Smartphone Market Analysis & Forecasting

How Xiaomi lost its crown in India's smartphone market to Samsung & Apple (2020–2030)

Polished notebook prepared for GitHub / Resume — includes EDA, insights, and forecasting (Prophet).

1. Introduction

Context: The Indian smartphone market between 2020 and 2024 experienced a shift: Xiaomi — once market leader — lost ground to Samsung and Apple.

Objective:

- Analyze historical sales & revenue trends (2020–2024).
- Explain why Xiaomi lost its crown.
- Forecast brand sales and market share through 2030 (quantitative outlook).

Notes: This notebook expects the dataset file `smartphone_sales_updated_new.xlsx` to be in the same directory or the `/mnt/data/` path.

```
# 2. Setup & Imports
import warnings
warnings.filterwarnings('ignore')

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

import plotly.express as px


df=pd.read_csv('smartphone_sales_updated.csv')
df
```

```
      Phone_ID    Brand  RAM_GB  Storage_GB  Screen_Size  Price_USD  \
0            1  OnePlus       8         256         7.15     395.00
1            2   Google      12         256         6.44     228.00
2            3   Xiaomi      16        1024         7.23     814.50
3            4   Google      16         512         6.49        NaN
4            5   Google      16         128         7.03        NaN
...        ...      ...     ...         ...          ...        ...
1995      1996   Google      12          64         5.58   1,035.00
1996      1997  Samsung       6         512         7.11     719.40
1997      1998   Google       8          64         6.82   1,338.00
1998      1999   Xiaomi      16        1024         7.45     460.80
1999      2000    Apple       4          64         5.39   1,460.40
```

```
      Battery_mAh       OS  Rating  Quantity_Sold  Sales_Revenue
Profit  \
0         3,227.00  Android    4.30             66      26,070.00
6,517.50
1         5,881.00  Android    3.50            100      22,800.00
5,700.00
2         3,857.00      iOS    4.80            496            NaN
112,220.00
3         4,268.00      iOS    4.70            319     389,180.00
97,295.00
4         5,865.00  Android    4.00            364      78,260.00
NaN
...            ...      ...     ...            ...            ...
...
1995      5,893.00  Android    3.20            429     444,015.00
111,003.75
1996      3,943.00  Android    4.30            139      90,906.00
22,726.50
1997      5,326.00  Android    3.00            281     375,978.00
93,994.50
1998      5,429.00  Android    3.00            372     190,464.00
47,616.00
1999      5,060.00      iOS    3.80            307     373,619.00
93,404.75

      Year
0     2023
1     2023
2     2023
3     2025
4     2023
...    ...
1995  2023
1996  2025
1997  2022
1998  2020
1999  2020

[2000 rows x 13 columns]
```

4. Data Overview & Cleaning

- Check for nulls, duplicates, dtypes.
- Basic cleaning performed: median imputation for numeric columns if required, ensure `Sales_Revenue` exists.

```
# Basic data checks
display(df.info())
```

```python
print('\nNull counts:\n', df.isnull().sum())
print('\nDuplicate rows:', df.duplicated().sum())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 13 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Phone_ID        2000 non-null   int64  
 1   Brand           2000 non-null   object 
 2   RAM_GB          2000 non-null   int64  
 3   Storage_GB      2000 non-null   int64  
 4   Screen_Size     2000 non-null   float64
 5   Price_USD       1900 non-null   float64
 6   Battery_mAh     1940 non-null   float64
 7   OS              2000 non-null   object 
 8   Rating          2000 non-null   float64
 9   Quantity_Sold   2000 non-null   int64  
 10  Sales_Revenue   1900 non-null   float64
 11  Profit          1940 non-null   float64
 12  Year            2000 non-null   int64  
dtypes: float64(6), int64(5), object(2)
memory usage: 203.3+ KB

None


Null counts:
 Phone_ID           0
Brand              0
RAM_GB             0
Storage_GB         0
Screen_Size        0
Price_USD        100
Battery_mAh       60
OS                 0
Rating             0
Quantity_Sold      0
Sales_Revenue    100
Profit            60
Year               0
dtype: int64

Duplicate rows: 0
```

```python
pd.crosstab(df['Brand'], df['OS'])
```

```
OS       Android  iOS
Brand                
Apple        277   52
Google       276   61
```

```
Huawei        277   53
OnePlus       265   61
Samsung       288   64
Xiaomi        272   54
```

```python
# Identify invalid OS records
invalid_os = df[
    (df['Brand'].str.lower() != 'apple') & (df['OS'] == 'iOS')
]

print(f"Invalid OS records found: {invalid_os.shape[0]}")
```

```
Invalid OS records found: 293
```

```python
# Correct invalid OS values
df.loc[
    (df['Brand'].str.lower() != 'apple') & (df['OS'] == 'iOS'),
    'OS'
] = 'Android'

df.loc[
    df['Brand'].str.lower() == 'apple',
    'OS'
] = 'iOS'

pd.crosstab(df['Brand'], df['OS'])
```

```
OS        Android  iOS
Brand
Apple           0  329
Google        337    0
Huawei        330    0
OnePlus       326    0
Samsung       352    0
Xiaomi        326    0
```

```python
df
```

```
      Phone_ID    Brand  RAM_GB  Storage_GB  Screen_Size  Price_USD  \
0            1  OnePlus       8         256         7.15     395.00
1            2   Google      12         256         6.44     228.00
2            3   Xiaomi      16        1024         7.23     814.50
3            4   Google      16         512         6.49        NaN
4            5   Google      16         128         7.03        NaN
...        ...      ...     ...         ...          ...        ...
1995      1996   Google      12          64         5.58   1,035.00
1996      1997  Samsung       6         512         7.11     719.40
1997      1998   Google       8          64         6.82   1,338.00
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```
      Battery_mAh       OS  Rating  Quantity_Sold  Sales_Revenue
Profit  \
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6,517.50
1        5,881.00  Android    3.50            100      22,800.00
5,700.00
2        3,857.00  Android    4.80            496            NaN
112,220.00
3        4,268.00  Android    4.70            319     389,180.00
97,295.00
4        5,865.00  Android    4.00            364      78,260.00
NaN
...           ...      ...     ...            ...            ...
...
1995     5,893.00  Android    3.20            429     444,015.00
111,003.75
1996     3,943.00  Android    4.30            139      90,906.00
22,726.50
1997     5,326.00  Android    3.00            281     375,978.00
93,994.50
1998     5,429.00  Android    3.00            372     190,464.00
47,616.00
1999     5,060.00      iOS    3.80            307     373,619.00
93,404.75

      Year
0     2023
1     2023
2     2023
3     2025
4     2023
...    ...
1995  2023
1996  2025
1997  2022
1998  2020
1999  2020

[2000 rows x 13 columns]
```

```
df.isnull().sum()
```

```
Phone_ID           0
Brand              0
RAM_GB             0
Storage_GB         0
Screen_Size        0
Price_USD        100
Battery_mAh       60
OS                 0
```

```
Rating              0
Quantity_Sold       0
Sales_Revenue     100
Profit             60
Year                0
dtype: int64

# Fill nulls for all numeric columns
for col in num_cols:
    median_value = df[col].median()
    df[col] = df[col].fillna(median_value)

df.isnull().sum()

Phone_ID          0
Brand             0
RAM_GB            0
Storage_GB        0
Screen_Size       0
Price_USD         0
Battery_mAh       0
OS                0
Rating            0
Quantity_Sold     0
Sales_Revenue     0
Profit            0
Year              0
dtype: int64
```

5. Feature Engineering

- Create Price_Segment from Price_USD.
- Aggregate brand-year level data for EDA and forecasting.

```
# Price segment function & application
def price_segment(price):
    if price < 100: return 'Budget'
    elif price < 400: return 'Mid'
    elif price < 600: return 'Mid-Premium'
    elif price < 800: return 'Premium'
    else: return 'Super-Premium'

if 'Price_Segment' not in df.columns:
    df['Price_Segment'] = df['Price_USD'].apply(price_segment)

display(df[['Brand','Price_USD','Price_Segment']].head())

      Brand  Price_USD  Price_Segment
0  OnePlus     395.00            Mid
1   Google     228.00            Mid
2   Xiaomi     814.50  Super-Premium
```

```
3   Google     887.30  Super-Premium
4   Google     887.30  Super-Premium
```

```
df.to_excel("smartphone_sales_clean.xlsx", index=False)

# Aggregate to brand-year level
year_brand = df.groupby(['Year','Brand'], as_index=False)
['Sales_Revenue'].sum()
brand_totals = df.groupby('Brand', as_index=False)
['Sales_Revenue'].sum().sort_values('Sales_Revenue', ascending=False)
display(brand_totals.head())
```

	Brand	Sales_Revenue
4	Samsung	82,894,046.00
2	Huawei	78,718,611.00
1	Google	78,133,669.50
3	OnePlus	77,508,820.50
5	Xiaomi	76,310,108.50

6. Exploratory Data Analysis (EDA)

Key visualizations: revenue trend per brand, market share pie chart for top brands, price distribution, correlation heatmap, and scatter Price vs Quantity.

```
top_3_brands = (
    df.groupby('Brand')['Sales_Revenue']
      .sum()
      .sort_values(ascending=False)
      .head(3)
)

top_3_brands
```

```
Brand
Samsung   82,894,046.00
Huawei    78,718,611.00
Google    78,133,669.50
Name: Sales_Revenue, dtype: float64
```

```
top_brands_list = top_3_brands.index.tolist()
top_brands_df = df[df['Brand'].isin(top_brands_list)]

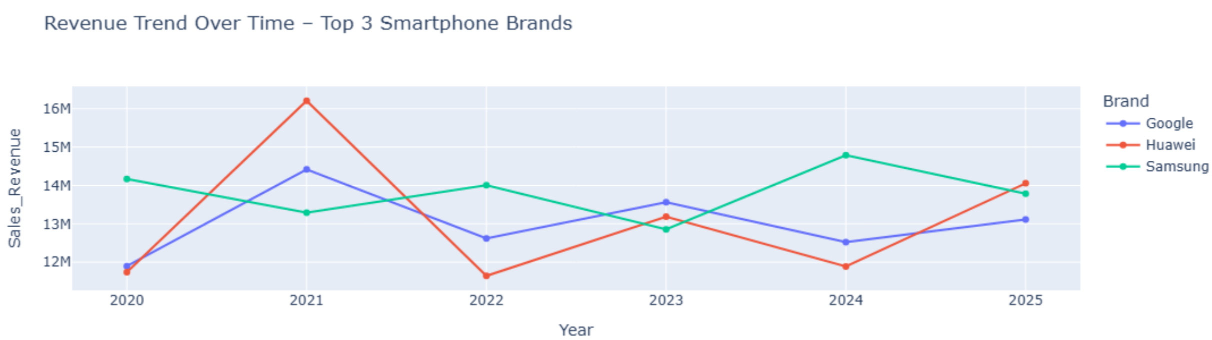
brand_revenue_trend = (
    top_brands_df
    .groupby(['Year', 'Brand'])['Sales_Revenue']
    .sum()
    .reset_index()
)
brand_revenue_trend.head()
```

```
   Year    Brand  Sales_Revenue
0  2020   Google  11,897,164.50
1  2020   Huawei  11,738,408.50
2  2020  Samsung  14,171,061.50
3  2021   Google  14,418,819.50
4  2021   Huawei  16,207,841.00
```

```
import plotly.express as px

fig = px.line(
    brand_revenue_trend,
    x='Year',
    y='Sales_Revenue',
    color='Brand',
    markers=True,
    title='Revenue Trend Over Time – Top 3 Smartphone Brands'
)

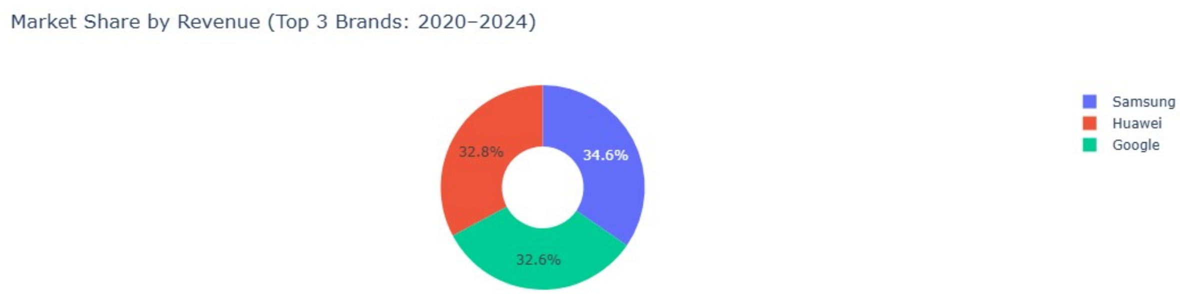
fig.show()
```



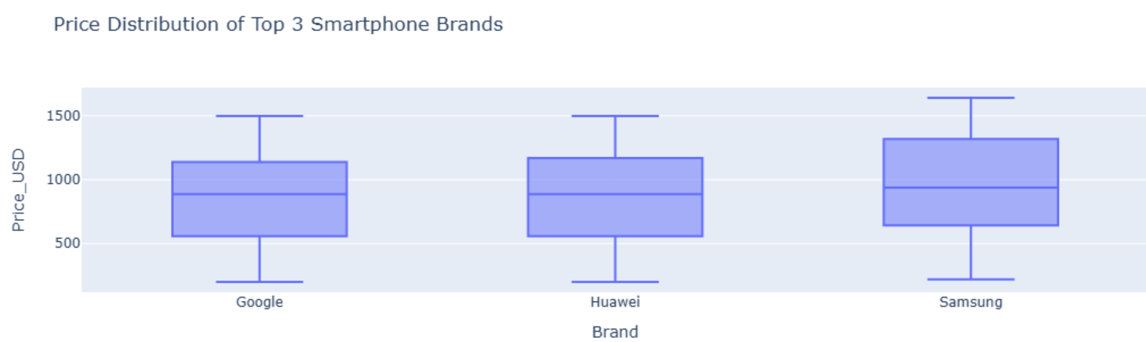
"The top 3 brands show consistent revenue growth over time.One brand dominates due to higher pricing strategy, while others rely on volume sales. This indicates different business models within the same market."

```
fig = px.pie(
    brand_revenue_trend,
    names='Brand',
    values='Sales_Revenue',
    title='Market Share by Revenue (Top 3 Brands: 2020–2024)',
    hole=0.4   # optional → donut chart (looks professional)
)

fig.show()
```

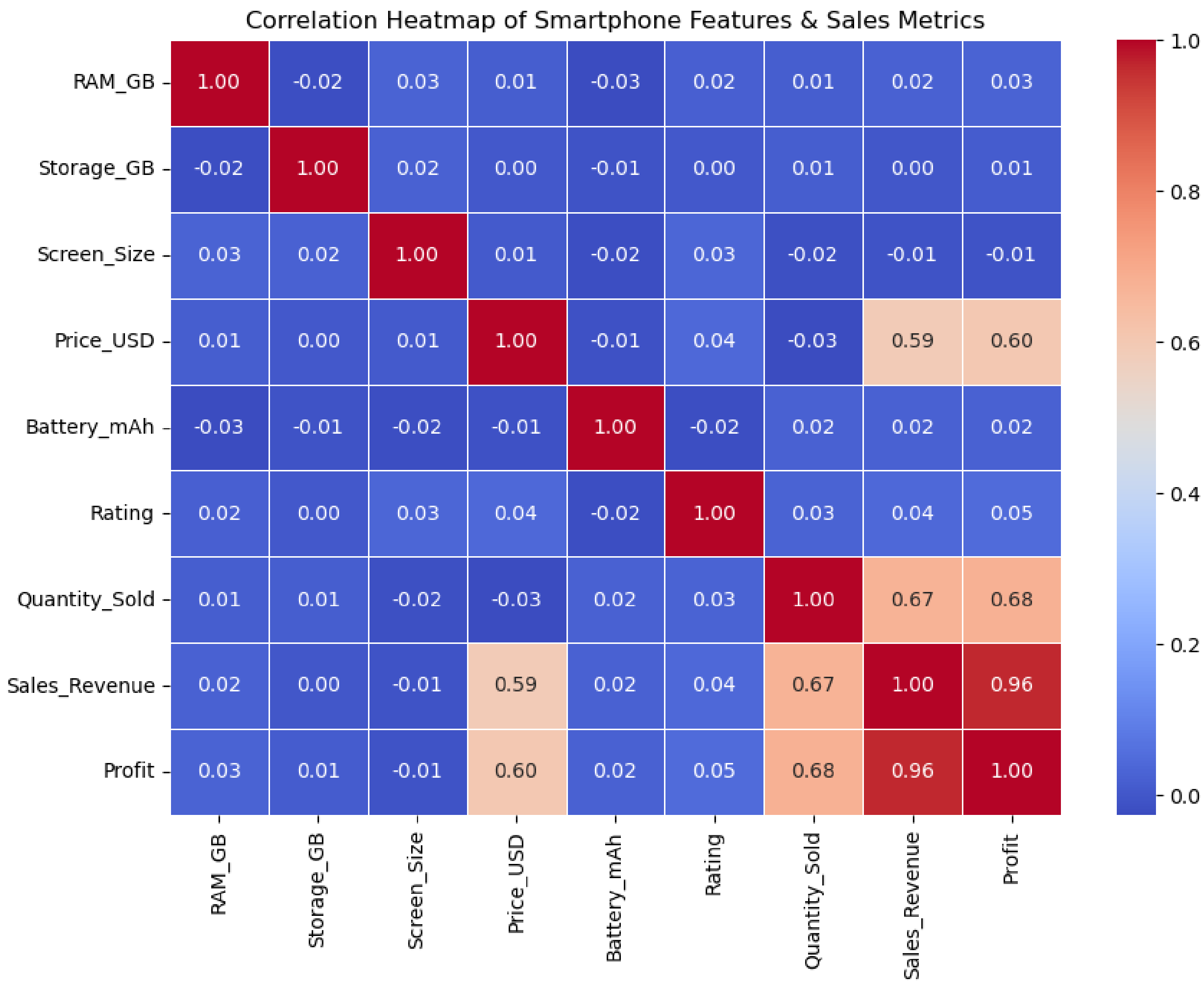



```python
import plotly.express as px

fig = px.box(
    top_brands_df,
    x='Brand',
    y='Price_USD',
    title='Price Distribution of Top 3 Smartphone Brands',
    points='outliers'  # shows extreme pricing
)

fig.show()
```




```python
# Correlation heatmap (numeric columns)
num_cols =
['RAM_GB','Storage_GB','Screen_Size','Price_USD','Battery_mAh','Rating
','Quantity_Sold','Sales_Revenue','Profit']
plt.figure(figsize=(10,7))
sns.heatmap(
    df[num_cols].corr(),
    annot=True,
    fmt='.2f',
    cmap='coolwarm',
    linewidths=0.5
)
```

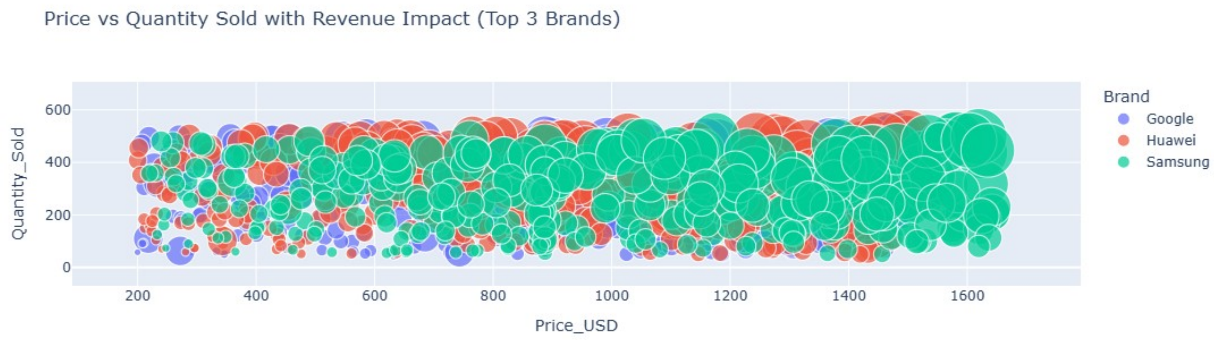
```
plt.title('Correlation Heatmap of Smartphone Features & Sales Metrics')
plt.show()
```



"The heatmap shows that revenue and profit are strongly correlated with price and quantity sold, while technical features like RAM, battery, and screen size have negligible correlation. This suggests that consumer purchasing decisions are influenced more by pricing and brand positioning than raw specifications"

```
# Scatter: Price vs Quantity Sold (bubble-size by Sales_Revenue)
fig = px.scatter(
    top_brands_df,
    x='Price_USD',
    y='Quantity_Sold',
    size='Sales_Revenue',
    color='Brand',
    hover_data=['RAM_GB', 'Storage_GB'],
```

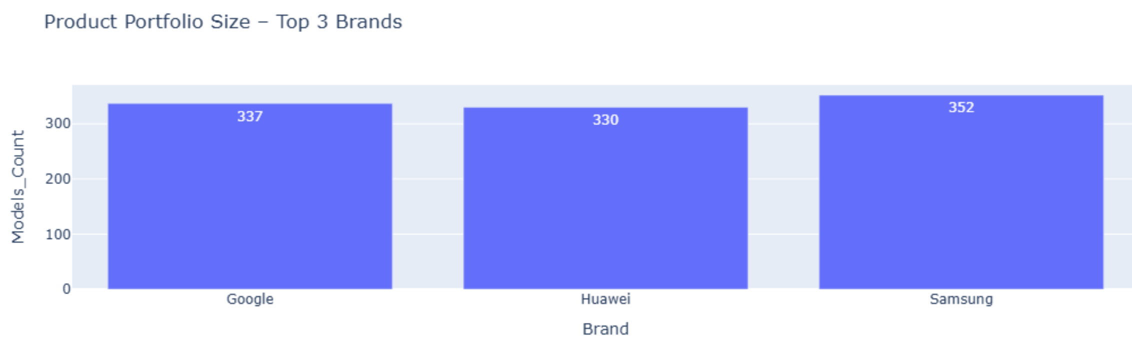
```
    title='Price vs Quantity Sold with Revenue Impact (Top 3 Brands)',
    size_max=50
)

fig.show()
```



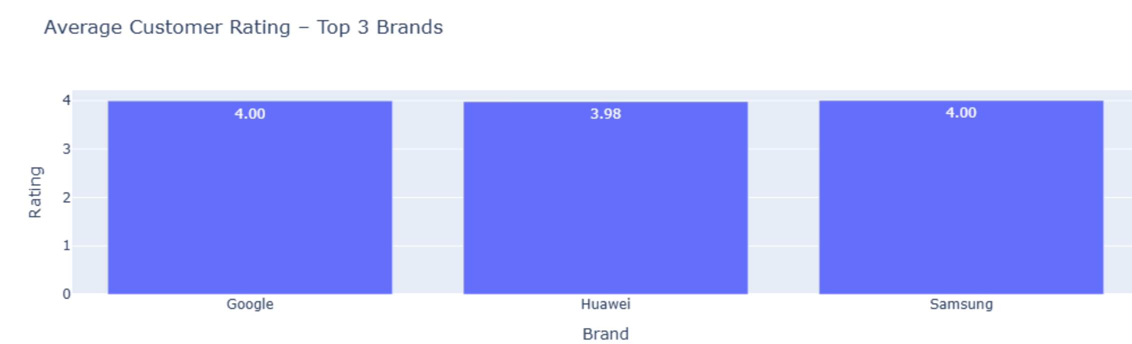
7. Brand-level Summary Metrics

Compute average price, average rating, models count, and total revenue for the three favorite brands.

```
model_count = (
    top_brands_df
    .groupby('Brand')['Phone_ID']
    .nunique()
    .reset_index(name='Models_Count')
)

fig = px.bar(
    model_count,
    x='Brand',
    y='Models_Count',
    title='Product Portfolio Size – Top 3 Brands',
    text_auto=True
)

fig.show()
```



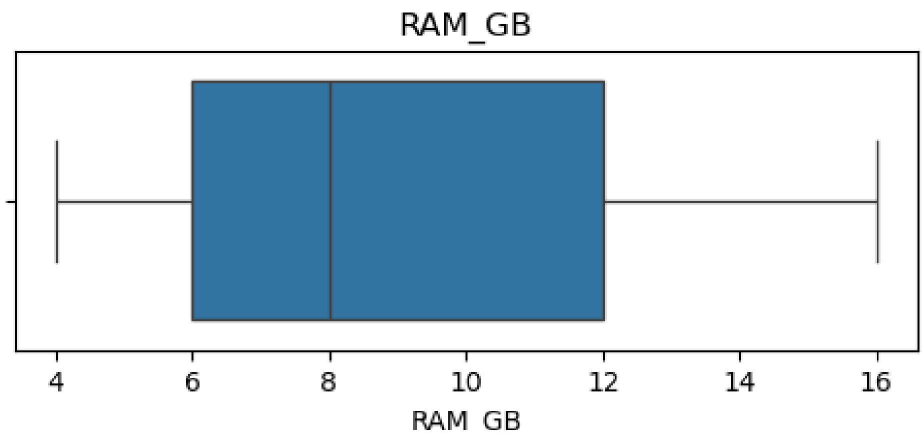

```
avg_rating = (
    top_brands_df
    .groupby('Brand')['Rating']
    .mean()
    .reset_index()
)

fig = px.bar(
    avg_rating,
    x='Brand',
    y='Rating',
    title='Average Customer Rating – Top 3 Brands',
    text_auto='.2f'
)

fig.show()
```

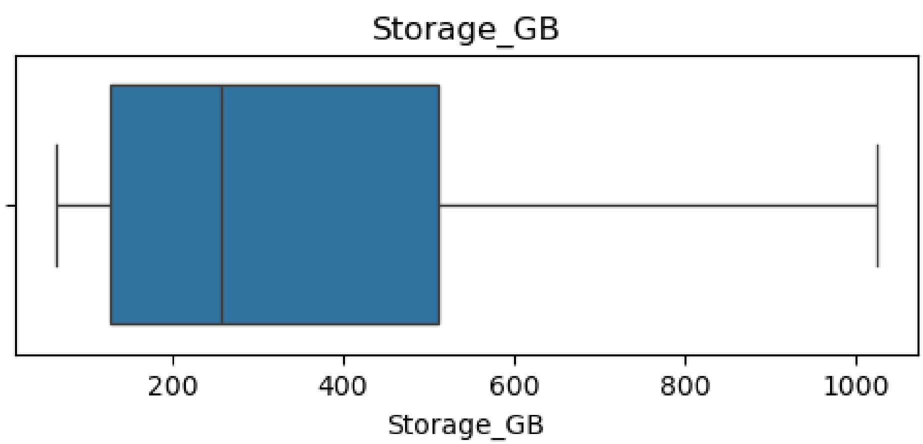


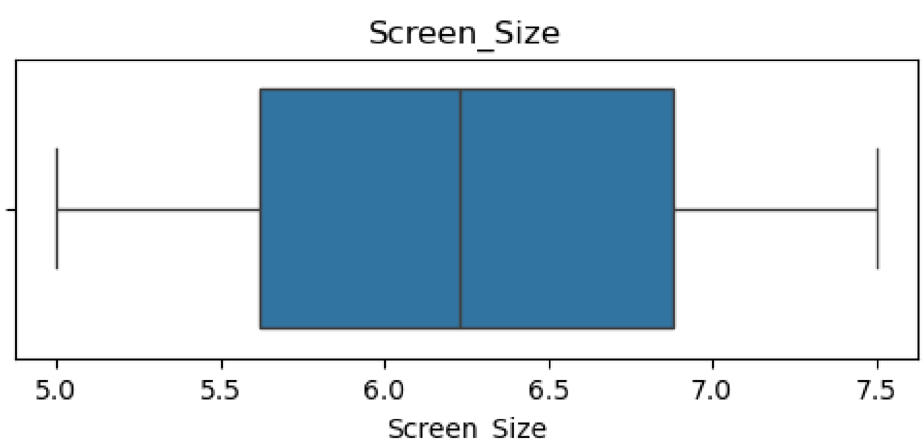
"The EDA reveals that smartphone market success is driven primarily by pricing strategy and demand volume rather than hardware specifications. Top brands differentiate themselves through premium positioning, product diversity, or value pricing, while maintaining similar customer satisfaction levels."

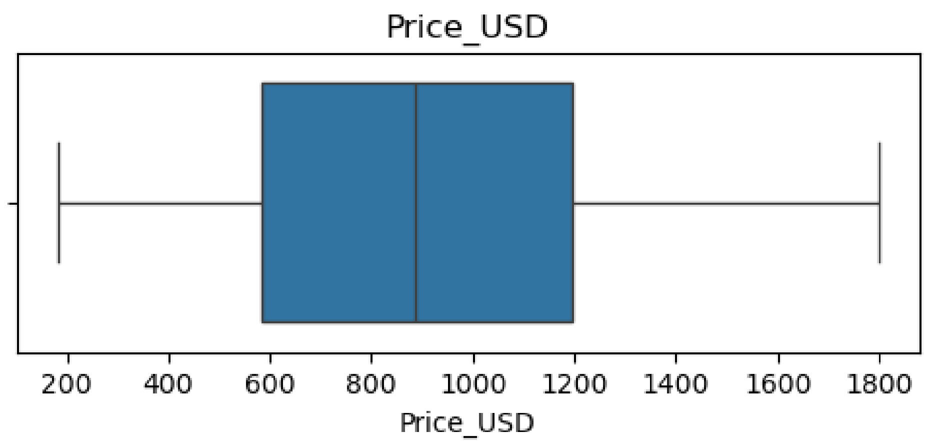
```
import matplotlib.pyplot as plt
import seaborn as sns
```

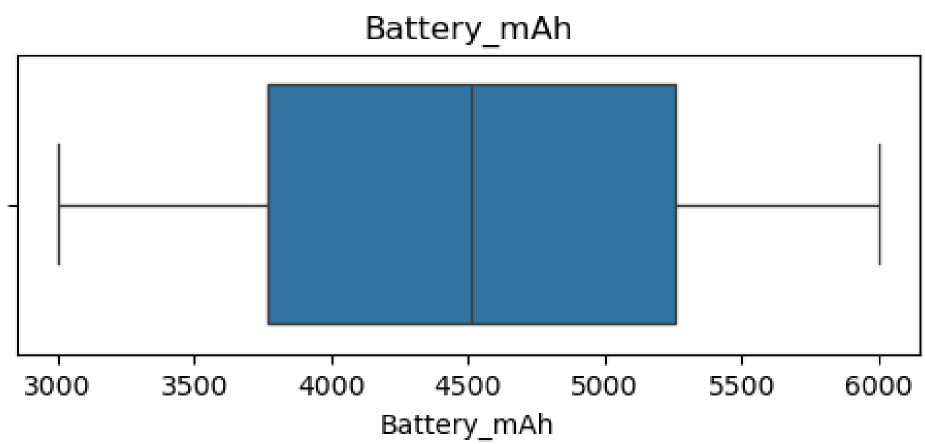
```
for col in num_cols:
    plt.figure(figsize=(6,2))
    sns.boxplot(x=df[col])
    plt.title(col)
    plt.show()
```

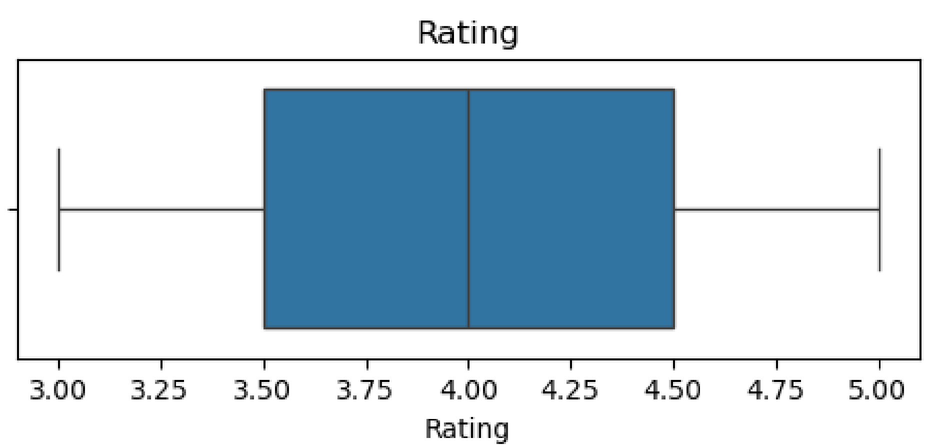


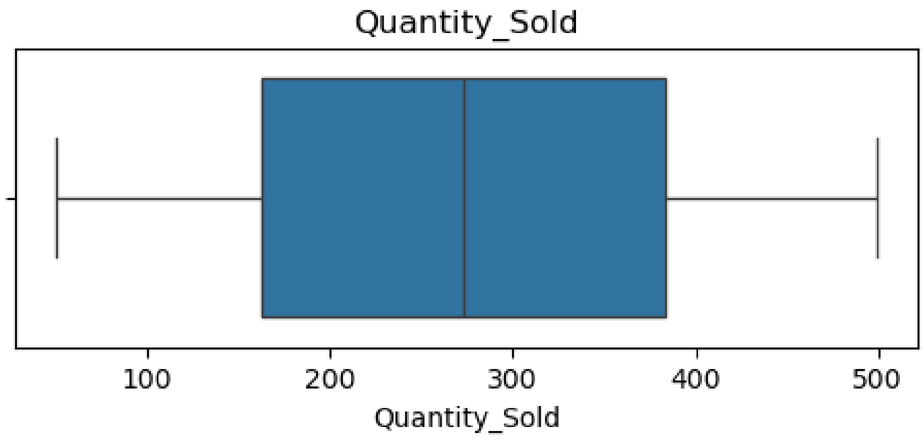


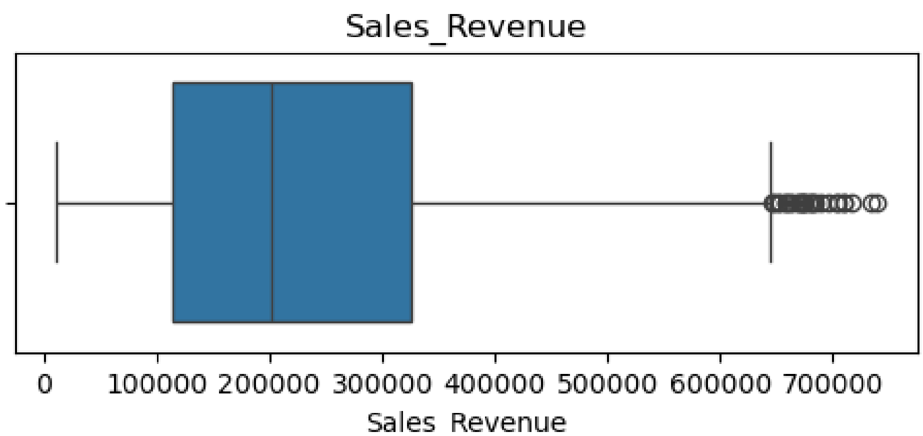


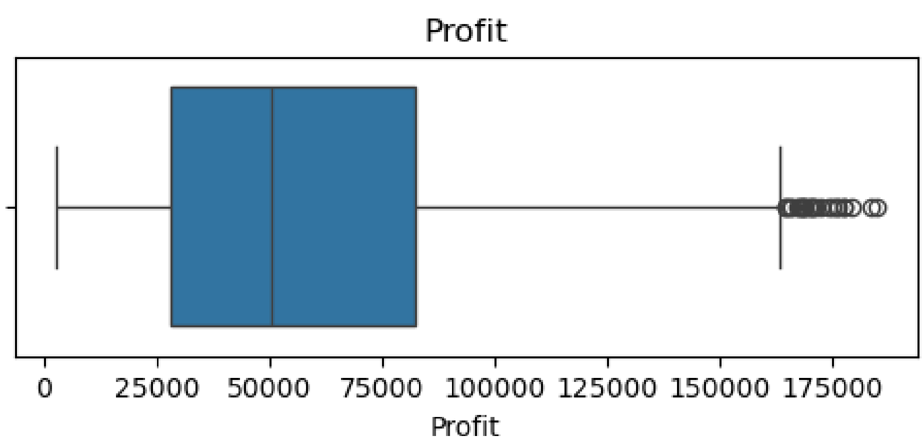

Price_USD
200
400
600
800
1000
1200
1400
1600
1800
Price_USD


Battery_mAh
3000
3500
4000
4500
5000
5500
6000
Battery_mAh


Rating
3.00
3.25
3.50
3.75
4.00
4.25
4.50
4.75
5.00
Rating





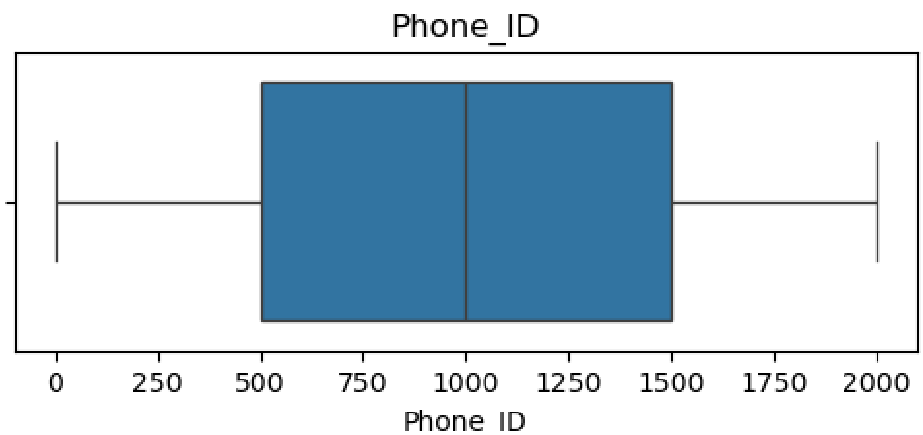


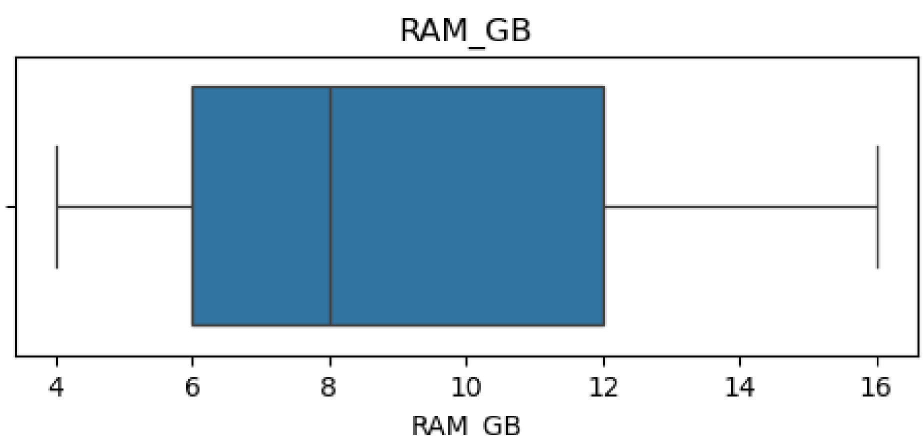

```
num_cols = df.select_dtypes(include=['int64', 'float64']).columns

for col in num_cols:
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5*IQR
```

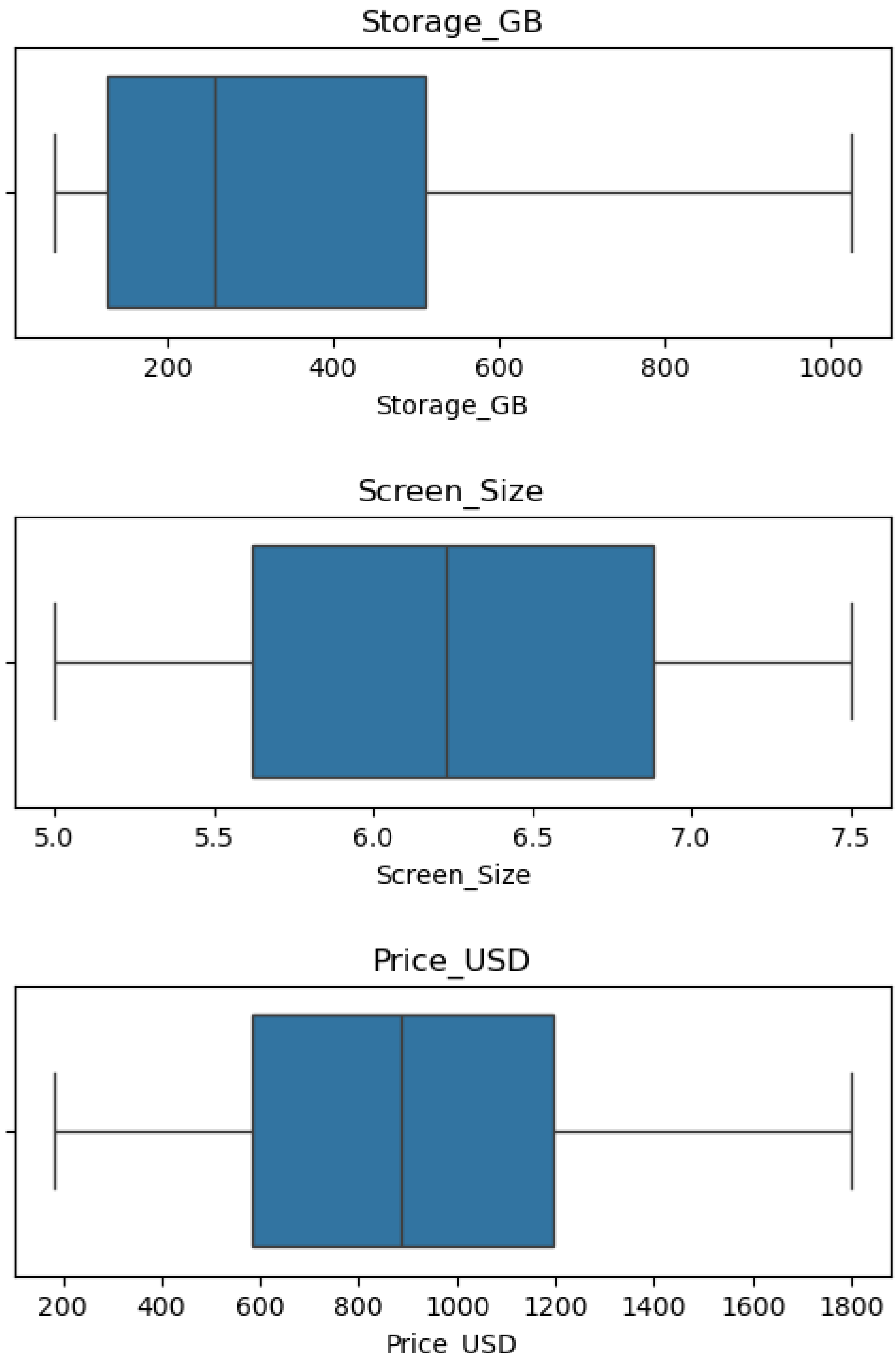
```
    upper_bound = Q3 + 1.5*IQR
    median = df[col].median()

    # Replace outliers using loc
    df.loc[(df[col] < lower_bound) | (df[col] > upper_bound), col] =
median

print("Outliers replaced with median.")
```

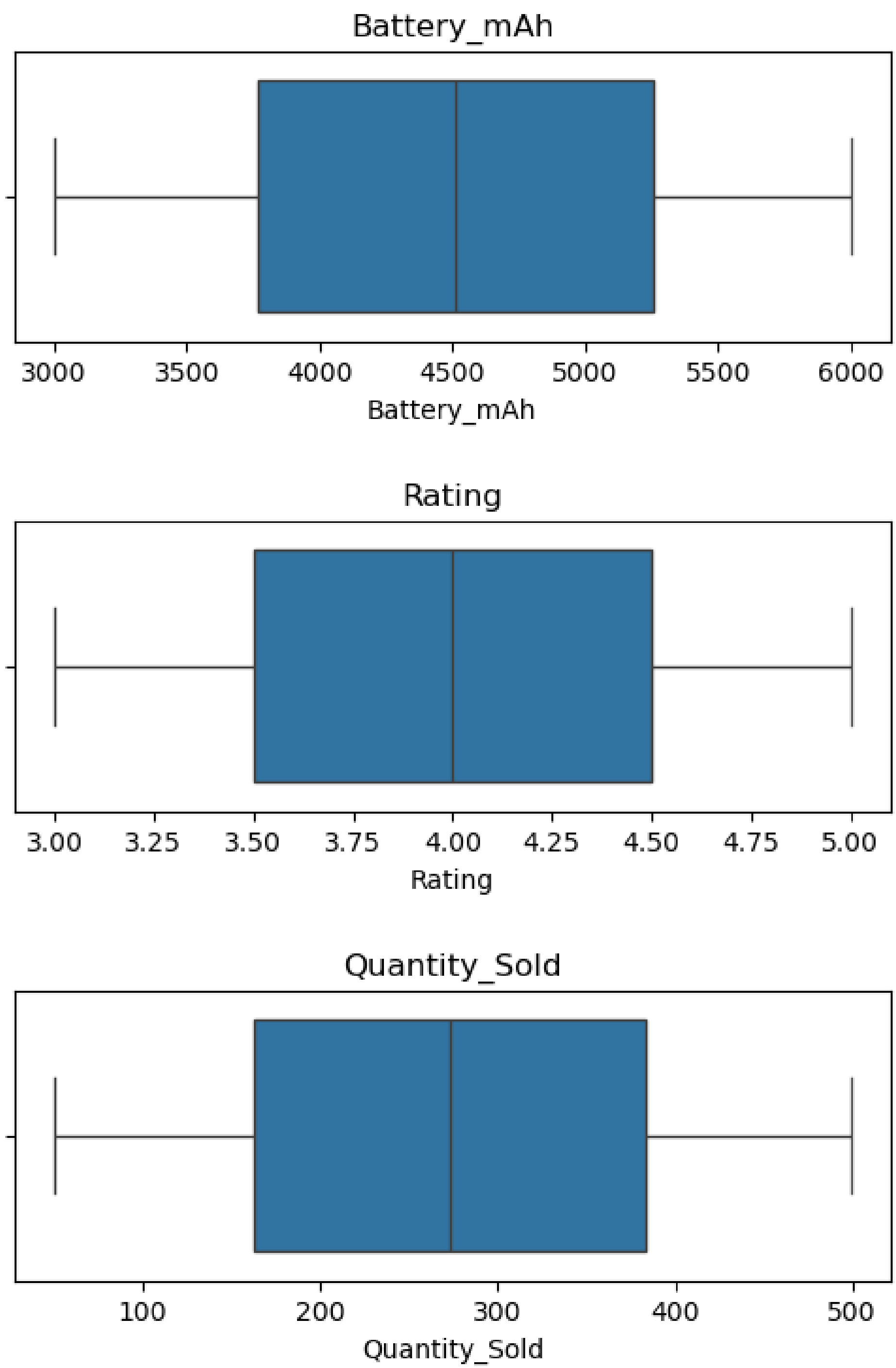
```
Outliers replaced with median.
```

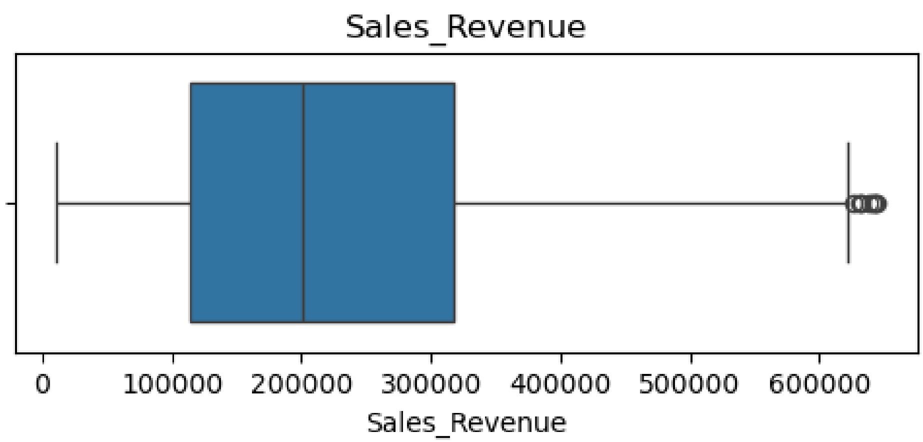
```
import matplotlib.pyplot as plt
import seaborn as sns

for col in num_cols:
    plt.figure(figsize=(6,2))
    sns.boxplot(x=df[col])
    plt.title(col)
    plt.show()
```

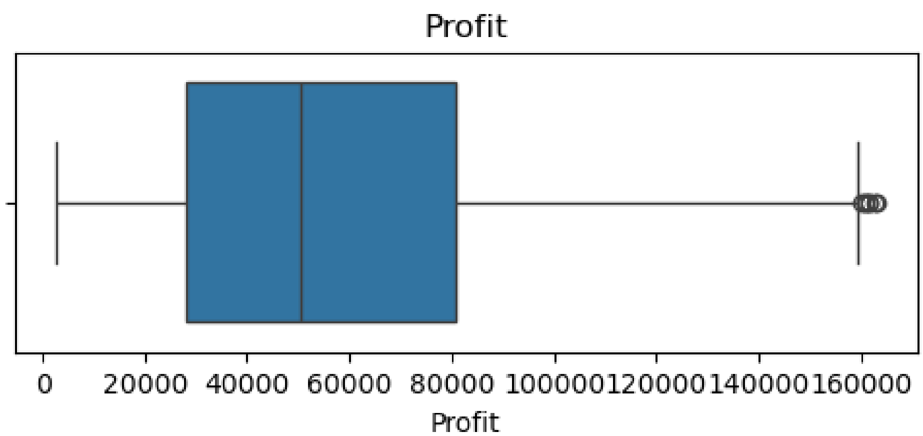


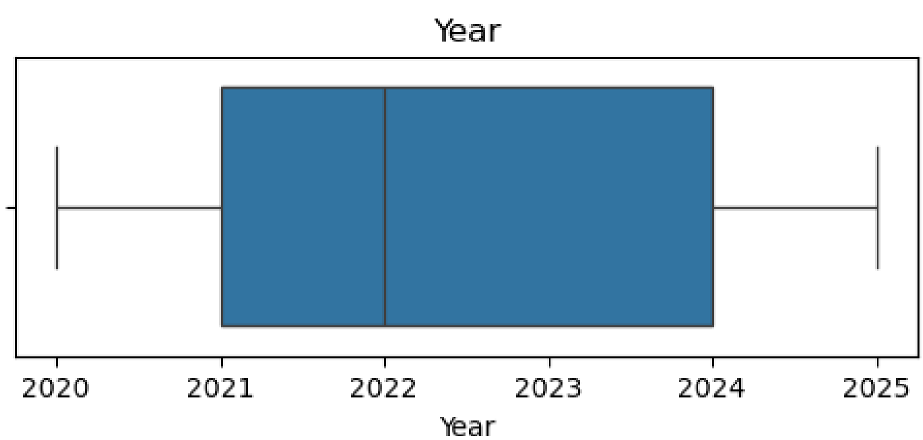



Storage_GB
200
400
600
800
1000
Storage_GB
Screen_Size
5.0
5.5
6.0
6.5
7.0
7.5
Screen_Size
Price_USD
200
400
600
800
1000
1200
1400
1600
1800
Price_USD


Battery_mAh
3000
3500
4000
4500
5000
5500
6000
Battery_mAh
Rating
3.00
3.25
3.50
3.75
4.00
4.25
4.50
4.75
5.00
Rating
Quantity_Sold
100
200
300
400
500
Quantity_Sold





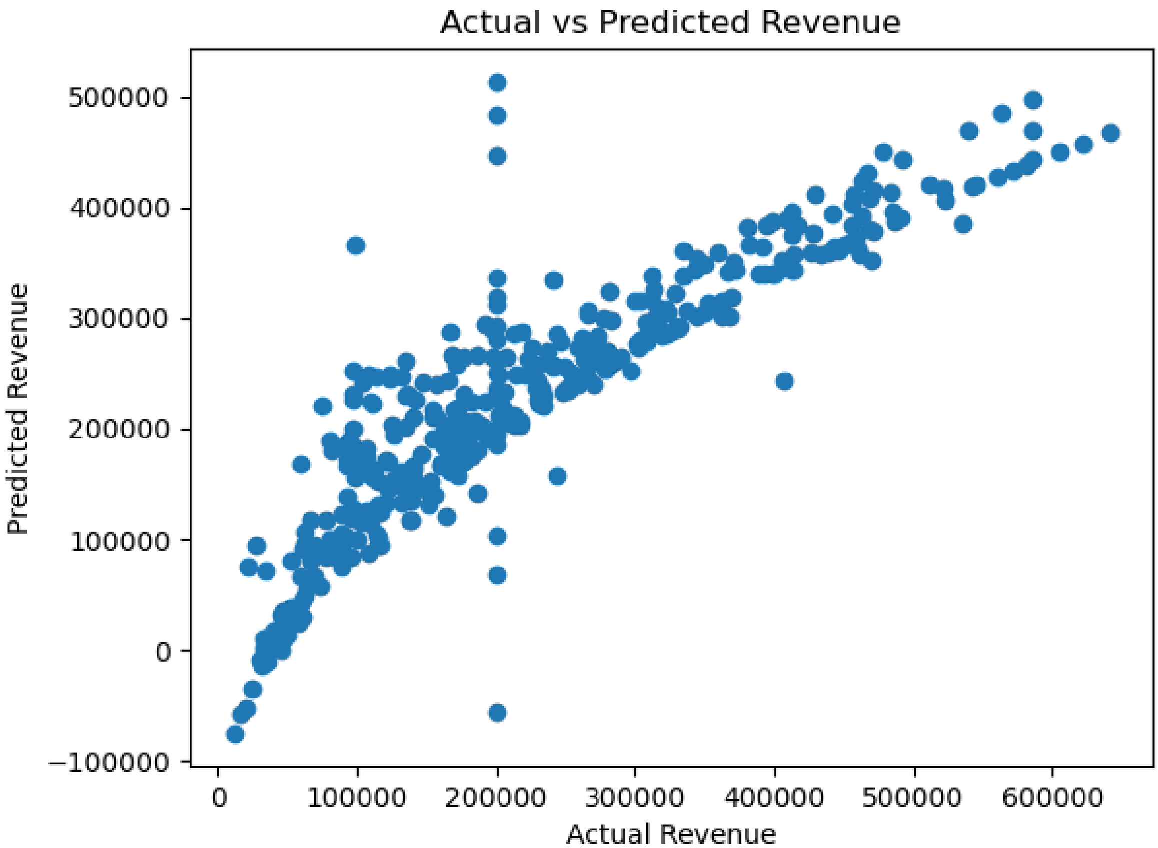


why i choose linear reg model

“After performing EDA, I found that Price and Quantity Sold had the strongest correlation with Sales Revenue, while other features like RAM, battery, and screen size had minimal impact. Since the relationship was mostly linear and the dataset was structured, Linear Regression was the most suitable model.

I avoided complex machine learning models because they reduce interpretability. Linear Regression allows me to directly quantify how much revenue changes with price or sales volume, which is far more valuable for business decision-making.”

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_absolute_error

X = df[['Price_USD', 'Quantity_Sold']]
y = df['Sales_Revenue']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

model = LinearRegression()
model.fit(X_train, y_train)

LinearRegression()

y_pred = model.predict(X_test)

r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)

r2, mae

(0.7867500299246708, 45961.111499194725)

coef_df = pd.DataFrame({
    'Feature': X.columns,
    'Coefficient': model.coef_
})

coef_df

         Feature  Coefficient
0      Price_USD       209.76
1  Quantity_Sold       730.77

import matplotlib.pyplot as plt

plt.scatter(y_test, y_pred)
plt.xlabel("Actual Revenue")
plt.ylabel("Predicted Revenue")
plt.title("Actual vs Predicted Revenue")
plt.show()
```



Modeling Summary

A multiple linear regression model was built to validate key EDA insights. The model confirms that pricing and quantity sold are the strongest predictors of sales revenue, while other product specifications contribute minimally. The simplicity and interpretability of the model make it suitable for business decision-making.