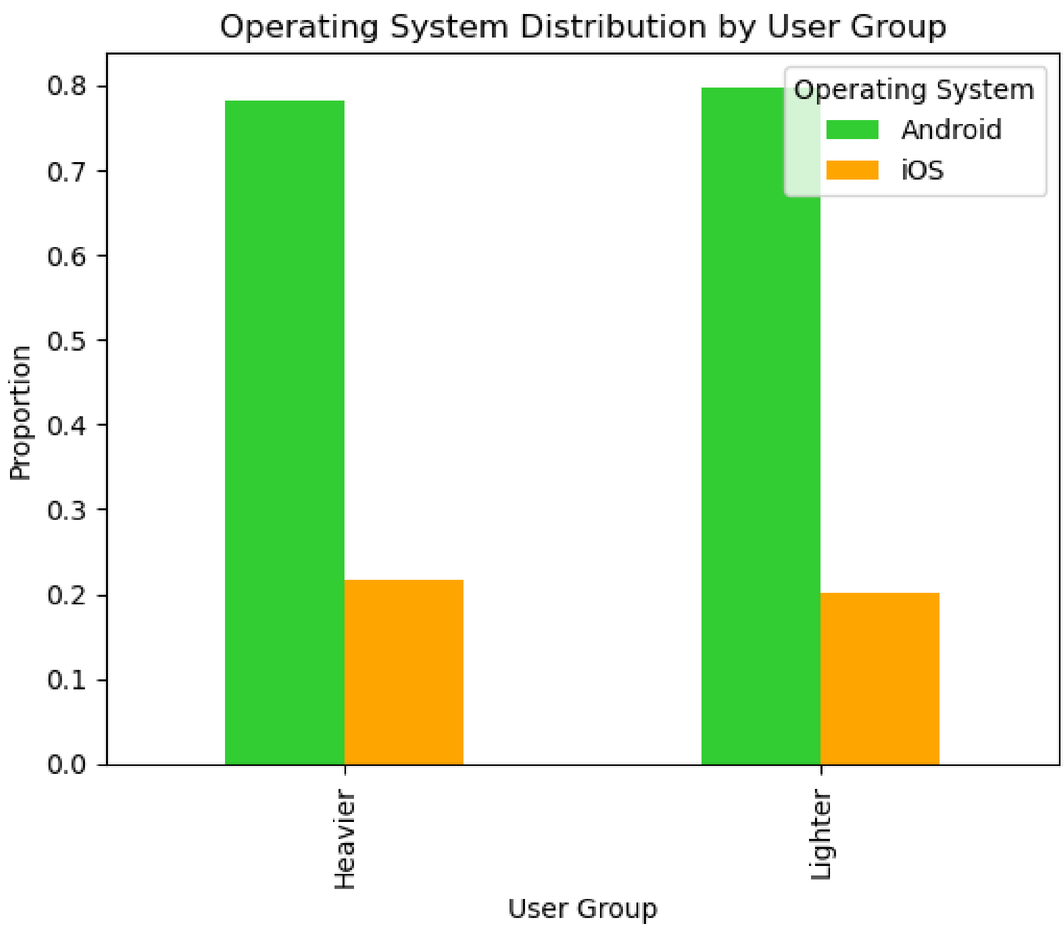
[19]:
```python
# Histogram of Age by User Group
sns.histplot(data=df, x='Age', hue='User Group', kde=True, palette='cool',␣
 ↪bins=10)
plt.title('Age Distribution by User Group')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



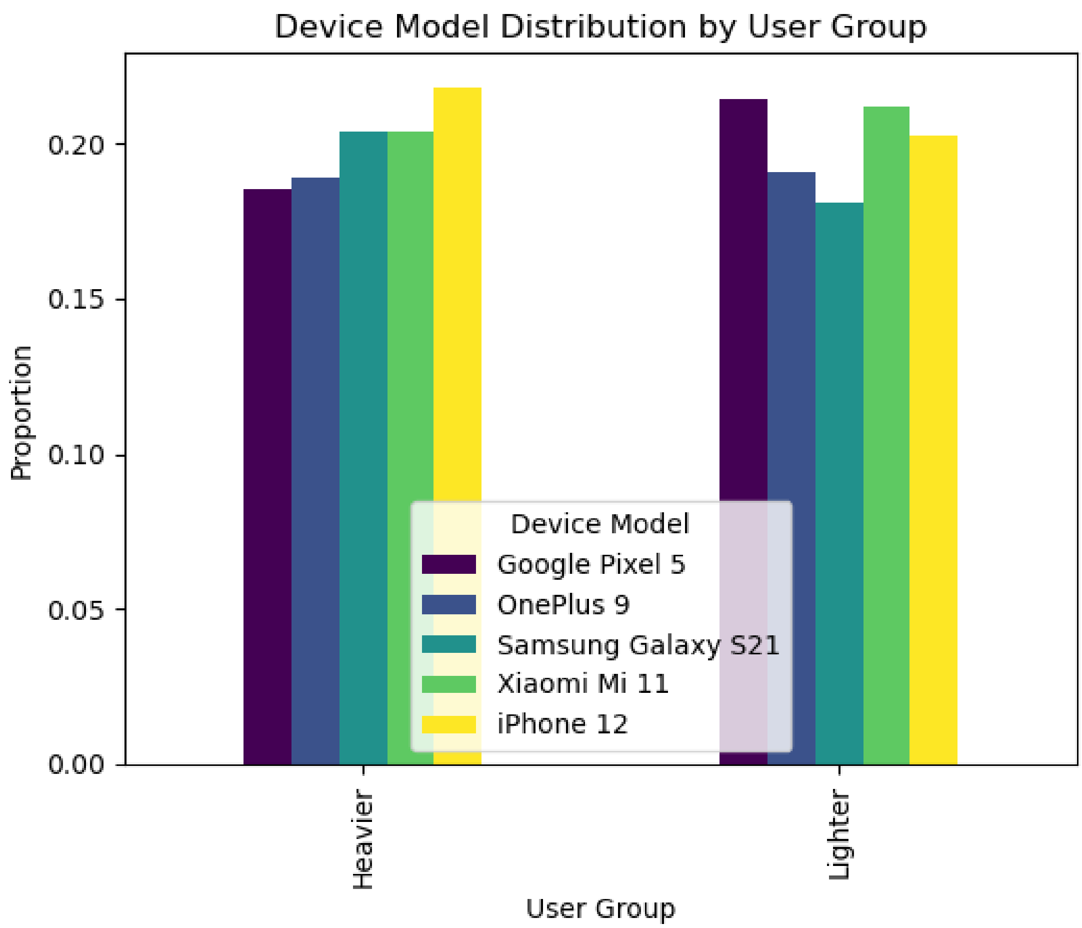
[20]:
```
gender_counts = df.groupby('User Group')['Gender'].value_counts(normalize=True).
    ↪unstack()
gender_counts.plot(kind='bar', stacked=False, color=['violet', 'lightblue'])
plt.title('Gender Distribution by User Group')
plt.xlabel('User Group')
plt.ylabel('Proportion')
plt.legend(title='Gender')
plt.show()
```



[21]:
```
os_counts = df.groupby('User Group')['Operating System'].
    ↪value_counts(normalize=True).unstack()
os_counts.plot(kind='bar', stacked=False, color=['limegreen', 'orange'])
plt.title('Operating System Distribution by User Group')
plt.xlabel('User Group')
plt.ylabel('Proportion')
plt.legend(title='Operating System')
plt.show()
```

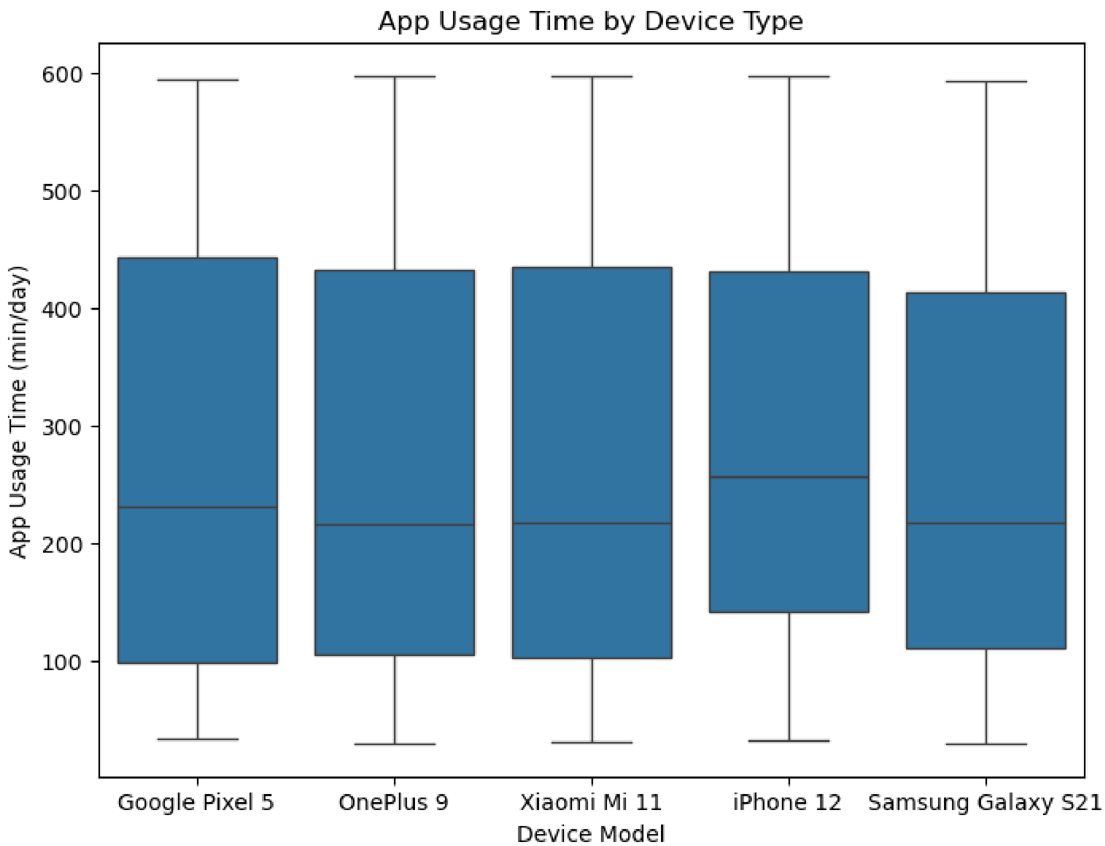



```
[22]: model_counts = df.groupby('User Group')['Device Model'].
       ↪value_counts(normalize=True).unstack()
      model_counts.plot(kind='bar', stacked=False, colormap=sns.
       ↪color_palette('viridis', as_cmap=True))
      plt.title('Device Model Distribution by User Group')
      plt.xlabel('User Group')
      plt.ylabel('Proportion')
      plt.show()
```



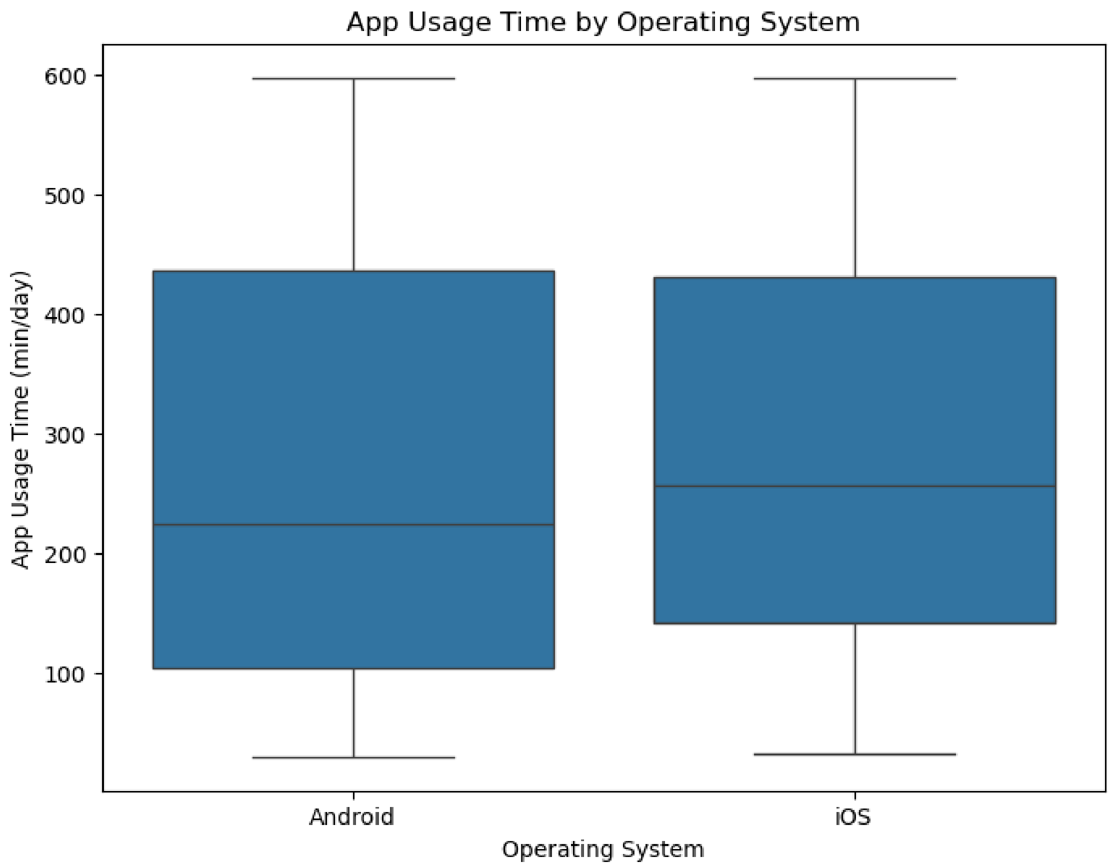
[23]:

```
# App Usage Time by Device

plt.figure(figsize=(8,6))
sns.boxplot(data=df, x='Device Model', y='App Usage Time (min/day)')
plt.title('App Usage Time by Device Type')
plt.xlabel('Device Model')
plt.ylabel('App Usage Time (min/day)')
plt.show()
```



[24]:

```
# App Usage Time by Operating System

plt.figure(figsize=(8,6))
sns.boxplot(data=df, x='Operating System', y='App Usage Time (min/day)')
plt.title('App Usage Time by Operating System')
plt.xlabel('Operating System')
plt.ylabel('App Usage Time (min/day)')
plt.show()
```



0.6 Models - Linear Regression, Random Forest, XGBoost

[25]:
```python
# Get the shape of the data
df.shape
```

[25]: (700, 13)

[26]:
```python
# Set Features and Target
X = df.drop(columns=['App Usage Time (min/day)', 'Age Group'])
y = df['App Usage Time (min/day)']

categorical_features = ['Device Model', 'Operating System', 'Gender']
numerical_features = ['Screen On Time (hours/day)', 'Battery Drain (mAh/day)',
                      'Number of Apps Installed', 'Data Usage (MB/day)']

#Preprocessing pipeline
preprocessor = ColumnTransformer(transformers=[
    ('num', StandardScaler(), numerical_features),
    ('cat', OneHotEncoder(), categorical_features)
```

```
])
# Train Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[27]:
```
# Linear Regression Model
lr_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('model', LinearRegression())
])

# Train and evaluate
lr_pipeline.fit(X_train, y_train)
y_pred_lr = lr_pipeline.predict(X_test)

mae_lr = mean_absolute_error(y_test, y_pred_lr)
mse_lr = mean_squared_error(y_test, y_pred_lr)
rmse_lr = np.sqrt(mse_lr)
r2_lr = r2_score(y_test, y_pred_lr)

# Print Results
print('Linear Regression Results')
print(f'MAE: {mae_lr}')
print(f'MSE: {mse_lr}')
print(f'RMSE: {np.sqrt(mse_lr)}')
print(f'R^2: {r2_score(y_test, y_pred_lr)}')
```

```
Linear Regression Results
MAE: 35.051906212117125
MSE: 1885.1893380352788
RMSE: 43.41876711786366
R^2: 0.9312093987635787
```

[28]:
```
# Random Forest Model
rf_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('model', RandomForestRegressor(random_state=42))
])

# Train and evaluate
rf_pipeline.fit(X_train, y_train)
y_pred_rf = rf_pipeline.predict(X_test)

mae_rf = mean_absolute_error(y_test, y_pred_rf)
mse_rf = mean_squared_error(y_test, y_pred_rf)
rmse_rf = np.sqrt(mse_rf)
r2_rf = r2_score(y_test, y_pred_rf)
```

```python
print('Random Forest Results:')
print(f'MAE: {mae_rf}')
print(f'MSE: {mse_rf}')
print(f'RMSE: {np.sqrt(mse_rf)}')
print(f'R^2: {r2_score(y_test, y_pred_rf)}')
```

```
Random Forest Results:
MAE: 27.30028571428572
MSE: 1231.0872942857143
RMSE: 35.08685358201436
R^2: 0.9550775970138398
```

[29]:
```python
# XGBoost Model
xgb_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('model', XGBRegressor(random_state=42))
])

# Train and evaluate
xgb_pipeline.fit(X_train, y_train)
y_pred_xgb = xgb_pipeline.predict(X_test)

mae_xgb = mean_absolute_error(y_test, y_pred_xgb)
mse_xgb = mean_squared_error(y_test, y_pred_xgb)
rmse_xgb = np.sqrt(mse_xgb)
r2_xgb = r2_score(y_test, y_pred_xgb)

print('XGBoost Results:')
print(f'MAE: {mae_xgb}')
print(f'MSE: {mse_xgb}')
print(f'RMSE: {np.sqrt(mse_xgb)}')
print(f'R^2: {r2_score(y_test, y_pred_xgb)}')
```

```
XGBoost Results:
MAE: 29.092661203656878
MSE: 1452.941171127899
RMSE: 38.11746543420613
R^2: 0.9469821440708955
```

[30]:
```python
# Put the scores into a dataframe
metrics_df = pd.DataFrame({
    'Model': ['Linear Regression', 'Random Forest', 'XGBoost'],
    'MAE': [mae_lr, mae_rf, mae_xgb],
    'MSE': [mse_lr, mse_rf, mse_xgb],
    'RMSE': [rmse_lr, rmse_rf, rmse_xgb],
    'R2': [r2_lr, r2_rf, r2_xgb]
})
```

```
print(metrics_df)
```

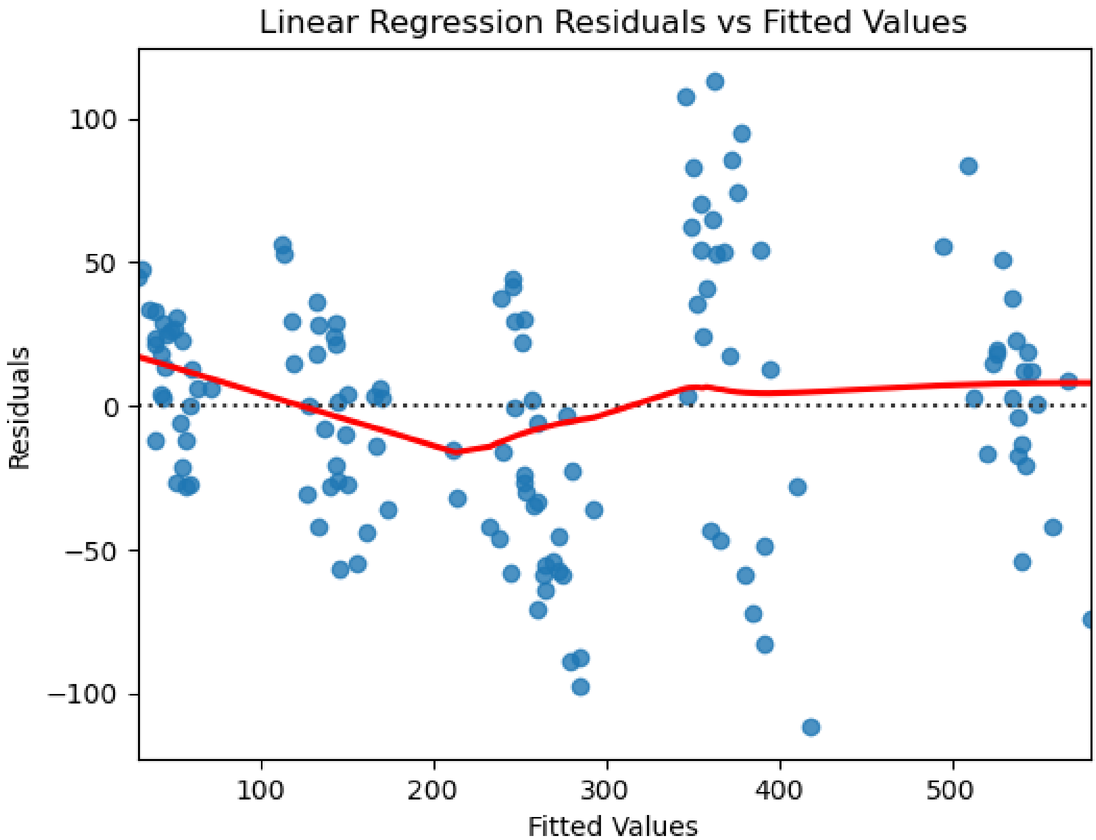
```
                Model        MAE          MSE       RMSE        R2
0  Linear Regression  35.051906  1885.189338  43.418767  0.931209
1      Random Forest  27.300286  1231.087294  35.086854  0.955078
2            XGBoost  29.092661  1452.941171  38.117465  0.946982
```

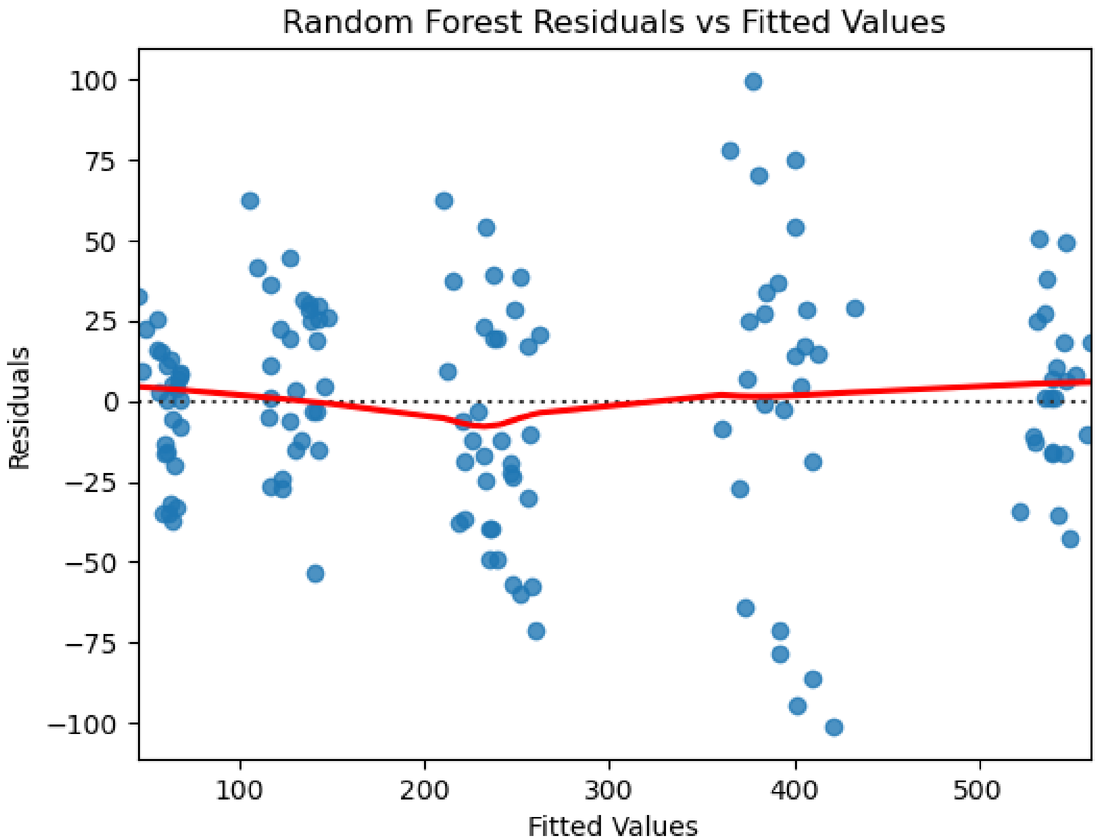
0.7 Graphing Model Performance

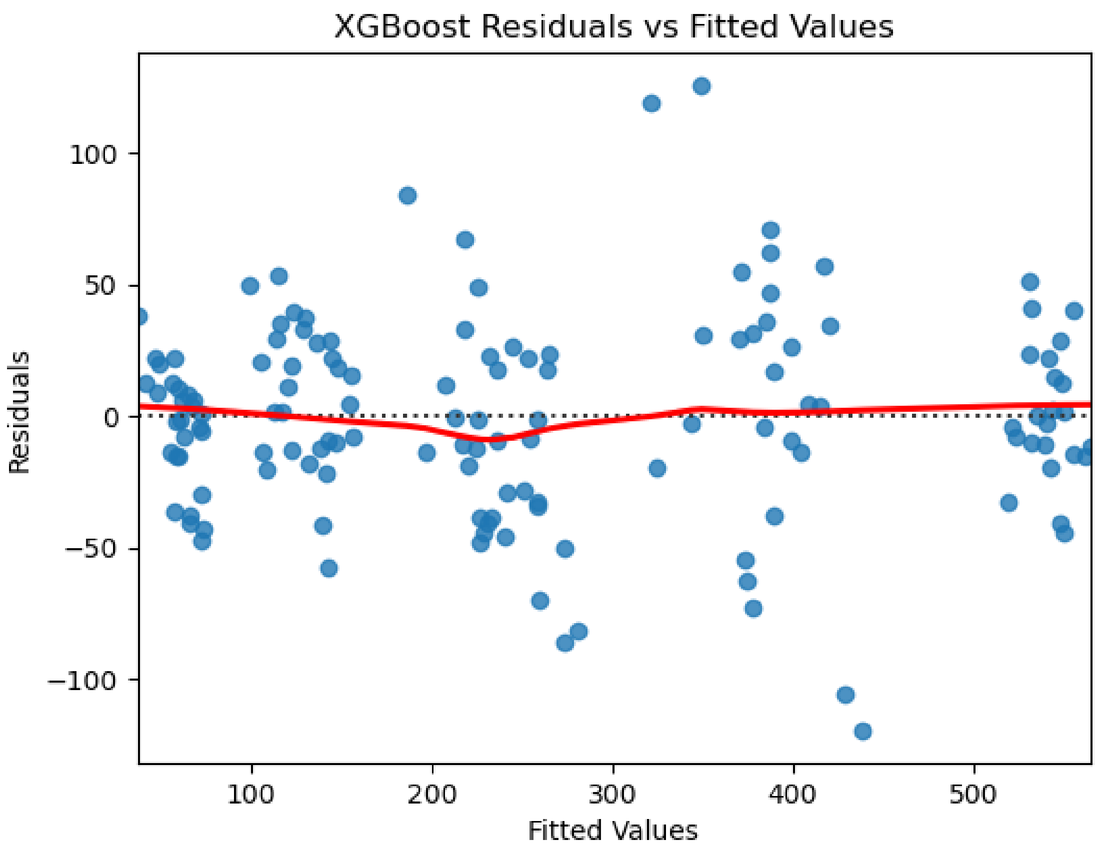
0.8 Residuals

[31]:

```
# Residual plot
residuals_lr = y_test - y_pred_lr
residuals_rf = y_test - y_pred_rf
residuals_xgb = y_test - y_pred_xgb

residuals = {'Linear Regression': [y_pred_lr, residuals_lr], 'Random Forest':␣
↪[y_pred_rf, residuals_rf], 'XGBoost': [y_pred_xgb, residuals_xgb]}

for key, model_residuals in residuals.items():
    sns.residplot(x=model_residuals[0], y=model_residuals[1], lowess=True,␣
↪line_kws={'color': 'red'})
    plt.title(f'{key} Residuals vs Fitted Values')
    plt.xlabel('Fitted Values')
    plt.ylabel('Residuals')
    plt.show()
```


Linear Regression Residuals vs Fitted Values
Residuals
Fitted Values
100
50
0
−50
−100
100
200
300
400
500


Random Forest Residuals vs Fitted Values
Residuals
Fitted Values
100
75
50
25
0
−25
−50
−75
−100
100
200
300
400
500



0.9 Model Analysis

From the performance metrics and graphs above, we can see that the Random Forest model performs the best. It has the lowest RMSE and highest R^2 score.

[32]:
```
# Let's get the feature importance from the Random Forest Model
rf_model = rf_pipeline.named_steps['model']

# Get the feature names after preprocessing
feature_names = preprocessor.get_feature_names_out(X_train.columns)

# Get the feature importances
feature_importance = rf_model.feature_importances_

# Create a dataframe to hold the results
importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': feature_importance
}).sort_values(by='Importance', ascending=False)
```

```
print(importance_df)
```

```
                              Feature  Importance
2          num__Number of Apps Installed    0.368334
3               num__Data Usage (MB/day)    0.300794
1            num__Battery Drain (mAh/day)    0.288011
0         num__Screen On Time (hours/day)    0.037086
4        cat__Device Model_Google Pixel 5    0.000895
6    cat__Device Model_Samsung Galaxy S21    0.000852
5           cat__Device Model_OnePlus 9    0.000750
7         cat__Device Model_Xiaomi Mi 11    0.000731
12                      cat__Gender_Male    0.000723
11                    cat__Gender_Female    0.000583
10            cat__Operating System_iOS    0.000501
8           cat__Device Model_iPhone 12    0.000387
9         cat__Operating System_Android    0.000354
```

0.10 Which features were the most important for predicting app usage time?

[33]:
```
# Plot the feature importance
plt.figure(figsize=(8,6))
sns.barplot(x='Importance', y='Feature', data=importance_df)
plt.title('Feature Importance for Random Forest')
plt.xlabel('Importance Score')
plt.ylabel('Feature')
plt.show()
```