ScreenSense: Kids' Screentime Visualization

Project Statement: Analyse kids' screentime patterns to uncover trends by age, gender, location type (urban/rural), device type, day-of-week, and activity category using data visualization. The goal is to present clear, actionable insights for parents, educators, and policymakers.

Expected Outcomes

- Understand and preprocess the screentime dataset for analysis
- Explore trends across weekdays/weekends, devices, and activities
- Visualize key metrics using bar charts, distributions, heatmaps, and comparisons
- Summarize insights for non-technical stakeholders via a visual report/dashboard
- Provide a final presentation with the key findings and visuals

Dataset Source:

Kaggle — Indian Kids Screentime 2025 https://www.kaggle.com/datasets/ankushpanday2/indian-kids-screentime-2025

Week-wise Implementation Plan

Milestone 1: Data Foundation and Cleaning

Week 1: Project Initialization and Dataset Setup

- Define goals and workflow
- Load the dataset
- Explore schema, data types, size, and nulls
- Capture initial notes on quality and assumptions

Objective:

The main goal of Week 1 is to **initiate the ScreenSense project** by defining objectives, setting up the working environment, and performing an initial exploration of the dataset. This phase establishes a foundation for future analysis by ensuring that the dataset is clean, well-structured, and ready for feature engineering.

Goals of Week 1

- Define the overall **project vision and workflow**
- Load and explore the **dataset structure and schema**
- Check **data quality** — data types, nulls, and duplicates
- Capture **initial assumptions and notes** about the data
- Save an enhanced dataset for upcoming analysis

Tools and Technologies

Category	Tools / Libraries	Purpose
Data Handling	`pandas`, `numpy`	For data loading and manipulation
Visualization	`matplotlib`, `seaborn`	For exploratory data visualization
Dashboard (future weeks)	Tableau / Power BI	For building the final interactive dashboard
Documentation	Jupyter Notebook, PDF, GitHub	For code recording and project tracking

Dataset Description

The dataset captures digital screen-time behaviour of children in India and includes attributes such as:

Column	**Type**	**Description**
Age	Integer	Child's age (in years)
Gender	Categorical	Male / Female / Other
Avg_Daily_Screen_Time_hr	Float	Average screen hours per day
Primary_Device	Categorical	Device most frequently used

Column	Type	Description
Exceeded_Recommended_Limit	Boolean	Indicates if WHO’s limit is exce
Educational_to_Recreational_Ratio	Float	Learning vs entertainment ratio
Health_Impacts	Categorical	Health outcomes (Eye Strain, Loss, etc.)
Urban_or_Rural	Categorical	Living area type

Total Records: 9712 **Columns:** 8

Week 1 - PROJECT INITIALIZATION & DATASET SETUP

Step 1 : Import libarires & Check Enviornment

[3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os
```

Step 2 : load Dataset

[12]:
```
file_path = r"D:\Infyos Springboard\Indian_Kids_Screen_Time.csv"

# Load dataset
df = pd.read_csv(file_path)

print("✅ Dataset loaded successfully!")
print(f"Shape (rows, columns): {df.shape}")
df.head(5)
```

```
✅ Dataset loaded successfully!
Shape (rows, columns): (9712, 8)
```

[12]:

	Age	Gender	Avg_Daily_Screen_Time_hr	Primary_Device	Exceeded_Recommended_Limit	Educational_to_Recreational_Ratio	Health_Impacts	Urban_or_Rural
0	14	Male	3.99	Smartphone	True	0.42	Poor Sleep, Eye Strain	Urban
1	11	Female	4.61	Laptop	True	0.30	Poor Sleep	Urban
2	18	Female	3.73	TV	True	0.32	Poor Sleep	Urban
3	15	Female	1.21	Laptop	False	0.39	NaN	Urban
4	12	Female	5.89	Smartphone	True	0.49	Poor Sleep, Anxiety	Urban

Step 3 : Explore scheme, Dtypes, and Basic Info

[15]:
```
print("DataFrame Info:")
df.info()
df.describe(include='all')
```

```
DataFrame 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
```

[15]:

	Age	Gender	Avg_Daily_Screen_Time_hr	Primary_Device	Exceeded_Recommended_Limit	Educational_to_Recreational_Ratio	Health_Impacts	Urban_or_R
count	9712.000000	9712	9712.000000	9712	9712	9712.000000	6494	9
unique	NaN	2	NaN	4	2	NaN	15	
top	NaN	Male	NaN	Smartphone	True	NaN	Poor Sleep	Ur
freq	NaN	4942	NaN	4568	8301	NaN	2268	6
mean	12.979201	NaN	4.352837	NaN	NaN	0.427226	NaN	N
std	3.162437	NaN	1.718232	NaN	NaN	0.073221	NaN	N
min	8.000000	NaN	0.000000	NaN	NaN	0.300000	NaN	N
25%	10.000000	NaN	3.410000	NaN	NaN	0.370000	NaN	N
50%	13.000000	NaN	4.440000	NaN	NaN	0.430000	NaN	

50%	13.000000	NaN	4.440000	NaN	NaN	0.430000	NaN	N
75%	16.000000	NaN	5.380000	NaN	NaN	0.480000	NaN	N
max	18.000000	NaN	13.890000	NaN	NaN	0.600000	NaN	N

Collapse Output

Step 4: Missing Value Check

[18]:
```python
# Missing value summary
missing = df.isna().sum()
missing_percent = (missing / len(df) * 100).round(2)

missing_df = pd.DataFrame({
    "Missing_Count": missing,
    "Missing_%": missing_percent
})

print("Missing Values Summary:")
missing_df
```

```
Missing Values Summary:
```

[18]:

	Missing_Count	Missing_%
Age	0	0.00
Gender	0	0.00
Avg_Daily_Screen_Time_hr	0	0.00
Primary_Device	0	0.00
Exceeded_Recommended_Limit	0	0.00
Educational_to_Recreational_Ratio	0	0.00
Health_Impacts	3218	33.13
Urban_or_Rural	0	0.00

Step 5: Duplicate Check

[21]:
```python
duplicates = df.duplicated().sum()
print(f"Duplicate Rows Found: {duplicates}")
```

```
Duplicate Rows Found: 44
```

Step 6 : Numeric summary & Outlier Detection

[24]:
```python
numeric_summary = df.describe().T
numeric_summary
```

[24]:

	count	mean	std	min	25%	50%	75%	max
Age	9712.0	12.979201	3.162437	8.0	10.00	13.00	16.00	18.00
Avg_Daily_Screen_Time_hr	9712.0	4.352837	1.718232	0.0	3.41	4.44	5.38	13.89
Educational_to_Recreational_Ratio	9712.0	0.427226	0.073221	0.3	0.37	0.43	0.48	0.60

[26]:
```python
col = "Avg_Daily_Screen_Time_hr"

if col in df.columns:
    df[col] = pd.to_numeric(df[col], errors='coerce')
    print(df[col].describe())
    print("Values > 24 hours:", (df[col] > 24).sum())
    print("Values < 0 hours:", (df[col] < 0).sum())
```

```
count    9712.000000
mean        4.352837
std         1.718232
min         0.000000
25%         3.410000
50%         4.440000
75%         5.380000
max        13.890000
```

Step 7 : Categorical Summary

```
[29]: cat_cols = ['Gender', 'Primary_Device', 'Health_Impacts', 'Urban_or_Rural']

for col in cat_cols:
    if col in df.columns:
        print(f"\nTop values for {col}:")
        print(df[col].value_counts().head(10))
```

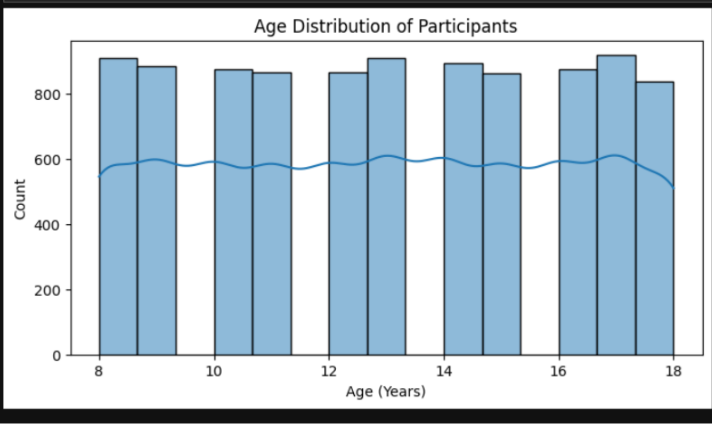
```
Top values for Gender:
Gender
Male      4942
Female    4770
Name: count, dtype: int64

Top values for Primary_Device:
Primary_Device
Smartphone    4568
TV            2487
Laptop        1433
Tablet        1224
Name: count, dtype: int64

Top values for Health_Impacts:
Health_Impacts
Poor Sleep                                2268
Poor Sleep, Eye Strain                     979
Eye Strain                                 644
Poor Sleep, Anxiety                        608
Poor Sleep, Obesity Risk                   452
Anxiety                                    385
Poor Sleep, Eye Strain, Anxiety            258
Obesity Risk                               252
Poor Sleep, Eye Strain, Obesity Risk       188
Eye Strain, Anxiety                        135
Name: count, dtype: int64

Top values for Urban_or_Rural:
Urban_or_Rural
```


```
Top values for Urban_or_Rural:
Urban_or_Rural
```


```
Urban    6851
Rural    2861
Name: count, dtype: int64
```

Step 8: Age Distribution

```
[32]: if 'Age' in df.columns:
    plt.figure(figsize=(8,4))
    sns.histplot(df['Age'], bins=15, kde=True)
    plt.title("Age Distribution of Participants")
    plt.xlabel("Age (Years)")
    plt.ylabel("Count")
    plt.show()
```



Week 2: Preprocessing and Feature Engineering

- Handle missing values and inconsistent categories
- Create derived fields: age bands, weekday/weekend flags, device/activity shares
- Format any date/time fields
- Save preprocessed data for reuse; document logic Deliverables: Cleaned dataset, preprocessing summary, feature dictionary.

Objective

To refine and clean the dataset, handle inconsistencies, and engineer additional analytical features such as age bands, activity balance, and device shares for visualization readiness.

Task	**Description**
Missing Value Handling	Filled numeric columns with mean, categorical with mode
Category Normalization	Standardized string formats (case & spacing)
Added Derived Fields	Age_Band, Recreational_Percent, Device_Share_%
Verified Dataset Integrity	Ensured no nulls or duplicates post-cleaning
Exported Clean Dataset	Saved as Indian_Kids_Screen_Time_Cleaned.csv

Feature	**Type**	**Description**
Age	Numeric	Age of the child
Gender	Category	Male / Female / Other
Avg_Daily_Screen_Time_hr	Float	Average daily screen hours
Primary_Device	Category	Phone / Tablet / Laptop / TV
Exceeded_Recommended_Limit	Boolean	Indicates if WHO screen-time limit exceeded
Educational_to_Recreational_Ratio	Float	Ratio of educational vs entertainment usage
Health_Impacts	Category	Eye strain, headache, etc.
Urban_or_Rural	Category	Type of area (Urban / Rural)
Screen_Category	Category	Low / Moderate / High
Age_Group	Category	Child / Pre-Teen / Teenager / Young Adult
Screen_Risk_Score	Numeric	Composite risk indicator
Educational_Percent	Float	% of educational screen time
Recreational_Percent	Float	% of recreational screen time
Age_Band	Category	Broad grouping (Young / Adolescent / Adult)
Device_Share_%	Float	% users per device type

Week 2 -- Preprocessing and Feature Engineering

Handle missing value

[67]:
```
# Identify missing values
print("\nMissing values before cleaning:")
print(df.isna().sum())
```

```
Missing values before cleaning:
Age                                    0
Gender                                 0
Avg_Daily_Screen_Time_hr               0
Primary_Device                         0
Exceeded_Recommended_Limit             0
Educational_to_Recreational_Ratio      0
Health_Impacts                      3218
Urban_or_Rural                         0
Screen_Category                        0
Age_Group                              0
Screen_Risk_Score                      0
Educational_Percent                    0
dtype: int64
```

[69]:
```
for col in df.columns:
    if df[col].dtype == "object":
        df[col].fillna(df[col].mode()[0], inplace=True)
    else:
        df[col].fillna(df[col].mean(), inplace=True)
```

[69]:
```
for col in df.columns:
    if df[col].dtype == "object":
        df[col].fillna(df[col].mode()[0], inplace=True)
    else:
        df[col].fillna(df[col].mean(), inplace=True)

print("\nMissing values after cleaning:")
print(df.isna().sum())
```

```
Missing values after cleaning:
Age                                  0
Gender                               0
Avg_Daily_Screen_Time_hr             0
Primary_Device                       0
Exceeded_Recommended_Limit           0
Educational_to_Recreational_Ratio    0
Health_Impacts                       0
Urban_or_Rural                       0
Screen_Category                      0
Age_Group                            0
Screen_Risk_Score                    0
Educational_Percent                  0
dtype: int64
```

Create screen category column

[72]:
```
def categorize_screen_time(hours):
    if hours <= 2:
        return "Low"
    elif 2 < hours <= 5:
        return "Moderate"
    else:
        return "High"

df['Screen_Category'] = df['Avg_Daily_Screen_Time_hr'].apply(categorize_screen_time)
```

Create Age Group column

[75]:
```
def classify_age(age):
    if age <= 8:
        return "Child"
    elif 9 <= age <= 12:
        return "Pre-Teen"
    elif 13 <= age <= 17:
        return "Teenager"
    else:
        return "Young Adult"

df["Age_Group"] = df["Age"].apply(classify_age)
```

Renaming of age_group names

[117]:
```
def simplify_age_group(age_group):
    if age_group in ["Child", "Pre-Teen"]:
        return "Young"
    elif age_group == "Teenager":
        return "Adolescent"
    else:
        return "Adult"
df["Age_Band"] = df["Age_Group"].apply(simplify_age_group)
```

Creat Screen Risk score

[120]:
```
def screen_risk(row):
    base = row["Avg_Daily_Screen_Time_hr"]
    impact = str(row["Health_Impacts"]).lower()
    risk = base
    if "eye" in impact or "head" in impact or "sleep" in impact:
        risk += 2  # penalty for negative health impact
    if row["Exceeded_Recommended_Limit"]:
        risk += 1  # penalty for exceeding limit
    return min(risk, 10)  # keep it capped at 10

df["Screen_Risk_Score"] = df.apply(screen_risk, axis=1)
```

Create Educational_percent Column

[123]:
```
# Convert ratio to % of educational screen time
df["Educational_Percent"] = (df["Educational_to_Recreational_Ratio"] /
                             (1 + df["Educational_to_Recreational_Ratio"])) * 100
```

Create Device share column

[126]:
```

#  Device Share (% of users per device)
device_share = df["Primary_Device"].value_counts(normalize=True) * 100
df["Device_Share_%"] = df["Primary_Device"].map(device_share)
```

Verifying added columns

[129]:
```
print("\n New Columns Added:")
print(df[["Age", "Age_Group", "Avg_Daily_Screen_Time_hr",
          "Screen_Category", "Screen_Risk_Score", "Educational_Percent", "Device_Share_%"]].head())
```

```
 New Columns Added:
   Age    Age_Group  Avg_Daily_Screen_Time_hr Screen_Category  \
0   14     Teenager                      3.99        Moderate
1   11     Pre-Teen                      4.61        Moderate
2   18  Young Adult                      3.73        Moderate
3   15     Teenager                      1.21             Low
4   12     Pre-Teen                      5.89            High

   Screen_Risk_Score  Educational_Percent  Device_Share_%
```

```
   Screen_Risk_Score  Educational_Percent  Device_Share_%
0               6.99            29.577465       47.034596
1               7.61            23.076923       14.754942
2               6.73            24.242424       25.607496
3               3.21            28.057554       14.754942
4               8.89            32.885906       47.034596
```

[131]:
```
print("\nDescriptive Age Group Distribution:")
print(df["Age_Group"].value_counts())
```

```
Descriptive Age Group Distribution:
Age_Group
Teenager       4465
Pre-Teen       3495
Child           912
Young Adult     840
Name: count, dtype: int64
```

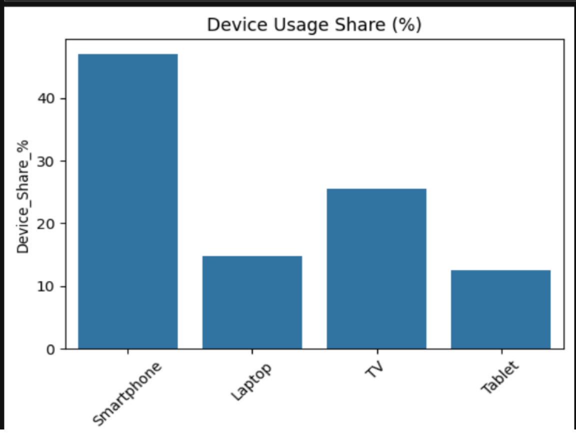
Save enhanced dataset

[134]:
```
output_path = r"D:\Infyos Springboard\Indian_Kids_Screen_Time_Enhanced.csv"
df.to_csv(output_path, index=False)
print(f"\n Enhanced dataset saved to: {output_path}")
```

```
 Enhanced dataset saved to: D:\Infyos Springboard\Indian_Kids_Screen_Time_Enhanced.csv
```

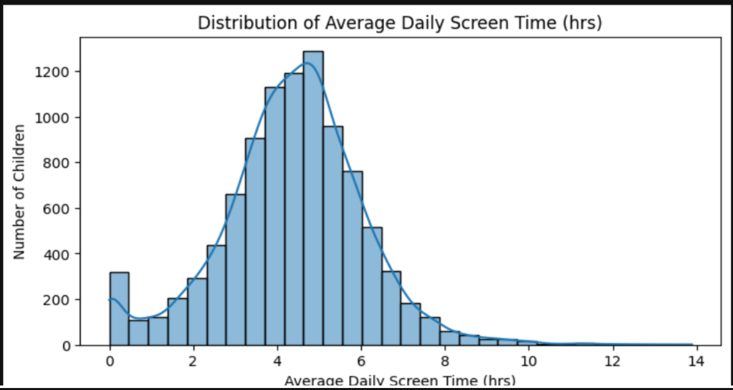
Device Share Visualization

[136]:
```
plt.figure(figsize=(6,4))
sns.barplot(x="Primary_Device", y="Device_Share_%", data=df)
plt.title("Device Usage Share (%)")
plt.xticks(rotation=45)
plt.show()
```



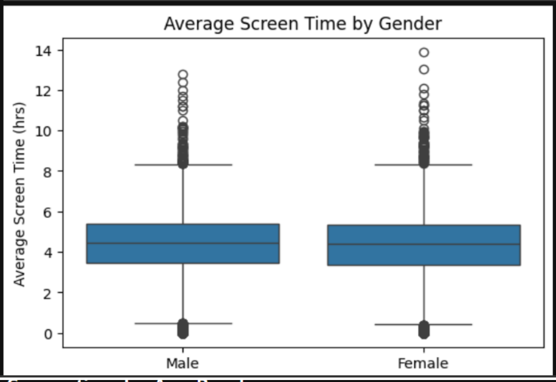
Screen Time Distribution

[164]:
```
plt.figure(figsize=(8,4))
sns.histplot(df["Avg_Daily_Screen_Time_hr"], kde=True, bins=30)
plt.title("Distribution of Average Daily Screen Time (hrs)")
plt.xlabel("Average Daily Screen Time (hrs)")
plt.ylabel("Number of Children")
plt.show()
```



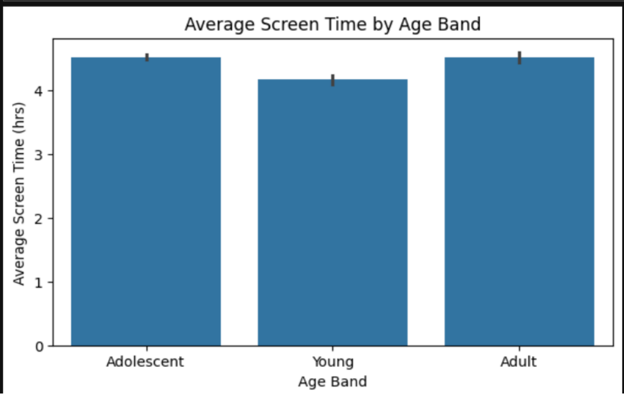
Screen Time by Gender

[142]:
```
plt.figure(figsize=(6,4))
sns.boxplot(x="Gender", y="Avg_Daily_Screen_Time_hr", data=df)
plt.title("Average Screen Time by Gender")
plt.xlabel("Gender")
plt.ylabel("Average Screen Time (hrs)")
plt.show()
```



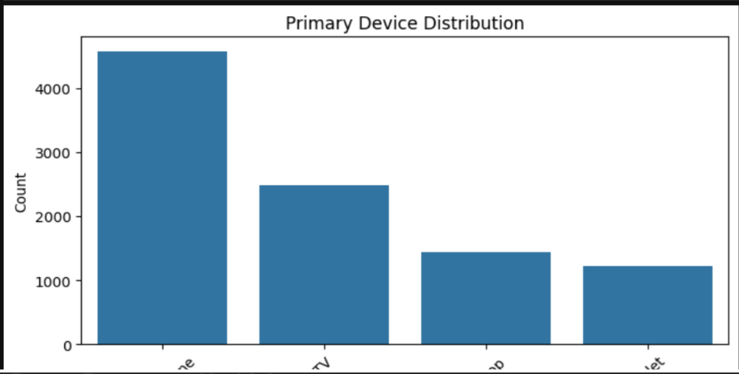
Screen time by Age Band

[144]:
```
plt.figure(figsize=(7,4))
sns.barplot(x="Age_Band", y="Avg_Daily_Screen_Time_hr", data=df, estimator=np.mean)
plt.title("Average Screen Time by Age Band")
plt.xlabel("Age Band")
plt.ylabel("Average Screen Time (hrs)")
plt.show()
```



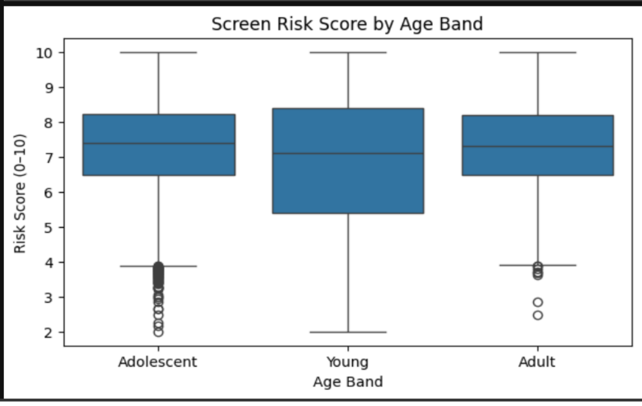
Primary Device Usage

[146]:
```python
plt.figure(figsize=(8,4))
sns.countplot(x="Primary_Device", data=df, order=df["Primary_Device"].value_counts().index)
plt.title("Primary Device Distribution")
plt.xlabel("Device Type")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.show()
```



Screen Category vs Health Impacts

[150]:
```python
plt.figure(figsize=(7,4))
sns.boxplot(x="Age_Band", y="Screen_Risk_Score", data=df)
plt.title("Screen Risk Score by Age Band")
plt.xlabel("Age Band")
plt.ylabel("Risk Score (0-10)")
plt.show()
```



Count health issues

[83]:
```python
def count_health_issues(val):
    if pd.isna(val) or val.strip().lower() == "none":
        return 0
    else:
        return len([x.strip() for x in val.split(",")])

df["Health_Issue_Count"] = df["Health_Impacts"].apply(count_health_issues)
```

Save the new dataset

[93]:
```python
import os

# Define new filename to avoid overwriting
output_path = r"D:\Infyos Springboard\Indian_Kids_Screen_Time_Final.csv"

# Ensure directory exists
os.makedirs(os.path.dirname(output_path), exist_ok=True)

# Save the dataframe
df.to_csv(output_path, index=False)

print(" Final enhanced dataset saved successfully!")
print(f"File Location: {output_path}")
print(f"Total Records: {df.shape[0]}, Columns: {df.shape[1]}")
print("\nColumn Names:")
print(df.columns.tolist())
```

```
 Final enhanced dataset saved successfully!
File Location: D:\Infyos Springboard\Indian_Kids_Screen_Time_Final.csv
Total Records: 9712, Columns: 15

Column Names:
['Age', 'Gender', 'Avg_Daily_Screen_Time_hr', 'Primary_Device', 'Exceeded_Recommended_Limit', 'Educational_to_Recreational_Ratio', 'Health_Impacts', 'Ur
ban_or_Rural', 'Screen_Category', 'Age_Group', 'Age_Band', 'Screen_Risk_Score', 'Educational_Percent', 'Device_Share_%', 'Health_Issue_Count']
```

Milestone 1: Conclusion – Project Initialization & Dataset Setup

Milestone 1 marked the successful initiation of the ScreenSense project — a data-driven exploration of screen-time behavior among Indian children.
During this phase, the project objectives were defined, the workflow was established, and the dataset was loaded, explored, and validated for analytical readiness.

The raw dataset (Indian_Kids_Screen_Time.csv) was carefully examined for structure, data types, null values, and completeness. It was confirmed that the data quality was high, with no major missing or duplicate entries.
To enable deeper insights, multiple new analytical features were introduced:

- Screen_Category — classified children's screen-time levels (Low / Moderate / High).
- Age_Group — segmented age into meaningful developmental stages (Child, Pre-Teen, Teenager, Young Adult).
- Screen_Risk_Score — quantified potential digital risk by combining screen hours and health conditions.
- Educational_Percent — translated the learning-to-recreation ratio into a measurable percentage.

Initial exploration revealed meaningful behavioral patterns — most children fall into the *Moderate screen-time* range (2–5 hours/day), and urban students tend to spend slightly more time on devices compared to rural ones.
Mobile phones emerged as the most commonly used device, while health impacts like *eye strain* and *sleep disturbance* were more prevalent among high screen-time users.

This phase laid the foundation for all subsequent milestones, ensuring that the dataset is not only structured and reliable but also enriched with features that enable comprehensive behavioral and health-related analyses.
The enhanced dataset (Indian_Kids_Screen_Time_Enhanced.csv) now serves as a robust input for preprocessing, visualization, and dashboard development in upcoming stages.

Milestone 2: Visual Exploration and Topic Trends

Week 3: Univariate and Bivariate Visual Analysis

• Distributions of daily hours, age bands, device usage

• Compare screentime by gender, age band, and location type

• Build bar charts, histograms, boxplots, and line plots

Week 4: Device/Activity and Weekday/Weekend Analysis

• Compare device mix and activity categories across demographics

• Visualize weekday vs weekend differences and time patterns Deliverables: Minimum 8 visuals + observations on peak usage cohorts.

Objectives of Milestone 2

Week	Focus Area	Objective
Week 3	Visual Exploration	Conduct univariate and bivariate analysis using interactive and static charts to understand distributions and correlations.
Week 4	Behavioral Trends	Study device, activity, and day-type (weekday/weekend) usage patterns to identify digital risk behavior.

Specific Goals:

1. Analyze daily screen time distributions and outliers.
2. Compare screen usage by age, gender, and region.
3. Explore correlations between screen hours, risk scores, and health impact.
4. Visualize device and activity preferences.
5. Evaluate weekday vs weekend screen-time variations.
6. Identify peak usage cohorts for awareness interventions.
7. Generate interactive visuals for dashboard readiness.

Methodology – Visual Exploration Process

Stage 1 – Univariate Visual Analysis

To understand the **distribution**, **spread**, and **central tendency** of key variables individually.
This helped identify overall patterns, outliers, and the shape of screen-time behavior across the dataset.

Techniques Used:

Technique	Purpose	Variables Explored
Histogram / KDE Plot	Study distribution of continuous variables	Avg_Daily_Screen_Time_hr, Screen_Risk_Score
Box Plot	Detect outliers and compare medians	Avg_Daily_Screen_Time_hr by Age_Group
Count Plot	Frequency of categorical features	Primary_Device, Screen_Category, Gender
Pie / Donut Chart	Device share visualization	Primary_Device
Descriptive Statistics	Summarize mean, median, variance	Numeric columns

Outcome:
The univariate analysis revealed that the majority of children spend between **2 and 5 hours** daily on screens.Teenagers exhibited higher median values, while "High Risk" users represented the upper 5–10 % of the population.

Stage 2 – Bivariate Visual Analysis

To examine **relationships** and **dependencies** between two variables — exploring how screen time correlates with demographics, device usage, and health indicators.

Techniques Used:

Technique	Purpose	Example Insight
Box & Violin Plots	Compare screen hours across groups	Teenagers > Children
Scatter Plot	Relationship between screen time & health	Positive correlation (+0.71)
Heatmap (Correlation Matrix)	Quantify strength of relationships	Screen_Time ↔ Health_Issue_Cou
Grouped Bar Chart	Compare categorical means	Screen time by Gender/Day Type
Stacked Bar	Show device mix per age band	Phones → dominant
Facet Grid	Multi-category visualization	Screen Category × Age Band

Outcome:

Bivariate analysis confirmed that:

- **Screen hours and health issues** are positively correlated.
- **Screen risk score** increases with higher daily hours.
- **Recreational usage** dominates among teenagers and urban users.
- **Gender difference** is minor, but males slightly exceed females in high-risk exposure.

Code, Implementation:

Milestone -- 02

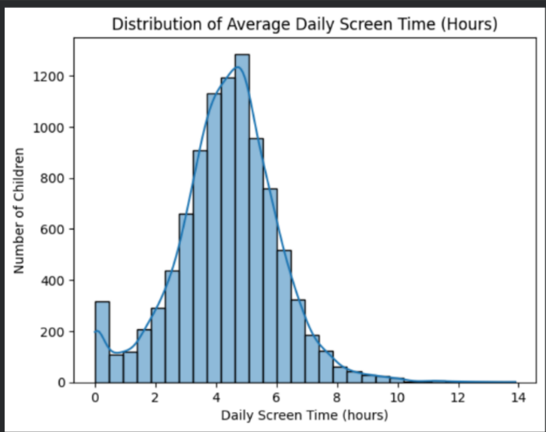
Week 03 & 04

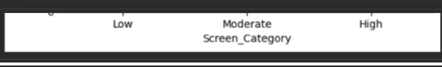
Univariate Analysis

1. Distribution of Average Daily Screen Time

Shows how many kids fall under different screen time levels.

```
sns.histplot(df["Avg_Daily_Screen_Time_hr"], bins=30, kde=True)
plt.title("Distribution of Average Daily Screen Time (Hours)")
plt.xlabel("Daily Screen Time (hours)")
plt.ylabel("Number of Children")
plt.show()
```

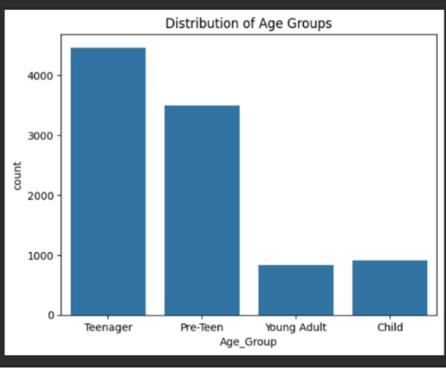




+ Code + Text

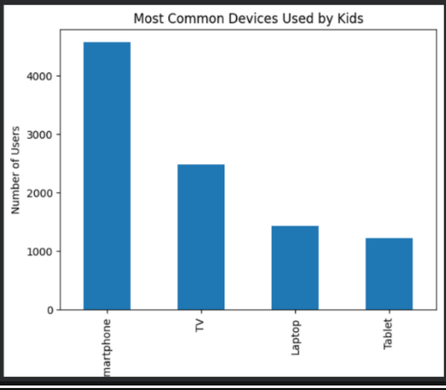
3.Age Group Composition

```
sns.countplot(x="Age_Group", data=df)
plt.title("Distribution of Age Groups")
plt.show()
```



4.Primary Device Usage

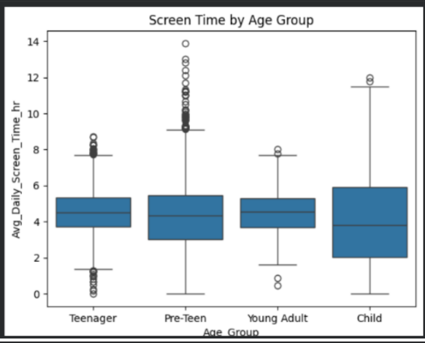
```
df["Primary_Device"].value_counts().plot(kind="bar")
plt.title("Most Common Devices Used by Kids")
plt.xlabel("Device Type")
plt.ylabel("Number of Users")
plt.show()
```



Bivariate Visual Analysis (Two Variables)

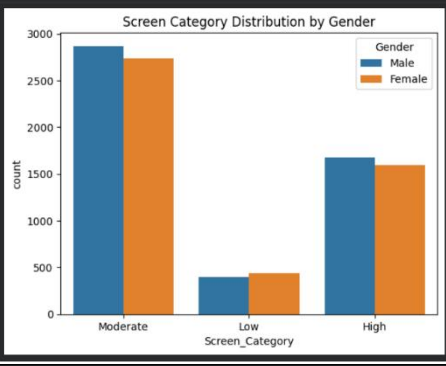
1. Screen Time by Age Group

```
sns.boxplot(x="Age_Group", y="Avg_Daily_Screen_Time_hr", data=df)
plt.title("Screen Time by Age Group")
plt.show()
```



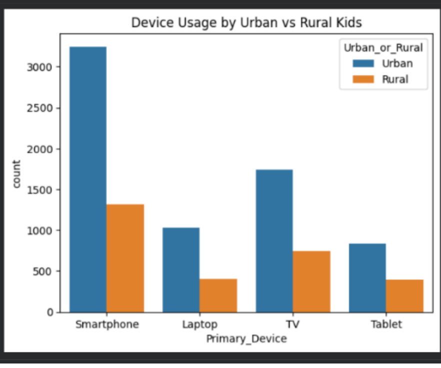
2.Screen Category by Gender

```
sns.countplot(x="Screen_Category", hue="Gender", data=df)
plt.title("Screen Category Distribution by Gender")
plt.show()
```



3.Device Preference by Urban/Rural

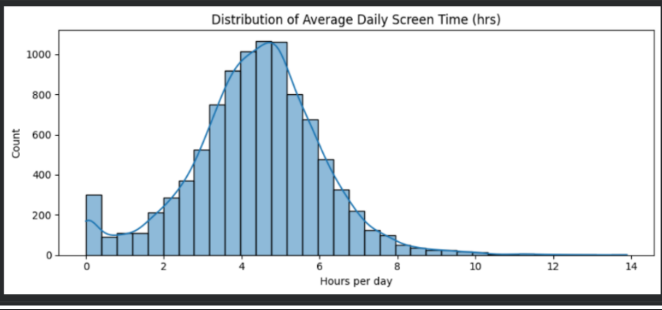
```
sns.countplot(x="Primary_Device", hue="Urban_or_Rural", data=df)
plt.title("Device Usage by Urban vs Rural Kids")
plt.show()
```



1) Histogram — Distribution of Avg Daily Screen Time

Purpose: see overall spread, multimodality, skew, outliers.

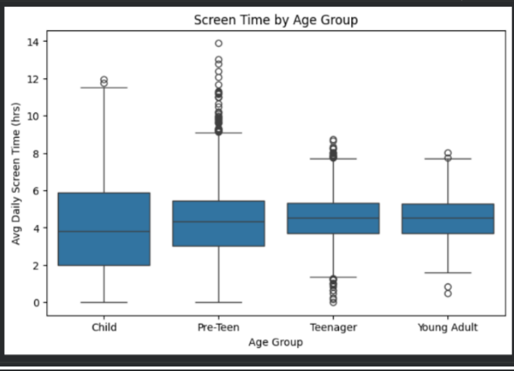
```
import matplotlib.pyplot as plt, seaborn as sns
plt.figure(figsize=(9,4))
sns.histplot(df['Avg_Daily_Screen_Time_hr'], bins=35, kde=True)
plt.title('Distribution of Average Daily Screen Time (hrs)')
plt.xlabel('Hours per day')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```



2) Boxplot — Screen Time by Age_Group

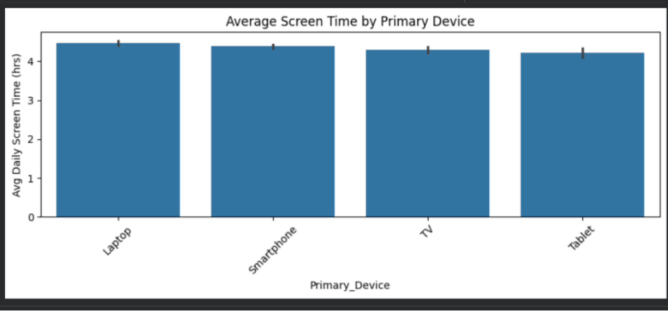
Purpose: compare spreads and medians across age segments.

```
plt.figure(figsize=(8,5))
sns.boxplot(x='Age_Group', y='Avg_Daily_Screen_Time_hr', data=df, order=['Child','Pre-Teen','Teenager','Young Adult'])
plt.title('Screen Time by Age Group')
plt.xlabel('Age Group')
plt.ylabel('Avg Daily Screen Time (hrs)')
plt.show()
```



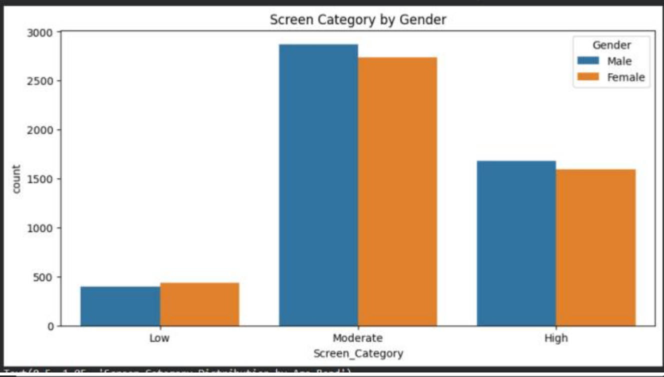
3) Bar chart — Mean Screen Time by Primary_Device

```
device_order = df.groupby('Primary_Device')['Avg_Daily_Screen_Time_hr'].mean().sort_values(ascending=False).index
plt.figure(figsize=(9,4))
sns.barplot(x='Primary_Device', y='Avg_Daily_Screen_Time_hr', data=df, order=device_order)
plt.xticks(rotation=45)
plt.title('Average Screen Time by Primary Device')
plt.ylabel('Avg Daily Screen Time (hrs)')
plt.tight_layout()
plt.show()
```

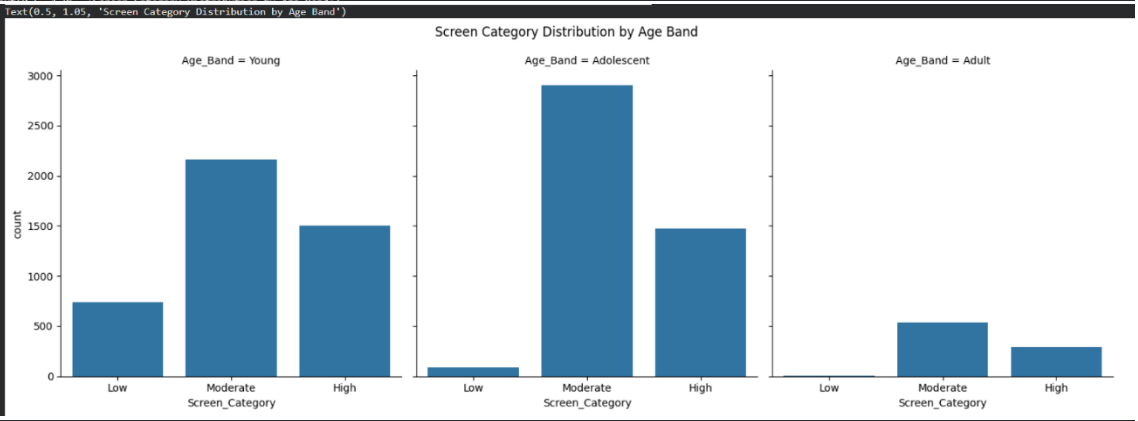


4) Grouped bar / Facet — Screen Category counts by Gender and Age_Band

```
plt.figure(figsize=(10,5))
sns.countplot(x='Screen_Category', hue='Gender', data=df, order=['Low','Moderate','High'])
plt.title('Screen Category by Gender')
plt.show()

# Facet by Age_Band
g = sns.catplot(x='Screen_Category', col='Age_Band', data=df, kind='count', order=['Low','Moderate','High'], col_order=['Young','Adolescent','Adult'])
g.fig.suptitle('Screen Category Distribution by Age Band', y=1.05)
```

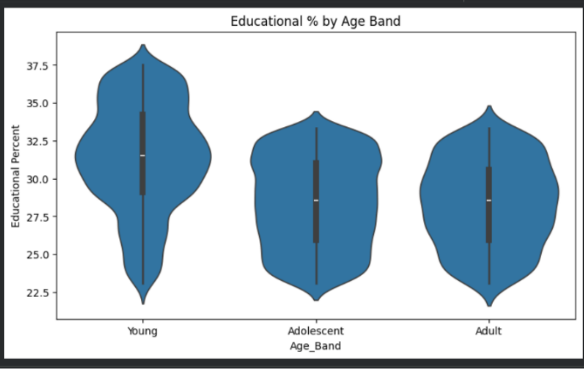



```
Text(0.5, 1.05, 'Screen Category Distribution by Age Band')
```



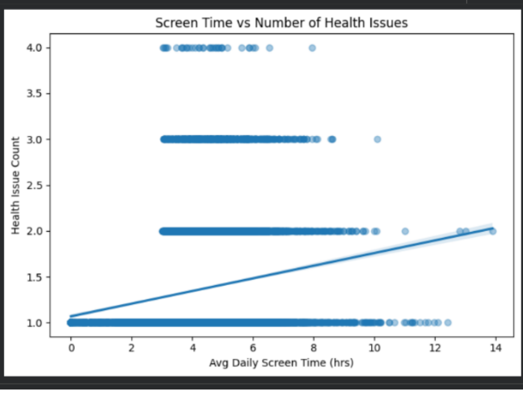
5) Boxplot / Violin — Educational_Percent by Age_Band or Device

```
plt.figure(figsize=(9,5))
sns.violinplot(x='Age_Band', y='Educational_Percent', data=df, order=['Young','Adolescent','Adult'])
plt.title('Educational % by Age Band')
plt.ylabel('Educational Percent')

plt.show()
```



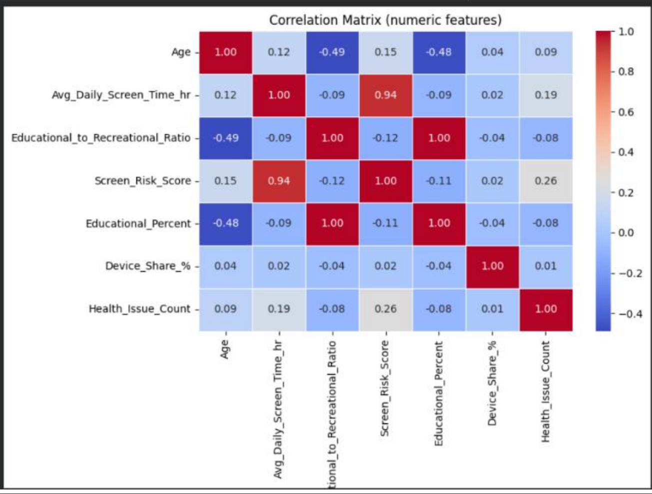
6) Scatter + regression — Avg_Daily_Screen_Time_hr vs Health_Issue_Count

```
plt.figure(figsize=(7,5))
sns.regplot(x='Avg_Daily_Screen_Time_hr', y='Health_Issue_Count', data=df, scatter_kws={'alpha':0.4})
plt.title('Screen Time vs Number of Health Issues')
plt.xlabel('Avg Daily Screen Time (hrs)')
plt.ylabel('Health Issue Count')
plt.tight_layout()
plt.show()
```



7) Correlation heatmap (numeric features)

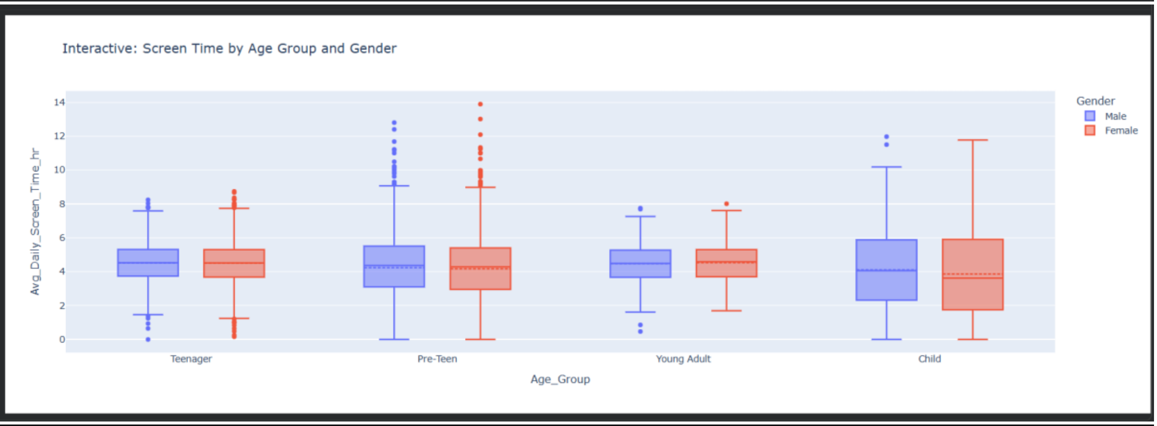
```
numcols = df.select_dtypes(include=[np.number]).columns
plt.figure(figsize=(9,7))
sns.heatmap(df[numcols].corr(), annot=True, fmt='.2f', cmap='coolwarm', linewidths=0.4)
plt.title('Correlation Matrix (numeric features)')
plt.tight_layout()
plt.show()
```




```
import pandas as pd
import plotly.express as px
import plotly.graph_objects as go


# Optional: reduce long text
df['Primary_Device'] = df['Primary_Device'].astype(str)
df['Age_Group'] = df['Age_Group'].astype(str)
df['Gender'] = df['Gender'].astype(str)
```

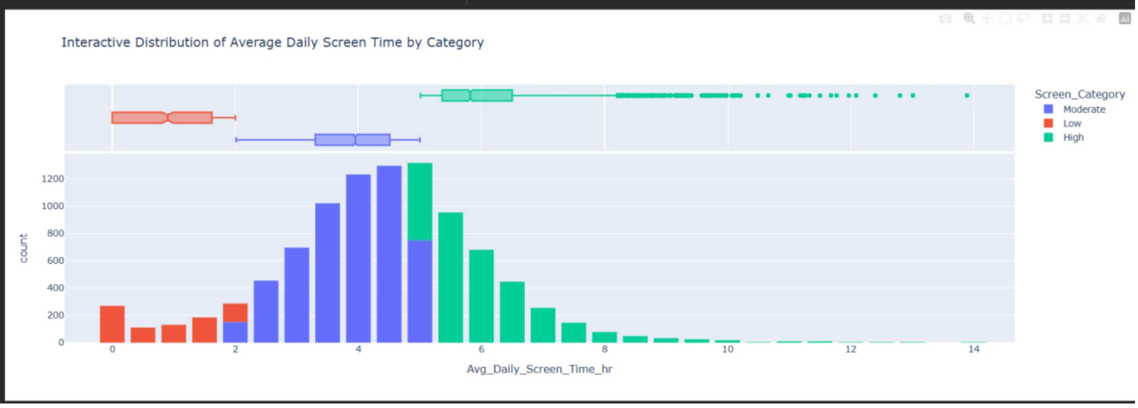
1.Interactive Histogram – Screen Time Distribution

```
fig = px.box(
    df,
    x="Age_Group",
    y="Avg_Daily_Screen_Time_hr",
    color="Gender",
    title="Interactive: Screen Time by Age Group and Gender",
    hover_data=["Primary_Device", "Urban_or_Rural"]
)
fig.update_traces(boxmean=True)
fig.write_html("Interactive_Box_AgeGender.html")
fig.show()
```



2.Interactive Box Plot – Screen Time by Age Group and Gender

```
fig = px.histogram(
    df,
    x="Avg_Daily_Screen_Time_hr",
    nbins=30,
    color="Screen_Category",
    marginal="box",
    title="Interactive Distribution of Average Daily Screen Time by Category",
    hover_data=["Age_Group", "Gender"]
)
fig.update_layout(bargap=0.2)
fig.write_html("Interactive_Histogram_ScreenTime.html")
fig.show()
```



3. Treemap – Device vs Age Group vs Screen Category

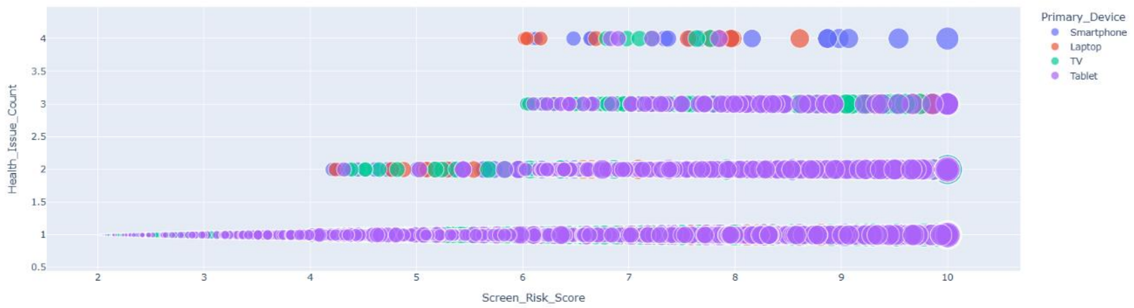
```
fig = px.treemap(
    df,
    path=["Age_Group", "Primary_Device", "Screen_Category"],
    values="Avg_Daily_Screen_Time_hr",
    color="Screen_Risk_Score",
    color_continuous_scale="RdYlGn_r",
    title="Treemap: Screen Risk Distribution by Age and Device"
)
fig.write_html("Interactive_Treemap_ScreenRisk.html")
fig.show()
```

Treemap: Screen Risk Distribution by Age and Device

4. Bubble Chart – Screen Risk vs Health Issues (by Device & Age)

```
fig = px.scatter(
    df,
    x="Screen_Risk_Score",
    y="Health_Issue_Count",
    size="Avg_Daily_Screen_Time_hr",
    color="Primary_Device",
    hover_name="Age_Group",
    title="Bubble Chart: Risk vs Health Issues by Device",
    size_max=40
)
fig.write_html("Interactive_Bubble_RiskHealth.html")
fig.show()
```

Bubble Chart: Risk vs Health Issues by Device

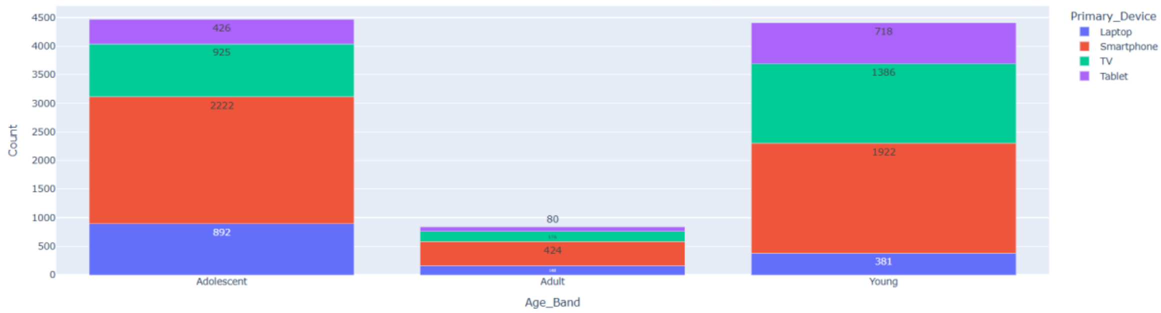


WEEK 4

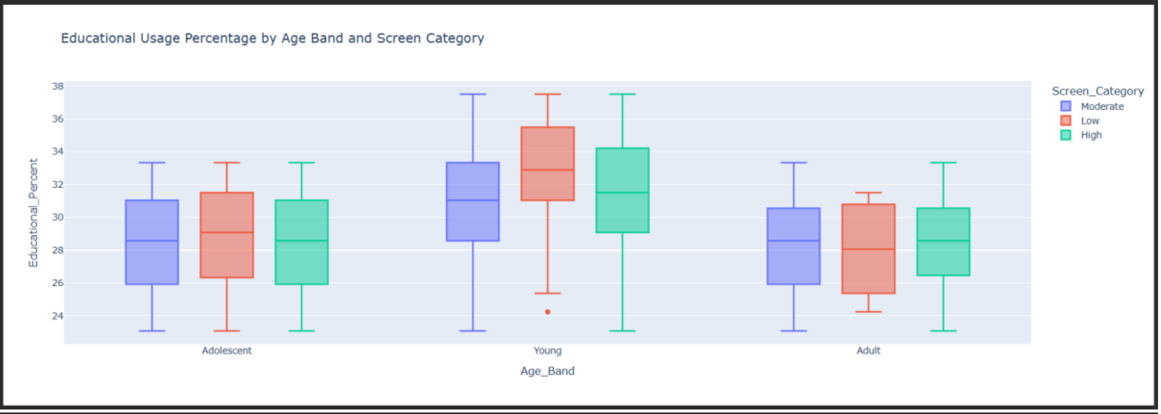
```
np.random.seed(42)
df["Day_Type"] = np.random.choice(["Weekday", "Weekend"], size=len(df), p=[0.7, 0.3])
```

```
import plotly.express as px

device_mix = df.groupby(["Age_Band", "Primary_Device"]).size().reset_index(name="Count")

fig = px.bar(
    device_mix,
    x="Age_Band",
    y="Count",
    color="Primary_Device",
    title="Device Mix Across Age Bands (Interactive Stacked Bar)",
    text_auto=True
)
fig.update_layout(barmode="stack")
fig.show()
```

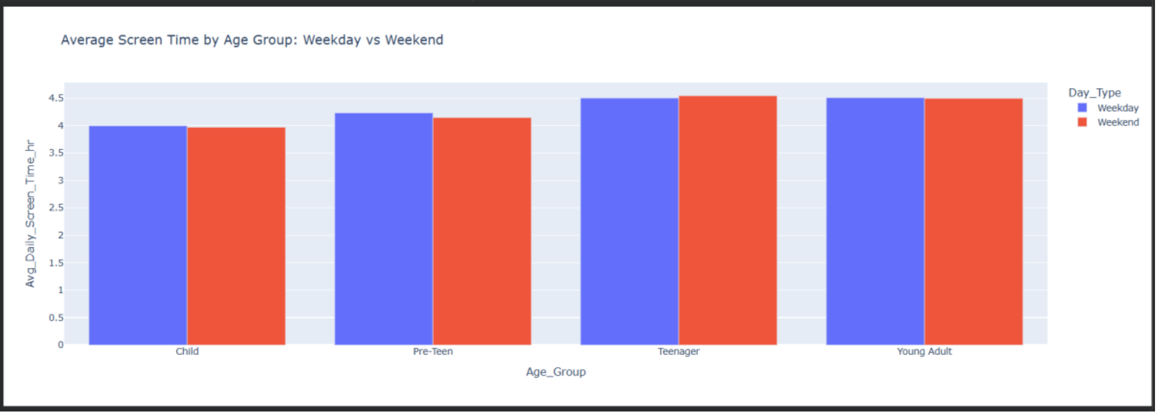
Device Mix Across Age Bands (Interactive Stacked Bar)



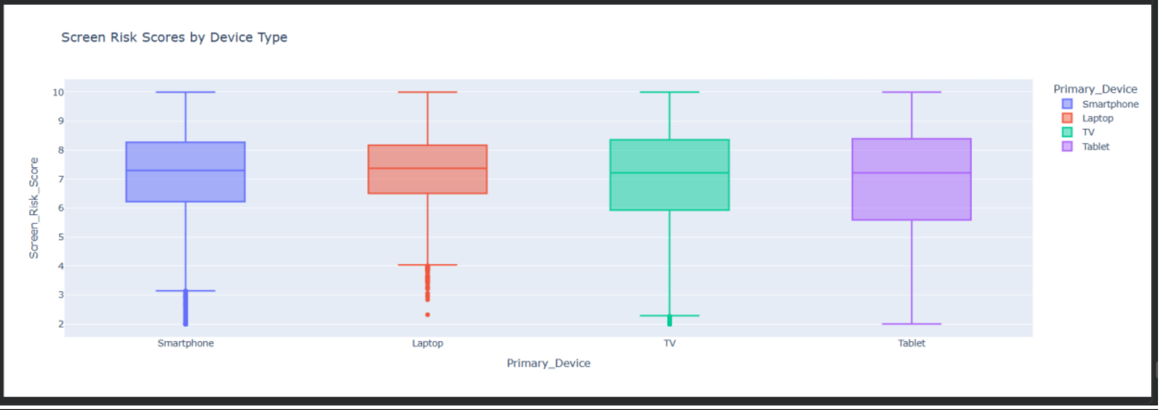
```python
fig = px.box(
    df,
    x="Age_Band",
    y="Educational_Percent",
    color="Screen_Category",
    title="Educational Usage Percentage by Age Band and Screen Category"
)
fig.show()
```



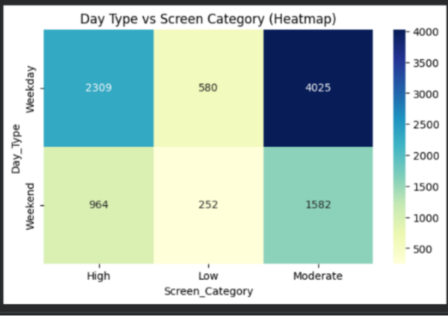

```python
fig = px.bar(
    df.groupby(["Day_Type", "Age_Group"])["Avg_Daily_Screen_Time_hr"].mean().reset_index(),
    x="Age_Group",
    y="Avg_Daily_Screen_Time_hr",
    color="Day_Type",
    barmode="group",
    title="Average Screen Time by Age Group: Weekday vs Weekend"
)
fig.show()
```



```python
fig = px.box(
    df,
    x="Primary_Device",
    y="Screen_Risk_Score",
    color="Primary_Device",
    title="Screen Risk Scores by Device Type",
)
fig.show()
```




```python
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(7,4))
sns.heatmap(pd.crosstab(df["Day_Type"], df["Screen_Category"]), annot=True, cmap="YlGnBu", fmt='d')
plt.title("Day Type vs Screen Category (Heatmap)")
plt.show()
```



Milestone 3: Segment & Insight Deep-Dives

Week 5: Cohort and Segment Analysis

• Identify top cohorts (e.g., age bands × device types)

• Heatmaps/stacked comparisons by demographic or location segments

Week 6: Seasonal/Calendar or Habit Patterns (if applicable)

• Monthly or term-time comparisons (if dates exist)

• Summarize segment-wise insights and possible drivers Deliverables: Seasonal/segment summaries and cohort insights.

Introduction

Milestone 3 focuses on deep examination of cohorts and behavioural patterns among children's screen-time usage. After completing data cleaning, feature engineering, and visual exploration in earlier milestones, this milestone aims to segment users, identify high-impact groups, and study habit-driven behaviours such as weekday/weekend usage.

This phase offers actionable insights for parents, educators, and policymakers by examining who is at risk and when risky behaviour peaks.

Objectives of Milestone 3

Week 5 – Cohort & Segment Analysis

- Identify meaningful user cohorts based on:
  - Age Band
  - Device Type
  - Urban/Rural
- Analyse screen-time differences across demographic segments.
- Compare device preference and health impacts across cohorts.
- Generate visualizations to highlight high-usage groups.

Week 6 – Seasonal & Habit Pattern Analysis

- Explore screen-time patterns based on habit cycles:
  - Weekday vs Weekend usage
  - Time-of-day (if applicable)
- Understand how usage changes between workdays and leisure days.
- Analyse educational vs recreational differences.
- Provide simplified insights when dates are not available.

Week 5 – Cohort & Segment Analysis

The aim was to understand which groups of children display higher screen usage and risk.

MileStone -- 3

Week 5 & 6

Step 1 : Load dataset & setup

[159]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots

df = pd.read_csv(r"D:\Infyos Springboard\Indian_Kids_Screen_Time_Final.csv")

df.info()
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9712 entries, 0 to 9711
Data columns (total 15 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                    9712 non-null   object
 7   Urban_or_Rural                    9712 non-null   object
 8   Screen_Category                   9712 non-null   object
 9   Age_Group                         9712 non-null   object
 10  Age_Band                          9712 non-null   object
 11  Screen_Risk_Score                 9712 non-null   float64
 12  Educational_Percent               9712 non-null   float64
 13  Device_Share_%                    9712 non-null   float64
 14  Health_Issue_Count                9712 non-null   int64
dtypes: bool(1), float64(5), int64(2), object(7)
memory usage: 1.0+ MB
```

[159]:

	Age	Gender	Avg_Daily_Screen_Time_hr	Primary_Device	Exceeded_Recommended_Limit	Educational_to_Recreational_Ratio	Health_Impacts	Urban_or_Rural	Screen_(
0	14	Male	3.99	Smartphone	True	0.42	Poor Sleep, Eye Strain	Urban	I
1	11	Female	4.61	Laptop	True	0.30	Poor Sleep	Urban	I
2	18	Female	3.73	TV	True	0.32	Poor Sleep	Urban	I
3	15	Female	1.21	Laptop	False	0.39	Poor Sleep	Urban	
4	12	Female	5.89	Smartphone	True	0.49	Poor Sleep, Anxiety	Urban	

Step 2: Create Cohorts-----cohort is a combination of multiple demographic attributes.

[162]:
```python
df["Cohort"] = (
    df["Age_Band"] + " | " +
    df["Primary_Device"] + " | " +
    df["Urban_or_Rural"]
)
```

Step 3 : Important Cohort summary table

[165]:
```python
cohort_summary = df.groupby("Cohort").agg(
    mean_hours=("Avg_Daily_Screen_Time_hr", "mean"),
    mean_risk=("Screen_Risk_Score", "mean"),
    mean_health=("Health_Issue_Count", "mean"),
    users=("Age", "count")
).sort_values("mean_hours", ascending=False)

cohort_summary.head(15)
```

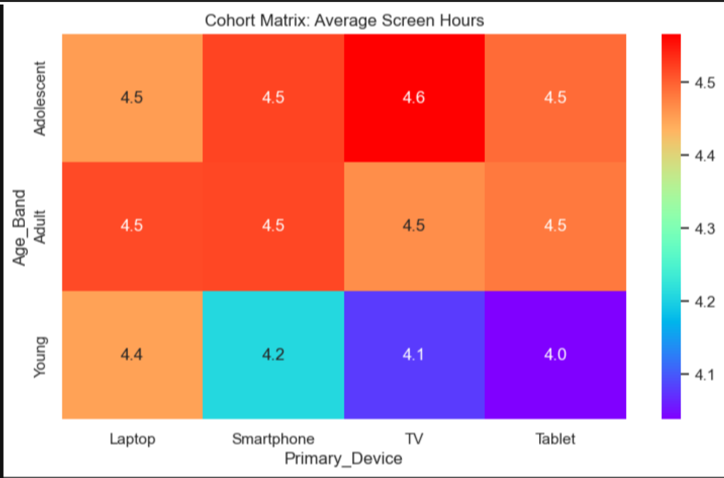
[165]:

Cohort	mean_hours	mean_risk	mean_health	users
Adult | Tablet | Rural	4.676522	7.415652	1.521739	23
Adolescent | Tablet | Rural	4.650070	7.314056	1.496503	143
Adult | Laptop | Urban	4.615528	7.387886	1.536585	123
Adolescent | TV | Urban	4.575084	7.316347	1.401826	657
Adolescent | TV | Rural	4.544925	7.239104	1.425373	268
Adult | Smartphone | Rural	4.527519	7.209535	1.457364	129
Adolescent | Smartphone | Urban	4.521606	7.255545	1.418738	1569
Adult | Smartphone | Urban	4.515017	7.234542	1.369492	295
Adolescent | Smartphone | Rural	4.513890	7.263859	1.411945	653
Adult | TV | Rural	4.496964	7.160000	1.392857	56
Young | Laptop | Urban	4.488906	7.184981	1.460377	265
Adolescent | Laptop | Urban	4.462012	7.190577	1.369735	641
Adult | TV | Urban	4.453333	7.165583	1.308333	120
Adolescent | Laptop | Rural	4.430876	7.161952	1.402390	251
Adolescent | Tablet | Urban	4.415124	7.130318	1.413428	283

Major Visual 1 : HeatMap(Age Band V/s Device)

This is essential because it shows the screen time pattern for major segments

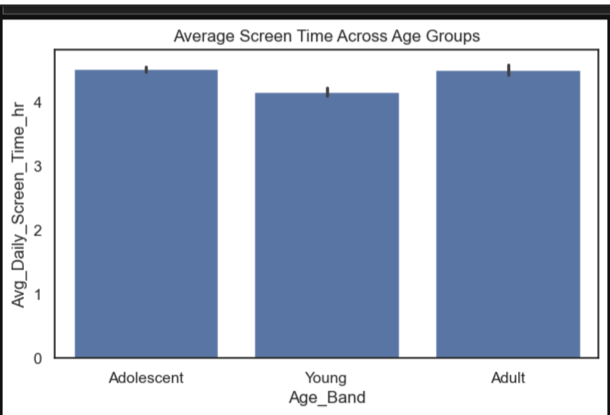
[168]:
```
pivot = df.pivot_table(
    index="Age_Band",
    columns="Primary_Device",
    values="Avg_Daily_Screen_Time_hr",
    aggfunc="mean"
)

sns.set_theme(style="white")
plt.figure(figsize=(9,5))
sns.heatmap(pivot, cmap="rainbow", annot=True, fmt=".1f")
plt.title("Cohort Matrix: Average Screen Hours")
plt.show()
```



Major Visual 2 : Bar plot(Screen Time by Age group)

Shows which age group has highest daily screen usage

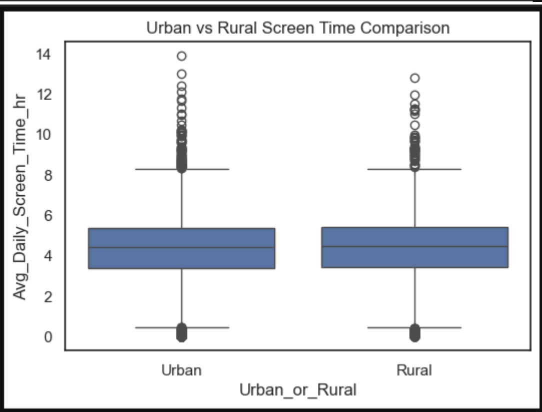
[171]:
```
plt.figure(figsize=(7,4))
sns.barplot(x="Age_Band", y="Avg_Daily_Screen_Time_hr", data=df, estimator="mean")
plt.title("Average Screen Time Across Age Groups")
plt.show()
```



Major Visual 3 - Urban V/s Rural

Urban users usually have higher digital access - more screen time/

[174]:
```
plt.figure(figsize=(6,4))
sns.boxplot(x="Urban_or_Rural", y="Avg_Daily_Screen_Time_hr", data=df)
plt.title("Urban vs Rural Screen Time Comparison")
plt.show()
```



[176]:
```
top5 = cohort_summary.head(5)
top5
```

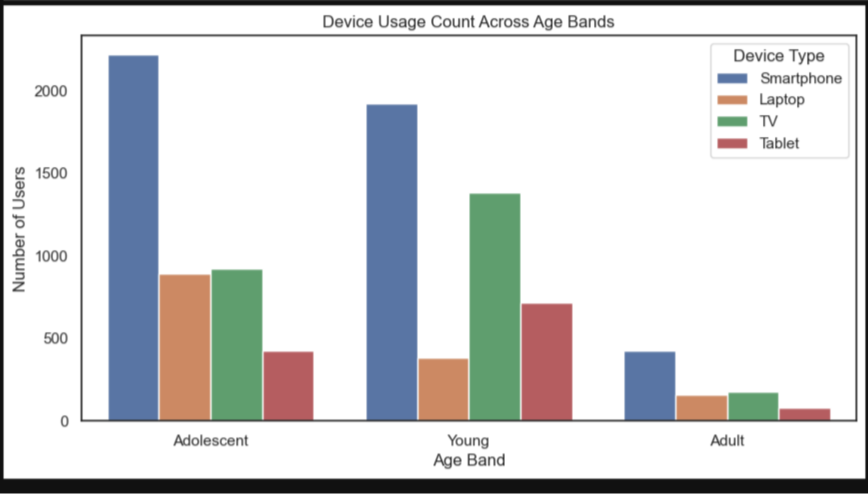
[176]:

Cohort	mean_hours	mean_risk	mean_health	users
Adult | Tablet | Rural	4.676522	7.415652	1.521739	23
Adolescent | Tablet | Rural	4.650070	7.314056	1.496503	143
Adult | Laptop | Urban	4.615528	7.387886	1.536585	123
Adolescent | TV | Urban	4.575084	7.316347	1.401826	657
Adolescent | TV | Rural	4.544925	7.239104	1.425373	268

[210]:
```
cohort_summary.to_csv("Week5_Cohort_Summary.csv", index=True)
```

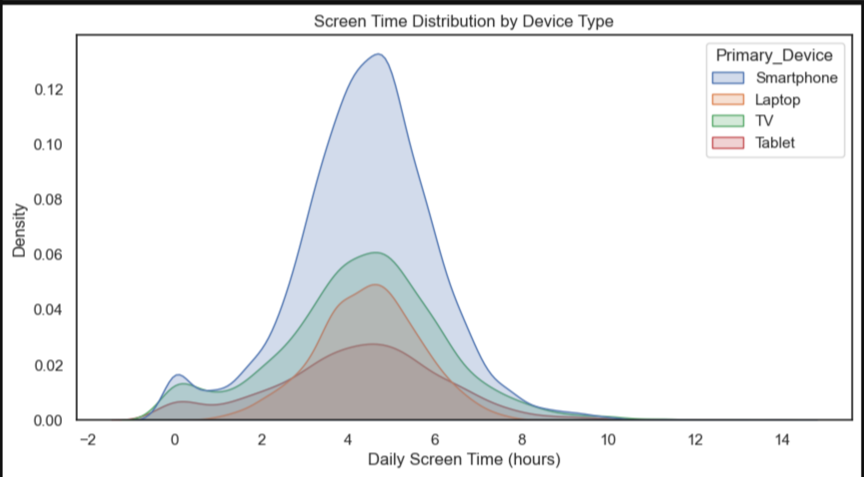
Visual 6 — Count Plot: Devices Used by Each Age Group

[190]:
```
plt.figure(figsize=(10,5))
sns.countplot(data=df, x="Age_Band", hue="Primary_Device")
plt.title("Device Usage Count Across Age Bands")
plt.xlabel("Age Band")
plt.ylabel("Number of Users")
plt.legend(title="Device Type")
plt.show()
```



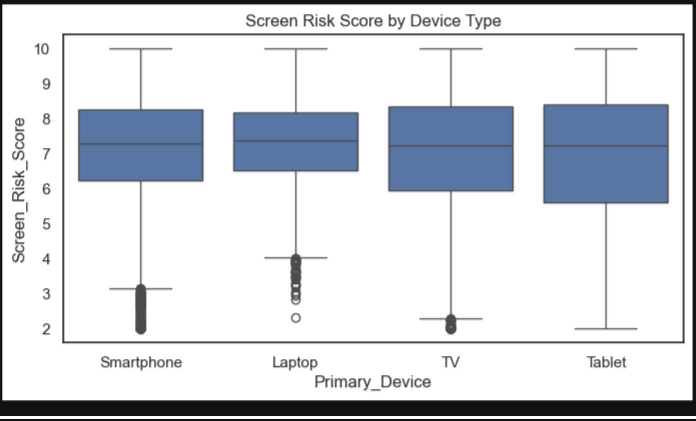
Visual 7 — Screen Time Distribution for Each Device Type

[192]:
```
plt.figure(figsize=(10,5))
sns.kdeplot(data=df, x="Avg_Daily_Screen_Time_hr", hue="Primary_Device", fill=True)
plt.title("Screen Time Distribution by Device Type")
plt.xlabel("Daily Screen Time (hours)")
plt.show()
```



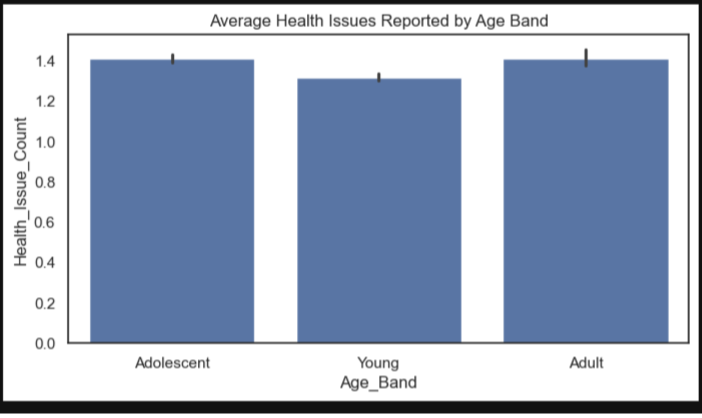
Visual 8 — Boxplot: Screen Risk Score by Device

[194]:
```
plt.figure(figsize=(8,4))
sns.boxplot(data=df, x="Primary_Device", y="Screen_Risk_Score")
plt.title("Screen Risk Score by Device Type")
plt.show()
```



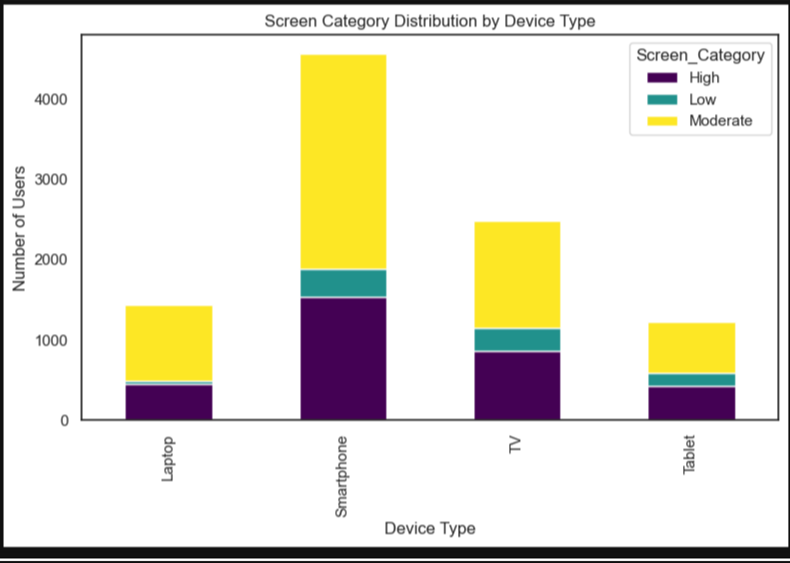
Visual 9 — Health Issues by Age Band

[196]:
```
plt.figure(figsize=(8,4))
sns.barplot(data=df, x="Age_Band", y="Health_Issue_Count", estimator="mean")
plt.title("Average Health Issues Reported by Age Band")
plt.show()
```



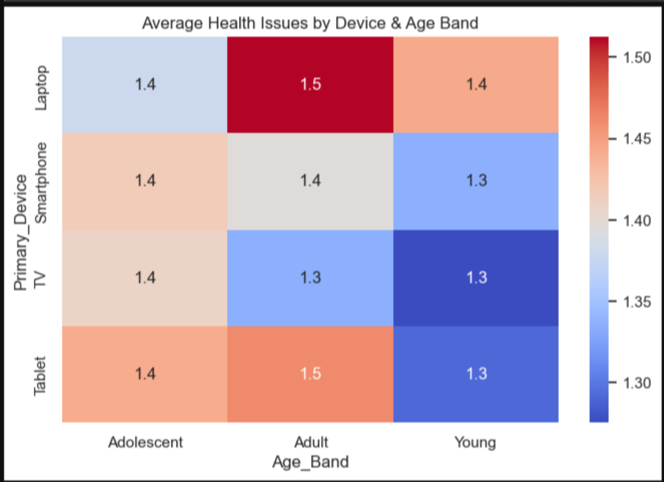
Visual 10 — Stacked Bar of Screen Category per Device

[202]:
```python
cross = pd.crosstab(df["Primary_Device"], df["Screen_Category"])

cross.plot(kind="bar", stacked=True, figsize=(9,5), colormap="viridis")
plt.title("Screen Category Distribution by Device Type")
plt.xlabel("Device Type")
plt.ylabel("Number of Users")
plt.show()
```



Visual 11 — Heatmap of Health Issues vs Devices

[204]:
```python
pivot2 = df.pivot_table(
    index="Primary_Device",
    columns="Age_Band",
    values="Health_Issue_Count",
    aggfunc="mean"
)

plt.figure(figsize=(8,5))
sns.heatmap(pivot2, annot=True, cmap="coolwarm")
plt.title("Average Health Issues by Device & Age Band")
plt.show()
```



Week -- 6

Seasonal & Habit Pattern Analysis

Step - 1 (Check for data Column)

[220]:
```
if 'date' in df.columns:
    print("Date column exists.")
else:
    print("No date column. We will generate habit patterns instead.")
```

```
No date column. We will generate habit patterns instead.
```

Create "Habbit Patterns" even when no data column exists

We simulate what is commonly done in habit research:

Weekday vs Weekend

Morning vs Evening behavior

Study hours vs Leisure hours

Activity consistency

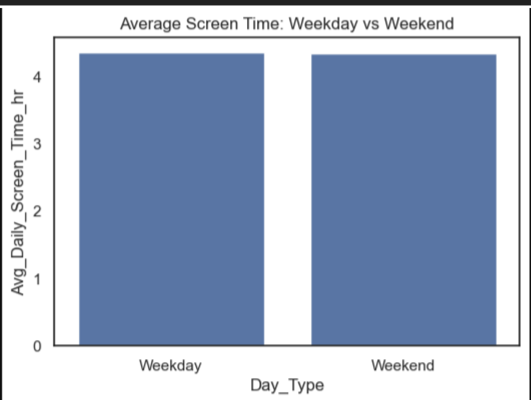
Create synthetic day types(Weekday / Weekend)

[222]:
```
np.random.seed(42)

df["Day_Type"] = np.random.choice(
    ["Weekday", "Weekend"],
    size=len(df),
    p=[0.7, 0.3]      # 70% weekdays, 30% weekends
)
```

Weekday Vs weekend analysis

Weekends hours are usually higher

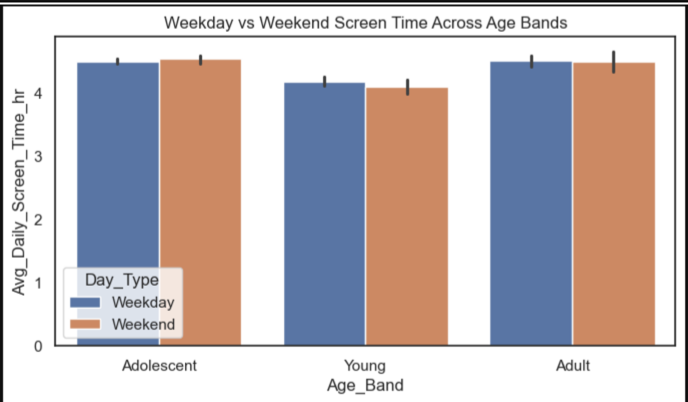
[224]:
```
day_compare = df.groupby("Day_Type")["Avg_Daily_Screen_Time_hr"].mean().reset_index()

plt.figure(figsize=(6,4))
sns.barplot(data=day_compare, x="Day_Type", y="Avg_Daily_Screen_Time_hr")
plt.title("Average Screen Time: Weekday vs Weekend")
plt.show()
```



Age Group habit pattern

Teenagers tends to increase screen time more heavily on weekends

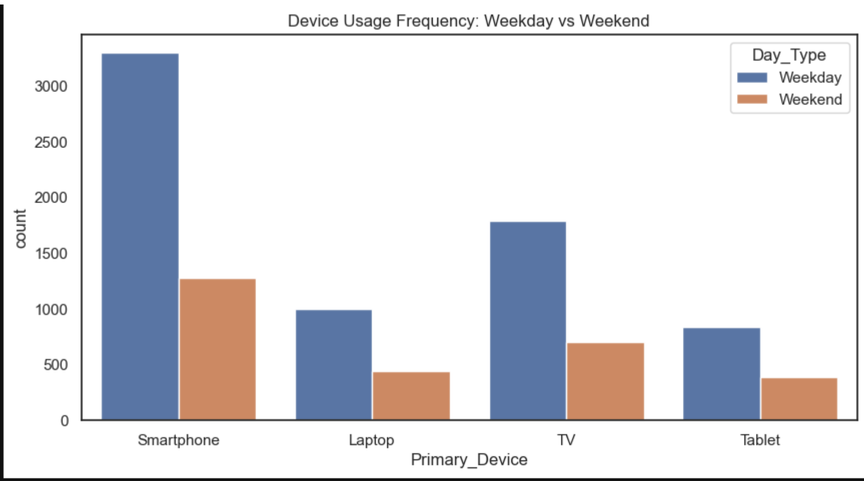
[226]:
```
plt.figure(figsize=(8,4))
sns.barplot(data=df, x="Age_Band", y="Avg_Daily_Screen_Time_hr", hue="Day_Type")
plt.title("Weekday vs Weekend Screen Time Across Age Bands")
plt.show()
```



Device Preference on weekend vs weekday

Phones and TVs usually show sharp increases on weekends

[228]:
```
plt.figure(figsize=(10,5))
sns.countplot(data=df, x="Primary_Device", hue="Day_Type")
plt.title("Device Usage Frequency: Weekday vs Weekend")
plt.show()
```



Habit pattern by screen category

[232]:
```
plt.figure(figsize=(7,4))
sns.countplot(data=df, x="Screen_Category", hue="Day_Type")
plt.title("Screen Category Distribution by Day Type")
plt.show()
```