```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

DATA PREPROCESSING

```
df = pd.read_csv('Indian_Kids_Screen_Time.csv',lineterminator= '\n')

df.head()
```

```
   Age  Gender  Avg_Daily_Screen_Time_hr Primary_Device  \
0   14    Male                      3.99     Smartphone
1   11  Female                      4.61         Laptop
2   18  Female                      3.73             TV
3   15  Female                      1.21         Laptop
4   12  Female                      5.89     Smartphone

   Exceeded_Recommended_Limit  Educational_to_Recreational_Ratio  \
0                        True                               0.42
1                        True                               0.30
2                        True                               0.32
3                       False                               0.39
4                        True                               0.49

            Health_Impacts Urban_or_Rural
0  Poor Sleep, Eye Strain          Urban
1              Poor Sleep          Urban
2              Poor Sleep          Urban
3                     NaN          Urban
4     Poor Sleep, Anxiety          Urban
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9712 entries, 0 to 9711
Data columns (total 8 columns):
 #   Column                             Non-Null Count  Dtype
---  ------                             --------------  -----
 0   Age                                9712 non-null   int64
 1   Gender                             9712 non-null   object
 2   Avg_Daily_Screen_Time_hr           9712 non-null   float64
 3   Primary_Device                     9712 non-null   object
 4   Exceeded_Recommended_Limit         9712 non-null   bool
 5   Educational_to_Recreational_Ratio  9712 non-null   float64
 6   Health_Impacts                     6494 non-null   object
 7   Urban_or_Rural                     9712 non-null   object
dtypes: bool(1), float64(2), int64(1), object(4)
memory usage: 540.7+ KB
```

```
df['Primary_Device'].value_counts
```

```
<bound method IndexOpsMixin.value_counts of 0       Smartphone
1           Laptop
2               TV
3           Laptop
4       Smartphone
           ...
9707    Smartphone
9708    Smartphone
9709    Smartphone
9710            TV
9711            TV
Name: Primary_Device, Length: 9712, dtype: object>
```

```
df.duplicated().sum()
```

```
np.int64(44)
```

```
df.describe()
```

```
               Age  Avg_Daily_Screen_Time_hr  \
count  9712.000000               9712.000000
mean     12.979201                  4.352837
std       3.162437                  1.718232
min       8.000000                  0.000000
25%      10.000000                  3.410000
50%      13.000000                  4.440000
75%      16.000000                  5.380000
max      18.000000                 13.890000

       Educational_to_Recreational_Ratio
count                        9712.000000
mean                            0.427226
std                             0.073221
min                             0.300000
25%                             0.370000
50%                             0.430000
75%                             0.480000
max                             0.600000
```

EDA - EXPLORATORY DATA ANALYSIS

```
df.columns = df.columns.str.strip().str.replace(' ', '_').str.lower()
df.drop_duplicates(inplace=True)
```

```
print(df.columns.tolist())
```

```
['age', 'gender', 'avg_daily_screen_time_hr', 'primary_device',
'exceeded_recommended_limit', 'educational_to_recreational_ratio',
'health_impacts', 'urban_or_rural']
```

```
df.columns = df.columns.str.strip().str.lower().str.replace(' ', '_')
print(df.columns.tolist())
```

```
['age', 'gender', 'avg_daily_screen_time_hr', 'primary_device',
'exceeded_recommended_limit', 'educational_to_recreational_ratio',
'health_impacts', 'urban_or_rural']
```

```
bins = [4, 10, 15, 20]
labels = ['5-10 yrs', '11-15 yrs', '16-20 yrs']

df['age_group'] = pd.cut(df['age'], bins=bins, labels=labels)
df[['age', 'age_group']]
```

```
      age  age_group
0      14  11-15 yrs
1      11  11-15 yrs
2      18  16-20 yrs
3      15  11-15 yrs
4      12  11-15 yrs
...   ...        ...
9707   17  16-20 yrs
9708   17  16-20 yrs
9709   16  16-20 yrs
9710   17  16-20 yrs
9711   15  11-15 yrs

[9668 rows x 2 columns]
```

```
print(df.columns.tolist())
```

```
['age', 'gender', 'avg_daily_screen_time_hr', 'primary_device',
'exceeded_recommended_limit', 'educational_to_recreational_ratio',
'health_impacts', 'urban_or_rural', 'age_group']
```

```
df.columns = df.columns.str.strip().str.lower().str.replace(' ', '_')
print(df.columns.tolist())  # Check new names
```

```
['age', 'gender', 'avg_daily_screen_time_hr', 'primary_device',
'exceeded_recommended_limit', 'educational_to_recreational_ratio',
'health_impacts', 'urban_or_rural', 'age_group']
```

```
df['primary_device'] = df['primary_device'].str.strip().str.title()

df.head()
```

```
   age  gender  avg_daily_screen_time_hr primary_device  \
0   14    Male                      3.99     Smartphone
1   11  Female                      4.61         Laptop
2   18  Female                      3.73             Tv
3   15  Female                      1.21         Laptop
4   12  Female                      5.89     Smartphone
```

```
   exceeded_recommended_limit  educational_to_recreational_ratio  \
0                        True                               0.42
1                        True                               0.30
2                        True                               0.32
3                       False                               0.39
4                        True                               0.49

           health_impacts urban_or_rural  age_group
0  Poor Sleep, Eye Strain          Urban  11-15 yrs
1              Poor Sleep          Urban  11-15 yrs
2              Poor Sleep          Urban  16-20 yrs
3                     NaN          Urban  11-15 yrs
4     Poor Sleep, Anxiety          Urban  11-15 yrs
```

Categorizing Educational to Recreational Screen Usage

The `Educational_to_Recreational_Ratio` column in our dataset is currently a continuous numeric value ranging from **0.30 to 0.60**. While this provides detailed granularity, it can be hard to interpret at a glance. To make this variable more meaningful for analysis and visualization, we converted it into **three distinct categories** based on thresholds:

- **Mostly Recreational**: Ratio less than 0.40
- **Balanced**: Ratio between 0.40 and 0.49
- **Mostly Educational**: Ratio 0.50 and above

This transformation helps group students by how they primarily use their screen time — either for **learning**, **entertainment**, or a **balanced** mix of both.

We implemented this using a simple custom function with the `apply()` method in pandas. The new column created is named `usage_category`.

This enables deeper insights when exploring trends by age, device type, or total screen time.

```
def categorize_ratio(ratio):
    if ratio < 0.4:
        return 'Mostly Recreational'
    elif 0.4 <= ratio < 0.5:
        return 'Balanced'
    else:
        return 'Mostly Educational'

df['usage_category'] =
df['educational_to_recreational_ratio'].apply(categorize_ratio)
df.head()
```

```
   age  gender  avg_daily_screen_time_hr primary_device  \
0   14    Male                      3.99     Smartphone
1   11  Female                      4.61         Laptop
2   18  Female                      3.73             Tv
3   15  Female                      1.21         Laptop
```

```
4   12  Female                          5.89     Smartphone

   exceeded_recommended_limit  educational_to_recreational_ratio  \
0                        True                               0.42
1                        True                               0.30
2                        True                               0.32
3                       False                               0.39
4                        True                               0.49

           health_impacts urban_or_rural  age_group
usage_category
0  Poor Sleep, Eye Strain          Urban  11-15 yrs
Balanced
1              Poor Sleep          Urban  11-15 yrs  Mostly
Recreational
2              Poor Sleep          Urban  16-20 yrs  Mostly
Recreational
3                     NaN          Urban  11-15 yrs  Mostly
Recreational
4     Poor Sleep, Anxiety          Urban  11-15 yrs
Balanced
```

Health Impact Classification Based on Screen Usage

To interpret screen time in terms of children's well-being, we classified each student into a **Health Impact Level** based on their screen usage patterns.

The logic is derived from the assumption that:

- High recreational use may lead to negative outcomes such as poor sleep and low physical activity.
- Balanced usage poses moderate risk.
- Mostly educational usage is generally healthier.

Usage Category	Health Impact
Mostly Recreational	High Risk
Balanced	Moderate Risk
Mostly Educational	Low Risk

This transformation adds a behavioral health context to the analysis, helping in assessing screen time not just quantitatively, but also qualitatively.

```
def assign_health_risk(category):
    if category == 'Mostly Recreational':
        return 'High Risk'
    elif category == 'Balanced':
        return 'Moderate Risk'
    else:
        return 'Low Risk'
```

```
df['health_impact_level'] =
df['usage_category'].apply(assign_health_risk)
df.head()

   age  gender  avg_daily_screen_time_hr primary_device  \
0   14    Male                      3.99     Smartphone
1   11  Female                      4.61         Laptop
2   18  Female                      3.73             Tv
3   15  Female                      1.21         Laptop
4   12  Female                      5.89     Smartphone

   exceeded_recommended_limit  educational_to_recreational_ratio  \
0                        True                               0.42
1                        True                               0.30
2                        True                               0.32
3                       False                               0.39
4                        True                               0.49

           health_impacts urban_or_rural  age_group
usage_category  \
0  Poor Sleep, Eye Strain          Urban  11-15 yrs
Balanced
1              Poor Sleep          Urban  11-15 yrs  Mostly
Recreational
2              Poor Sleep          Urban  16-20 yrs  Mostly
Recreational
3                     NaN          Urban  11-15 yrs  Mostly
Recreational
4     Poor Sleep, Anxiety          Urban  11-15 yrs
Balanced

  health_impact_level
0       Moderate Risk
1           High Risk
2           High Risk
3           High Risk
4       Moderate Risk

df['daily_screen_time_min'] = (df['avg_daily_screen_time_hr'] *
60).round().astype(int)
df.drop(columns=['avg_daily_screen_time_hr'], inplace=True)
df['daily_screen_time_min'] = df['daily_screen_time_min'].astype(int)
df.head()

   age  gender primary_device  exceeded_recommended_limit  \
0   14    Male     Smartphone                        True
1   11  Female         Laptop                        True
2   18  Female             Tv                        True
3   15  Female         Laptop                       False
```

```
4   12  Female     Smartphone                        True

   educational_to_recreational_ratio          health_impacts
urban_or_rural  \
0                                0.42  Poor Sleep, Eye Strain
Urban
1                                0.30              Poor Sleep
Urban
2                                0.32              Poor Sleep
Urban
3                                0.39                     NaN
Urban
4                                0.49     Poor Sleep, Anxiety
Urban

   age_group       usage_category health_impact_level
daily_screen_time_min
0  11-15 yrs             Balanced       Moderate Risk
239
1  11-15 yrs  Mostly Recreational           High Risk
277
2  16-20 yrs  Mostly Recreational           High Risk
224
3  11-15 yrs  Mostly Recreational           High Risk
73
4  11-15 yrs             Balanced       Moderate Risk
353
```

Categorizing Screen Time Risk Based on Age and Usage

To make our screen time analysis more actionable and informative, we transformed the raw screen time values into meaningful risk categories.

Rather than using a simple True/False flag to indicate whether a child exceeded the recommended screen time, we introduced a new column: **`screen_time_risk`**, which classifies each student into one of three health impact levels:

Classification Logic:

Age Group	Recommended Daily Limit	Category
≤ 10 years	≤ 90 minutes	- Within Limit - Slightly Over Limit (91–150 mins) - Excessive Usage (>150 mins)
11–15 years	≤ 120 minutes	- Within Limit - Slightly Over Limit (121–180 mins) - Excessive Usage (>180 mins)
16–20 years	≤ 150 minutes	- Within Limit - Slightly Over Limit (151–210 mins) - Excessive Usage (>210 mins)

The new `screen_time_risk` column will be used in later sections to analyze trends and visualize health impacts.

```
def screen_time_category(row):
    if row['age'] <= 10:
        if row['daily_screen_time_min'] <= 90:
            return 'Within Limit'
        elif row['daily_screen_time_min'] <= 150:
            return 'Slightly Over Limit'
        else:
            return 'Excessive Usage'

    elif row['age'] <= 15:
        if row['daily_screen_time_min'] <= 120:
            return 'Within Limit'
        elif row['daily_screen_time_min'] <= 180:
            return 'Slightly Over Limit'
        else:
            return 'Excessive Usage'

    else:
        if row['daily_screen_time_min'] <= 150:
            return 'Within Limit'
        elif row['daily_screen_time_min'] <= 210:
            return 'Slightly Over Limit'
        else:
            return 'Excessive Usage'

df['screen_time_risk'] = df.apply(screen_time_category, axis=1)
df.head()
```

```
   age   gender primary_device  exceeded_recommended_limit  \
0   14     Male     Smartphone                        True
1   11   Female         Laptop                        True
2   18   Female             Tv                        True
3   15   Female         Laptop                       False
4   12   Female     Smartphone                        True

   educational_to_recreational_ratio          health_impacts
urban_or_rural  \
0                               0.42  Poor Sleep, Eye Strain
Urban
1                               0.30              Poor Sleep
Urban
2                               0.32              Poor Sleep
Urban
3                               0.39                     NaN
Urban
4                               0.49     Poor Sleep, Anxiety
Urban
```

```
   age_group       usage_category health_impact_level
daily_screen_time_min  \
0  11-15 yrs             Balanced       Moderate Risk
239
1  11-15 yrs  Mostly Recreational           High Risk
277
2  16-20 yrs  Mostly Recreational           High Risk
224
3  11-15 yrs  Mostly Recreational           High Risk
73
4  11-15 yrs             Balanced       Moderate Risk
353

  screen_time_risk
0  Excessive Usage
1  Excessive Usage
2  Excessive Usage
3     Within Limit
4  Excessive Usage
```

```
df.drop(columns=['exceeded_recommended_limit'], inplace=True)
df.head()
```

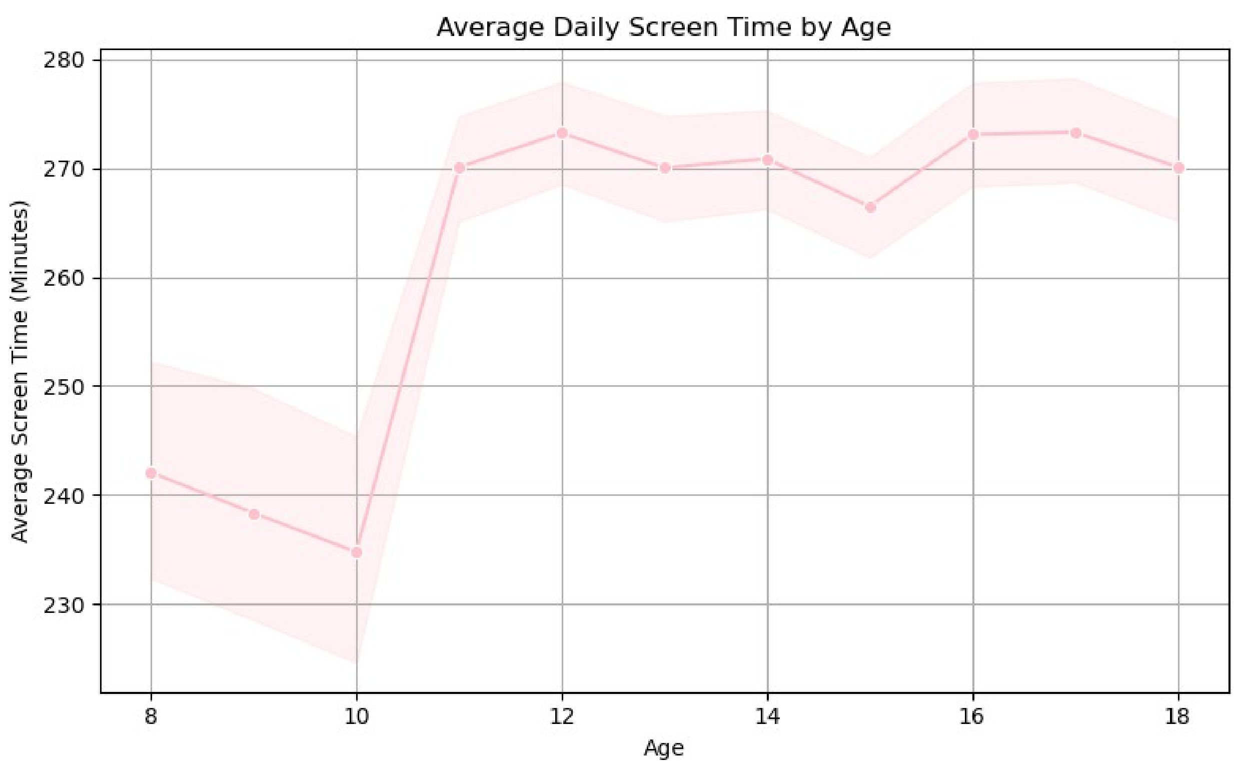
```
   age  gender primary_device  educational_to_recreational_ratio  \
0   14    Male     Smartphone                               0.42
1   11  Female         Laptop                               0.30
2   18  Female             Tv                               0.32
3   15  Female         Laptop                               0.39
4   12  Female     Smartphone                               0.49

           health_impacts urban_or_rural  age_group
usage_category  \
0  Poor Sleep, Eye Strain          Urban  11-15 yrs
Balanced
1              Poor Sleep          Urban  11-15 yrs  Mostly
Recreational
2              Poor Sleep          Urban  16-20 yrs  Mostly
Recreational
3                     NaN          Urban  11-15 yrs  Mostly
Recreational
4     Poor Sleep, Anxiety          Urban  11-15 yrs
Balanced

  health_impact_level  daily_screen_time_min screen_time_risk
0       Moderate Risk                    239  Excessive Usage
1           High Risk                    277  Excessive Usage
2           High Risk                    224  Excessive Usage
3           High Risk                     73     Within Limit
4       Moderate Risk                    353  Excessive Usage
```

Data Visualization

1. Average Daily Screen Time by Age

This visualization helps us understand how screen time habits change as children grow older. By plotting the average daily screen time against age, we can identify trends such as whether older kids tend to spend more time on screens or if usage peaks at certain age groups.

```
plt.figure(figsize=(8, 5))
sns.lineplot(data=df, x='age', y='daily_screen_time_min', marker='o',
color='pink')
plt.title('Average Daily Screen Time by Age')
plt.xlabel('Age')
plt.ylabel('Average Screen Time (Minutes)')
plt.grid(True)
plt.tight_layout()
plt.show()
```

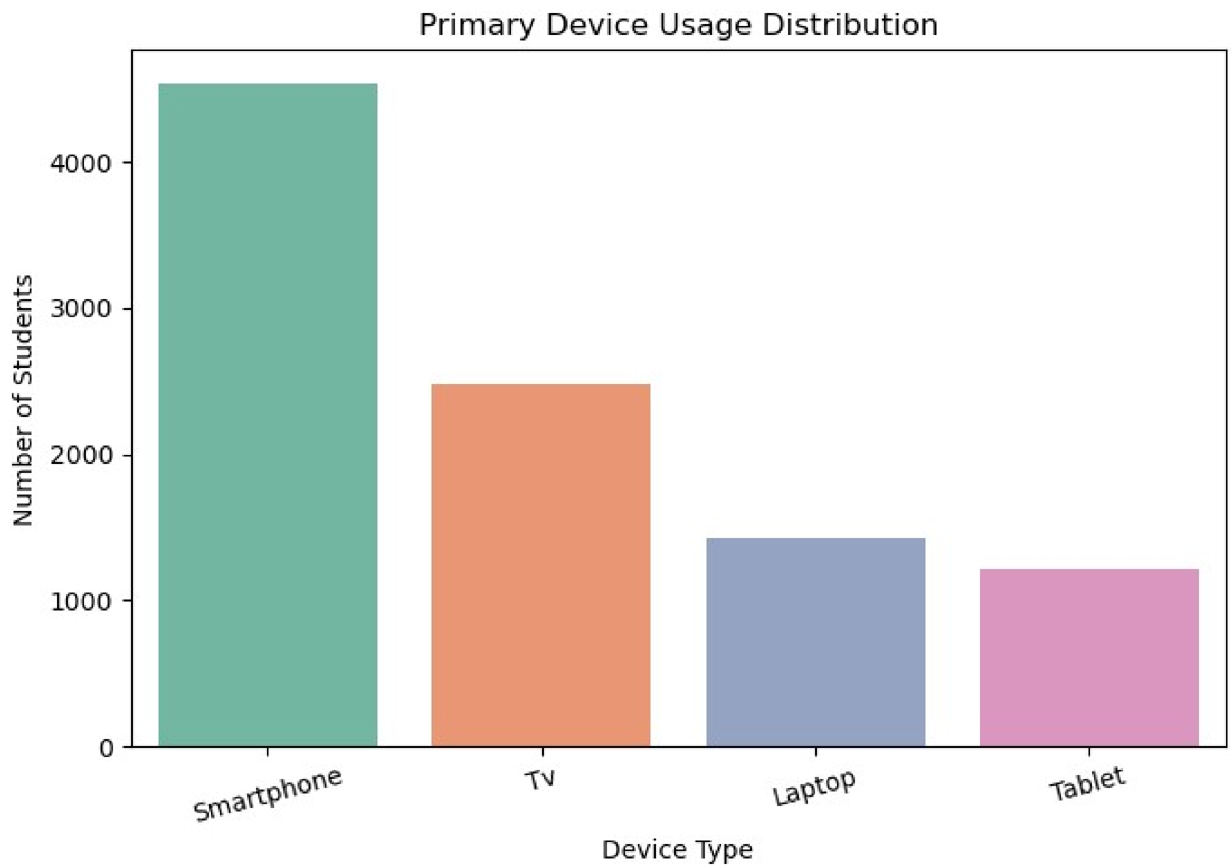


2. Primary Device Usage Distribution

This chart displays which digital devices are most commonly used by children for screen time. Understanding device preference helps identify exposure patterns and potential risks related to each type of screen.

```
# Strip column names just in case
df.columns = df.columns.str.strip()

# Count the frequency of each device type
device_counts = df['primary_device'].value_counts()

# Plot
plt.figure(figsize=(7, 5))
sns.barplot(x=device_counts.index, y=device_counts.values,
palette='Set2')
plt.title('Primary Device Usage Distribution')
plt.xlabel('Device Type')
plt.ylabel('Number of Students')
plt.xticks(rotation=15)
plt.tight_layout()
plt.show()
```

```
C:\Users\bikha\AppData\Local\Temp\ipykernel_29068\1016042403.py:9:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x=device_counts.index, y=device_counts.values,
palette='Set2')
```

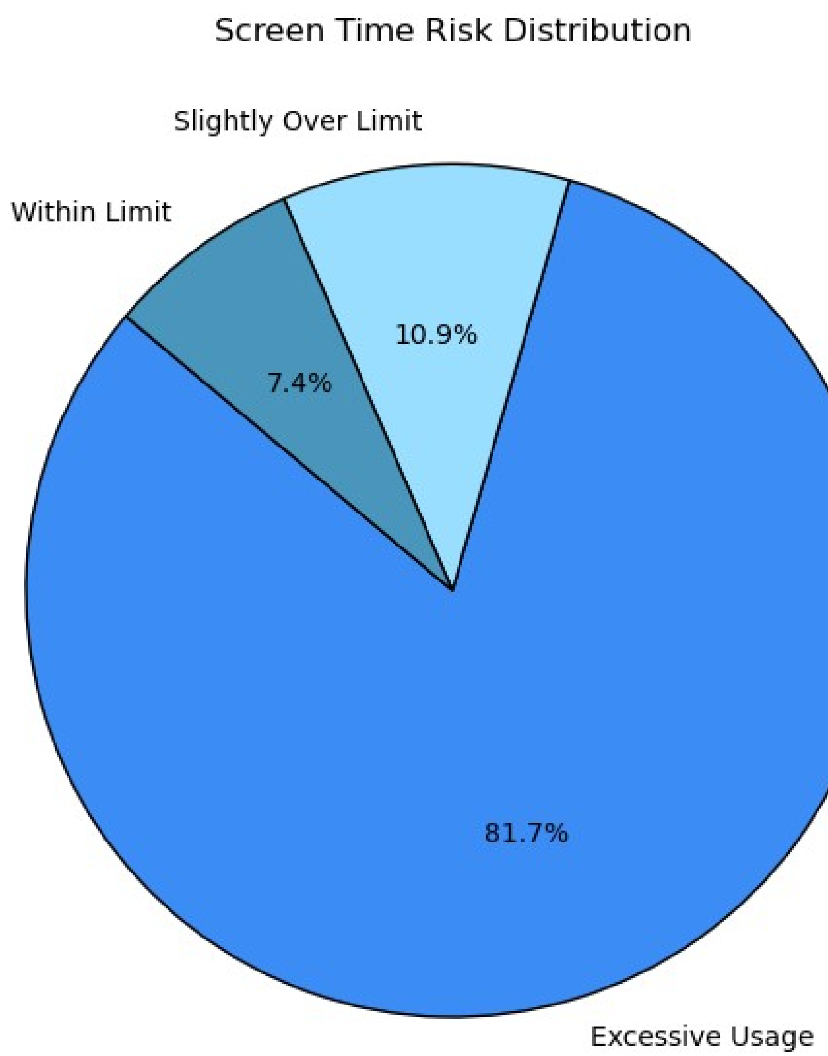


3. Screen Time Risk Classification

This chart shows how children's screen time is distributed across different risk levels such as "Within Limit", "Slightly Over", and "Excessive Usage". These categories are based on age-adjusted screen time thresholds and help assess potential overuse and its implications.

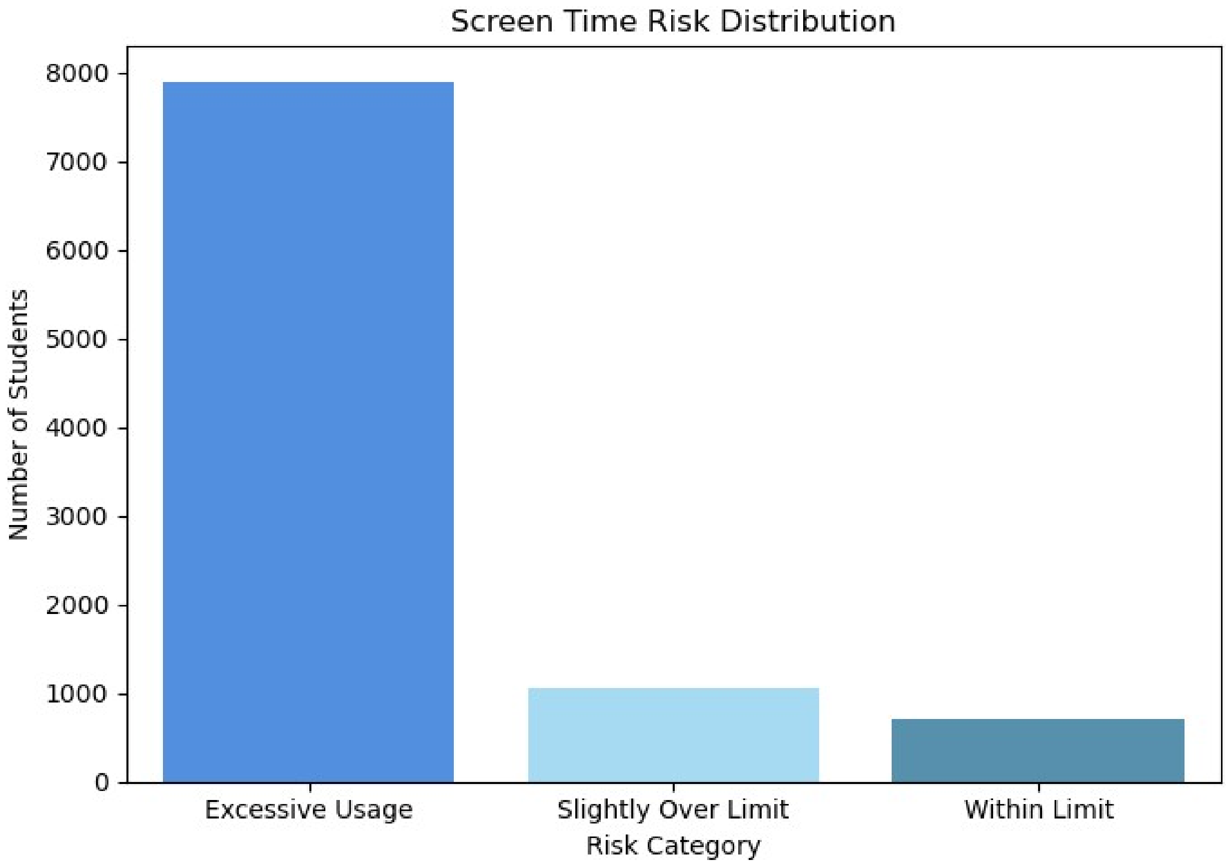
```
# Ensure column names are clean
df.columns = df.columns.str.strip()

# Count the number of students in each risk category
risk_counts = df['screen_time_risk'].value_counts()

# Plot pie chart
plt.figure(figsize=(6, 6))
risk_counts.plot.pie(
    autopct='%1.1f%%',
    startangle=140,
    colors=["#3C8CF6", "#99DDFF", "#4995BB"],
    labels=risk_counts.index,
    wedgeprops={'edgecolor': 'black'}
)
plt.title('Screen Time Risk Distribution')
plt.ylabel('')
```

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




```
# Count risk category occurrences
risk_counts = df['screen_time_risk'].value_counts()

# Plot bar chart
plt.figure(figsize=(7, 5))
sns.barplot(x=risk_counts.index, y=risk_counts.values,
palette=["#3C8CF6", "#99DDFF", "#4995BB"])
plt.title('Screen Time Risk Distribution')
plt.xlabel('Risk Category')
plt.ylabel('Number of Students')
plt.tight_layout()
plt.show()
```

```
C:\Users\bikha\AppData\Local\Temp\ipykernel_29068\2680317636.py:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=risk_counts.index, y=risk_counts.values, palette=["#3C8CF6", "#99DDFF", "#4995BB"])
```



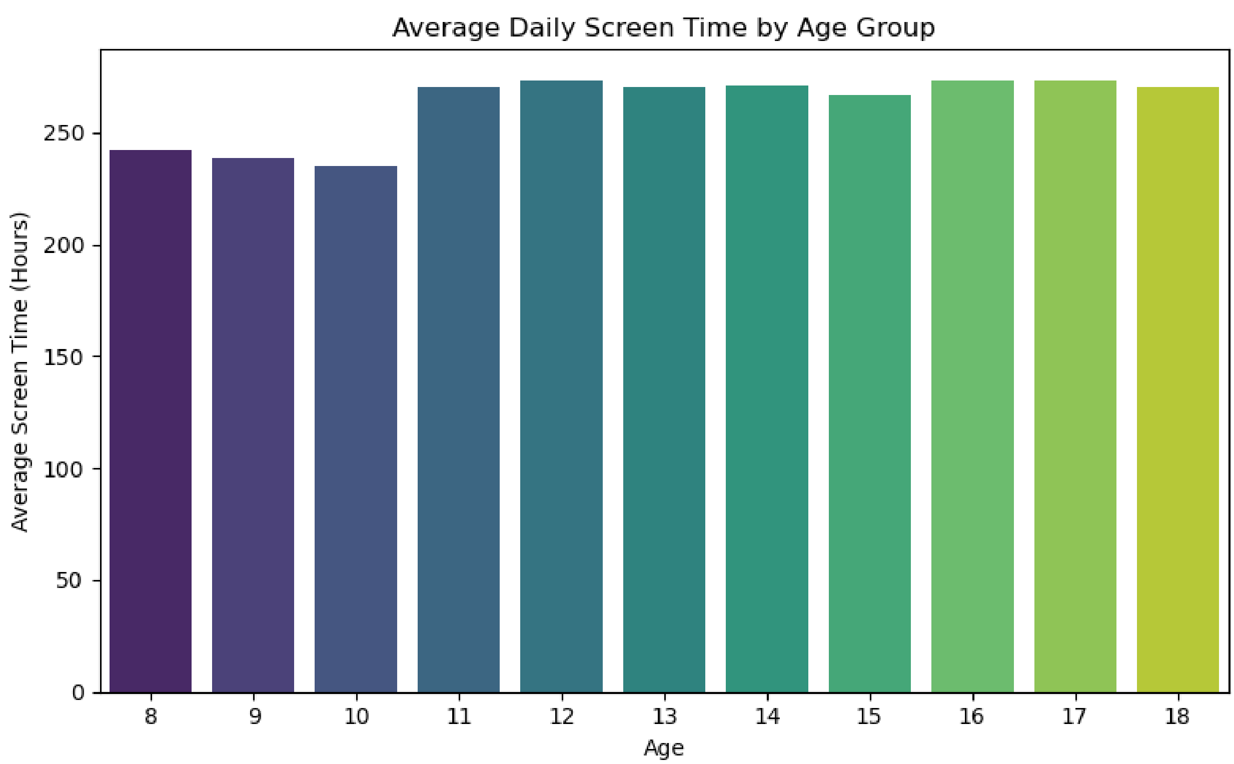
4. Age Group-wise Average Screen Time

This chart highlights the average daily screen time across different age groups. It helps identify which age brackets are most engaged with screens, allowing for targeted interventions and awareness efforts.

```
print(df.columns.tolist())

['age', 'gender', 'primary_device', 'educational_to_recreational_ratio', 'health_impacts', 'urban_or_rural', 'age_group', 'usage_category', 'health_impact_level', 'daily_screen_time_min', 'screen_time_risk']
```

```
df.columns = df.columns.str.strip()

# Group by Age and calculate average screen time (in hours or minutes)
age_avg = df.groupby('age')
['daily_screen_time_min'].mean().reset_index()

# Plot
plt.figure(figsize=(8, 5))
sns.barplot(data=age_avg, x='age', y='daily_screen_time_min',
palette='viridis')
plt.title('Average Daily Screen Time by Age Group')
plt.xlabel('Age')
plt.ylabel('Average Screen Time (Hours)')
plt.tight_layout()
plt.show()
```

```
C:\Users\bikha\AppData\Local\Temp\ipykernel_29068\2831414502.py:8:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(data=age_avg, x='age', y='daily_screen_time_min',
palette='viridis')
```

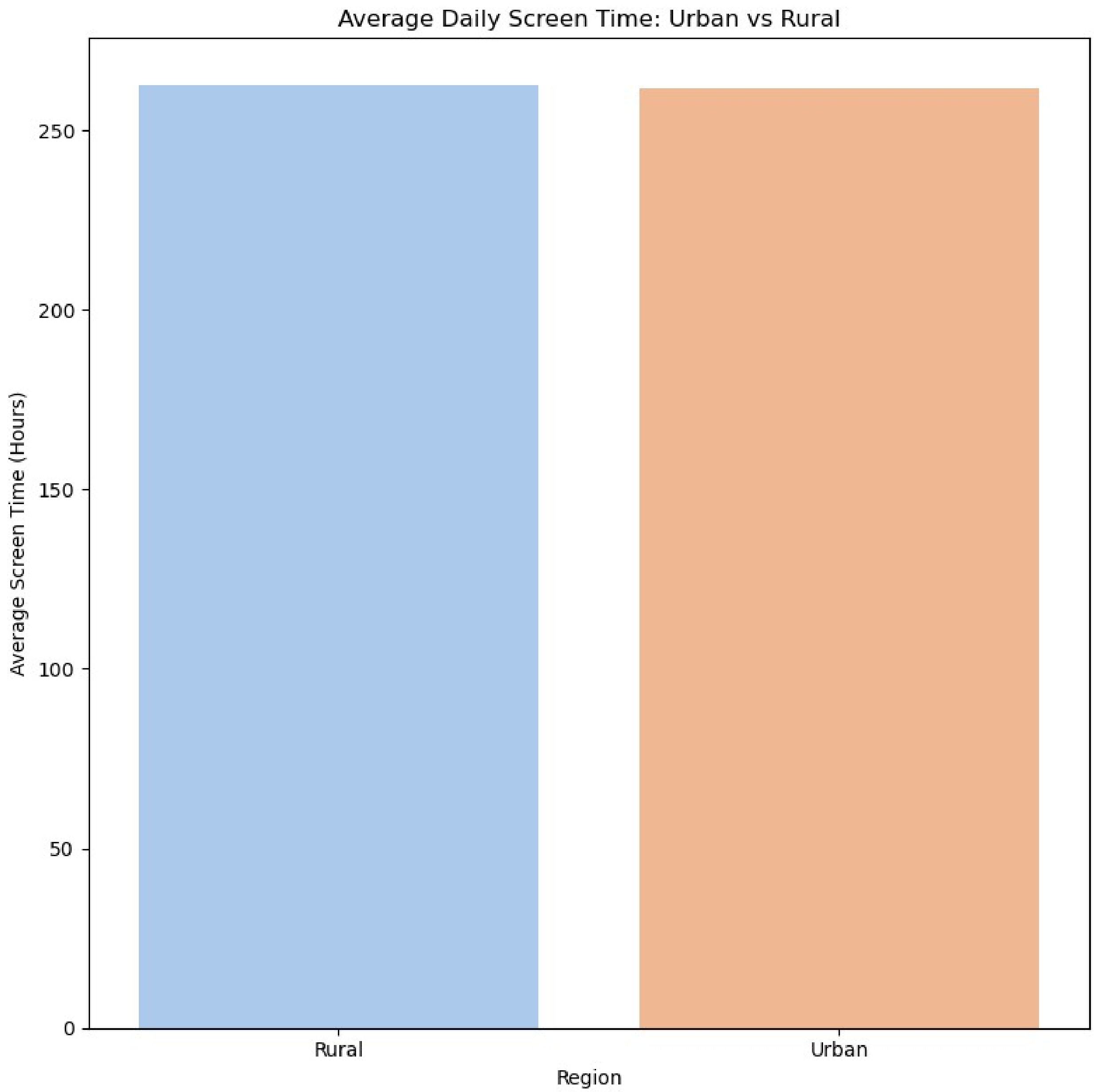


5. Urban vs Rural Screen Time Trends

This chart compares average daily screen time between students from urban and rural backgrounds. It provides insights into how access, environment, and lifestyle may influence screen usage patterns across these regions.

```
df.columns = df.columns.str.strip()

# Group by Region and calculate average screen time
region_avg = df.groupby('urban_or_rural')
['daily_screen_time_min'].mean().reset_index()

# Plot
plt.figure(figsize=(8, 8))
sns.barplot(data=region_avg, x='urban_or_rural',
y='daily_screen_time_min', palette='pastel')
plt.title('Average Daily Screen Time: Urban vs Rural')
plt.xlabel('Region')
plt.ylabel('Average Screen Time (Hours)')
plt.tight_layout()
plt.show()
```

```
C:\Users\bikha\AppData\Local\Temp\ipykernel_29068\3893208381.py:8:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(data=region_avg, x='urban_or_rural',
y='daily_screen_time_min', palette='pastel')
```


Average Daily Screen Time: Urban vs Rural
Average Screen Time (Hours)
0
50
100
150
200
250
Rural
Urban
Region