understanding-and-predicting-player-engagement-in-online-games

June 20, 2025

Understanding & Predicting Player Engagement in Online Games

0.0.1 Project Objective

The primary aim of this project is to explore how behavioral patterns, gameplay preferences, and demographic factors contribute to player engagement. This project will look at:

1. **Key Engagement Drivers**
   Identify features that most influence engagement, such as frequency, achievements, and session duration.
2. **Predictive Models**
   Apply machine learning to categorize players into Low, Medium, or High engagement segments with strong performance and interpretability.
3. **Actionable Insights**
   Help game developers and marketing teams tailor their strategies to boost engagement and retention.
4. **Engagement Tactics**
   Recommend targeted strategies such as personalized rewards, adaptive challenges, or curated content to keep players involved longer.g strategies**, and** player retention**.

[1]:
```python
# Libraries
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
from scipy.stats import shapiro, probplot
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

from sklearn.ensemble import IsolationForest
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from lightgbm import LGBMClassifier
```

```
from catboost import CatBoostClassifier
from sklearn.metrics import accuracy_score, roc_auc_score,␣
↪classification_report, confusion_matrix

import shap
import lime
import lime.lime_tabular

import warnings
warnings.filterwarnings("ignore")
```

[2]:
```
# Load dataset
df = pd.read_csv('online_gaming_behavior_dataset.csv')

# Shape of the dataset
print("Shape of the dataset:", df.shape)
df
```

```
Shape of the dataset: (40034, 13)
```

[2]:
```
       PlayerID  Age  Gender Location   GameGenre  PlayTimeHours  \
0          9000   43    Male    Other    Strategy      16.271119
1          9001   29  Female      USA    Strategy       5.525961
2          9002   22  Female      USA      Sports       8.223755
3          9003   35    Male      USA      Action       5.265351
4          9004   33    Male   Europe      Action      15.531945
…           …   …     …       …           …            …
40029     49029   32    Male      USA    Strategy      20.619662
40030     49030   44  Female    Other  Simulation      13.539280
40031     49031   15  Female      USA         RPG       0.240057
40032     49032   34    Male      USA      Sports      14.017818
40033     49033   19    Male      USA      Sports      10.083804

       InGamePurchases GameDifficulty  SessionsPerWeek  \
0                    0         Medium                6
1                    0         Medium                5
2                    0           Easy               16
3                    1           Easy                9
4                    0         Medium                2
…                  …             …               …
40029                0           Easy                4
40030                0           Hard               19
40031                1           Easy               10
40032                1         Medium                3
40033                0           Easy               13

       AvgSessionDurationMinutes  PlayerLevel  AchievementsUnlocked  \
```

```
0                           108          79                      25
1                           144          11                      10
2                           142          35                      41
3                            85          57                      47
4                           131          95                      37
…                           …            …                       …
40029                        75          85                      14
40030                       114          71                      27
40031                       176          29                       1
40032                       128          70                      10
40033                        84          72                      39

      EngagementLevel
0              Medium
1              Medium
2                High
3              Medium
4              Medium
…                 …
40029          Medium
40030            High
40031            High
40032          Medium
40033          Medium

[40034 rows x 13 columns]
```

[3]:
```python
# Clean column names (standardize)
df.columns = df.columns.str.strip()
df.columns
```

[3]:
```
Index(['PlayerID', 'Age', 'Gender', 'Location', 'GameGenre', 'PlayTimeHours',
       'InGamePurchases', 'GameDifficulty', 'SessionsPerWeek',
       'AvgSessionDurationMinutes', 'PlayerLevel', 'AchievementsUnlocked',
       'EngagementLevel'],
      dtype='object')
```

[4]:
```python
# Basic information
print("Dataset Information:")
df.info()
```

```
Dataset Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 40034 entries, 0 to 40033
Data columns (total 13 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   PlayerID                   40034 non-null  int64
```

```
 1   Age                        40034 non-null  int64
 2   Gender                     40034 non-null  object
 3   Location                   40034 non-null  object
 4   GameGenre                  40034 non-null  object
 5   PlayTimeHours              40034 non-null  float64
 6   InGamePurchases            40034 non-null  int64
 7   GameDifficulty             40034 non-null  object
 8   SessionsPerWeek            40034 non-null  int64
 9   AvgSessionDurationMinutes  40034 non-null  int64
 10  PlayerLevel                40034 non-null  int64
 11  AchievementsUnlocked       40034 non-null  int64
 12  EngagementLevel            40034 non-null  object
dtypes: float64(1), int64(7), object(5)
memory usage: 4.0+ MB
```

0.0.2 Dataset Overview & Key Insights

The dataset consists of **40,034 records** and **13 features**, offering a solid foundation for analyzing player behavior and engagement in online games. It includes both **numerical** and **categorical** variables that capture demographics, gameplay behavior, and engagement metrics.

Feature Breakdown & Highlights

- **Player Demographics**
  - `PlayerID`: Unique identifier for each player
  - `Age`: Age of the player
  - `Gender`: Gender identity
  - `Location`: Geographic region
- **Gameplay Attributes**
  - `GameGenre`: Type of game played (e.g., RPG, Action, Strategy)
  - `GameDifficulty`: Game's difficulty level (Easy, Medium, Hard)
  - `PlayerLevel`: Current level achieved in the game
  - `AchievementsUnlocked`: Total achievements earned
- **Engagement Metrics**
  - `PlayTimeHours`: Average hours spent per session
  - `InGamePurchases`: Indicates whether the player makes in-game purchases (0 = No, 1 = Yes)
  - `SessionsPerWeek`: Number of gaming sessions per week
  - `AvgSessionDurationMinutes`: Average duration of each session in minutes

- **Target Variable**
  - `EngagementLevel`: Categorical variable representing player engagement, labeled as `'High'`, `'Medium'`, or `'Low'`, making it a **multi-class classification problem**

Data Quality & Modeling Readiness

- The dataset is **clean**, with **no missing values** in any column.

- It includes **7 numerical** and **5 categorical** features.

- Categorical variables such as `Gender`, `Location`, `GameGenre`, `GameDifficulty`, and `EngagementLevel` will require **encoding** before modeling.

- The presence of rich behavioral features enables both **exploratory analysis** and the development of **predictive models** aimed at understanding and improving player engagement. analysis.

[5]:
```
# Missing values
print("Missing values:")
print(df.isnull().sum())

# Check duplicates
print("\nNumber of duplicates:", df.duplicated().sum())
```

```
Missing values:
PlayerID                     0
Age                          0
Gender                       0
Location                     0
GameGenre                    0
PlayTimeHours                0
InGamePurchases              0
GameDifficulty               0
SessionsPerWeek              0
AvgSessionDurationMinutes    0
PlayerLevel                  0
AchievementsUnlocked         0
EngagementLevel              0
dtype: int64

Number of duplicates: 0
```

The dataset is **clean and ready for analysis**:

- **No missing values**

- **No duplicate records**ed!

[6]:
```
# Statistical summary
df.describe()
```

[6]:
```
           PlayerID           Age  PlayTimeHours  InGamePurchases  \
count  40034.000000  40034.000000   40034.000000     40034.000000
mean   29016.500000     31.992531      12.024365         0.200854
std    11556.964675     10.043227       6.914638         0.400644
min     9000.000000     15.000000       0.000115         0.000000
25%    19008.250000     23.000000       6.067501         0.000000
50%    29016.500000     32.000000      12.008002         0.000000
75%    39024.750000     41.000000      17.963831         0.000000
max    49033.000000     49.000000      23.999592         1.000000

       SessionsPerWeek  AvgSessionDurationMinutes   PlayerLevel  \
count     40034.000000               40034.000000  40034.000000
mean          9.471774                  94.792252     49.655568
std           5.763667                  49.011375     28.588379
min           0.000000                  10.000000      1.000000
25%           4.000000                  52.000000     25.000000
50%           9.000000                  95.000000     49.000000
75%          14.000000                 137.000000     74.000000
max          19.000000                 179.000000     99.000000

       AchievementsUnlocked
count          40034.000000
mean              24.526477
std               14.430726
min                0.000000
25%               12.000000
50%               25.000000
75%               37.000000
max               49.000000
```

0.0.3 Key Insights from Statistical Summary

Numerical Features Overview:

- **Age**:
  - Average player age is **32**, mostly ranging from **23 to 41** years.

  - Indicates a primarily **young to middle-aged** gaming population.
- **PlayTimeHours**:
  - Players spend an average of **12 hours per session**, with a wide range (up to 24 hours).

  - Reflects a mix of **casual and heavy users**.
- **InGamePurchases**:
  - Around **20%** of players make purchases.

  - Indicates a small but likely **high-value monetization group**.
- **SessionsPerWeek**:
  - Average of **9 sessions weekly**, with most players between **4 and 14** sessions.

  - Serves as a strong **engagement indicator**.
- **AvgSessionDurationMinutes**:
  - Sessions last around **95 minutes** on average.

  - Longer durations may correlate with **higher engagement**.
- **PlayerLevel**:
  - Average level is **50**, with most between **25 and 74**.

  - Suggests a player base with **moderate to advanced progress**.
- **AchievementsUnlocked**:
  - Players unlock about **25 achievements** on average.

  - Higher achievements often signal **greater engagement or skill**.

[7]:
```python
# Random spot check
df.sample(5)
```

[7]:
```
       PlayerID  Age  Gender Location   GameGenre  PlayTimeHours  \
18006     27006   19    Male     Asia      Sports      13.988594
39503     48503   36  Female   Europe    Strategy       7.545703
8017      17017   44    Male   Europe  Simulation      23.718402
32000     41000   42    Male      USA    Strategy       6.996367
12327     21327   44    Male   Europe  Simulation      10.110106

       InGamePurchases GameDifficulty  SessionsPerWeek  \
18006                0           Easy                5
39503                1           Hard               10
8017                 0           Hard                8
32000                0         Medium               19
12327                1         Medium               11

       AvgSessionDurationMinutes  PlayerLevel  AchievementsUnlocked  \
18006                        172           51                     8
39503                        130           93                    19
8017                         149           60                    22
32000                        167           26                     9
12327                        147           59                    46

      EngagementLevel
18006          Medium
39503            High
8017           Medium
32000            High
```

```
12327            High
```

[8]:
```
# Display the number of unique values in each column
unique = df.nunique()
unique
```

[8]:
```
PlayerID                    40034
Age                            35
Gender                          2
Location                        4
GameGenre                       5
PlayTimeHours               40034
InGamePurchases                 2
GameDifficulty                  3
SessionsPerWeek                20
AvgSessionDurationMinutes     170
PlayerLevel                    99
AchievementsUnlocked           50
EngagementLevel                 3
dtype: int64
```

[9]:
```
# Identify numeric and categorical feature columns
numeric_features = df.select_dtypes(include=['int64', 'float64']).columns.
 ↪tolist()
categorical_features = df.select_dtypes(include=['object']).columns.tolist()

# Identified column types
print("  Numeric Features:\n", numeric_features)
print("\n  Categorical Features:\n", categorical_features)
```

```
 Numeric Features:
 ['PlayerID', 'Age', 'PlayTimeHours', 'InGamePurchases', 'SessionsPerWeek',
'AvgSessionDurationMinutes', 'PlayerLevel', 'AchievementsUnlocked']

 Categorical Features:
 ['Gender', 'Location', 'GameGenre', 'GameDifficulty', 'EngagementLevel']
```

[10]:
```
# Display unique values for each categorical feature
for feature in categorical_features:
    print(f"\n  Feature: {feature}")
    print(f"  Unique Values: {df[feature].unique()}")
```

```
 Feature: Gender
 Unique Values: ['Male' 'Female']

 Feature: Location
 Unique Values: ['Other' 'USA' 'Europe' 'Asia']
```

```
Feature: GameGenre
Unique Values: ['Strategy' 'Sports' 'Action' 'RPG' 'Simulation']

Feature: GameDifficulty
Unique Values: ['Medium' 'Easy' 'Hard']

Feature: EngagementLevel
Unique Values: ['Medium' 'High' 'Low']
```

Unique Values per Column

- **PlayerID**: 40,034 unique entries — each player has a distinct ID.
- **Age**: 35 distinct ages, ranging from 15 to 49.
- **Gender**: 2 values — `Male` and `Female`.
- **Location**: 4 regions — `USA`, `Europe`, `Asia`, `Other`.
- **GameGenre**: 5 categories — `Strategy`, `Sports`, `Action`, `RPG`, `Simulation`.
- **PlayTimeHours**: 40,034 unique values — suggests continuous data.
- **InGamePurchases**: 2 binary values — `0` (No), `1` (Yes).
- **GameDifficulty**: 3 levels — `Easy`, `Medium`, `Hard`.
- **SessionsPerWeek**: 20 values — from 0 to 19 sessions.
- **AvgSessionDurationMinutes**: 170 unique durations in minutes.
- **PlayerLevel**: 99 levels — from 1 to 99.
- **AchievementsUnlocked**: 50 values — from 0 to 49.
- **EngagementLevel**: 3 classes — `High`, `Medium`, `Low`.

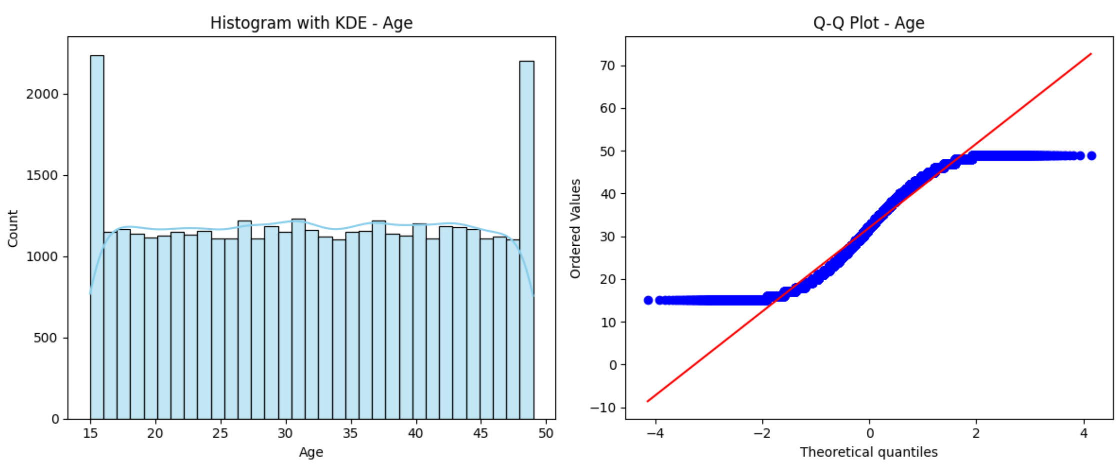
Feature Classification

- **Numerical Features**:
  `PlayerID`, `Age`, `PlayTimeHours`, `InGamePurchases`, `SessionsPerWeek`, `AvgSessionDurationMinutes`, `PlayerLevel`, `AchievementsUnlocked`
- **Categorical Features**:
  `Gender`, `Location`, `GameGenre`, `GameDifficulty`, `EngagementLevel`

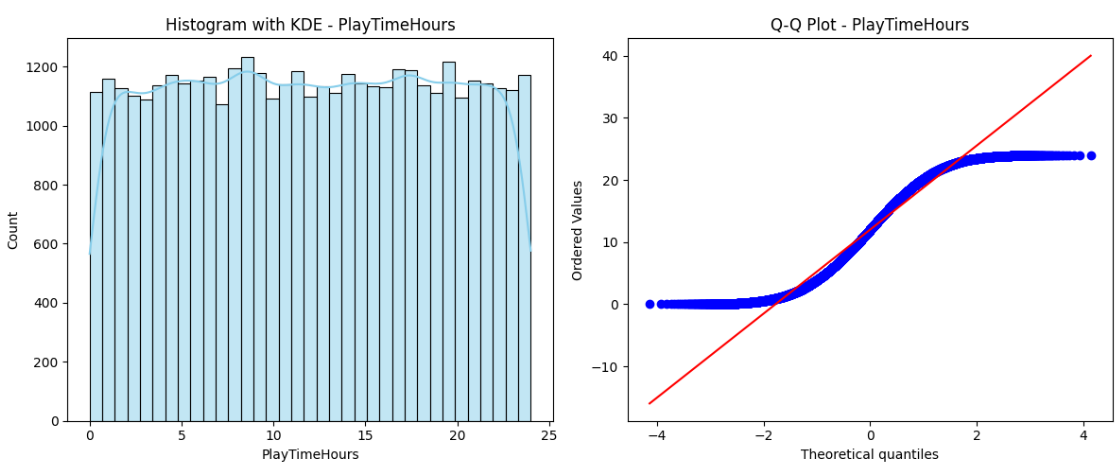
Input Feature Analysis

[11]:
```python
#   Distribution Check for Numerical Features
numerical_cols = [
    'Age', 'PlayTimeHours', 'SessionsPerWeek',
    'AvgSessionDurationMinutes', 'PlayerLevel', 'AchievementsUnlocked'
]

for col in numerical_cols:
    # Plot histogram with KDE
    plt.figure(figsize=(12, 5))

    plt.subplot(1, 2, 1)
```

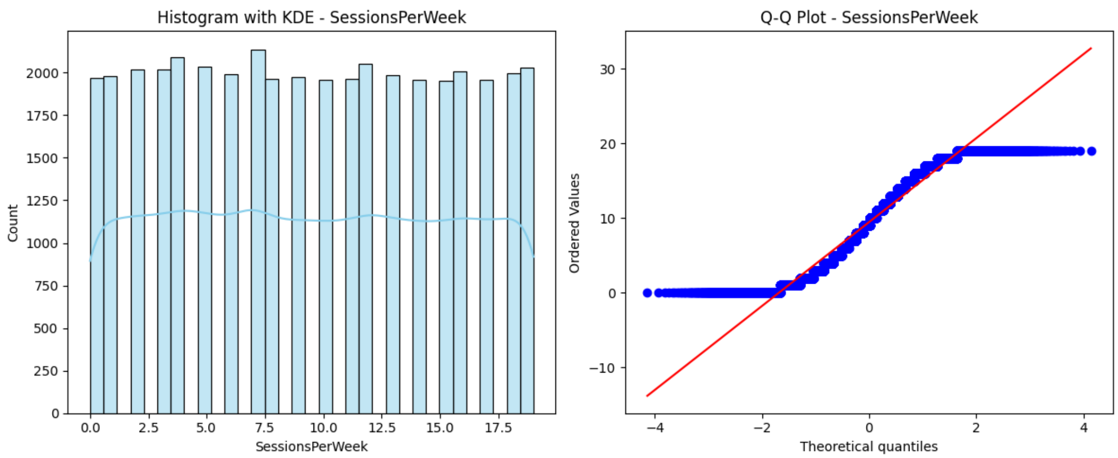
```
    sns.histplot(df[col], kde=True, color='skyblue')
    plt.title(f'Histogram with KDE - {col}')

    # Plot Q-Q plot
    plt.subplot(1, 2, 2)
    probplot(df[col], dist='norm', plot=plt)
    plt.title(f'Q-Q Plot - {col}')

    plt.tight_layout()
    plt.show()

    # Perform Shapiro-Wilk test
    stat, p = shapiro(df[col])
    result = "  Gaussian" if p > 0.05 else "  Not Gaussian"
    print(f"{col}: Shapiro-Wilk p-value = {p:.4f} → {result}\n")
```



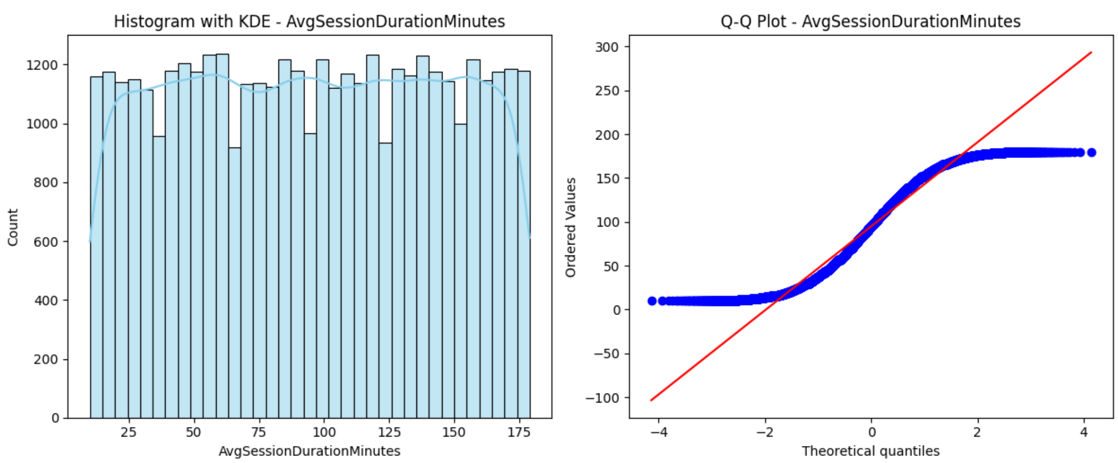

```
Age: Shapiro-Wilk p-value = 0.0000 →   Not Gaussian
```



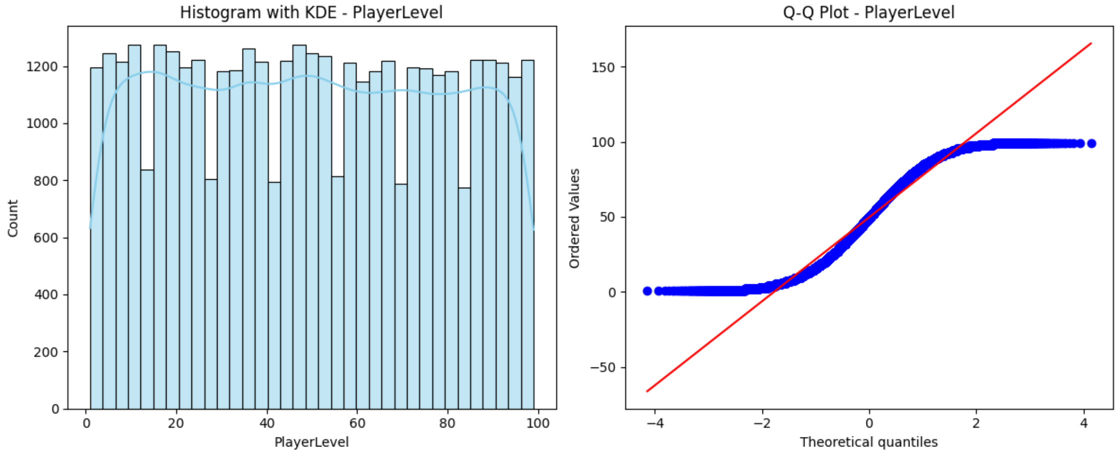
```
PlayTimeHours: Shapiro-Wilk p-value = 0.0000 → Not Gaussian
```



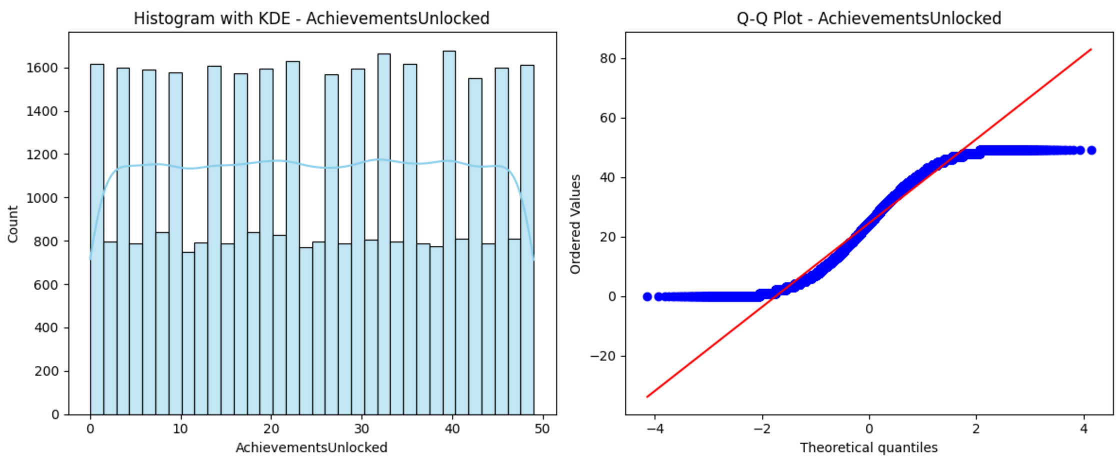

```
SessionsPerWeek: Shapiro-Wilk p-value = 0.0000 → Not Gaussian
```




```
AvgSessionDurationMinutes: Shapiro-Wilk p-value = 0.0000 → Not Gaussian
```




```
PlayerLevel: Shapiro-Wilk p-value = 0.0000 →  Not Gaussian
```

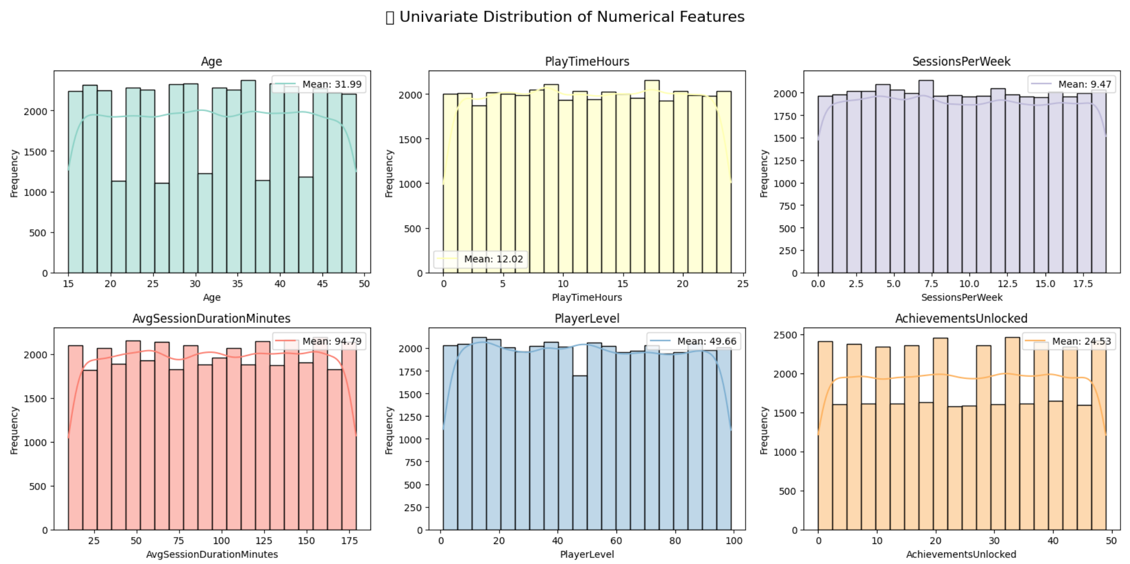



```
AchievementsUnlocked: Shapiro-Wilk p-value = 0.0000 →  Not Gaussian
```

[12]:

```python
def plot_univariate_distributions(df, numeric_features):
    """
    Plots histograms with KDE overlays for each numerical feature.
    """
    num_features = len(numeric_features)
    num_cols = 3
    num_rows = (num_features + num_cols - 1) // num_cols  # automatic row count

    plt.figure(figsize=(num_cols * 5.5, num_rows * 4))
    color_palette = sns.color_palette("Set3", num_features)
```

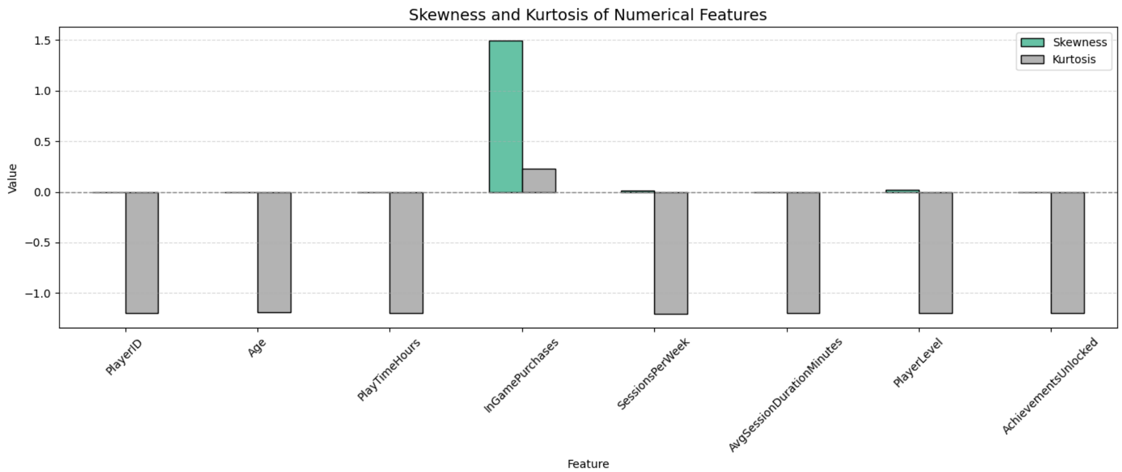
```
    for idx, feature in enumerate(numeric_features):
        plt.subplot(num_rows, num_cols, idx + 1)
        sns.histplot(df[feature], kde=True, bins=20, color=color_palette[idx])
        plt.title(f'{feature.replace("_", " ")}', fontsize=12)
        plt.xlabel(feature.replace("_", " "))
        plt.ylabel('Frequency')
        plt.legend([f'Mean: {df[feature].mean():.2f}'])

    plt.suptitle("  Univariate Distribution of Numerical Features",␣
↪fontsize=16, y=1.02)
    plt.tight_layout()
    plt.show()

plot_univariate_distributions(df, numerical_cols)
```



[13]:
```
#  Skewness and Kurtosis Analysis of Numerical Features

# Select numerical data
numerical_df = df.select_dtypes(include=[np.number])

# Compute skewness and kurtosis
skewness = numerical_df.skew()
kurtosis = numerical_df.kurt()

# Combine into a single DataFrame
distribution_stats = pd.DataFrame({
    'Feature': skewness.index,
```

```python
    'Skewness': skewness.values,
    'Kurtosis': kurtosis.values
})

# Display the table
print("  Skewness and Kurtosis Summary:\n")
display(distribution_stats)

# Plot skewness and kurtosis
plt.figure(figsize=(14, 6))
distribution_stats.set_index('Feature')[['Skewness', 'Kurtosis']].plot(
    kind='bar',
    figsize=(14, 6),
    colormap='Set2',
    edgecolor='black'
)

plt.axhline(0, color='gray', linestyle='--', linewidth=1)
plt.title('Skewness and Kurtosis of Numerical Features', fontsize=14)
plt.ylabel('Value')
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.5)
plt.tight_layout()
plt.legend(loc='upper right')

plt.show()
```

```
  Skewness and Kurtosis Summary:


                     Feature  Skewness  Kurtosis
0                   PlayerID  0.000000 -1.200000
1                        Age -0.004466 -1.192417
2              PlayTimeHours -0.002225 -1.195706
3            InGamePurchases  1.493398  0.230249
4            SessionsPerWeek  0.015517 -1.206566
5  AvgSessionDurationMinutes -0.005632 -1.199556
6                PlayerLevel  0.018754 -1.199738
7       AchievementsUnlocked -0.005136 -1.199623

<Figure size 1400x600 with 0 Axes>
```



0.0.4 Distribution Analysis Summary & Feature Insights

Visual and statistical analysis confirms that the **numerical features do not follow a Gaussian (normal) distribution**:

- **Shapiro-Wilk p-values** for all tested features (`Age`, `PlayTimeHours`, `SessionsPerWeek`, `AvgSessionDurationMinutes`, `PlayerLevel`, `AchievementsUnlocked`) are $<$ **0.05**, providing strong evidence **against normality**.
- **Q-Q plots** further validate this by showing consistent deviations from the theoretical normal line.
- Most distributions are **uniform, skewed, or multimodal**, which aligns with expectations for behavioral data in gaming contexts.
- **Skewness and kurtosis values** for all features are close to 0 and well below kurtosis = 3, confirming that distributions are **not heavily tailed** and generally exhibit **low peakedness**.
- A notable exception is `InGamePurchases`, which shows **high right skew (1.49)—suggesting most players don't purchase, but a few outliers contribute significantly to in-game monetization**.

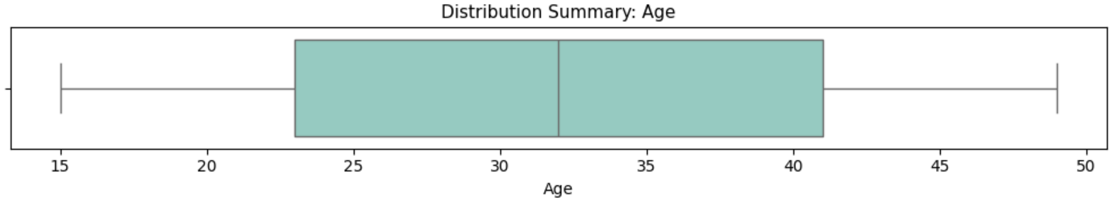
0.0.5 Feature-wise Insights

Feature	Key Observations
Age	Near-zero skew (-0.00) and low kurtosis (-1.19); distribution is flat and slightly right-skewed. Majority aged 20–40, peaking at 25–30.
PlayTimeHours	Very slight left skew (-0.00) and low kurtosis (-1.20); players typically log 10–15 hours per session.

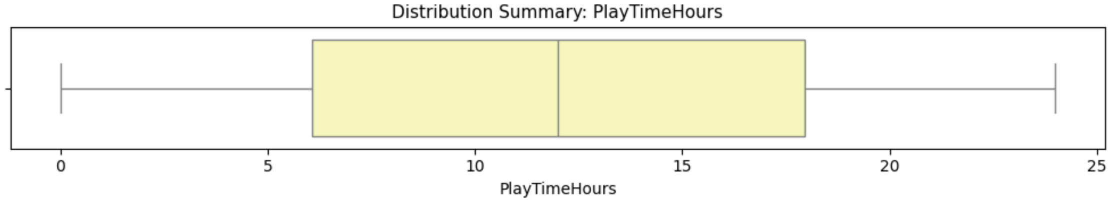
Feature	Key Observations
SessionsPerWeek	Almost symmetric (skew = 0.02), flat-tailed (-1.21); most players engage 5–10 times per week.
AvgSessionDurationMinutes	Near-normal appearance (skew = -0.01); centered around 90–100 mins with typical range of 50–150 mins.
PlayerLevel	Symmetric (skew = 0.02) and flat (-1.20); uniformly distributed from levels 1–99, suggesting balanced progression.
AchievementsUnlocked	Slight left skew (-0.01) with low kurtosis (-1.20); most players unlock 15–30 achievements, few reach high totals.
InGamePurchases	**Highly right-skewed (1.49)** and slightly peaked (0.23); suggests most players don't purchase, but a few outliers contribute significantly to monetization.

[14]:
```python
# Visual Exploration: Boxplots for Key Quantitative Features
# Horizontal boxplots for selected numeric attributes to visually examine value
↪distribution and detect potential outliers.

# Function to draw a boxplot for each feature
def draw_feature_boxplot(dataframe, feature_name, display_name):
    plt.figure(figsize=(10, 2))

    # Choose a distinct color from the palette based on index
    color_choice = sns.color_palette("Set3")[numerical_cols.index(feature_name)
↪% len(sns.color_palette("Set3"))]

    # Create the horizontal boxplot
    sns.boxplot(x=dataframe[feature_name], color=color_choice)
    plt.title(f'Distribution Summary: {display_name}', fontsize=11)
    plt.xlabel(display_name)

    plt.tight_layout()
    plt.show()

# Generate boxplots for each numerical column
for feature in numerical_cols:
    readable_label = feature.replace('_', ' ')
    draw_feature_boxplot(df, feature, readable_label)
```

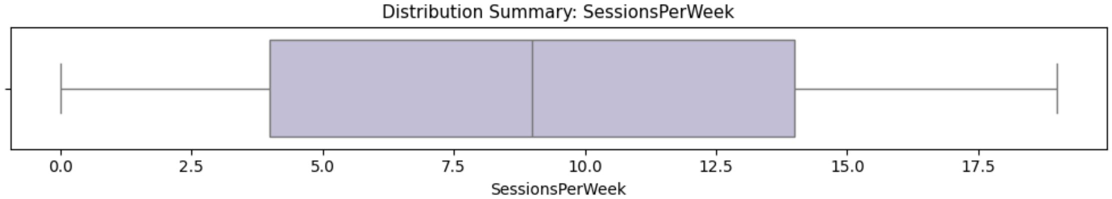
Distribution Summary: Age



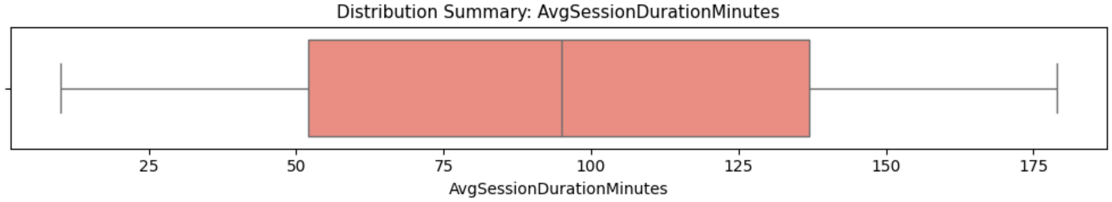
Distribution Summary: PlayTimeHours



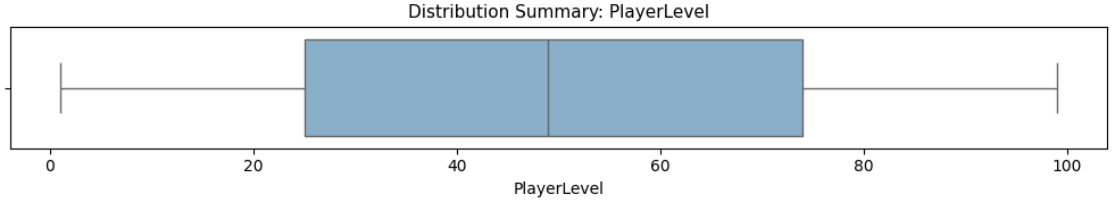
Distribution Summary: SessionsPerWeek

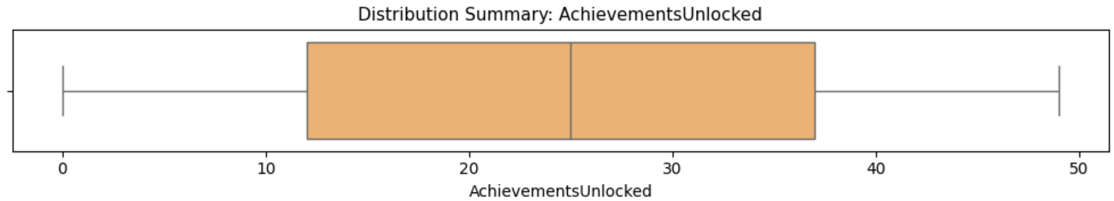


Distribution Summary: AvgSessionDurationMinutes



Distribution Summary: PlayerLevel





0.0.6 Insights and Recommendations

1. Age

- Average player age is around **32**, with a broad range from 15 to 49. This indicates a **mature and diverse player base**.

Recommendations: - **Game Design**: Blend nostalgic and fast-paced elements to appeal across age groups. - **Marketing**: Use generational targeting in ads (e.g., nostalgic references for older players, trend-driven content for younger ones).

---

2. PlayTimeHours

- Average session time is **12 hours**, with some players showing minimal and others extensive engagement.

Recommendations: - **Engagement Boosters**: Implement unlockable goals or streak-based rewards to lengthen playtime. - **Reactivation**: Target low-time users with re-engagement campaigns like XP boosts or exclusive events.

---

3. InGamePurchases

- Most users do **not** purchase, but a small group of players contributes **disproportionately** to revenue.

Recommendations: - **Pricing Strategy**: Create multiple price tiers with diverse value propositions. - **Conversion Tactics**: Highlight the benefits of premium content in a non-intrusive way (e.g., free trials, "try-before-you-buy" events).

---

4. SessionsPerWeek

- Players average about **9 sessions weekly**, showing consistent re-engagement.

Recommendations: - **Retention Mechanics**: Use login streaks and daily challenges to encourage consistent return. - **Social Motivation**: Introduce cooperative or competitive features to drive habitual play.

---

5. AvgSessionDurationMinutes

- Sessions average **95 minutes**, indicating strong content depth.

Recommendations: - **Content Structure**: Offer both short-session modes and longer immersive missions to serve different play styles. - **Optimize Onboarding**: Reduce early-game friction to ensure new users stay long enough to experience the core loop.

---

6. PlayerLevel

- Players are spread fairly evenly across all levels, with an average near **50**.

Recommendations: - **Progressive Rewards**: Offer milestone perks every 10–20 levels to keep advancement exciting. - **Endgame Content**: Introduce elite-level features or prestige tiers for high-level players.

---

7. AchievementsUnlocked

- On average, players unlock about **half of the available achievements**.

Recommendations: - **Diverse Achievement Paths**: Include achievements for social play, exploration, and creativity. - **Progress Visibility**: Show achievement progress bars or "near-complete" nudges to motivate completion.

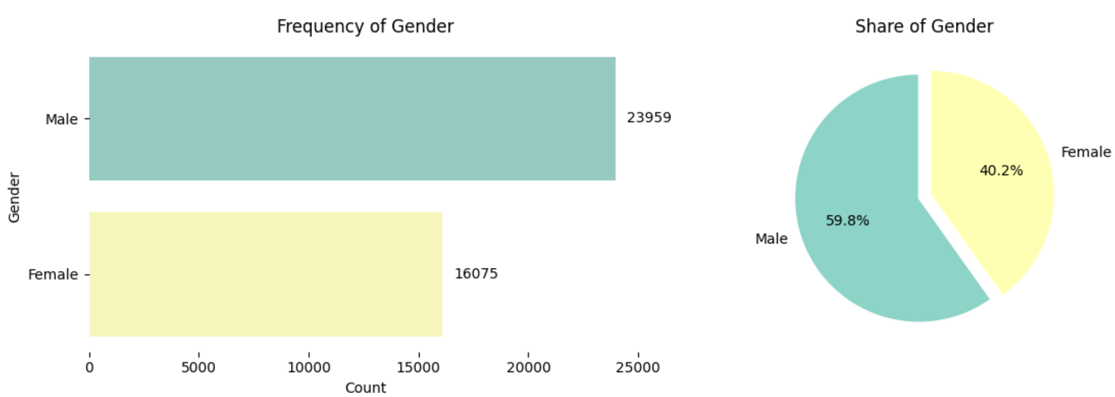
0.0.7 Strategic Summary

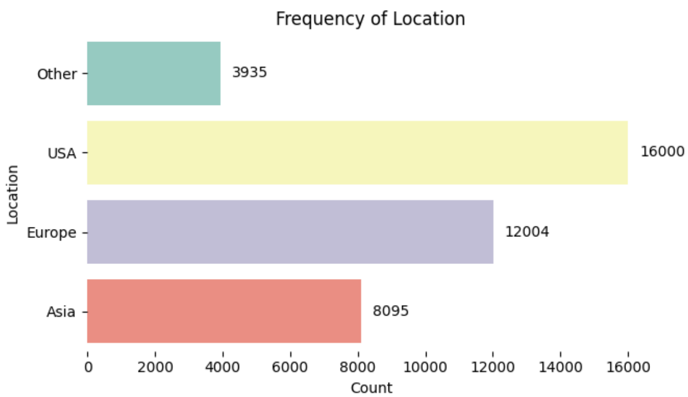
By combining behavioral metrics with thoughtful design, the following strategies can improve both experience and monetization:

- **Tailored Game Features**: Design flexible content paths for different engagement styles.
- **Smart Monetization**: Use behavioral segmentation to match pricing and value.
- **Player Retention**: Implement structured rewards, seasonal content, and meaningful progression systems. ompleting achievement lists.

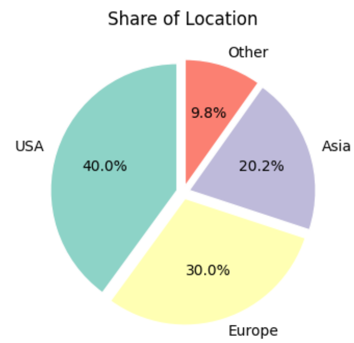
[15]:
```python
#  Visualization: Distribution of Categorical Features

def visualize_category_distribution(feature, dataframe=df):
    plt.figure(figsize=(12, 4))

    # Bar Plot (Horizontal) - Frequency count
    plt.subplot(1, 2, 1)
    sns.countplot(y=feature, data=dataframe, palette='Set3')
    plt.title(f'Frequency of {feature}')
    plt.xlabel('Count')
    plt.ylabel(feature)

    # Annotate bar values
```

```
    ax = plt.gca()
    for bar in ax.patches:
        count = int(bar.get_width())
        ax.annotate(f'{count}',
                    xy=(bar.get_width(), bar.get_y() + bar.get_height() / 2),
                    xytext=(8, 0), textcoords='offset points',
                    va='center', ha='left')

    sns.despine(left=True, bottom=True)

    # Pie Chart - Percentage share
    plt.subplot(1, 2, 2)
    dataframe[feature].value_counts().plot.pie(
        autopct='%1.1f%%',
        startangle=90,
        colors=sns.color_palette('Set3'),
        explode=[0.05] * dataframe[feature].nunique(),
        wedgeprops={'edgecolor': 'white'}
    )
    plt.title(f'Share of {feature}')
    plt.ylabel('')  # Remove default y-label for pie chart

    plt.tight_layout()
    plt.show()

# Plots for each categorical column
for col in categorical_features:
    visualize_category_distribution(col, df)
```

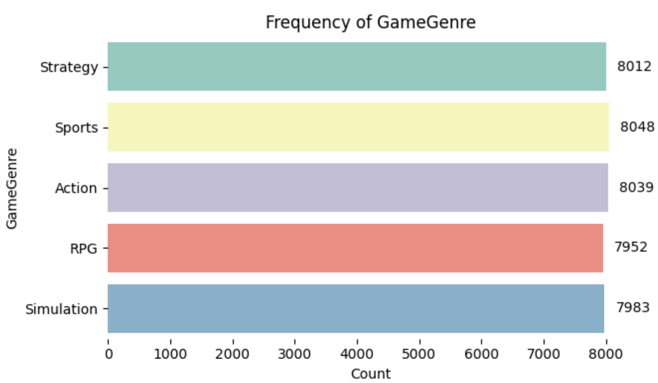




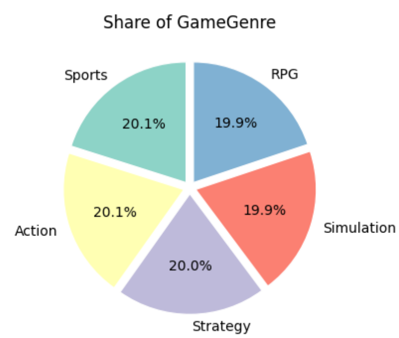
Frequency of Location
Other
USA
Europe
Asia
Location
3935
16000
12004
8095
0
2000
4000
6000
8000
10000
12000
14000
16000
Count



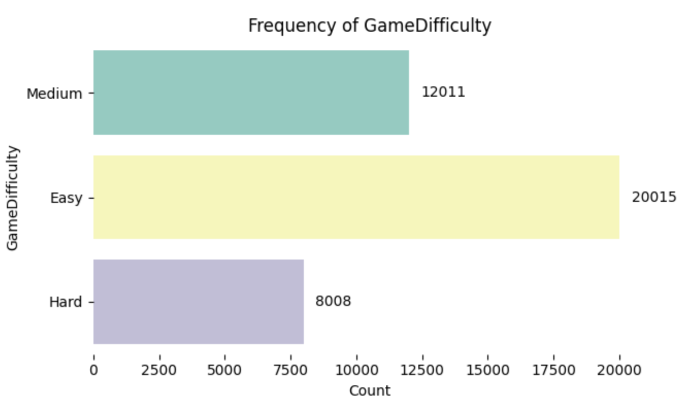
Share of Location
Other
9.8%
Asia
20.2%
Europe
30.0%
USA
40.0%



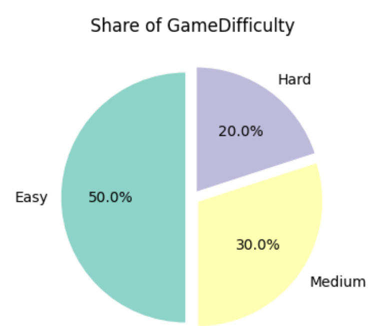
Frequency of GameGenre
Strategy
Sports
Action
RPG
Simulation
GameGenre
8012
8048
8039
7952
7983
0
1000
2000
3000
4000
5000
6000
7000
8000
Count



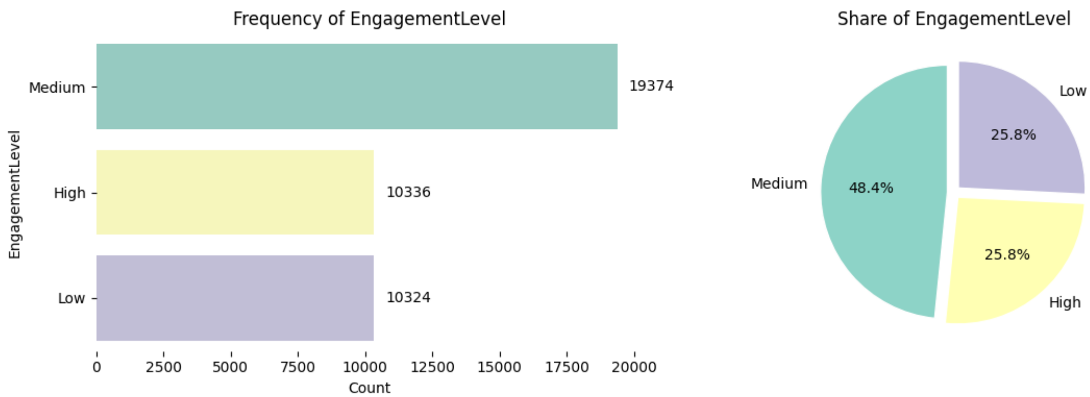
Share of GameGenre
Sports
20.1%
RPG
19.9%
Simulation
19.9%
Strategy
20.0%
Action
20.1%



Frequency of GameDifficulty
Medium
Easy
Hard
GameDifficulty
12011
20015
8008
0
2500
5000
7500
10000
12500
15000
17500
20000
Count



Share of GameDifficulty
Hard
20.0%
Medium
30.0%
Easy
50.0%



0.0.8 Insights from Categorical Features

1. Gender

- The player base shows a clear majority of male participants, making up close to 60% of the total. This gender imbalance opens up opportunities to make the game more appealing to female players. Developers and marketers could introduce features like storylines with strong female leads, inclusive character customization, or community events that foster diversity and engagement among underrepresented groups.

2. Location

- Players are predominantly based in the United States, with Europe and Asia following closely. This regional breakdown highlights the importance of tailoring experiences to specific geographic audiences. Localized content, cultural references, and region-specific promotions can help deepen user engagement and expand market reach across different areas.

3. Game Genre

- Player preferences are distributed relatively evenly across genres, with a slight tilt toward Sports and Action titles. This diversity in interests suggests room for innovation through multi-genre or hybrid experiences. Game developers might consider blending mechanics (e.g., strategy in action games or RPG elements in sports titles) to appeal to overlapping player interests.

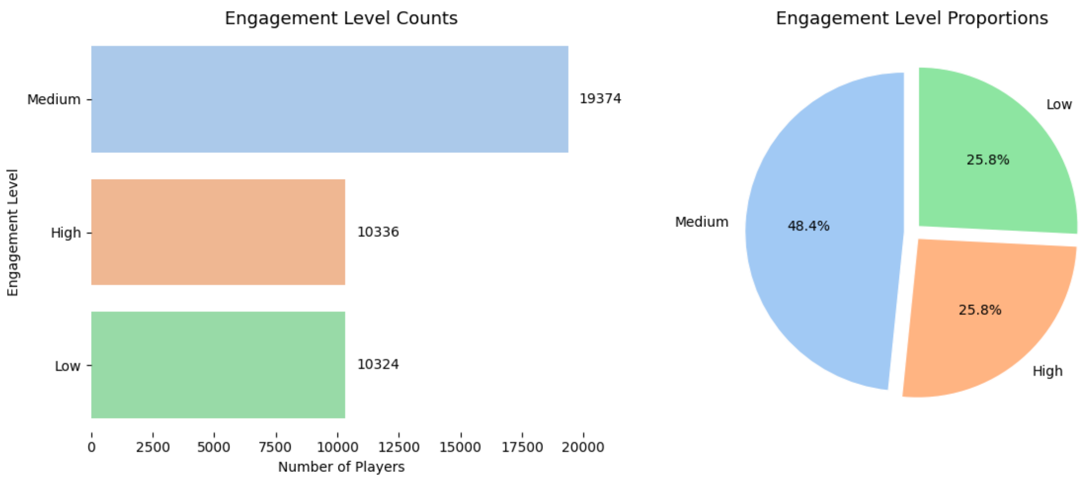
4. Game Difficulty

- Half of the player population favors easier gameplay, reflecting a strong presence of casual gamers. To cater to this broad range of skill levels, developers should provide flexible difficulty settings, onboarding tutorials, and optional challenges. This allows newcomers to enjoy the experience while still delivering depth and difficulty for more competitive players.

Target Variable Analysis

[16]:

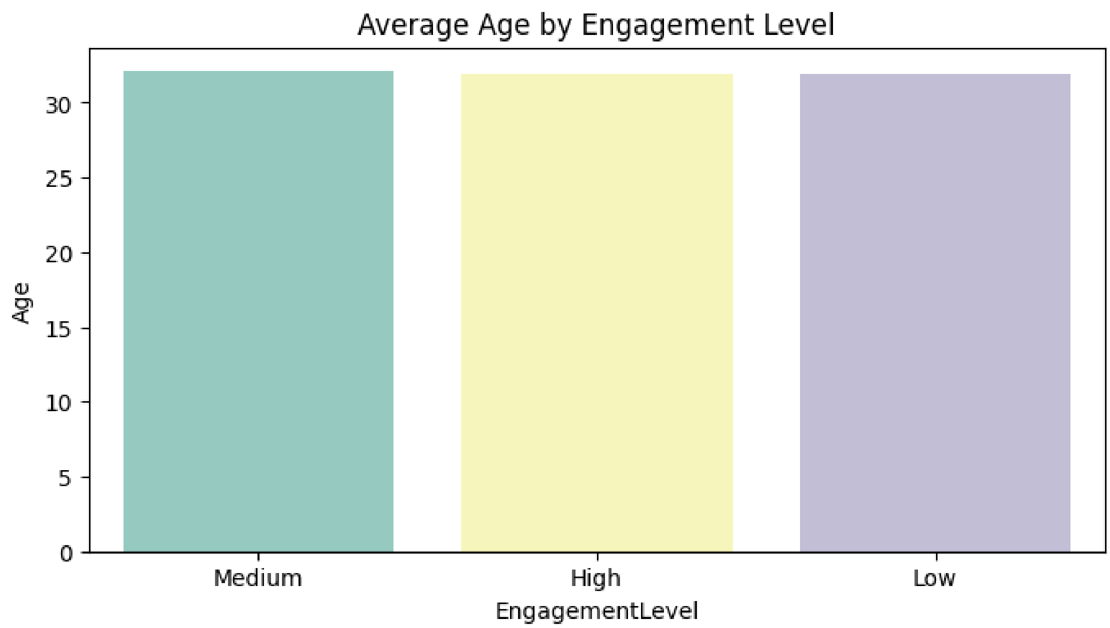
```
#  Engagement Level Distribution Analysis
'''This visualization block compares the distribution of the target variable␣
↪`EngagementLevel` '''

target_feature = 'EngagementLevel'
plot_colors = sns.color_palette('pastel')  # Updated for a softer palette

plt.figure(figsize=(12, 5))

# Subplot 1: Horizontal Count Plot
plt.subplot(1, 2, 1)
sns.countplot(y=target_feature, data=df, palette=plot_colors)
plt.title('Engagement Level Counts', fontsize=13)
plt.xlabel('Number of Players')
plt.ylabel('Engagement Level')

# Annotate counts next to bars
ax = plt.gca()
for bar in ax.patches:
    count = int(bar.get_width())
    ax.annotate(f'{count}',
                xy=(bar.get_width(), bar.get_y() + bar.get_height() / 2),
                xytext=(8, 0), textcoords='offset points',
                va='center', ha='left', fontsize=10)

sns.despine(left=True, bottom=True)

# Subplot 2: Pie Chart of Class Proportions
plt.subplot(1, 2, 2)
df[target_feature].value_counts().plot.pie(
    autopct='%1.1f%%',
    startangle=90,
    colors=plot_colors,
    explode=[0.05] * df[target_feature].nunique(),
    wedgeprops={'linewidth': 1, 'edgecolor': 'white'}
)
plt.title('Engagement Level Proportions', fontsize=13)
plt.ylabel('')  # Remove default ylabel

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

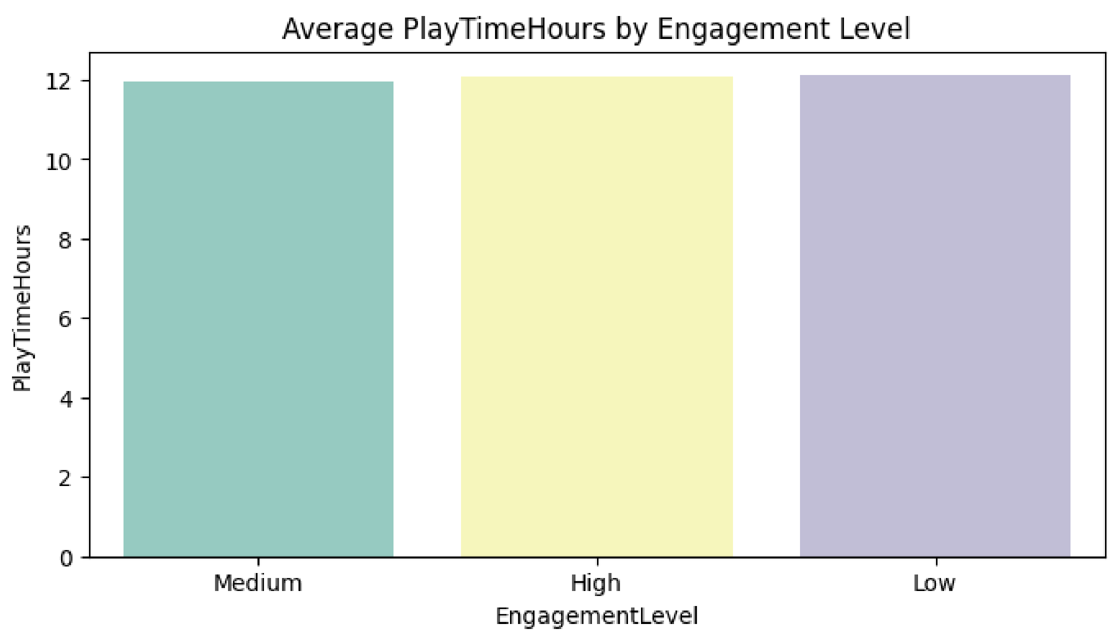


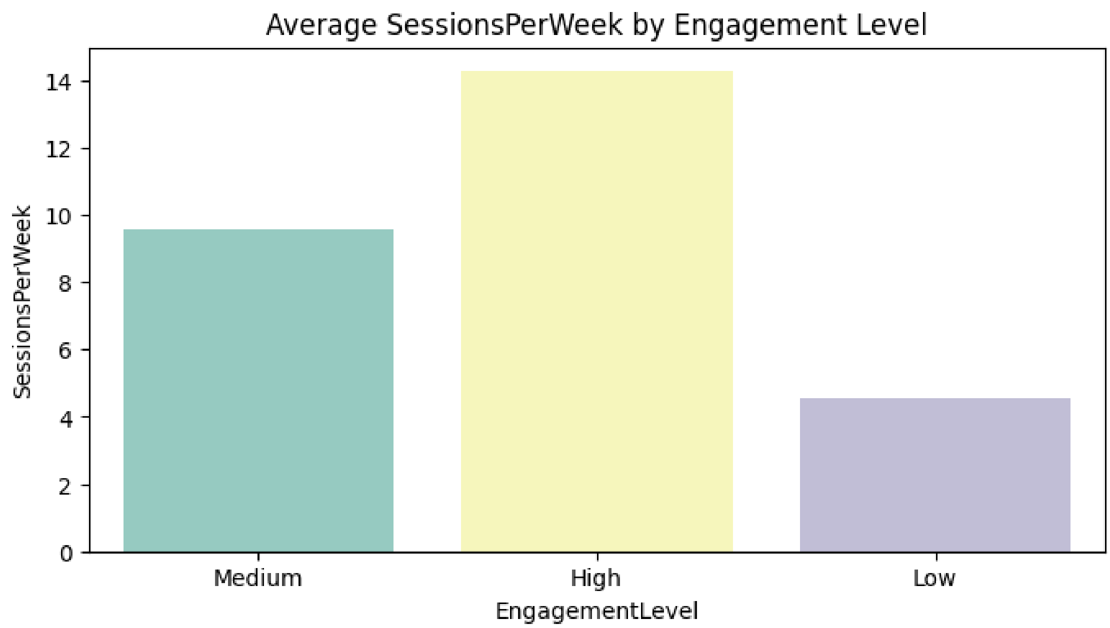
[17]:
```
#  Comparative Analysis: Numeric Feature Trends by Engagement Level

# Loop through each feature for grouped statistics and bar plot
for feature in numerical_cols:
    # Compute mean, median, and count by Engagement Level
    grouped_stats = df.groupby('EngagementLevel')[feature].agg(['mean',␣
↪'median', 'count'])

    # Display computed statistics
    print(f"\n  Summary Statistics for '{feature}' by Engagement Level:")
    print(grouped_stats)

    # Bar plot: mean value of the feature across engagement levels
    plt.figure(figsize=(8, 4))
    sns.barplot(data=df, x='EngagementLevel', y=feature, ci=None,␣
↪palette='Set3')

    # Add custom titles and labels
    plt.title(f'Average {feature.replace("_", " ")} by Engagement Level',␣
↪fontsize=12)
    plt.xlabel
```

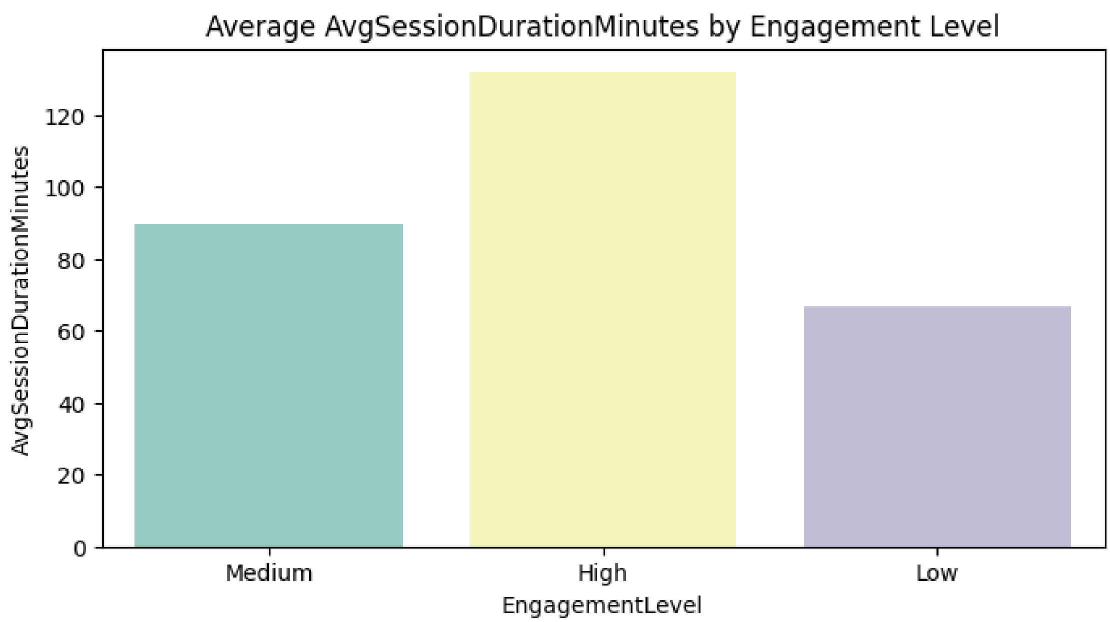
```
  Summary Statistics for 'Age' by Engagement Level:
                      mean  median  count
EngagementLevel
High             31.920085    32.0  10336
Low              31.896939    32.0  10324
Medium           32.082120    32.0  19374

  Summary Statistics for 'PlayTimeHours' by Engagement Level:
```

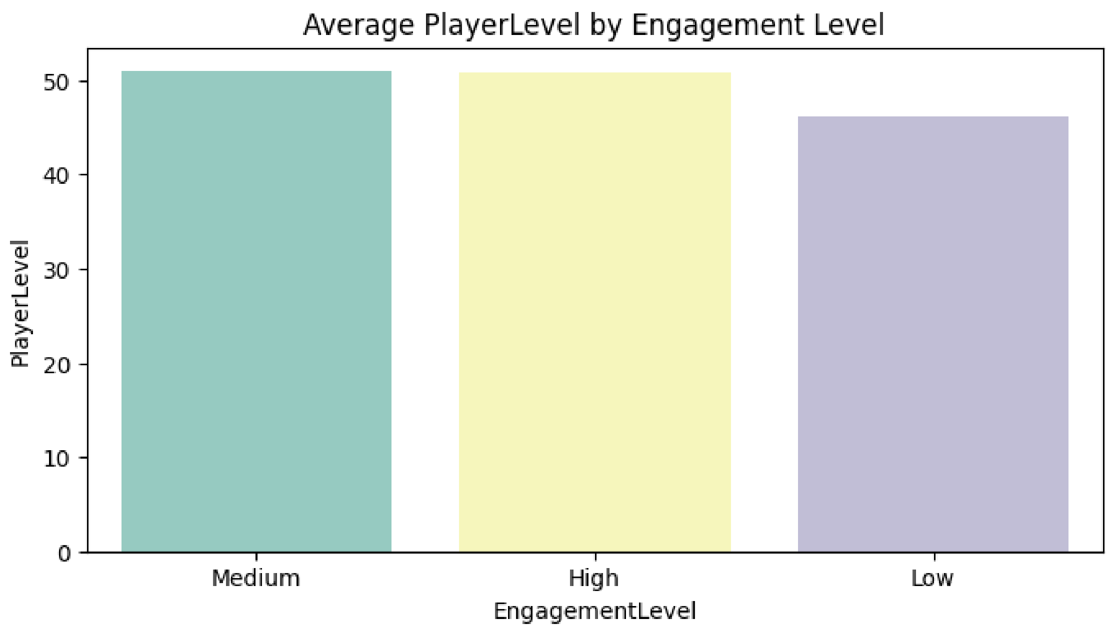
```
                     mean     median  count
EngagementLevel
High            12.069238  11.981024  10336
Low             12.104915  12.074409  10324
Medium          11.957503  11.992280  19374

 Summary Statistics for 'SessionsPerWeek' by Engagement Level:
                     mean  median  count
EngagementLevel
High            14.254547    15.0  10336
Low              4.530511     3.0  10324
Medium           9.553267     9.0  19374

 Summary Statistics for 'AvgSessionDurationMinutes' by Engagement Level:
                      mean  median  count
EngagementLevel
High            131.921827   137.0  10336
Low              66.882119    53.0  10324
Medium           89.856405    84.0  19374

 Summary Statistics for 'PlayerLevel' by Engagement Level:
                     mean  median  count
EngagementLevel
High            50.823723    51.0  10336
Low             46.101414    44.0  10324
Medium          50.926293    51.0  19374

 Summary Statistics for 'AchievementsUnlocked' by Engagement Level:
                     mean  median  count
EngagementLevel
High            25.095975    25.0  10336
Low             22.661565    22.0  10324
Medium          25.216424    26.0  19374
```

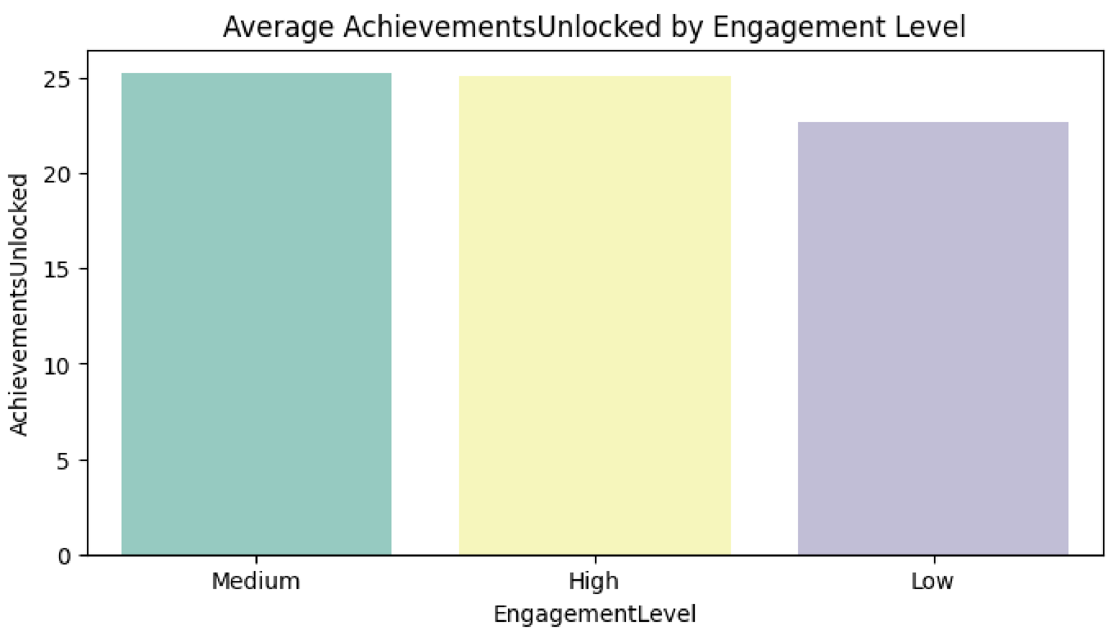

Average Age by Engagement Level
Age
30
25
20
15
10
5
0
Medium
High
Low
EngagementLevel


Average PlayTimeHours by Engagement Level
PlayTimeHours
12
10
8
6
4
2
0
Medium
High
Low
EngagementLevel


Average SessionsPerWeek by Engagement Level
SessionsPerWeek
0
2
4
6
8
10
12
14
Medium
High
Low
EngagementLevel

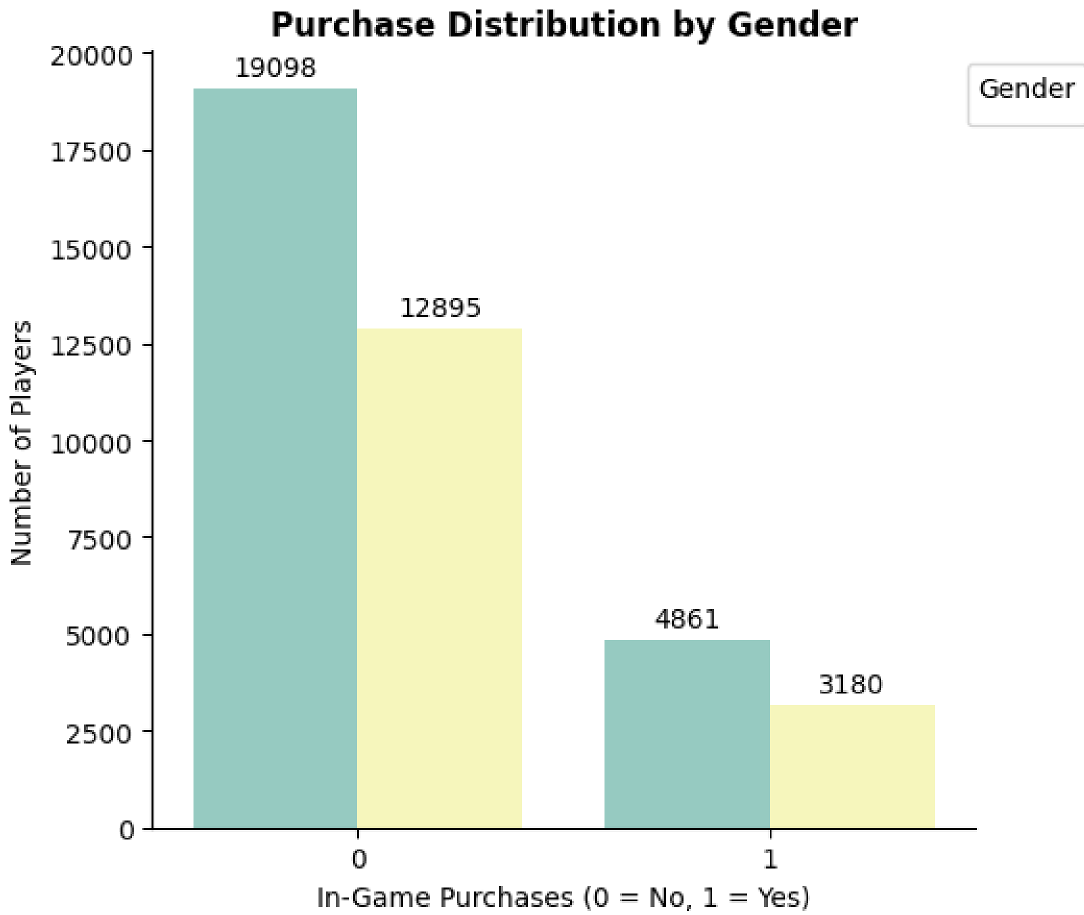

Average AvgSessionDurationMinutes by Engagement Level
AvgSessionDurationMinutes
0
20
40
60
80
100
120
Medium
High
Low
EngagementLevel

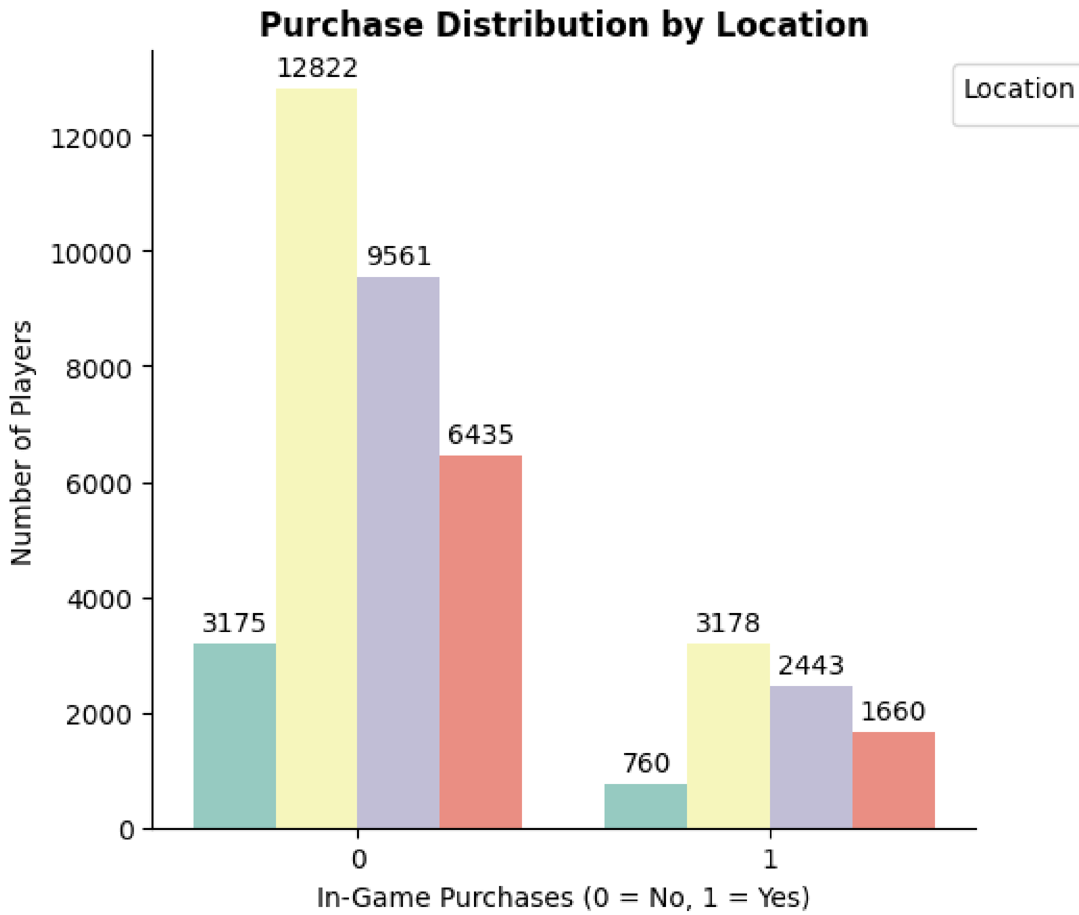


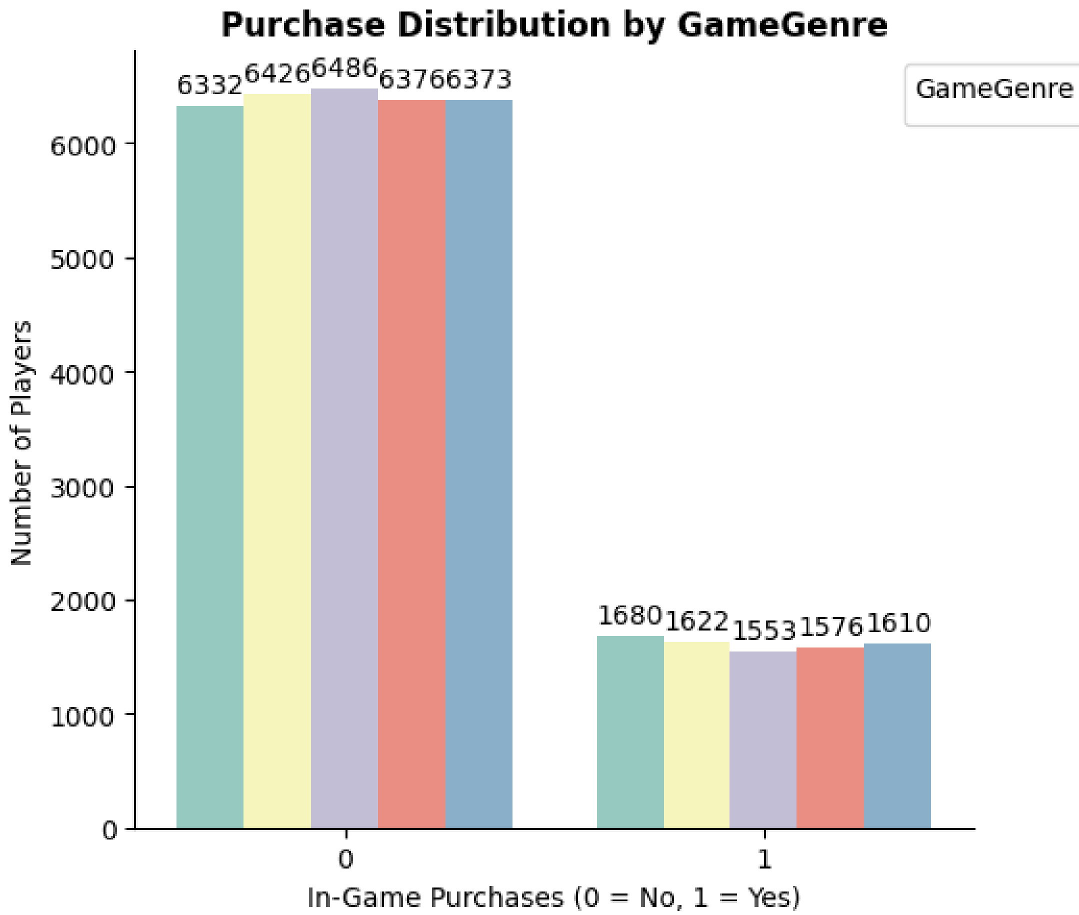


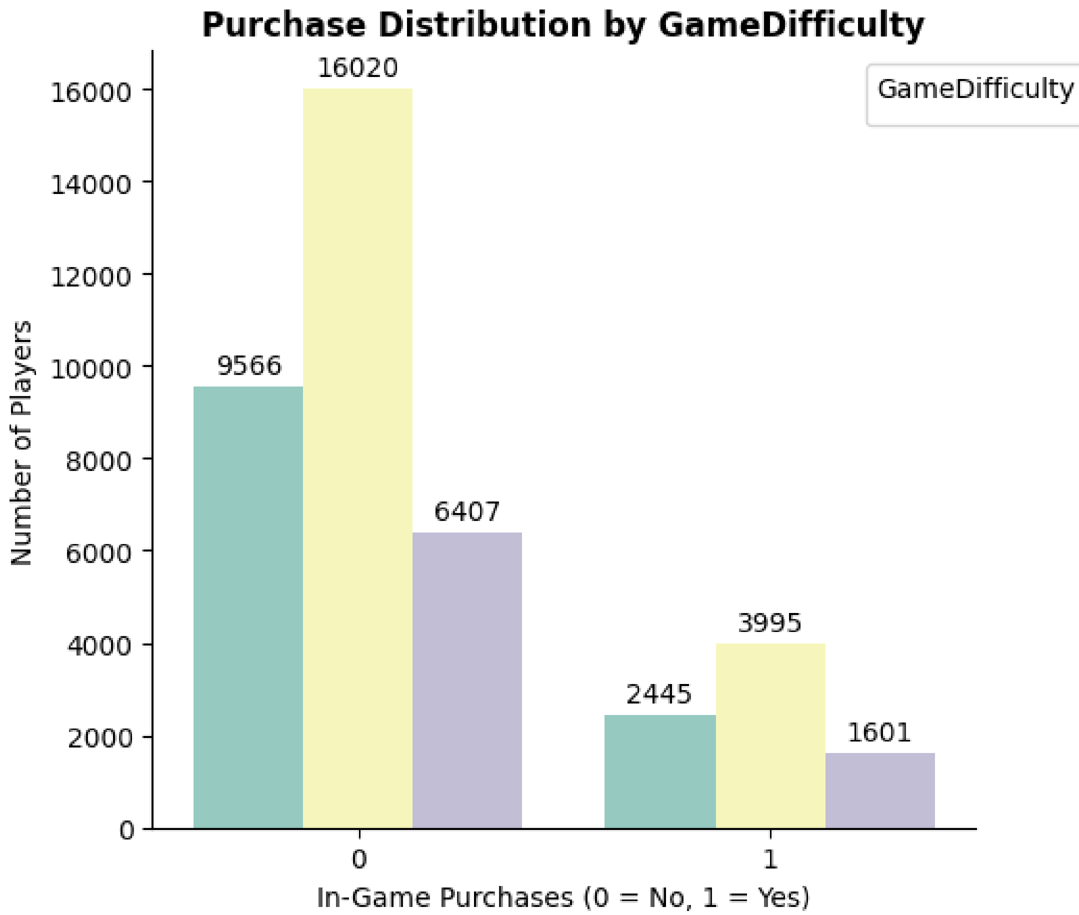
[18]:
```
#   In-Game Purchase Behavior Across Categorical Segments

# Loop through each categorical feature to create annotated catplots
for feature in categorical_features:
    # Create count plot comparing InGamePurchases across current feature
```

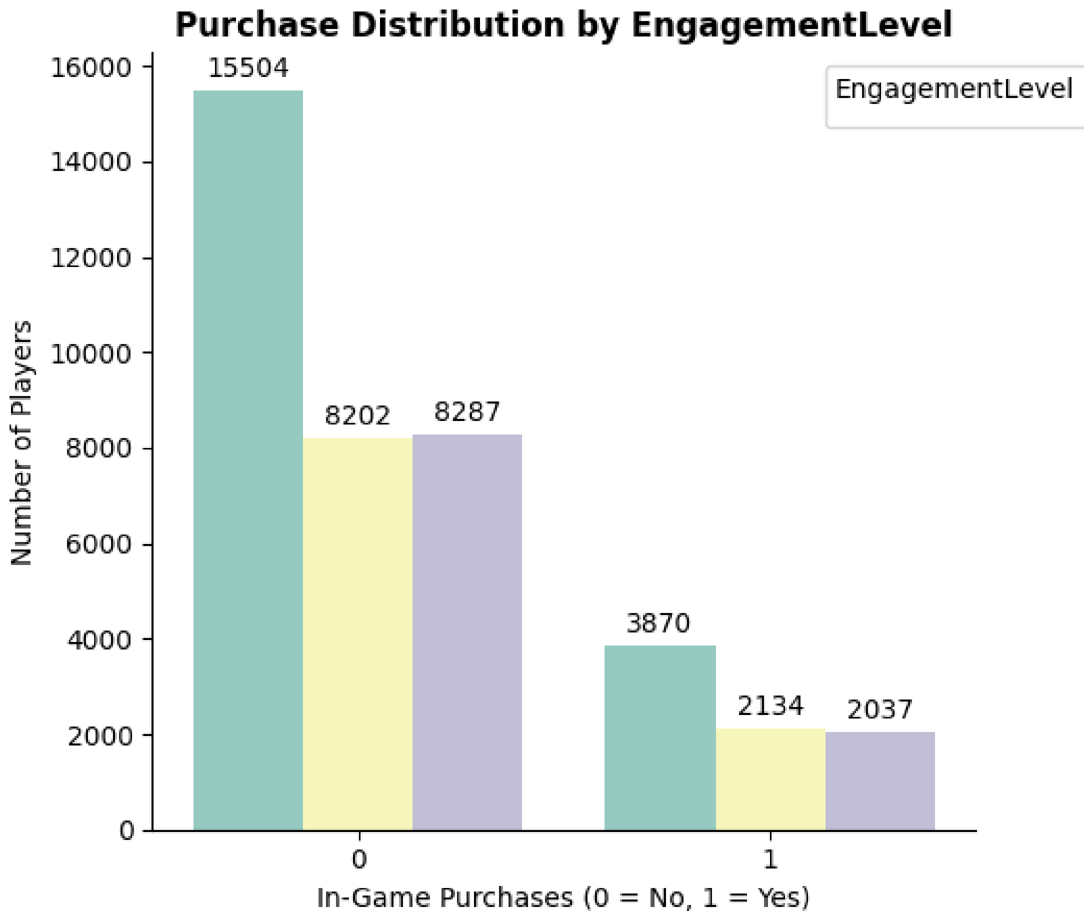
```
plot = sns.catplot(
    data=df,
    x='InGamePurchases',
    hue=feature,
    kind='count',
    height=5,
    aspect=1.2,
    palette='Set3',
    legend=False  # Custom legend placement
)

# Set axis labels and title
plot.set_axis_labels("In-Game Purchases (0 = No, 1 = Yes)", "Number of␣
↪Players")
plt.title(f'Purchase Distribution by {feature}', weight='bold')

# Annotate bar values with count labels
for ax in plot.axes.flat:
    for bar in ax.patches:
        ax.annotate(f'{int(bar.get_height())}',
                    (bar.get_x() + bar.get_width() / 2., bar.get_height()),
                    ha='center', va='baseline',
                    fontsize=10, color='black',
                    xytext=(0, 5), textcoords='offset points')

# Adjust legend location outside the plot
plt.legend(
    title=feature,
    loc='upper right',
    bbox_to_anchor=(1.15, 1)
)

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


Purchase Distribution by Gender
Number of Players
In-Game Purchases (0 = No, 1 = Yes)
Gender
19098
12895
4861
3180
0
1
20000
17500
15000
12500
10000
7500
5000
2500
0


Purchase Distribution by Location
Location
12822
9561
6435
3175
3178
2443
1660
760
12000
10000
8000
6000
4000
2000
0
Number of Players
0
1
In-Game Purchases (0 = No, 1 = Yes)


Purchase Distribution by GameGenre
GameGenre
Number of Players
In-Game Purchases (0 = No, 1 = Yes)
6332
6426
6486
6376
6373
1680
1622
1553
1576
1610
0
1000
2000
3000
4000
5000
6000
0
1


Purchase Distribution by GameDifficulty
GameDifficulty
Number of Players
In-Game Purchases (0 = No, 1 = Yes)
0
1
16000
14000
12000
10000
8000
6000
4000
2000
0
9566
16020
6407
2445
3995
1601



0.1 Player Behavior Insights

0.1.1 Demographics & Play Patterns

- **Age**: Consistent across all engagement levels, indicating it's not a key driver of engagement.
  - *Recommendation*: Prioritize behavioral traits over demographics for engagement strategies.
- **PlayTimeHours**: Surprisingly, highly engaged users play slightly fewer hours. Possibly due to more focused or efficient play sessions.
  - *Recommendation*: Explore session quality—offer bite-sized challenges or time-limited events.
- **SessionsPerWeek & AvgSessionDuration**: Strong positive link with engagement. More engaged players log in more often and play longer per session.
  - *Recommendation*: Introduce login rewards, streak bonuses, and immersive content to lengthen playtime.
- **PlayerLevel & AchievementsUnlocked**: High and medium engagement users show more progression and unlocked achievements compared to low-engagement users.
  - *Recommendation*: Create motivational systems for lower-engagement players like milestone badges or guided missions.

0.2 In-Game Purchase Patterns

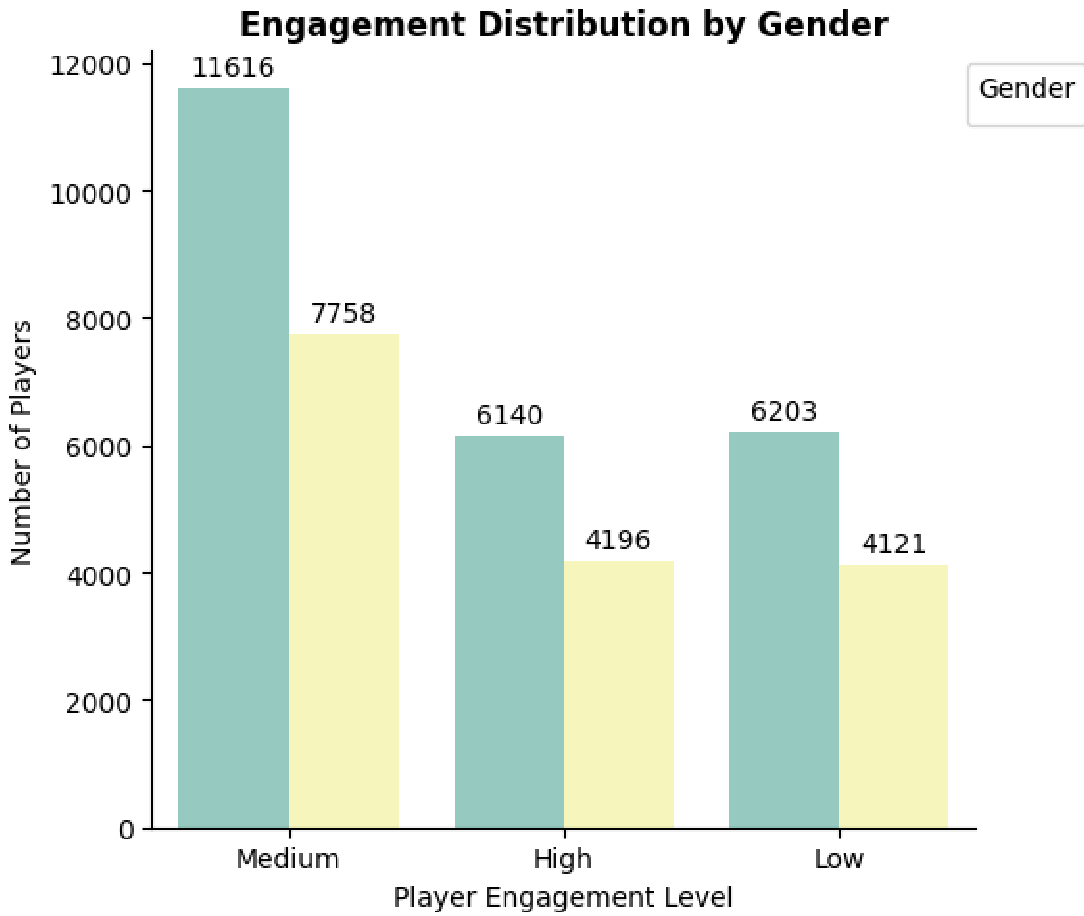
Category	Highest Purchase Rate	Key Insight
Gender	Male (20.3%)	Minimal gender gap; majority of players don't purchase.
Location	Asia (20.5%)	Despite fewer players, Asia leads in conversion rate.
Game Genre	Strategy (21.0%)	Players in strategy games spend more; Action genre lags slightly.
Game Difficulty	Medium (20.4%)	Balanced difficulty seems to drive more purchases.
Engagement Level	High (20.6%)	Direct correlation between engagement and spending observed.

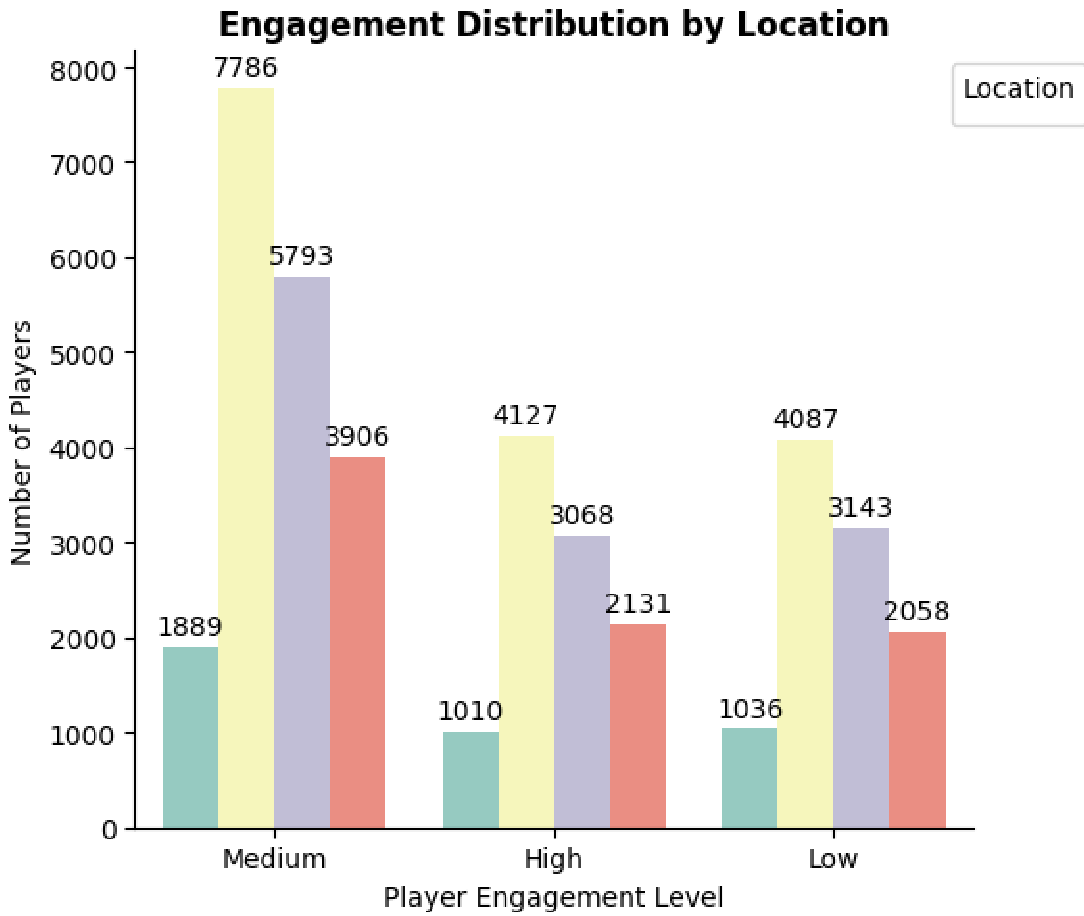
0.2.1 Recommendations:

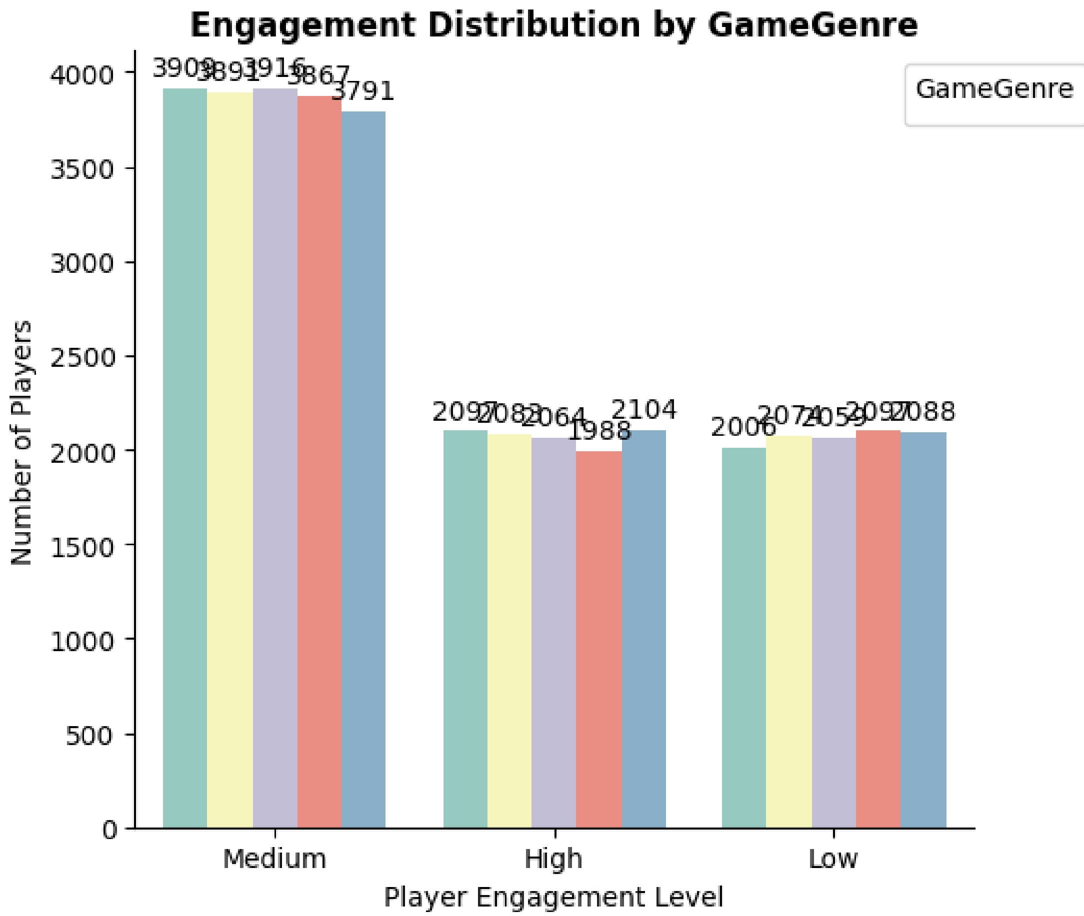
- **Gender Targeting**: Develop tailored campaigns (e.g., female-centric cosmetics or avatars) to improve conversion among underrepresented segments.
- **Region-Specific Promotions**: Optimize pricing, event timing, and themes based on region-specific behavior (e.g., boost U.S. purchase rate).
- **Genre-Specific Monetization**: Incentivize Action game purchases through time-limited bundles, while expanding Strategy game content.
- **Difficulty Adjustments**: Offer bonus items or incentives to Easy-mode players to nudge spending without compromising game balance.
- **Engagement-Based Offers**: Push exclusive offers to medium-engagement users to move them into the high-spending tier.

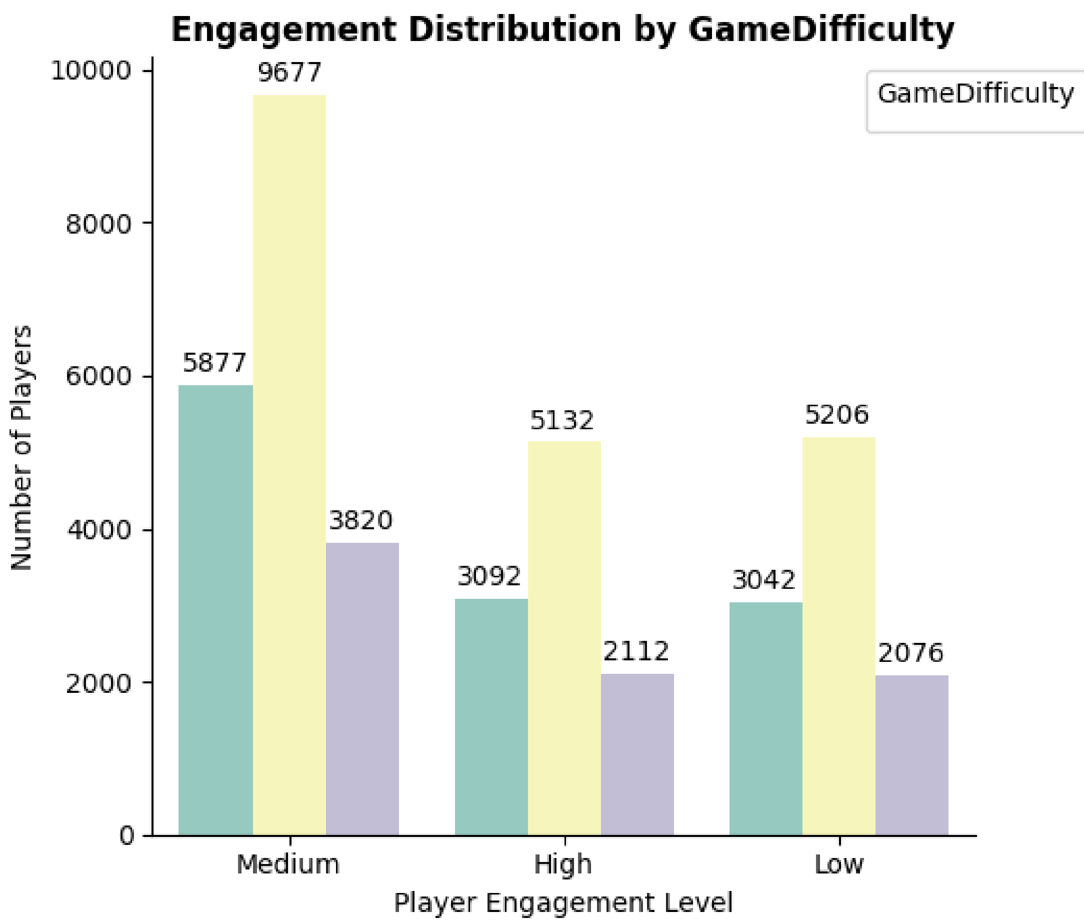
[19]:
```python
#  Engagement Level Analysis by Categorical Segments

# Categorical variables to analyze engagement variation
engagement_features = ['Gender', 'Location', 'GameGenre', 'GameDifficulty']

# Iterate over each feature to generate comparative count plots
for feature in engagement_features:
    # Generate count plot grouped by Engagement Level and colored by feature␣
 ↪category
    plot = sns.catplot(
        data=df,
        x='EngagementLevel',
        hue=feature,
        kind='count',
        height=5,
        aspect=1.2,
        palette='Set3',
        legend=False
    )
```

```python
# Customize axis labels and plot title
plot.set_axis_labels("Player Engagement Level", "Number of Players")
plt.title(f'Engagement Distribution by {feature}', weight='bold')

# Annotate bars with actual count values
for ax in plot.axes.flat:
    for bar in ax.patches:
        ax.annotate(f'{int(bar.get_height())}',
                    (bar.get_x() + bar.get_width() / 2., bar.get_height()),
                    ha='center', va='baseline',
                    fontsize=10, color='black',
                    xytext=(0, 5), textcoords='offset points')

# Adjust legend placement outside the plot for clarity
plt.legend(
    title=feature,
    loc='upper right',
    bbox_to_anchor=(1.15, 1)
)

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


Engagement Distribution by Gender
Gender
11616
7758
6140
4196
6203
4121
Number of Players
0
2000
4000
6000
8000
10000
12000
Medium
High
Low
Player Engagement Level


Engagement Distribution by Location
Location
Number of Players
Player Engagement Level
Medium
High
Low
0
1000
2000
3000
4000
5000
6000
7000
8000
1889
7786
5793
3906
1010
4127
3068
2131
1036
4087
3143
2058


Engagement Distribution by GameGenre
GameGenre
Number of Players
Player Engagement Level
Medium
High
Low
3909
3891
3916
3867
3791
2097
2083
2064
1988
2104
2006
2074
2059
2097
2088
0
500
1000
1500
2000
2500
3000
3500
4000



0.2.2 Engagement Patterns by Player Segments

0.2.3 Gender

Gender	High (%)	Low (%)	Medium (%)
Female	26.1	25.6	48.3
Male	25.6	25.9	48.5

- **Insight**: Medium engagement is dominant for both. Female players show slightly lower high/low engagement.
- **Tip**: Introduce inclusive features and community events to boost female participation at higher engagement levels.

0.2.4 Location

Region	High (%)	Low (%)	Medium (%)
Asia	26.3	25.4	48.3

Region	High (%)	Low (%)	Medium (%)
USA	25.8	25.5	48.7
Europe	25.6	26.2	48.3
Other	25.7	26.3	48.0

- **Insight**: Asia has the highest high-engagement share; USA leads in overall players.
- **Tip**: Leverage Asia's high engagement with exclusive content; tailor regional promos for Europe and Other to boost loyalty.

0.2.5 Game Genre

Genre	High (%)	Low (%)	Medium (%)
Strategy	26.2	25.0	48.8
RPG	25.0	26.4	48.6
Simulation	26.4	26.2	47.5

- **Insight**: Strategy games drive the highest engagement; RPGs lag with higher low-engagement rates.
- **Tip**: Refine RPG elements to improve retention; replicate successful features from Strategy games across other genres.

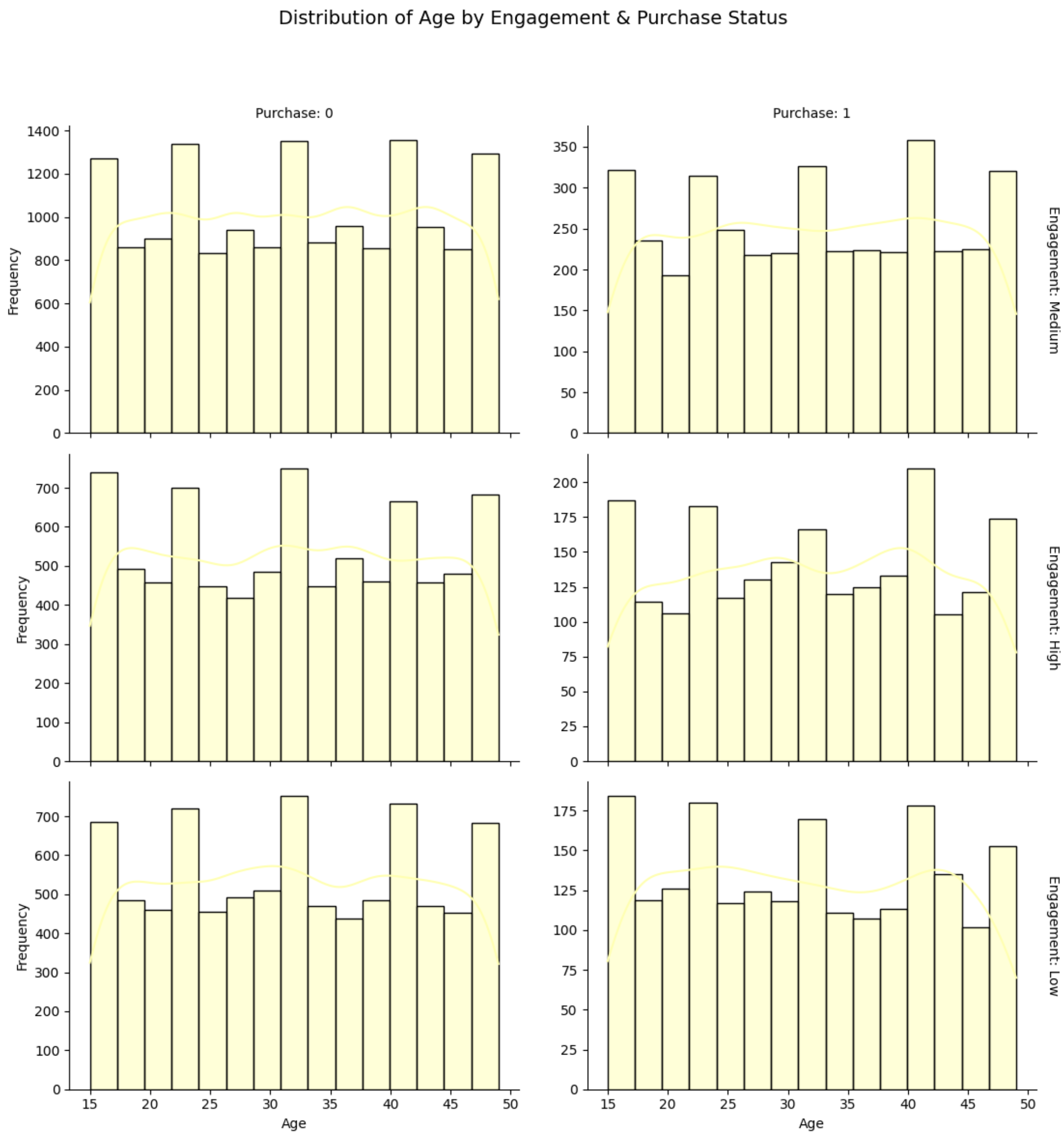
0.2.6 Game Difficulty

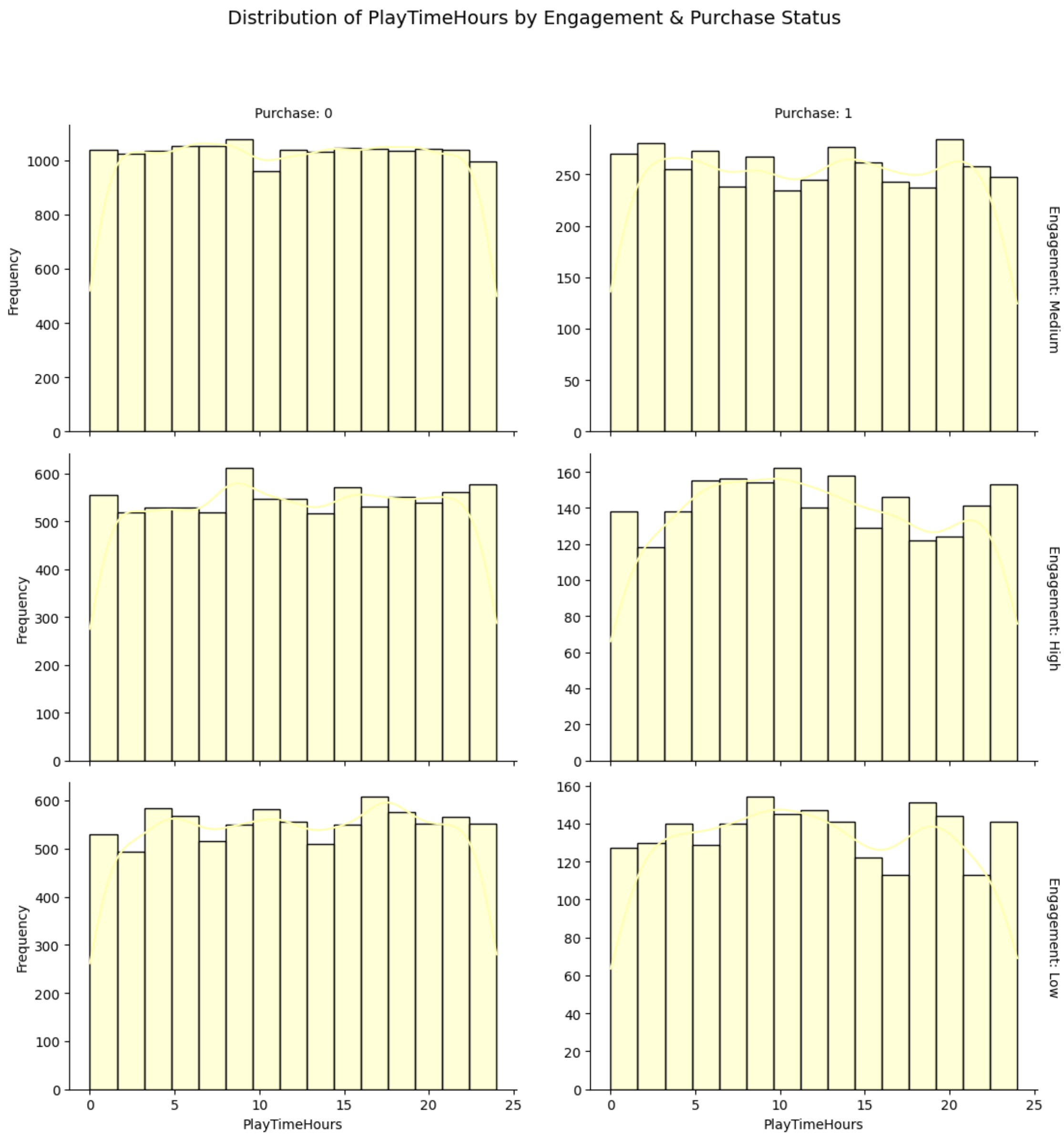
Difficulty	High (%)	Low (%)	Medium (%)
Hard	26.4	25.9	47.7
Medium	25.7	25.3	48.9
Easy	25.6	26.0	48.4

- **Insight**: Hard mode players are most engaged; medium difficulty sees highest medium-level engagement.
- **Tip**: Offer exclusive rewards in Hard mode to encourage retention; gently guide Easy mode players to progress further. sive incentives to encourage players to increase their engagement.

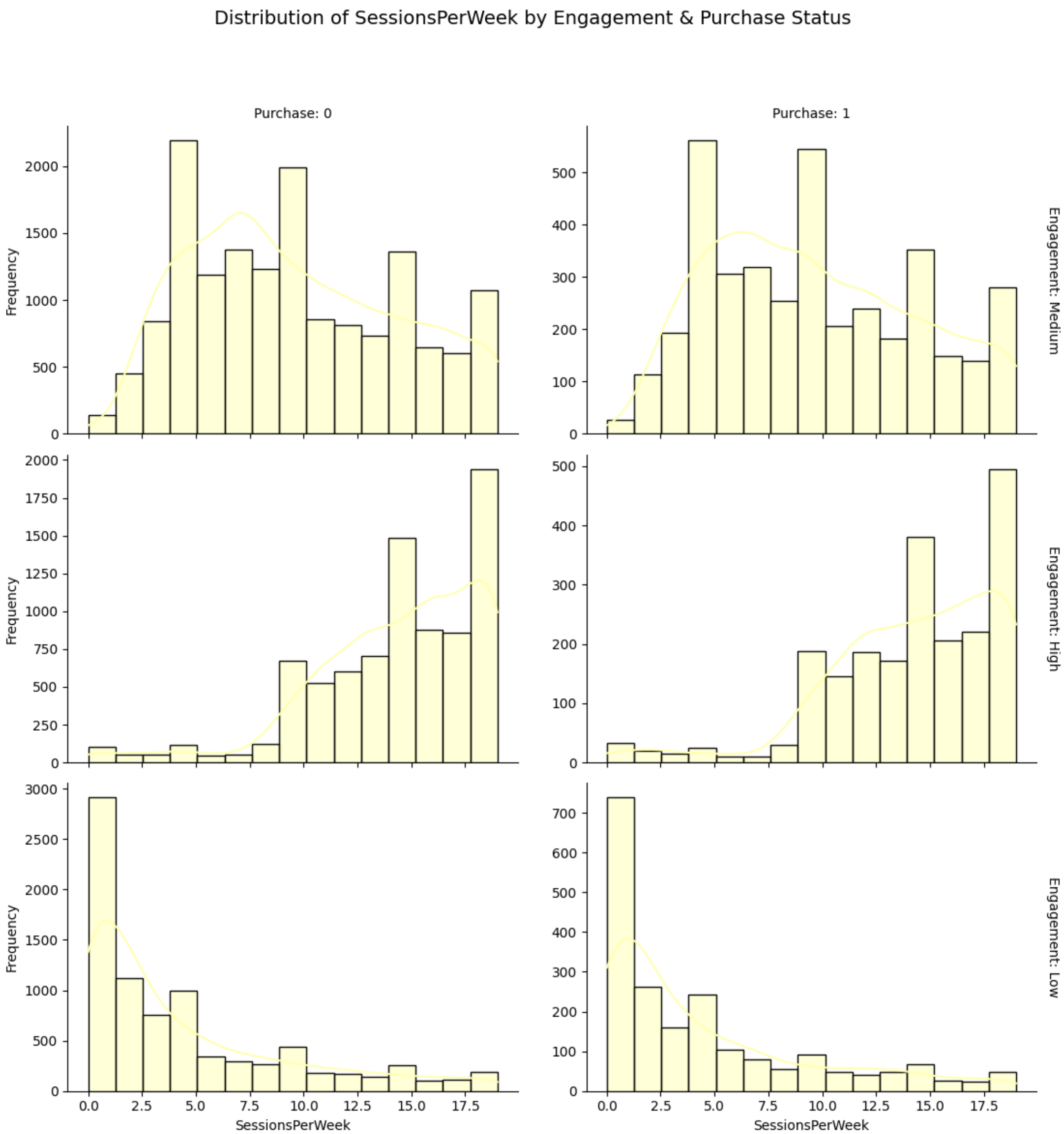
[20]:
```
# Define the numerical features to plot against InGamePurchases by␣
↪EngagementLevel

for metric in numerical_cols:
    g = sns.FacetGrid(
        df,
        row='EngagementLevel',
        col='InGamePurchases',
        margin_titles=True,
        height=4,
        aspect=1.4,
        sharex=True,
        sharey=False
```

```
    )

    g.map(
        sns.histplot,
        metric,
        kde=True,
        bins=15,
        color=sns.color_palette("Set3")[1]
    )

    g.set_axis_labels(x_var=metric.replace('_', ' '), y_var='Frequency')
    g.set_titles(row_template='Engagement: {row_name}', col_template='Purchase:␣
↪{col_name}')
    g.fig.subplots_adjust(top=0.88)
    g.fig.suptitle(
        f'Distribution of {metric.replace("_", " ")} by Engagement & Purchase␣
↪Status',
        fontsize=14
    )

    plt.show()
```

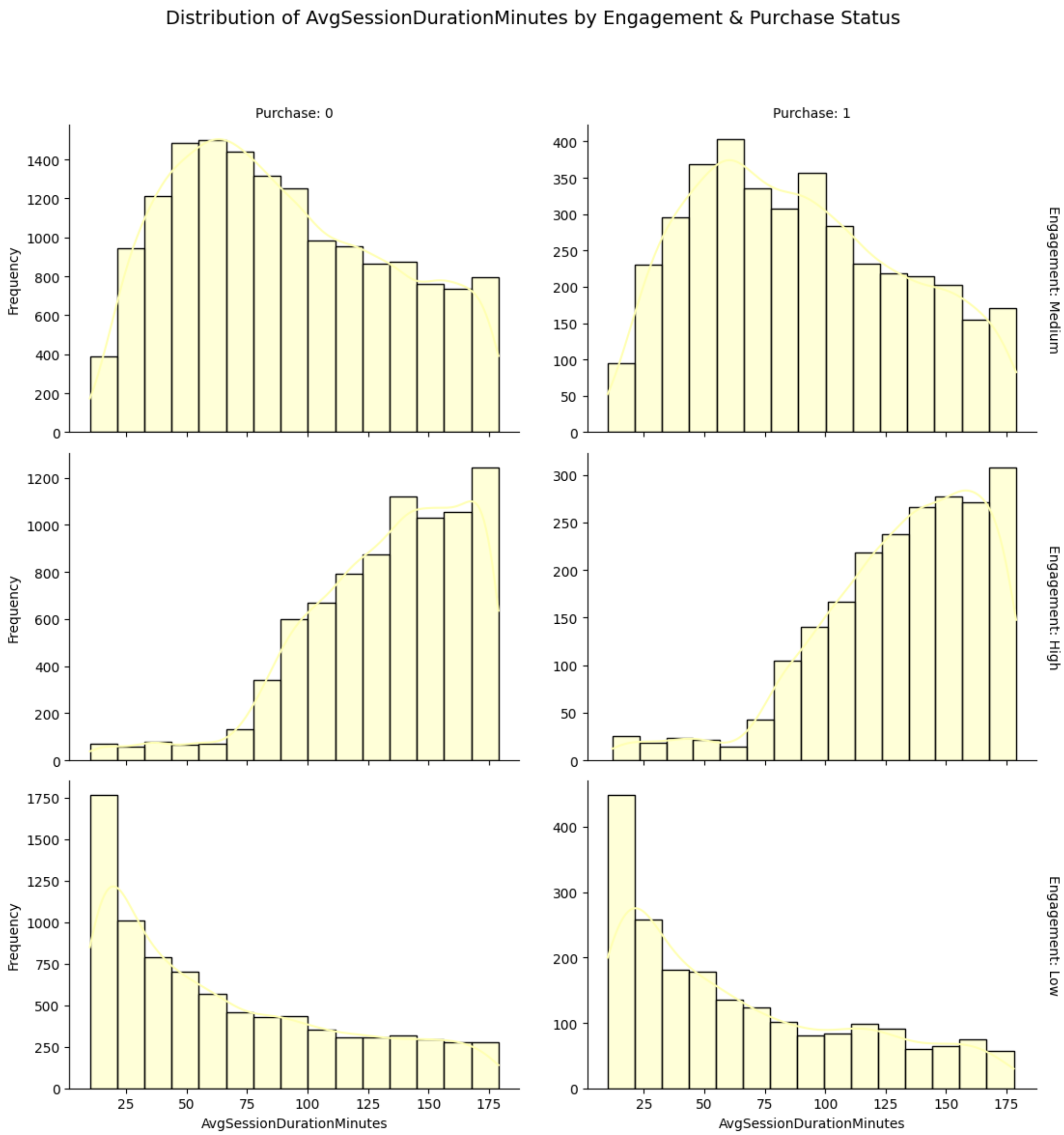

Distribution of Age by Engagement & Purchase Status
Purchase: 0
Purchase: 1
Engagement: Medium
Engagement: High
Engagement: Low
Frequency
Age

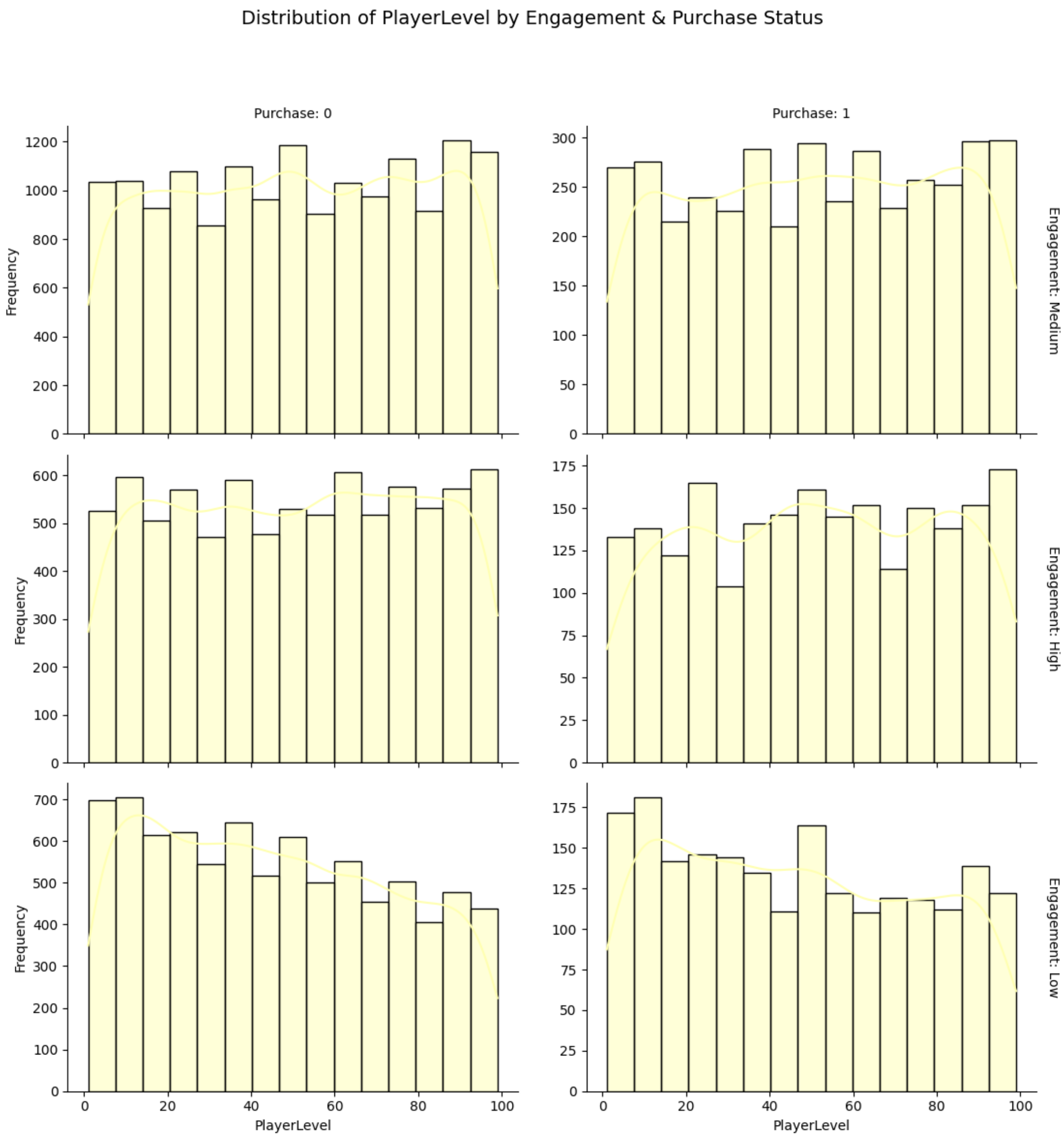


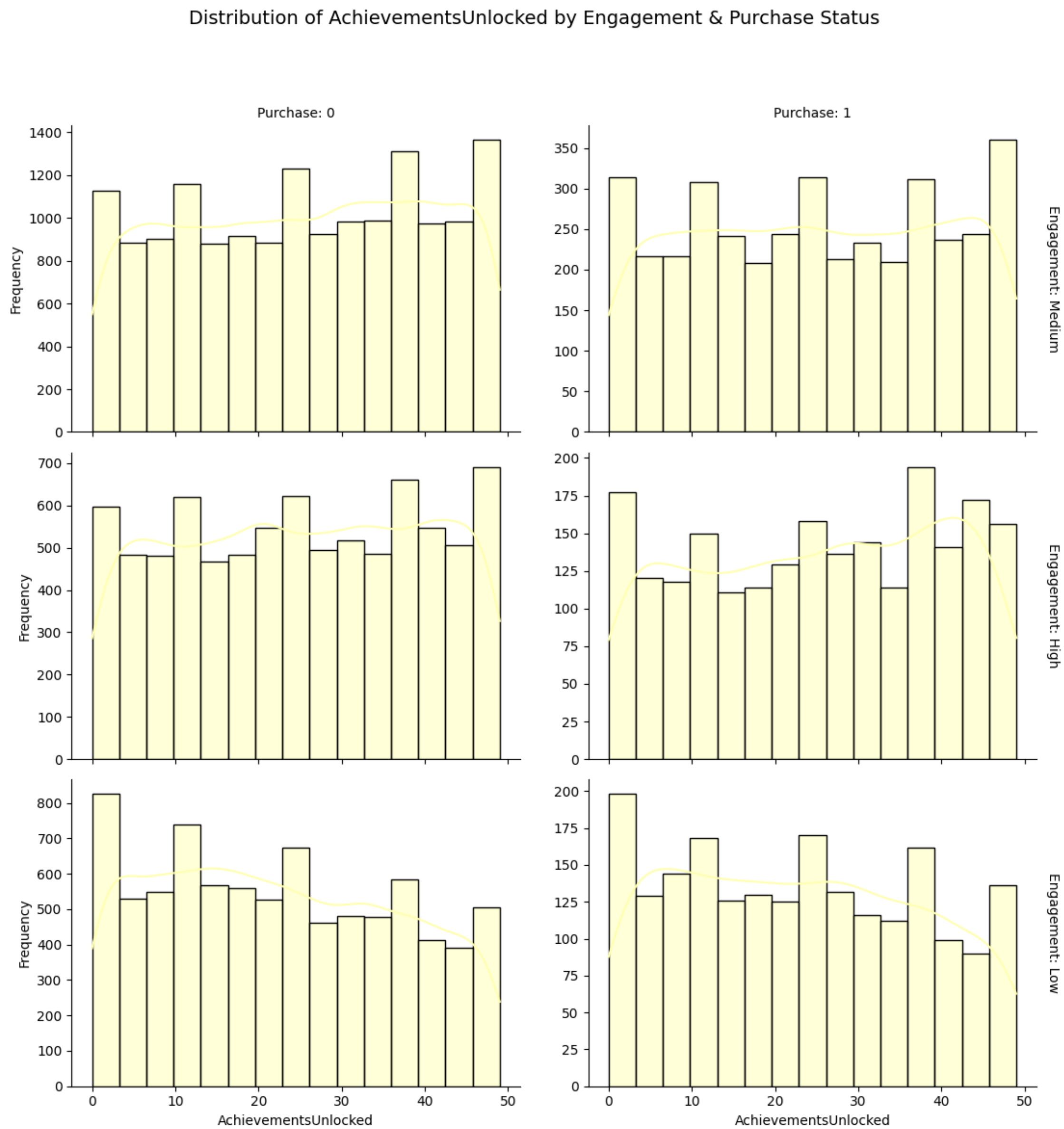
Distribution of PlayTimeHours by Engagement & Purchase Status
Purchase: 0
Purchase: 1
Engagement: Medium
Engagement: High
Engagement: Low
Frequency
PlayTimeHours



Distribution of SessionsPerWeek by Engagement & Purchase Status
Purchase: 0
Purchase: 1
Frequency
Engagement: Medium
Engagement: High
Engagement: Low
SessionsPerWeek


Distribution of AvgSessionDurationMinutes by Engagement & Purchase Status
Purchase: 0
Purchase: 1
Engagement: Medium
Engagement: High
Engagement: Low
Frequency
AvgSessionDurationMinutes


Distribution of PlayerLevel by Engagement & Purchase Status
Purchase: 0
Purchase: 1
Engagement: Medium
Engagement: High
Engagement: Low
Frequency
PlayerLevel
0
20
40
60
80
100



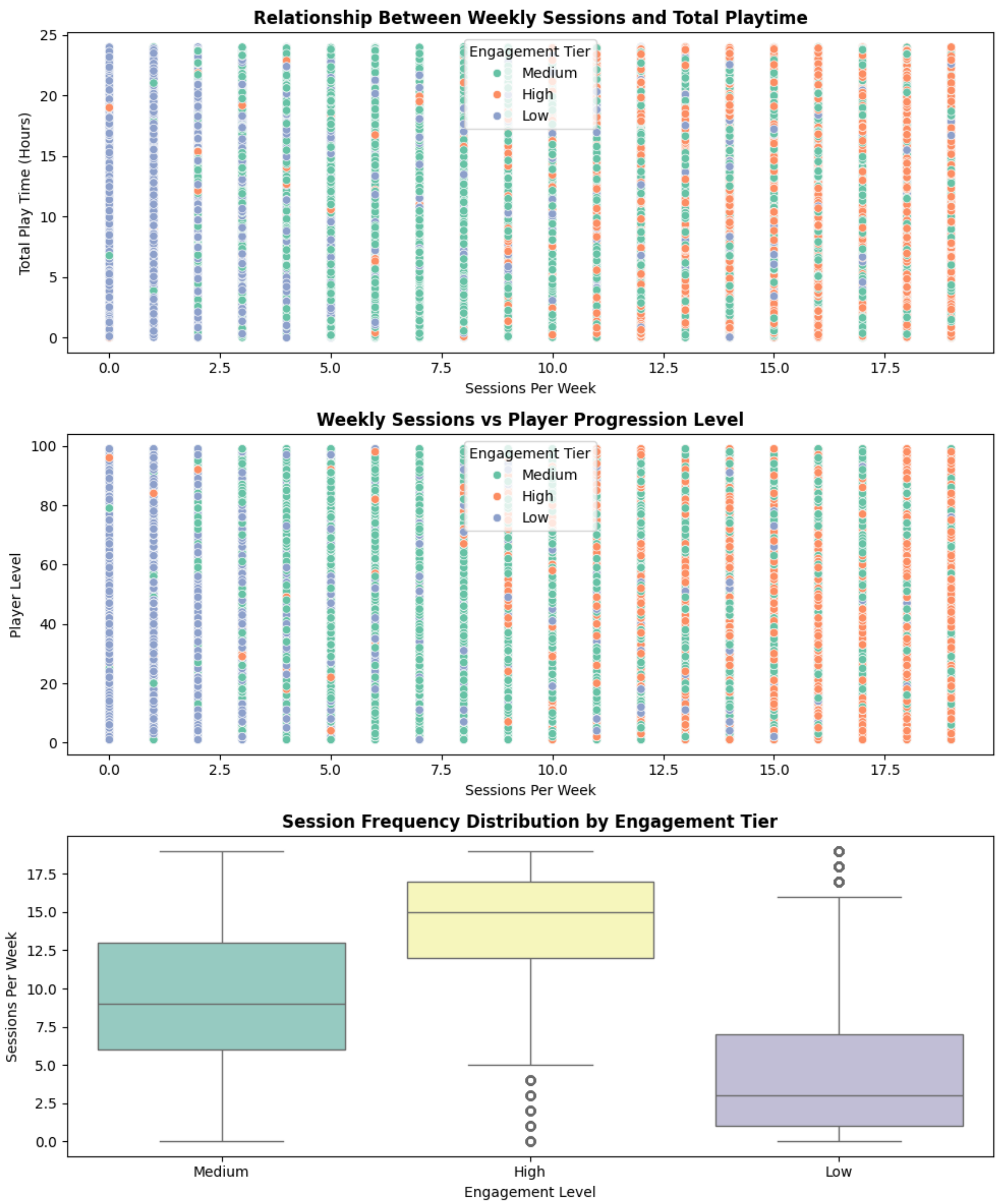
0.2.7 Key Insights

- **Age**: Most players are between 20–40 across all groups; age has minimal influence on engagement or purchases.
- **Play Time**: Purchasers and highly engaged users play more. Playtime rises with both engagement and spending.
- **Sessions per Week**: Frequent sessions (10–15/week) are common among purchasers and high-engagement players. It's a strong signal for spending.
- **Session Duration**: Purchasers, especially those highly engaged, spend longer per session. Longer sessions reflect deeper involvement.

- **Player Level**: Higher levels are linked to purchases. Non-purchasers are clustered at lower levels.
- **Achievements**: More achievements unlocked = more likely to purchase. High engagement + high achievements often go hand-in-hand. ement and potential spending.

[21]:
```python
# Visualize how weekly gaming frequency relates to total playtime, player␣
↪level, and engagement classification
plt.figure(figsize=(10, 12))

# Plot 1: Weekly sessions vs total playtime by engagement
plt.subplot(3, 1, 1)
sns.scatterplot(
    data=df,
    x='SessionsPerWeek',
    y='PlayTimeHours',
    hue='EngagementLevel',
    palette='Set2'
)
plt.title("Relationship Between Weekly Sessions and Total Playtime",␣
↪weight='bold')
plt.xlabel("Sessions Per Week")
plt.ylabel("Total Play Time (Hours)")
plt.legend(title='Engagement Tier')

# Plot 2: Weekly sessions vs player level by engagement
plt.subplot(3, 1, 2)
sns.scatterplot(
    data=df,
    x='SessionsPerWeek',
    y='PlayerLevel',
    hue='EngagementLevel',
    palette='Set2'
)
plt.title("Weekly Sessions vs Player Progression Level", weight='bold')
plt.xlabel("Sessions Per Week")
plt.ylabel("Player Level")
plt.legend(title='Engagement Tier')

# Plot 3: Distribution of weekly sessions across engagement levels
plt.subplot(3, 1, 3)
sns.boxplot(
    data=df,
    x='EngagementLevel',
    y='SessionsPerWeek',
    palette='Set3'
)
plt.title("Session Frequency Distribution by Engagement Tier", weight='bold')
```

```
plt.xlabel("Engagement Level")
plt.ylabel("Sessions Per Week")

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



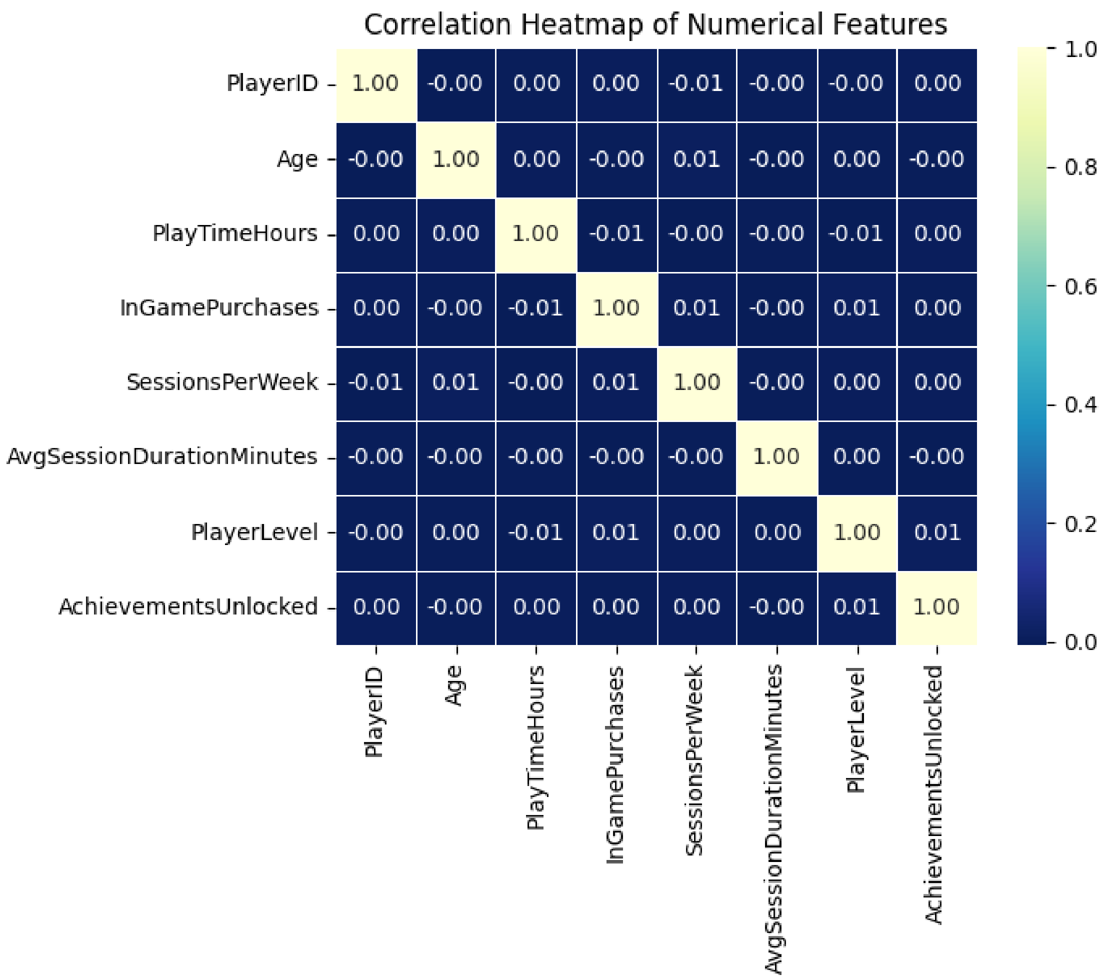
0.2.8 Key Insights from Engagement vs Sessions, Playtime & Player Level

1. **Sessions vs Playtime**
   - High engagement players cluster around **10–15 sessions** and **15–20 hours** of playtime.
   - Medium and low engagement players are spread out with **lower session counts** and **less playtime**.
   - *More sessions and playtime = higher engagement.*
2. **Sessions vs Player Level**
   - High engagement: **Level 60–100**, **frequent sessions**.
   - Medium: **Level 30–60**, **moderate sessions**.
   - Low: **Below level 30**, **few sessions**.
   - *Higher levels and frequent play signal strong engagement.*
3. **Boxplot: Sessions per Week by Engagement**
   - Median sessions: **High = 12+, Medium = 7–8, Low = 2–3**.
   - *Boosting session frequency can elevate engagement tiers.*

0.2.9 Actionable Tips

- **Drive Sessions & Playtime**: Add challenges and events to encourage more frequent, longer sessions.
- **Incentivize Progress**: Reward level milestones to motivate progression.
- **Customize Strategies**: Tailor retention efforts by engagement level for maximum impact.

[22]:
```
# Correlation heatmap
numerical_columns = df.select_dtypes(include=['int64', 'float64'])
correlation_matrix = numerical_columns.corr()

sns.heatmap(correlation_matrix, annot=True, cmap="YlGnBu_r", fmt=".2f",␣
 ↪linewidths=0.5)
plt.title("Correlation Heatmap of Numerical Features")
plt.show()
```



0.2.10 Takeaways from Heatmap

1. **Minimal Correlation**
   - Most features show little direct correlation—suggesting no single metric drives player behavior.
2. **Notable Signals**
   - Slight links between `PlayerLevel`, `SessionsPerWeek`, and `AchievementsUnlocked` hint at their influence on engagement and spending.
3. **Actionable Focus**
   - Analyze player behavior using combined metrics for better insights.

   - Target low-frequency or low-achievement players to boost playtime and progression.ogression.

Preparing data for model development

0.2.11 Categorical Feature Encoding

1. **Gender**
   - Binary Encoding: `Male = 1`, `Female = 0`
2. **Location**
   - One-Hot Encoding: Creates columns like `Location_Europe`, `Location_Other`, `Location_USA`
3. **Game Genre**
   - One-Hot Encoding: Generates columns such as `Genre_Action`, `Genre_RPG`, `Genre_Simulation`
4. **Game Difficulty**
   - Ordinal Encoding: `Easy = 1`, `Medium = 2`, `Hard = 3`
5. **Engagement Level**
   - Ordinal Encoding: `Low = 1`, `Medium = 2`, `High = 32,High = 3`‘.

[23]:
```python
def transform_categorical_columns(dataframe):

    df_copy = dataframe.copy()  # Prevent modifying original df

    # Convert Gender to binary values: Male → 1, Female → 0
    df_copy['Gender'] = df_copy['Gender'].map({'Male': 1, 'Female': 0})

    # Apply one-hot encoding to the Location column (drop first category to␣
↪avoid multicollinearity)
    df_copy = pd.get_dummies(df_copy, columns=['Location'], drop_first=True,␣
↪prefix='Loc')

    # Apply one-hot encoding to the GameGenre column
    df_copy = pd.get_dummies(df_copy, columns=['GameGenre'], drop_first=True,␣
↪prefix='Genre')

    # Map GameDifficulty to ordinal scale: Easy → 1, Medium → 2, Hard → 3
    difficulty_scale = {'Easy': 1, 'Medium': 2, 'Hard': 3}
    df_copy['GameDifficulty'] = df_copy['GameDifficulty'].map(difficulty_scale)

    # Map EngagementLevel to ordinal scale: Low → 1, Medium → 2, High → 3
    engagement_scale = {'Low': 1, 'Medium': 2, 'High': 3}
    df_copy['EngagementLevel'] = df_copy['EngagementLevel'].
↪map(engagement_scale)

    return df_copy

# Transform the original dataset
processed_df = transform_categorical_columns(df)

# Preview the transformed dataset
processed_df
```

[23]:

```
       PlayerID  Age  Gender  PlayTimeHours  InGamePurchases  GameDifficulty  \
0          9000   43       1      16.271119                0               2
1          9001   29       0       5.525961                0               2
2          9002   22       0       8.223755                0               1
3          9003   35       1       5.265351                1               1
4          9004   33       1      15.531945                0               2
…             …  …   …          …                …              …
40029     49029   32       1      20.619662                0               1
40030     49030   44       0      13.539280                0               3
40031     49031   15       0       0.240057                1               1
40032     49032   34       1      14.017818                1               2
40033     49033   19       1      10.083804                0               1

       SessionsPerWeek  AvgSessionDurationMinutes  PlayerLevel  \
0                    6                        108           79
1                    5                        144           11
2                   16                        142           35
3                    9                         85           57
4                    2                        131           95
…                …                        …          …
40029                4                         75           85
40030               19                        114           71
40031               10                        176           29
40032                3                        128           70
40033               13                         84           72

       AchievementsUnlocked  EngagementLevel  Loc_Europe  Loc_Other  Loc_USA  \
0                        25                2       False       True    False
1                        10                2       False      False     True
2                        41                3       False      False     True
3                        47                2       False      False     True
4                        37                2        True      False    False
…                    …              …          …         …       …
40029                    14                2       False      False     True
40030                    27                3       False       True    False
40031                     1                3       False      False     True
40032                    10                2       False      False     True
40033                    39                2       False      False     True

       Genre_RPG  Genre_Simulation  Genre_Sports  Genre_Strategy
0          False             False         False            True
1          False             False         False            True
2          False             False          True           False
3          False             False         False           False
4          False             False         False           False
…          …               …            …             …
40029      False             False         False            True
```

```
40030      False                True         False            False
40031       True               False         False            False
40032      False               False          True            False
40033      False               False          True            False

[40034 rows x 18 columns]
```

[24]:
```
# Columns name of encoded features
encoded_columns = ['Gender', 'GameDifficulty', 'EngagementLevel',
                   'Loc_Europe', 'Loc_Other', 'Loc_USA',
                   'Genre_RPG', 'Genre_Simulation', 'Genre_Sports',␣
 ↪'Genre_Strategy']

unique_values = {feature_column: processed_df[feature_column].unique() for␣
 ↪feature_column in encoded_columns}

# Unique values for each encoded feature
unique_values
```

[24]:
```
{'Gender': array([1, 0]),
 'GameDifficulty': array([2, 1, 3]),
 'EngagementLevel': array([2, 3, 1]),
 'Loc_Europe': array([False,  True]),
 'Loc_Other': array([ True, False]),
 'Loc_USA': array([False,  True]),
 'Genre_RPG': array([False,  True]),
 'Genre_Simulation': array([False,  True]),
 'Genre_Sports': array([False,  True]),
 'Genre_Strategy': array([ True, False])}
```

[25]:
```
# Compute feature correlations with EngagementLevel
engagement_correlations = processed_df.corr()['EngagementLevel'].
 ↪sort_values(ascending=False)

# Convert the correlation series to a DataFrame
correlation_df = engagement_correlations.
 ↪to_frame(name='CorrelationWithEngagement').reset_index()

# Rename columns for better readability
correlation_df.rename(columns={'index': 'Feature'}, inplace=True)

# Show the resulting correlation table
display(correlation_df)
```

	Feature	CorrelationWithEngagement
0	EngagementLevel	1.000000
1	SessionsPerWeek	0.605996
2	AvgSessionDurationMinutes	0.476698

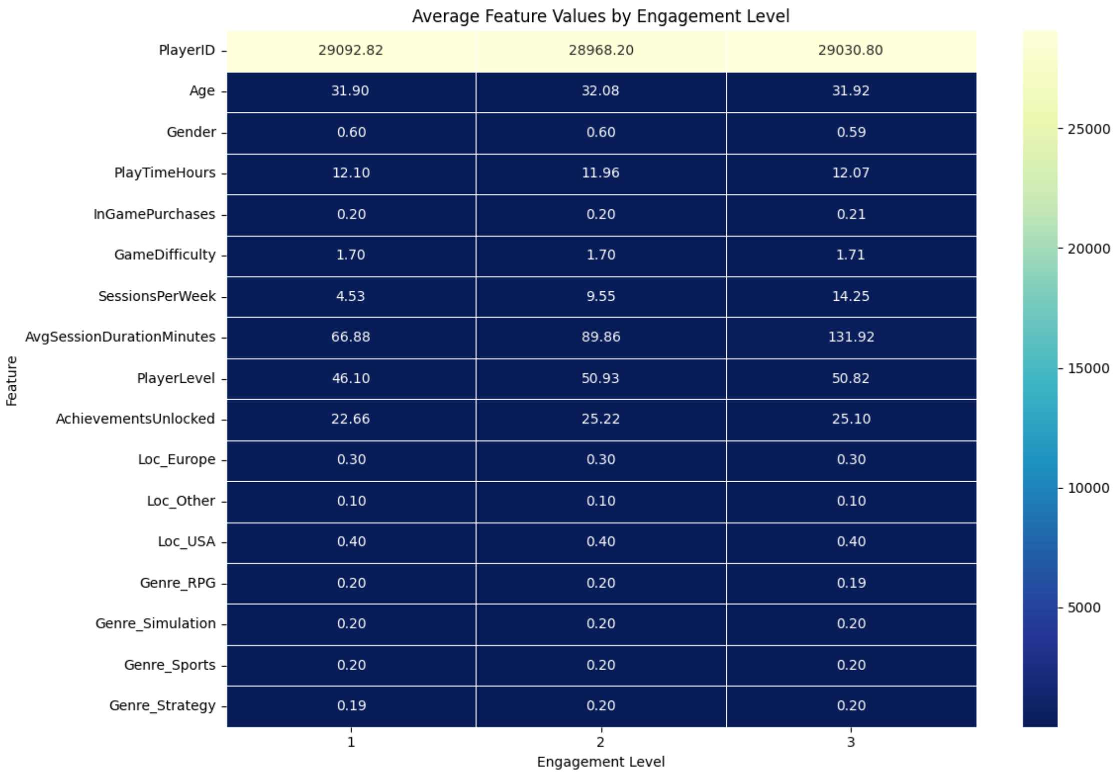
```
3        AchievementsUnlocked                    0.060576
4                 PlayerLevel                    0.059315
5             InGamePurchases                    0.008209
6              Genre_Strategy                    0.007700
7              GameDifficulty                    0.005057
8                     Loc_USA                    0.002499
9            Genre_Simulation                    0.001184
10                        Age                    0.000824
11               Genre_Sports                    0.000572
12               PlayTimeHours                  -0.001849
13                   PlayerID                   -0.001926
14                  Loc_Other                   -0.003174
15                     Gender                   -0.004978
16                 Loc_Europe                   -0.005965
17                  Genre_RPG                   -0.009707
```

0.2.12 Correlation Highlights: `EngagementLevel`

1. **High Correlation**
   - **SessionsPerWeek** (0.61): Strongest driver of engagement.
     → *More weekly sessions = higher engagement.*
2. **Moderate Correlation**
   - **AvgSessionDurationMinutes** (0.48):
     → *Longer play sessions help boost engagement.*
3. **Weak but Positive**
   - **AchievementsUnlocked** (0.06) & **PlayerLevel** (0.06):
     → *Progress and achievements slightly reflect engagement.*
4. **Minimal to No Impact**
   - Features like `GameDifficulty`, `InGamePurchases`, `Age`, and `Location` show negligible correlation.
     → These don't directly influence engagement level._nfluence engagement.

[26]:
```
# Calculate average values of each feature grouped by engagement level
feature_means_by_engagement = processed_df.groupby('EngagementLevel').mean().T

# Visualize how feature values vary across engagement levels
plt.figure(figsize=(12, 8))
sns.heatmap(
    feature_means_by_engagement,
    annot=True,
    cmap='YlGnBu_r',
    fmt='.2f',
    linewidths=0.5,
    cbar_kws={"shrink": 1}
)
plt.title('Average Feature Values by Engagement Level')
plt.ylabel('Feature')
plt.xlabel('Engagement Level')
```

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



0.2.13 Key Insights from Average Feature Values by Engagement Level

1. **Session Behavior**
   - Players with higher engagement log **more frequent** (14.25/week) and **longer sessions** (~132 mins), compared to ~4.5 sessions and ~67 mins for low engagement.
2. **Player Progress**
   - High engagement users show higher **levels (50.8+)** and **more achievements unlocked (25+)** than low-engagement players.
3. **Purchase Trends**
   - In-game purchase behavior slightly increases with engagement: 21% for high vs. 20% for low.
4. **Genre & Difficulty**
   - Genre and difficulty preferences remain stable across levels, but slight shifts may still exist (e.g., Strategy genre dips slightly at high engagement).
5. **Demographics**
   - Gender and location proportions remain mostly constant across engagement levels.

0.2.14 Strategic Recommendations

1. **Increase Session Frequency**
   - Introduce daily login rewards or short timed challenges to encourage consistent play.
2. **Enhance Progression Systems**
   - Offer progression-based incentives like XP boosts, badges, or unlockable content.
3. **Retain High-Value Users**
   - Develop more advanced challenges for highly engaged players to sustain long sessions.
4. **Boost Monetization**
   - Use engagement-based offers or bundles to convert medium-level users into spenders.
5. **Localized Campaigns**
   - While location doesn't vary much, tailor content and offers for the USA and top regional markets. for Europe and Asia.

Split into train and test

[27]:
```
# Copy and Remove PlayerID since it's not useful for prediction
player_ids = processed_df['PlayerID'].copy()
processed_df = processed_df.drop(columns=['PlayerID'])

# Separate input features and target variable
X = processed_df.drop(columns=['EngagementLevel'])  # Independent variables
y = processed_df['EngagementLevel']  # Target: engagement level classification
```

[28]:
```
# Split the dataset into training and testing sets (80% train, 20% test),␣
↪preserving class distribution
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# Check the dimensions of each split
print(f"X_train shape: {X_train.shape}")
print(f"X_test shape: {X_test.shape}")
print(f"y_train shape: {y_train.shape}")
print(f"y_test shape: {y_test.shape}")
```

```
X_train shape: (32027, 16)
X_test shape: (8007, 16)
y_train shape: (32027,)
y_test shape: (8007,)
```

[29]:
```
# Standardize the feature values using StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)  # Fit on training data and␣
↪transform
X_test_scaled = scaler.transform(X_test)        # Apply same transformation to␣
↪test data
```

0.2.15 Model Training and Evaluation

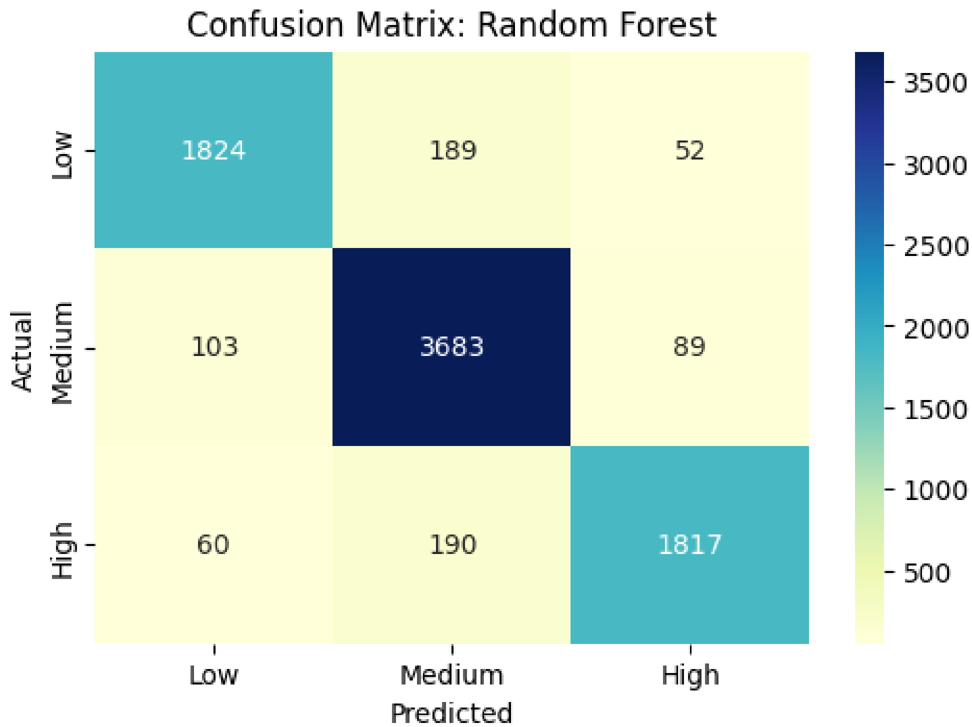
[30]:
```
# Initialize Models
models = {
    "Random Forest": RandomForestClassifier(random_state=42,␣
 ↪class_weight='balanced'),
    "Gradient Boosting": GradientBoostingClassifier(random_state=42),
    "LightGBM": LGBMClassifier(verbose=-1, random_state=42,␣
 ↪class_weight='balanced'),
    "CatBoost": CatBoostClassifier(verbose=0, random_state=42),
    "Logistic Regression": LogisticRegression(multi_class='multinomial',␣
 ↪solver='lbfgs', max_iter=1000, class_weight='balanced', random_state=42),
    "SVC": SVC(kernel='rbf', probability=True, class_weight='balanced',␣
 ↪random_state=42)
}

# Confirm initialized models
print("Models initialized:", list(models.keys()))
```

```
Models initialized: ['Random Forest', 'Gradient Boosting', 'LightGBM',
'CatBoost', 'Logistic Regression', 'SVC']
```

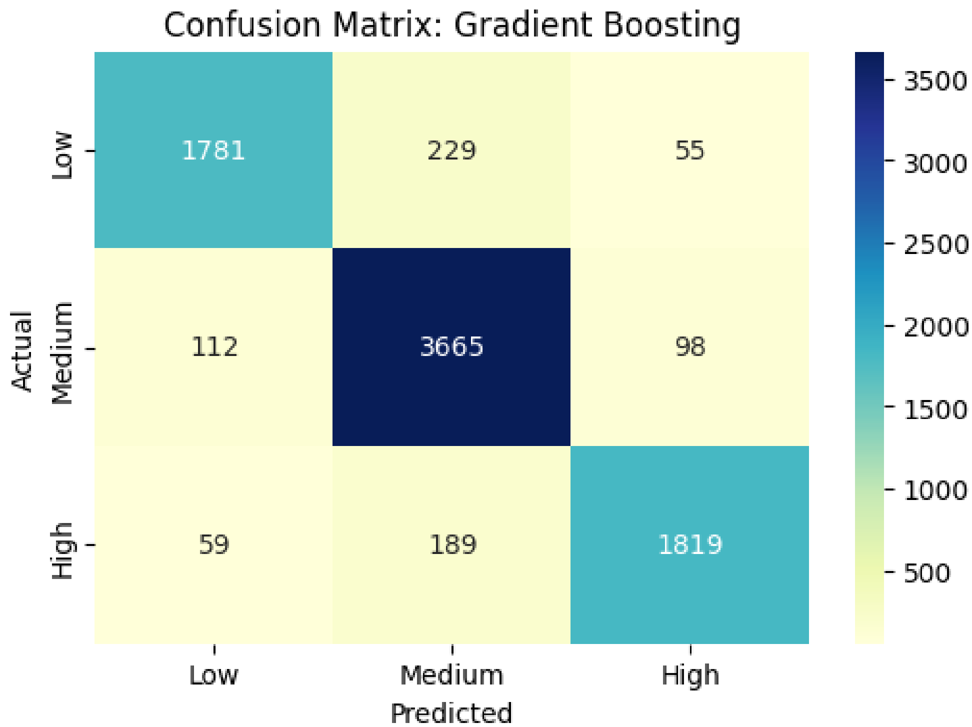
[31]:
```
# Initialize a list to collect model evaluation results
evaluation_summary = []

# Loop through each model for training and evaluation
for name, clf in models.items():
    print(f"Evaluating model: {name}")

    # Train the model on the scaled training data
    clf.fit(X_train_scaled, y_train)

    # Generate predictions
    y_pred = clf.predict(X_test_scaled)
    y_proba = clf.predict_proba(X_test_scaled) if hasattr(clf, "predict_proba")␣
 ↪else None

    # Compute performance metrics
    acc = accuracy_score(y_test, y_pred)
    auc_score = roc_auc_score(y_test, y_proba, multi_class='ovr') if y_proba is␣
 ↪not None else "N/A"

    # Save results
    evaluation_summary.append({
        "Model": name,
        "Accuracy": acc,
        "AUC": auc_score
```

```python
    })

    # Display classification report
    print(f"\nClassification Report: {name}")
    print(classification_report(y_test, y_pred))

    # Plot confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=True, cmap="YlGnBu", fmt='d',
                xticklabels=['Low', 'Medium', 'High'],
                yticklabels=['Low', 'Medium', 'High'])
    plt.title(f"Confusion Matrix: {name}")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

# Summarize and display all model performances
results_df = pd.DataFrame(evaluation_summary).sort_values(by="Accuracy",␣
 ↪ascending=False).reset_index(drop=True)
print("\nModel Evaluation Summary:")
display(results_df)
```

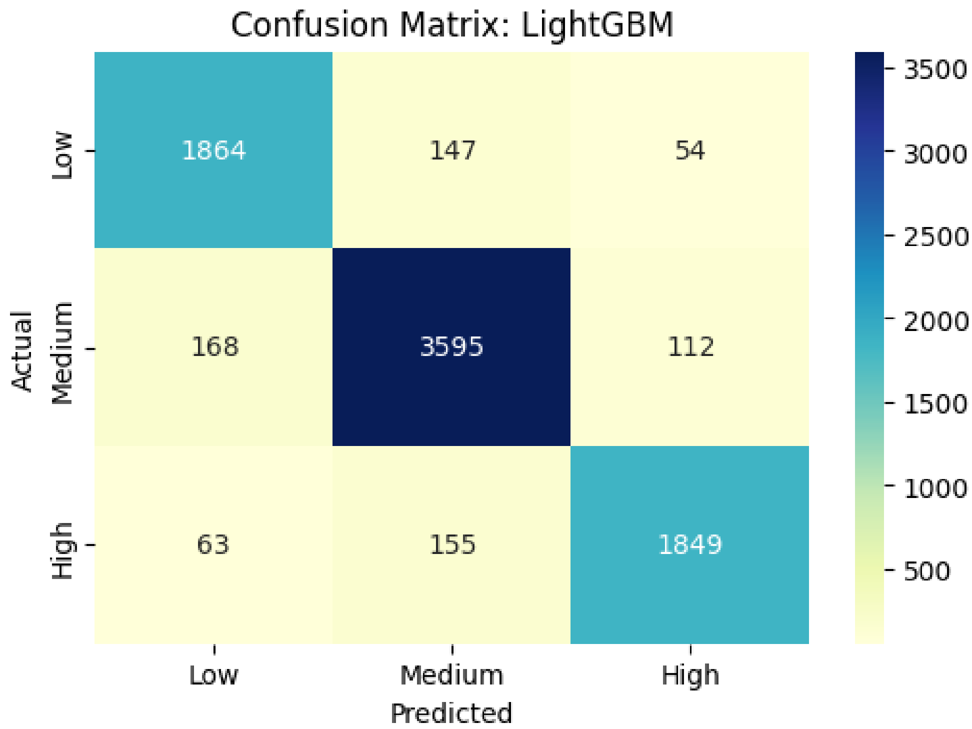
```
Evaluating model: Random Forest

Classification Report: Random Forest
              precision    recall  f1-score   support

           1       0.92      0.88      0.90      2065
           2       0.91      0.95      0.93      3875
           3       0.93      0.88      0.90      2067

    accuracy                           0.91      8007
   macro avg       0.92      0.90      0.91      8007
weighted avg       0.92      0.91      0.91      8007
```



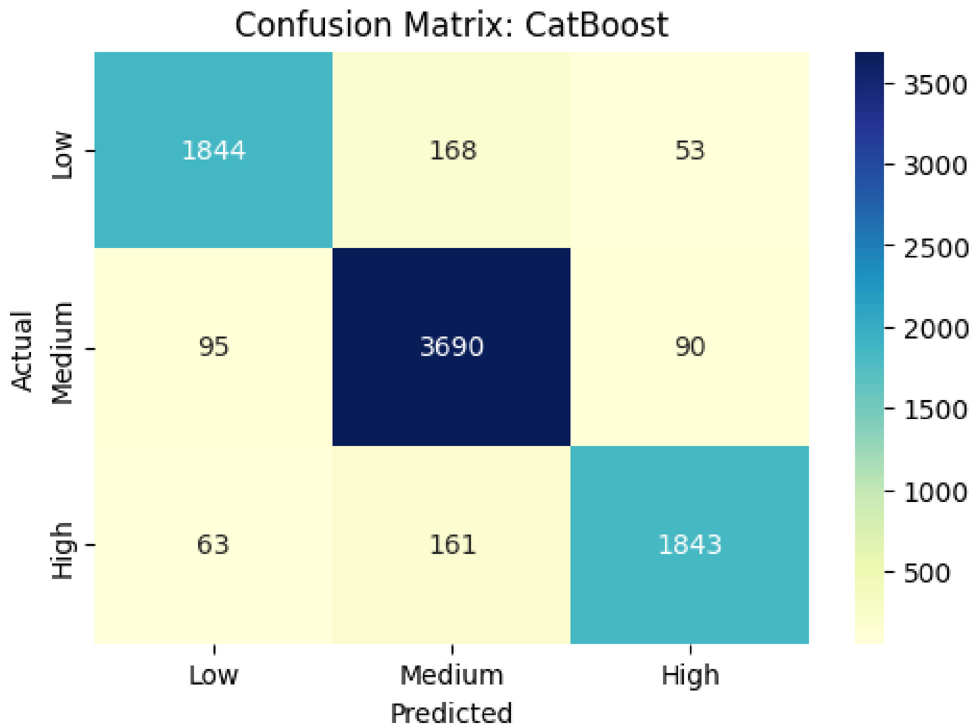

```
Evaluating model: Gradient Boosting

Classification Report: Gradient Boosting
              precision    recall  f1-score   support

           1       0.91      0.86      0.89      2065
           2       0.90      0.95      0.92      3875
           3       0.92      0.88      0.90      2067

    accuracy                           0.91      8007
   macro avg       0.91      0.90      0.90      8007
weighted avg       0.91      0.91      0.91      8007
```




```
Evaluating model: LightGBM

Classification Report: LightGBM
              precision    recall  f1-score   support

           1       0.89      0.90      0.90      2065
           2       0.92      0.93      0.93      3875
           3       0.92      0.89      0.91      2067

    accuracy                           0.91      8007
   macro avg       0.91      0.91      0.91      8007
weighted avg       0.91      0.91      0.91      8007
```



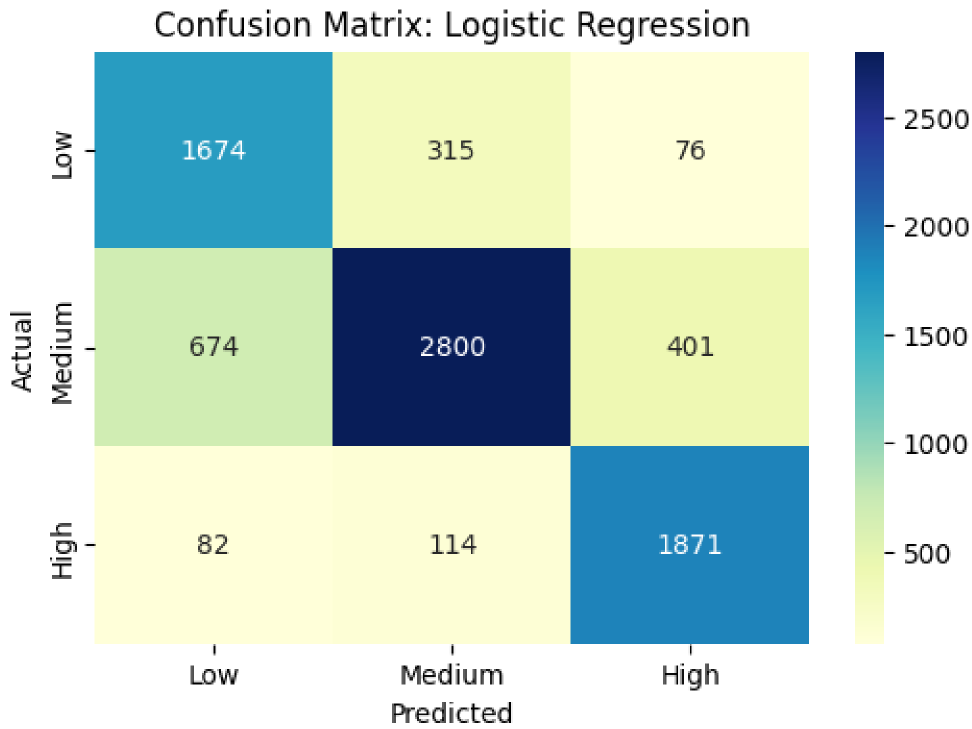

```
Evaluating model: CatBoost

Classification Report: CatBoost
              precision    recall  f1-score   support

           1       0.92      0.89      0.91      2065
           2       0.92      0.95      0.93      3875
           3       0.93      0.89      0.91      2067

    accuracy                           0.92      8007
   macro avg       0.92      0.91      0.92      8007
weighted avg       0.92      0.92      0.92      8007
```



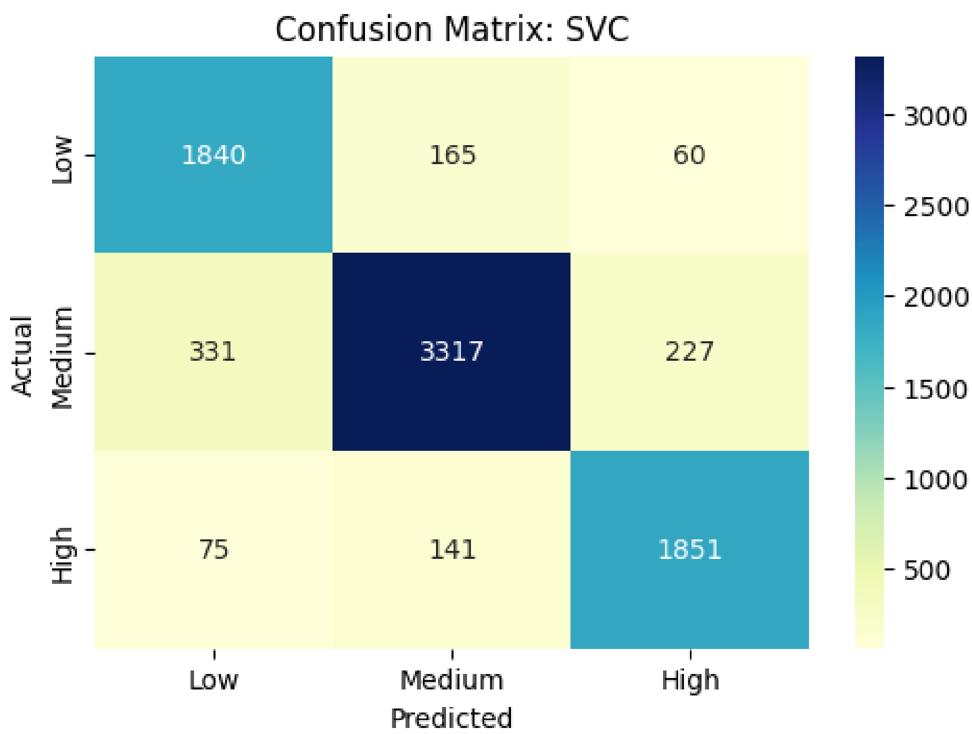
Evaluating model: Logistic Regression

Classification Report: Logistic Regression

	precision	recall	f1-score	support
1	0.69	0.81	0.74	2065
2	0.87	0.72	0.79	3875
3	0.80	0.91	0.85	2067
accuracy			0.79	8007
macro avg	0.78	0.81	0.79	8007
weighted avg	0.80	0.79	0.79	8007




```
Evaluating model: SVC

Classification Report: SVC
              precision    recall  f1-score   support

           1       0.82      0.89      0.85      2065
           2       0.92      0.86      0.88      3875
           3       0.87      0.90      0.88      2067

    accuracy                           0.88      8007
   macro avg       0.87      0.88      0.87      8007
weighted avg       0.88      0.88      0.88      8007
```




```
Model Evaluation Summary:
                 Model  Accuracy       AUC
0             CatBoost  0.921319  0.946353
1        Random Forest  0.914700  0.944671
2             LightGBM  0.912701  0.946413
3    Gradient Boosting  0.907331  0.945354
4                  SVC  0.875234  0.943830
5  Logistic Regression  0.792432  0.916146
```

0.2.16 Summary of Model Evaluation

1. Overall Performance

- **CatBoost** had the highest accuracy and tied for best AUC, showing top-tier performance.
- **LightGBM** delivered the best AUC and closely matched CatBoost in accuracy.
- **Logistic Regression** lagged behind, especially in recall and F1-score for classifying `Medium` engagement.

---

2. Confusion Matrix Highlights

- Most models excelled at predicting the `Medium` class, with strong true positive rates.
- **CatBoost and Random Forest** had the most balanced performance across all three classes.

- **Logistic Regression** showed high misclassification, especially for `Medium` engagement users.

---

3. Classification Report Summary

- All ensemble models (CatBoost, LightGBM, Random Forest, Gradient Boosting) exhibited:
  - **High precision and recall across all classes**
  - **Macro and weighted F1-scores above 0.90**
- **SVC** performed reasonably well but slightly trailed the ensemble models.
- **Logistic Regression** had limited performance, particularly underpredicting `Medium` engagement.

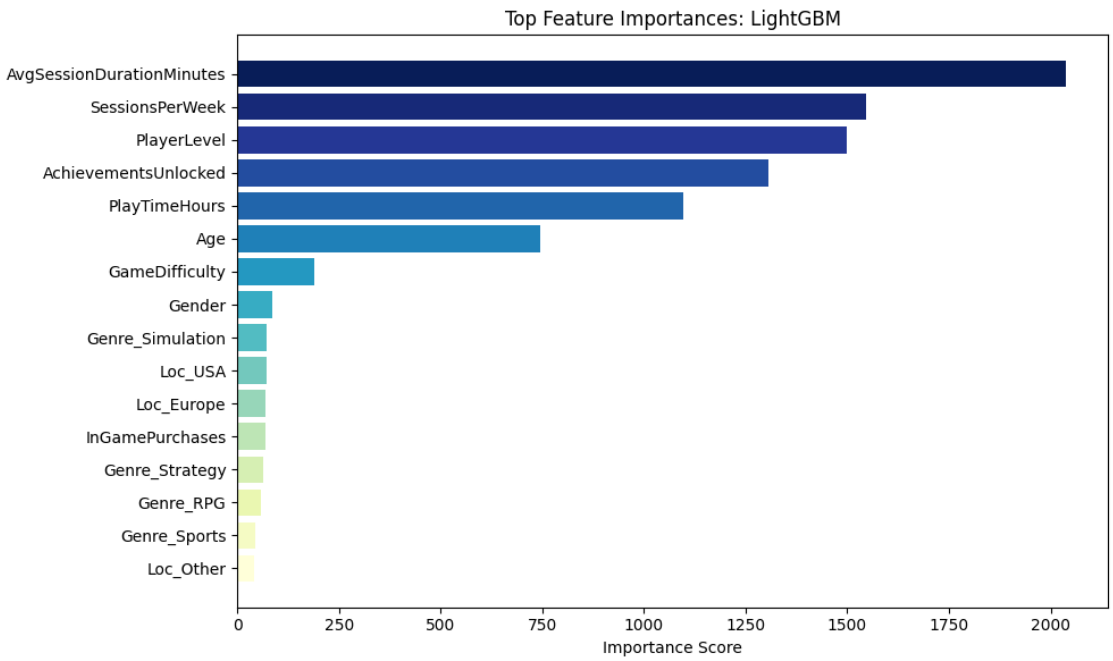
Final Recommendation

- For production deployment, **CatBoost** or **LightGBM** are strong choices due to their high accuracy and AUC.
- Consider **Random Forest** for interpretability or feature importance visualization.
- Avoid relying solely on **Logistic Regression** for this task due to underperformance.s all metrics.

[32]:
```python
#  Select the top-performing model based on highest AUC (LightGBM)
top_model_name = results_df.loc[results_df['AUC'].idxmax(), "Model"]
print(f" Best performing model: {top_model_name}\n")

# Retrieve and retrain the best model
top_model = models[top_model_name]
top_model.fit(X_train_scaled, y_train)

#  Plot feature importances (if supported by the model)
if hasattr(top_model, "feature_importances_"):
    importances = top_model.feature_importances_
    features = X.columns
    sorted_indices = importances.argsort()[::-1]

    # Create a horizontal bar chart of feature importances
    plt.figure(figsize=(10, 6))
    colors = plt.cm.YlGnBu_r(np.linspace(0, 1, len(importances)))
    plt.barh(range(len(sorted_indices)), importances[sorted_indices],␣
↪color=colors, align='center')
    plt.yticks(range(len(sorted_indices)), [features[i] for i in␣
↪sorted_indices])
    plt.xlabel("Importance Score")
    plt.title(f"Top Feature Importances: {top_model_name}")
    plt.gca().invert_yaxis()
    plt.tight_layout()
    plt.show()
```

```
else:
    print(f"  {top_model_name} does not provide built-in feature importances.")
```

```
Best performing model: LightGBM
```



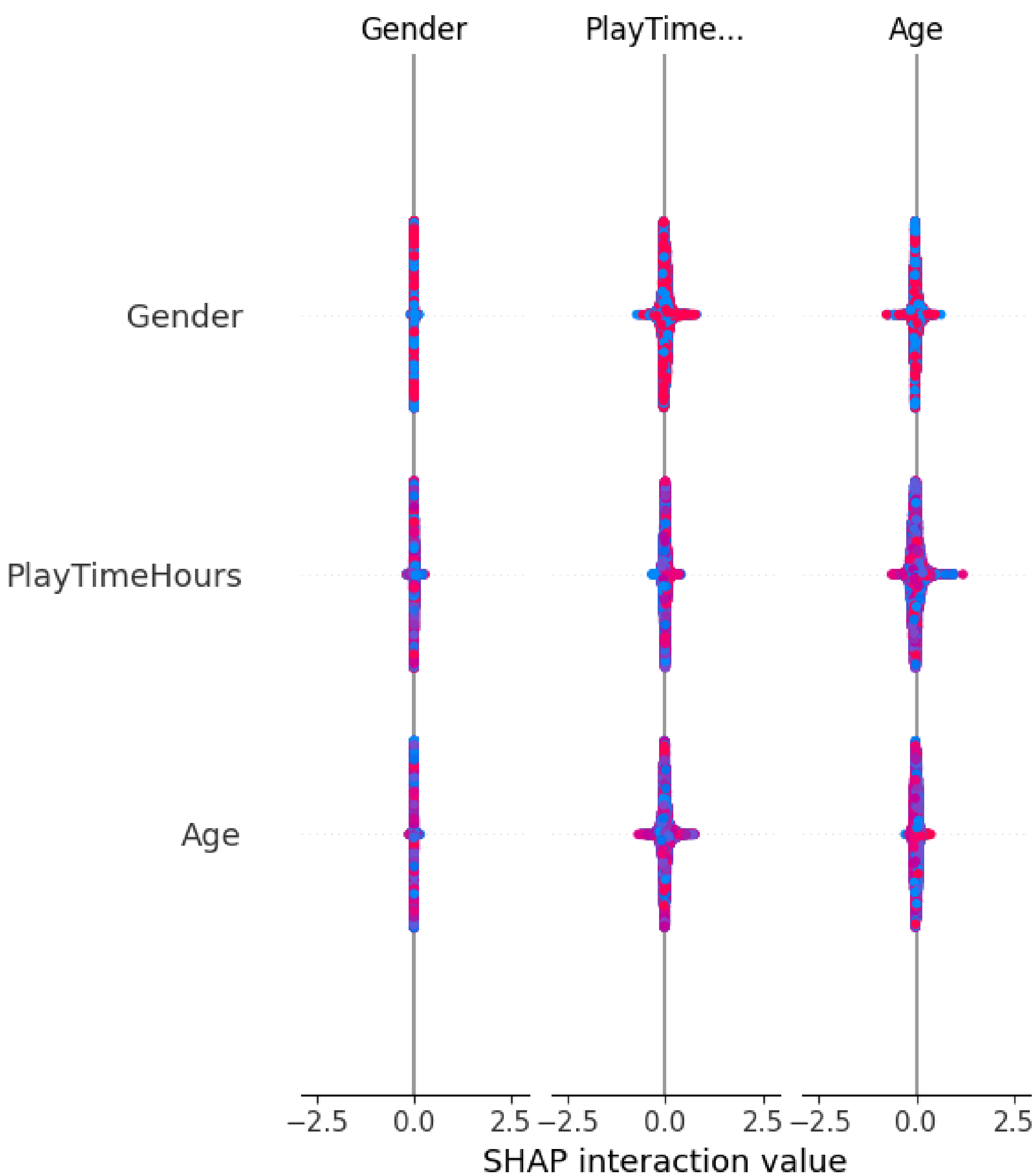
0.2.17 Insights from Feature Importance (LightGBM)

1. **Key Drivers of Engagement:**
   - **`AvgSessionDurationMinutes`** is the most influential feature — players spending more time per session are highly engaged.
   - **`SessionsPerWeek`** and **`PlayerLevel`** also rank high, emphasizing the role of frequent play and player progression.
   - **`AchievementsUnlocked`** reflects moderate influence, showing that unlocking goals supports engagement.
2. **Supporting Factors:**
   - **`PlayTimeHours`** and **`Age`** contribute meaningfully, suggesting that both total playtime and player demographics play a role.
   - **`GameDifficulty`** has a minor influence, possibly indicating interest in balanced or challenging gameplay.
3. **Minimal Contributors:**
   - **`Genre`** and **`Location`**-based features, along with **`InGamePurchases`**, have low importance, suggesting these don't heavily affect engagement predictions.

Implication: Engagement is driven more by behavior (how often and how long players play) than static attributes like geography or game genre.s of engagement.

Explaining Model - LightGBM

[33]:
```
# Initialize TreeExplainer with the trained model
explainer = shap.TreeExplainer(top_model)

# Get SHAP values for the test set
shap_values = explainer.shap_values(X_test_scaled)

# Plot summary of SHAP values
shap.summary_plot(shap_values, X_test_scaled, feature_names=X.columns)
```



0.2.18 SHAP Interaction Plot Insights

This SHAP interaction plot visualizes how pairs of features (`Gender`, `PlayTimeHours`, and `Age`) interact to influence the model's predictions.

What It Shows:

- **Diagonal cells** (e.g., `Gender × Gender`) represent how much each feature contributes to the model **on its own** (main effect).
- **Off-diagonal cells** (e.g., `Gender × PlayTimeHours`) capture **interaction effects**, showing how the combination of two features jointly influences the prediction.

Key Observations:

- The **SHAP interaction values are mostly centered around 0**, indicating **weak or minimal interactions** between these features.
- No strong positive or negative interactions are observed, meaning these features primarily act **independently** rather than influencing predictions through complex interdependencies.

Interpretation:

- This supports the idea that the model's behavior is **largely additive** for these features.
- There's **no immediate need for feature crosses or interaction terms** involving `Gender`, `PlayTimeHours`, or `Age`, as their combined effect is not significantly stronger than their individual effects.

Takeaway:

Focus on single-feature explanations and importance scores for model interpretation. Interactions among these specific features do not appear to significantly enhance model performance or interpretability.

[35]:
```
# Initialize LIME explainer
lime_explainer = lime.lime_tabular.LimeTabularExplainer(
    training_data=X_train_scaled,
    feature_names=X.columns.tolist(),
    class_names=['Low', 'Medium', 'High'],
    mode='classification'
)

# Instance from test data to explain
i = 5
lime_exp = lime_explainer.explain_instance(
    X_test_scaled[i],
    top_model.predict_proba,
    num_features=10
)
```

```python
lime_exp.save_to_file('lime_explanation.html')

# Get the index of the test instance in the original DataFrame
original_index = y_test.index[i]

# Retrieve and print the corresponding PlayerID
player_id = player_ids.loc[original_index]
print(f"Explaining prediction for PlayerID: {player_id}")

from IPython.display import IFrame
IFrame('lime_explanation.html', width=1000, height=600)
```

```
Explaining prediction for PlayerID: 43281
```

[35]: <IPython.lib.display.IFrame at 0x108aaa7b0>

0.2.19 LIME Explanation: Why PlayerID: 43281 Was Classified as "Medium Engagement" ??

Prediction Overview:

- **Predicted Engagement Level: Medium**
- **Prediction Probabilities:**
  - Low: **31%**
  - **Medium: 61%**
  - High: **8%**

Key Feature Influences:

Feature	Contribution	Impact Direction
SessionsPerWeek (-0.95)	-0.27	Negative influence (pushed away from Medium)
AvgSessionDurationMinutes (-0.30)	+0.22	Positive influence (pushed toward Medium)
PlayerLevel (+1.45)	+0.04	Positive
Loc_USA (-0.82)	+0.03	Positive
Loc_Other (-0.33)	+0.02	Positive
Genre_RPG (-0.50)	+0.02	Positive
Genre_Strategy (-0.50)	+0.01	Positive
Gender (0.82)	+0.01	Positive
AchievementsUnlocked (-0.45)	-0.01	Negative
Genre_Simulation (-0.50)	-0.01	Negative

0.2.20 Interpretation:

- **Biggest factor reducing engagement score:**
  - Low value for `SessionsPerWeek` had the highest **negative impact** on predicting "Medium" engagement.
- **Strongest positive drivers:**
  - Longer session durations (`AvgSessionDurationMinutes`) and player progression (`PlayerLevel`) helped classify this player as Medium.

0.2.21 Recommendations:

1. **Boost Session Frequency**
   - Introduce **daily login rewards** or **time-limited events** to motivate this player to log in more frequently.
2. **Reinforce Progression**
   - Since player level is high, use **level-based incentives** to transition them to **High Engagement**.
3. **Leverage Regional & Genre Data**
   - Since features like `Loc_USA` and `Genre_RPG` had subtle effects, tailor **genre-specific content** or **regional campaigns** for better engagement uplift.