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	N

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

```
Duplicate Rows Found: 44
```

Step 6 : Numeric summary & Outlier Detection

[24]:
```

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]:
```
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
```

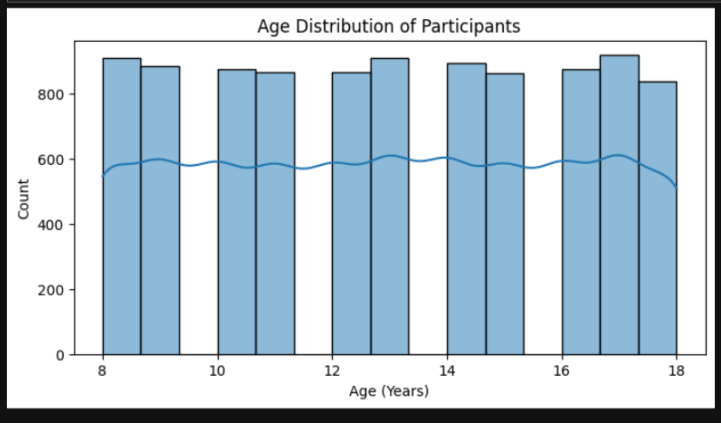
Step 7 : Categorical Summary

```
[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
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_%
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
```

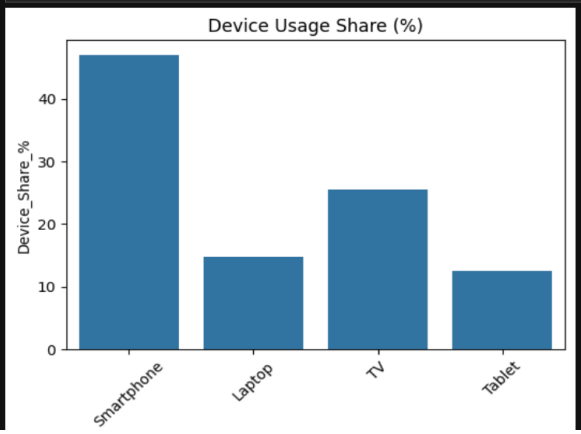
Save enhanced dataset

[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
```

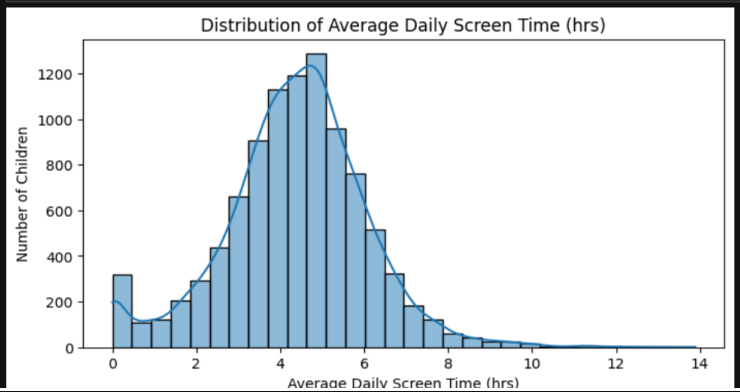
Device Share Visualization

[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()
```



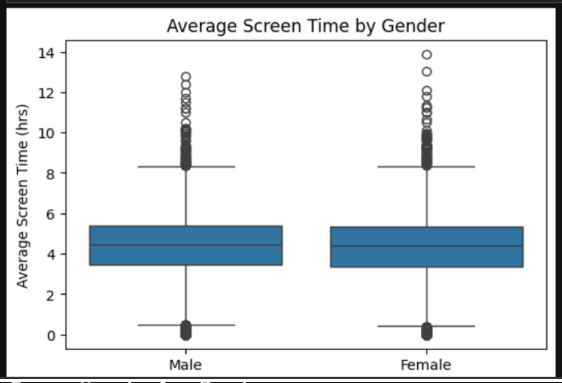
Screen Time Distribution

[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()
```



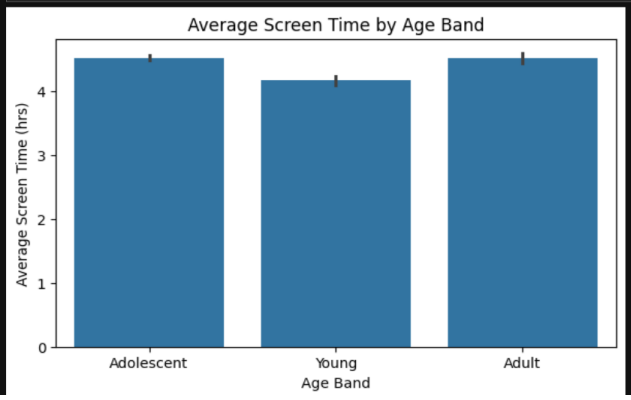
Screen Time by Gender

[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()
```



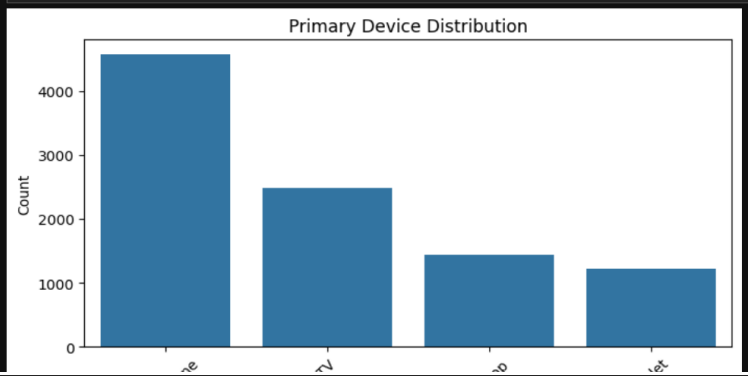
Screen time by Age Band

[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()
```



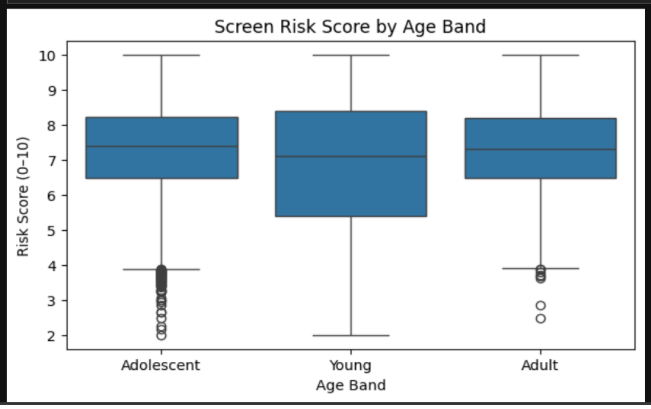
Primary Device Usage

[146]:
```
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]:
```
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]:
```
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]:
```
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.