E-Commerce Price Optimization

Business Understanding

- Imagine you're a new seller joining a large online marketplace like Jumia. You know your costs, and you have an idea of the margins you'd like to achieve but what you don't know is how your competitors are pricing similar products.
- This uncertainty leads to two major risks:
  - Overpricing → If your price is too high, customers will simply choose a cheaper alternative.
  - Underpricing → If your price is too low, you might make sales, but at the expense of your profits.
- On top of that, new sellers often face two extra challenges:
  - Price variability – Within the same category, prices can vary widely (e.g., a phone cover sold for KSh 499 vs. another listed at KSh 8,900). It's hard to know what the "right" range is.
  - Discount strategies – Discounts strongly influence buying decisions, but finding the "sweet spot" is not obvious.

What we want to achieve

- The goal of this project is to provide sellers with data-driven insights about market prices. By analyzing product listings (categories, ratings, reviews, discounts), we can benchmark competitors and guide new sellers toward pricing that is:
  - Competitive (aligned with market expectations)
  - Profitable (doesn't eat into margins unnecessarily)

Who benefits from this (Stakeholders)?

- New Sellers → Gain clarity on product selection and pricing decisions.
- Marketplace (Jumia) → Benefits from better customer experiences and onboarding more sellers.
- Business Development Teams → Can use these insights to attract and support vendors.

Why it matters

- If successful, this tool can:
  - Help sellers price products competitively from day one.
  - Reduce the time spent on manual competitor research.
  - Improve sales conversions by aligning listings with market-accepted ranges.

Data Understanding

In [ ]:

```
# Data Manipulation and Analysis
import pandas as pd             # for working with tabular data (DataFrames)
import numpy as np              # for fast numerical computations and arrays

# Data Visualization
import matplotlib.pyplot as plt  # for creating plots and charts
import seaborn as sns            # for advanced and prettier statistical plots

# Web Scraping
import requests                  # to send HTTP requests and get webpage conte
from bs4 import BeautifulSoup    # to parse and extract data from HTML content

# Data Storage and File Operations
import csv                       # to write scraped data into CSV files
import os                        # to handle file and folder paths

# Time Management and Randomization
import time                      # to control scraping speed with delays
import random                    # to add random wait times between requests (

# Date and Time
from datetime import datetime     # to track scraping date/time or log progres


# Machine Learning and Modeling
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer

# Models
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.neural_network import MLPRegressor

# Model Evaluation
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

Data Source

- The dataset used is from scrapped product listings on [**Jumia Kenya**](https://www.jumia.co.ke/).

How it was collected:

- Scraped 50 listing pages, opened each product's detail page, and extracted fields such as title, price (current & original),image, discount, ratings, seller, and category.
- Data is saved incrementally to a CSV (one row per product), with resume logic to

continue from the last scraped page if interrupted.

- To avoid being blocked, we used a browser (User-Agent), added random delays (3–8s between products, 10–20s between pages), and wrapped product loops in (try/except) for fault tolerance.

Variable Descriptions

- Final datasets consist of 1,999 product listings with 13 features (columns) including:
  - current_price → Current product price.
  - original_price → Price before discount
  - discount → Discount percentage
  - main_category → Product category (electronics, fashion, etc.)
  - rating_number & verified_ratings → Customer satisfaction.
  - seller → Who is selling the item.
  - title → Product description.

Reading data into a dataframe named df, a copy is made later and saved as data. We will work on dataframe data leaving df untouched.

In [87]:
```
#Read the data and save it in a dataframe called df
df = pd.read_csv("./Data/New_Price_Change_Monitoring_System.csv")

#read the first 5 rows
df.head()
```

Out[87]:

	date_scraped	page_number	product_url	in
0	2025-09-14	1	https://www.jumia.co.ke/ailyons-fk-0301-stainl...	https://ke.jumia.is/unsaf in/300x300
1	2025-09-14	1	https://www.jumia.co.ke/oking-ok310-1.7-wirele...	https://ke.jumia.is/unsaf in/300x300
2	2025-09-14	1	https://www.jumia.co.ke/samsung-galaxy-a05-6.7...	https://ke.jumia.is/unsaf in/300x300

3	2025-09-14	1	https://www.jumia.co.ke/ailyons-afk-111-water-...	https://ke.jumia.is/unsaf in/300x300
4	2025-09-14	1	https://www.jumia.co.ke/fashion-couple-canvas-...	https://ke.jumia.is/unsaf in/300x300

In [88]:
```
#Make a copy and save it as data. we will work on data, and leave df as the or
data=df.copy()
data.head()
```

Out[88]:

	date_scraped	page_number	product_url	in
0	2025-09-14	1	https://www.jumia.co.ke/ailyons-fk-0301-stainl...	https://ke.jumia.is/unsaf in/300x300
1	2025-09-14	1	https://www.jumia.co.ke/oking-ok310-1.7-wirele...	https://ke.jumia.is/unsaf in/300x300
2	2025-09-14	1	https://www.jumia.co.ke/samsung-galaxy-a05-6.7...	https://ke.jumia.is/unsaf in/300x300
3	2025-09-14	1	https://www.jumia.co.ke/ailyons-afk-111-water-...	https://ke.jumia.is/unsaf in/300x300
4	2025-09-14	1	https://www.jumia.co.ke/fashion-couple-canvas-...	https://ke.jumia.is/unsaf in/300x300

Data Cleaning

- Before diving into analysis, we need to make sure the dataset is usable. That means doing a quick health check to understand its structure:
  - How many rows and columns do we have?
  - Are there missing values that need attention?
  - Do the datatypes (numeric, text, dates) look correct?
  - Are there columns we don't really need?
  - Checking for duplicating

In [89]:
```
#check the number of rows and columns
data.shape
```

Out[89]: (1999, 13)

In [90]:
```
#Check for missing values, datatypes.
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1999 entries, 0 to 1998
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   date_scraped      1999 non-null   object 
 1   page_number       1999 non-null   int64  
 2   product_url       1999 non-null   object 
 3   image             1999 non-null   object 
 4   current_price     1999 non-null   object 
 5   title             1999 non-null   object 
 6   brand             0 non-null      float64
 7   original_price    1798 non-null   object 
 8   discount          1798 non-null   object 
 9   verified_ratings  1549 non-null   object 
 10  rating_number     1999 non-null   float64
 11  seller            1999 non-null   object 
 12  main_category     1999 non-null   object 
dtypes: float64(2), int64(1), object(10)
memory usage: 203.2+ KB
```

In [91]:
```
#Drop brand since the column is empty
data = data.drop(columns=['brand'], errors='ignore')
data.shape
```

Out[91]: (1999, 12)

- Before analyzing the price columns, we need to clean them since they came in as text.

- Removing currency symbols and commas
- Convert to floats
- If a range is given (e.g. `699 - 729`), take the average
- Keep `NaN` where conversion isn't possible

In [92]:

```
# 2. Clean current_price & original_price. make them numeric
def clean_price(x):
    if pd.isna(x):
        return np.nan
    x = str(x).replace("KSh", "").replace(",", "").strip()
    if "-" in x:  # handle ranges like "699 - 729" It will take the average of
        parts = x.split("-")
        nums = [float(p.strip()) for p in parts if p.strip().replace('.', '',
        return np.mean(nums) if nums else np.nan
    return float(x) if x.replace('.', '', 1).isdigit() else np.nan

data['current_price'] = data['current_price'].apply(clean_price)
data['original_price'] = data['original_price'].apply(clean_price)
data.head()
```

Out[92]:

	date_scraped	page_number	product_url	in
0	2025-09-14	1	https://www.jumia.co.ke/ailyons-fk-0301-stainl...	https://ke.jumia.is/unsaf in/300x300
1	2025-09-14	1	https://www.jumia.co.ke/oking-ok310-1.7-wirele...	https://ke.jumia.is/unsaf in/300x300
2	2025-09-14	1	https://www.jumia.co.ke/samsung-galaxy-a05-6.7...	https://ke.jumia.is/unsaf in/300x300
3	2025-09-14	1	https://www.jumia.co.ke/ailyons-afk-111-water-...	https://ke.jumia.is/unsaf in/300x300
4	2025-09-14	1	https://www.jumia.co.ke/fashion-couple-canvas-...	https://ke.jumia.is/unsaf in/300x300

- Removing the `%` sign in `discount` column so it's numeric-friendly.

In [93]:
```
#Clean discount, remove %
data['discount'] = data['discount'].str.replace('%', '', regex=False)
data.head(2)
```

Out[93]:

	date_scraped	page_number	product_url	ima
0	2025-09-14	1	https://www.jumia.co.ke/ailyons-fk-0301-stainl...	https://ke.jumia.is/unsafe/ in/300x300/fi
1	2025-09-14	1	https://www.jumia.co.ke/oking-ok310-1.7-wirele...	https://ke.jumia.is/unsafe/ in/300x300/fi

- Cleaned `verified_ratings` by extracting the numeric part from the text and converting it to a number.

In [94]:
```
#Clean verified_ratings. Extract numeric value from the sring.
data['verified_ratings'] = (
    data['verified_ratings']
    .str.extract(r'(\d+)')
    .astype(float)
)
data.head(2)
```

Out[94]:

	date_scraped	page_number	product_url	ima
0	2025-09-14	1	https://www.jumia.co.ke/ailyons-fk-0301-stainl...	https://ke.jumia.is/unsafe/ in/300x300/fi

1	2025-09-14	1	https://www.jumia.co.ke/oking-ok310-1.7-wirele...	https://ke.jumia.is/unsafe/in/300x300/fi

Handling Missing Values

In [95]:
```
#Recheck missing values
data.isna().sum()
```

Out[95]:
```
date_scraped          0
page_number           0
product_url           0
image                 0
current_price         0
title                 0
original_price      201
discount            201
verified_ratings    488
rating_number         0
seller                0
main_category         0
dtype: int64
```

In [96]:
```
# For original_price, the missing value is set equal to current_price (assume
data['original_price'] = data['original_price'].fillna(data['current_price'])
data.isna().sum()
```

Out[96]:
```
date_scraped          0
page_number           0
product_url           0
image                 0
current_price         0
title                 0
original_price        0
discount            201
verified_ratings    488
rating_number         0
seller                0
main_category         0
dtype: int64
```

In [97]:
```
# Discount, we filled missing values with 0
data['discount'] = data['discount'].fillna(0)
data.isna().sum()
```

Out[97]:
```
date_scraped          0
page_number           0
product_url           0
```

```
image                0
current_price        0
title                0
original_price       0
discount             0
verified_ratings    488
rating_number        0
seller               0
main_category        0
dtype: int64
```

In [98]:

```
# verified_ratings, missing = 0
data['verified_ratings'] = data['verified_ratings'].fillna(0)
data.isna().sum()
```

Out[98]:

```
date_scraped        0
page_number         0
product_url         0
image               0
current_price       0
title               0
original_price      0
discount            0
verified_ratings    0
rating_number       0
seller              0
main_category       0
dtype: int64
```

Handling Duplicates in column product_url

In [99]:

```
# Count duplicates based on product_url
if 'product_url' in data.columns:
    print(data.duplicated(subset=['product_url']).sum()) # marks the first occ
```

```
94
```

In [100…

```
# Select only duplicated product_urls
dupes = data[data['product_url'].duplicated(keep=False)]

# Sort so that the same URLs appear next to each other
dupes = dupes.sort_values(by='product_url')

# Show just the product_url column
print(dupes['product_url'])
```

```
321     https://www.jumia.co.ke/3-in-1-rechargeable-ho...
319     https://www.jumia.co.ke/3-in-1-rechargeable-ho...
195     https://www.jumia.co.ke/ailyons-2.0-l-electric...
751     https://www.jumia.co.ke/ailyons-2.0-l-electric...
352     https://www.jumia.co.ke/airpods-pro3-bluetooth...
                              ...
980     https://www.jumia.co.ke/xiaomi-redmi-15c-6.9up...
887     https://www.jumia.co.ke/xiaomi-redmi-15c-6.9up...
399     https://www.jumia.co.ke/xiaomi-redmi-15c-6.9up...
1954    https://www.jumia.co.ke/xiaomi-redmi-a3x-6.71-...
```

```
594     https://www.jumia.co.ke/xiaomi-redmi-a3x-6.71-...
Name: product_url, Length: 187, dtype: object
```

In [101…

```
print(len(dupes)) # marks all duplicates as True, including the first occurrer
```

```
187
```

In [102…

```
if 'product_url' in data.columns:
    # Count product_url occurrences
    url_counts = data['product_url'].value_counts()

    # Keep only duplicates
    dupes = url_counts[url_counts > 1]

    # Convert to DataFrame for the same look as before
    dupes_df = dupes.reset_index()
    dupes_df.columns = ['product_url', 'url_count']

    # Show top 10 duplicate products
    print(dupes_df.head(20))
```

```
                                          product_url  url_count
0   https://www.jumia.co.ke/derma-roller-for-beard...          3
1   https://www.jumia.co.ke/sunlight-solar-200-wat...          2
2   https://www.jumia.co.ke/fashion-3-in-1-school-...          2
3   https://www.jumia.co.ke/kijani-organics-castor...          2
4   https://www.jumia.co.ke/ailyons-2.0-l-electric...          2
5   https://www.jumia.co.ke/aroamas-scar-scar-remo...          2
6   https://www.jumia.co.ke/nice-one-yg-105-2-colu...          2
7   https://www.jumia.co.ke/generic-36-pieces-simu...          2
8   https://www.jumia.co.ke/top-fry-top-fry-vegeta...          2
9   https://www.jumia.co.ke/xiaomi-redmi-15c-6.9up...          2
10  https://www.jumia.co.ke/globalstar-32uk-32-inc...          2
11  https://www.jumia.co.ke/generic-hdtv-hdmi-to-h...          2
12  https://www.jumia.co.ke/oraimo-spacebox-8w-fm-...          2
13  https://www.jumia.co.ke/the-ordinary-concentra...          2
14  https://www.jumia.co.ke/tilecc-tilecc-air-pro-...          2
15  https://www.jumia.co.ke/tv-guard-or-fridge-gua...          2
16  https://www.jumia.co.ke/fashion-womens-multila...          2
17  https://www.jumia.co.ke/dynamic-black-permanen...          2
18  https://www.jumia.co.ke/fashion-student-backpa...          2
19  https://www.jumia.co.ke/tecno-spark-40-6.67-hd...          2
```

In [103…

```
# Drop duplicate product URLs (keep the first occurrence)
if 'product_url' in data.columns:
    data = data.drop_duplicates(subset=['product_url'], keep='first')
data.shape
```

Out[103… (1905, 12)

In [104…

```
data.head()
```

Out[104…

	date_scraped	page_number	product_url	in

0	2025-09-14	1	https://www.jumia.co.ke/ailyons-fk-0301-stainl...	https://ke.jumia.is/unsaf in/300x300
1	2025-09-14	1	https://www.jumia.co.ke/oking-ok310-1.7-wirele...	https://ke.jumia.is/unsaf in/300x300
2	2025-09-14	1	https://www.jumia.co.ke/samsung-galaxy-a05-6.7...	https://ke.jumia.is/unsaf in/300x300
3	2025-09-14	1	https://www.jumia.co.ke/ailyons-afk-111-water-...	https://ke.jumia.is/unsaf in/300x300
4	2025-09-14	1	https://www.jumia.co.ke/fashion-couple-canvas-...	https://ke.jumia.is/unsaf in/300x300

Outliers Based on main_category

In [105…

```
numeric_cols = ['current_price', 'original_price', 'verified_ratings']

# Loop through numeric columns and detect outliers within each main_category
for col in numeric_cols:
    print(f"\nChecking outliers for column: {col}\n")
    for category, group in data.groupby('main_category'):
        Q1 = group[col].quantile(0.25)
        Q3 = group[col].quantile(0.75)
        IQR = Q3 - Q1
        lower = Q1 - 1.5 * IQR
        upper = Q3 + 1.5 * IQR

        outliers = group[(group[col] < lower) | (group[col] > upper)]

        if not outliers.empty:
            print(f"Category: {category}, Outliers: {outliers.shape[0]}")
            display(outliers[[col, 'main_category']].head(5))  # show 5 sample
```

```
Checking outliers for column: current_price
```

```
Category: Automobile, Outliers: 4
```

	current_price	main_category
631	36999.0	Automobile
862	24000.0	Automobile
1091	12500.0	Automobile
1445	23999.0	Automobile

```
Category: Baby Products, Outliers: 3
```

	current_price	main_category
1005	7500.0	Baby Products
1242	1698.0	Baby Products
1776	2000.0	Baby Products

```
Category: Books, Movies and Music, Outliers: 2
```

	current_price	main_category
934	12000.0	Books, Movies and Music
976	2999.0	Books, Movies and Music

```
Category: Computing, Outliers: 19
```

	current_price	main_category
203	39999.0	Computing
210	15999.0	Computing
233	28499.0	Computing
615	67860.0	Computing
676	11470.0	Computing

```
Category: Electronics, Outliers: 3
```

	current_price	main_category
928	44990.0	Electronics
1049	52999.0	Electronics
1753	44890.0	Electronics

```
Category: Fashion, Outliers: 17
```

	current_price	main_category
54	3445.0	Fashion
165	2399.0	Fashion

200	5500.0	Fashion
340	2949.0	Fashion
444	3949.5	Fashion

```
Category: Gaming, Outliers: 1
```

	current_price	main_category
949	3750.0	Gaming

```
Category: Garden & Outdoors, Outliers: 2
```

	current_price	main_category
538	40000.0	Garden & Outdoors
739	29299.0	Garden & Outdoors

```
Category: Grocery, Outliers: 1
```

	current_price	main_category
1875	3499.0	Grocery

```
Category: Health & Beauty, Outliers: 30
```

	current_price	main_category
43	3647.0	Health & Beauty
167	2873.0	Health & Beauty
217	5200.0	Health & Beauty
300	2824.0	Health & Beauty
427	3300.0	Health & Beauty

```
Category: Home & Office, Outliers: 58
```

	current_price	main_category
12	6999.0	Home & Office
16	8799.0	Home & Office
36	16999.0	Home & Office
39	17499.0	Home & Office
55	23599.0	Home & Office

```
Category: Industrial & Scientific, Outliers: 2
```

	current_price	main_category
239	14999.0	Industrial & Scientific
699	21199.0	Industrial & Scientific

```
Category: Musical Instruments, Outliers: 1
```

	current_price	main_category

1066	30990.0	Musical Instruments

```
Category: Pet Supplies, Outliers: 2
```

	current_price	main_category
915	3780.0	Pet Supplies
1680	5900.0	Pet Supplies

```
Category: Phones & Tablets, Outliers: 8
```

	current_price	main_category
916	33190.0	Phones & Tablets
1162	32399.0	Phones & Tablets
1228	32489.0	Phones & Tablets
1460	45599.0	Phones & Tablets
1552	32585.0	Phones & Tablets

```
Category: Sporting Goods, Outliers: 4
```

	current_price	main_category
601	98999.0	Sporting Goods
659	9990.0	Sporting Goods
701	11999.0	Sporting Goods
1092	12299.0	Sporting Goods

```
Category: Toys & Games, Outliers: 7
```

	current_price	main_category
657	16199.0	Toys & Games
672	8999.0	Toys & Games
929	37999.0	Toys & Games
1360	13000.0	Toys & Games
1646	6999.0	Toys & Games

```
Checking outliers for column: original_price

Category: Automobile, Outliers: 3
```

	original_price	main_category
631	85810.0	Automobile
862	32000.0	Automobile
1445	35000.0	Automobile

```
Category: Baby Products, Outliers: 1
```

	original_price	main_category

1005	8500.0	Baby Products

```
Category: Books, Movies and Music, Outliers: 2
```

	original_price	main_category
934	12000.0	Books, Movies and Music
976	2999.0	Books, Movies and Music

```
Category: Computing, Outliers: 20
```

	original_price	main_category
121	19000.0	Computing
203	45000.0	Computing
210	25000.0	Computing
233	35000.0	Computing
615	135720.0	Computing

```
Category: Electronics, Outliers: 9
```

	original_price	main_category
559	100000.0	Electronics
667	110000.0	Electronics
733	100000.0	Electronics
737	80000.0	Electronics
928	110000.0	Electronics

```
Category: Fashion, Outliers: 16
```

	original_price	main_category
165	4449.0	Fashion
200	7500.0	Fashion
261	4124.0	Fashion
303	3600.0	Fashion
340	4849.0	Fashion

```
Category: Gaming, Outliers: 1
```

	original_price	main_category
949	7500.0	Gaming

```
Category: Garden & Outdoors, Outliers: 1
```

	original_price	main_category
739	55000.0	Garden & Outdoors

```
Category: Grocery, Outliers: 2
```

	original_price	main_category
891	2599.0	Grocery
1875	5500.0	Grocery

```
Category: Health & Beauty, Outliers: 20
```

	original_price	main_category
43	5610.0	Health & Beauty
167	4420.0	Health & Beauty
217	6500.0	Health & Beauty
300	4345.0	Health & Beauty
427	5500.0	Health & Beauty

```
Category: Home & Office, Outliers: 51
```

	original_price	main_category
12	11995.0	Home & Office
16	11800.0	Home & Office
36	26199.0	Home & Office
39	25399.0	Home & Office
55	23599.0	Home & Office

```
Category: Industrial & Scientific, Outliers: 3
```

	original_price	main_category
239	19000.0	Industrial & Scientific
412	11790.0	Industrial & Scientific
699	23999.0	Industrial & Scientific

```
Category: Musical Instruments, Outliers: 1
```

	original_price	main_category
1066	70000.0	Musical Instruments

```
Category: Pet Supplies, Outliers: 2
```

	original_price	main_category
915	3780.0	Pet Supplies
1680	5999.0	Pet Supplies

```
Category: Phones & Tablets, Outliers: 10
```

	original_price	main_category
916	60000.0	Phones & Tablets

1162	50000.0	Phones & Tablets
1434	50999.0	Phones & Tablets
1460	65000.0	Phones & Tablets
1588	60999.0	Phones & Tablets

```
Category: Sporting Goods, Outliers: 4
```

	original_price	main_category
601	170000.0	Sporting Goods
659	19000.0	Sporting Goods
701	21598.0	Sporting Goods
1092	21998.0	Sporting Goods

```
Category: Toys & Games, Outliers: 7
```

	original_price	main_category
657	21999.0	Toys & Games
672	11999.0	Toys & Games
929	49999.0	Toys & Games
1360	15500.0	Toys & Games
1646	14900.0	Toys & Games

```
Checking outliers for column: verified_ratings
```

```
Category: Automobile, Outliers: 7
```

	verified_ratings	main_category
459	19.0	Automobile
473	17.0	Automobile
1083	19.0	Automobile
1264	36.0	Automobile
1299	23.0	Automobile

```
Category: Baby Products, Outliers: 2
```

	verified_ratings	main_category
59	259.0	Baby Products
1242	36.0	Baby Products

```
Category: Books, Movies and Music, Outliers: 8
```

	verified_ratings	main_category
514	1.0	Books, Movies and Music
640	1.0	Books, Movies and Music

649	1.0	Books, Movies and Music
749	1.0	Books, Movies and Music
885	9.0	Books, Movies and Music
946	2.0	Books, Movies and Music

```
Category: Computing, Outliers: 12
```

	verified_ratings	main_category
107	2117.0	Computing
120	2190.0	Computing
156	631.0	Computing
270	434.0	Computing
296	373.0	Computing

```
Category: Electronics, Outliers: 24
```

	verified_ratings	main_category
8	1550.0	Electronics
14	501.0	Electronics
100	3700.0	Electronics
103	839.0	Electronics
108	298.0	Electronics

```
Category: Fashion, Outliers: 39
```

	verified_ratings	main_category
4	734.0	Fashion
13	1679.0	Fashion
18	410.0	Fashion
20	520.0	Fashion
21	884.0	Fashion

```
Category: Gaming, Outliers: 1
```

	verified_ratings	main_category
1836	69.0	Gaming

```
Category: Garden & Outdoors, Outliers: 5
```

	verified_ratings	main_category
1153	42.0	Garden & Outdoors
1222	35.0	Garden & Outdoors
1542	37.0	Garden & Outdoors

1666	49.0	Garden & Outdoors
1910	31.0	Garden & Outdoors

```
Category: Grocery, Outliers: 2
```

	verified_ratings	main_category
198	1587.0	Grocery
1224	1711.0	Grocery

```
Category: Health & Beauty, Outliers: 59
```

	verified_ratings	main_category
6	1312.0	Health & Beauty
10	1082.0	Health & Beauty
11	2165.0	Health & Beauty
15	3255.0	Health & Beauty
17	419.0	Health & Beauty

```
Category: Home & Office, Outliers: 60
```

	verified_ratings	main_category
0	3867.0	Home & Office
3	2092.0	Home & Office
5	3891.0	Home & Office
7	1164.0	Home & Office
9	1919.0	Home & Office

```
Category: Industrial & Scientific, Outliers: 3
```

	verified_ratings	main_category
565	494.0	Industrial & Scientific
754	19.0	Industrial & Scientific
1485	64.0	Industrial & Scientific

```
Category: Musical Instruments, Outliers: 2
```

	verified_ratings	main_category
1947	36.0	Musical Instruments
1986	50.0	Musical Instruments

```
Category: Pet Supplies, Outliers: 2
```

	verified_ratings	main_category
1388	27.0	Pet Supplies
1752	17.0	Pet Supplies

```
Category: Phones & Tablets, Outliers: 48
```

	verified_ratings	main_category
1	557.0	Phones & Tablets
2	523.0	Phones & Tablets
99	4080.0	Phones & Tablets
101	2866.0	Phones & Tablets
104	296.0	Phones & Tablets

```
Category: Sporting Goods, Outliers: 1
```

	verified_ratings	main_category
1209	195.0	Sporting Goods

```
Category: Toys & Games, Outliers: 4
```

	verified_ratings	main_category
58	104.0	Toys & Games
348	50.0	Toys & Games
541	8.0	Toys & Games
748	8.0	Toys & Games

Expolatory Data Analysis

Discount analysis

Cleaning the Price Data

In [106…

```python
# Function to handle price ranges by calculating the average price
def handle_price_range(price):
    if isinstance(price, str) and '-' in price:
        # Split the range and calculate the average
        low, high = price.split(' - ')
        low = pd.to_numeric(low.replace('KSh', '').replace(',', '').strip(), e
        high = pd.to_numeric(high.replace('KSh', '').replace(',', '').strip(),
        return (low + high) / 2
    return price

# Clean 'current_price' and 'original_price' columns
df['current_price_numeric'] = df['current_price'].apply(clean_price)
df['original_price_numeric'] = df['original_price'].apply(clean_price)

# Apply the function to handle price ranges
df['current_price_numeric'] = df['current_price_numeric'].apply(handle_price_r
df['original_price_numeric'] = df['original_price_numeric'].apply(handle_price
```

Cleaning the Discount Column

In [107…

```
# Clean 'discount' column to ensure it's numeric
df['discount_percentage'] = df['discount'].replace({'%': '', ',': ''}, regex=T
```

Calculating the Correlation

In [108…

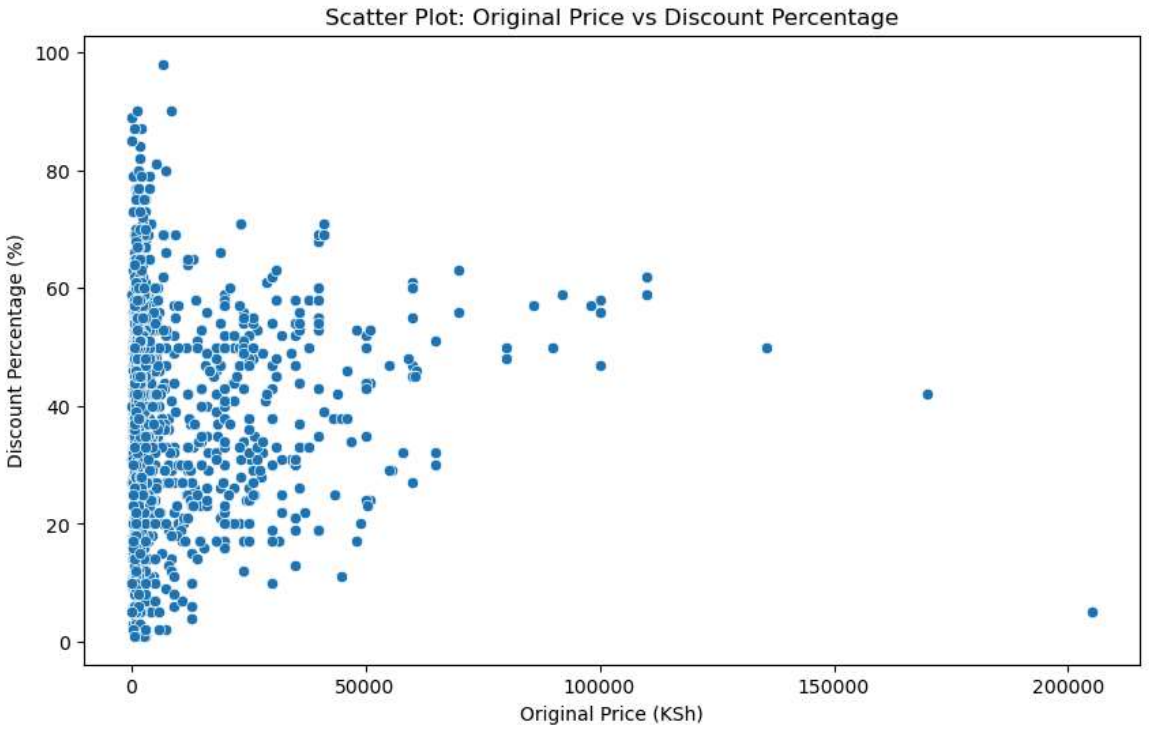
```
# Calculate the correlation between original price and discount percentage
correlation = df['original_price_numeric'].corr(df['discount_percentage'])

# Display the correlation result
print(f"Correlation between original price and discount percentage: {correlati
```

```
Correlation between original price and discount percentage: 0.07583960344314469
```

Visualizing the Data with a Scatter Plot

In [109…

```
# Scatter plot to visualize the relationship between original price and discou
plt.figure(figsize=(10, 6))
sns.scatterplot(x='original_price_numeric', y='discount_percentage', data=df)
plt.title("Scatter Plot: Original Price vs Discount Percentage")
plt.xlabel("Original Price (KSh)")
plt.ylabel("Discount Percentage (%)")
plt.show()
```



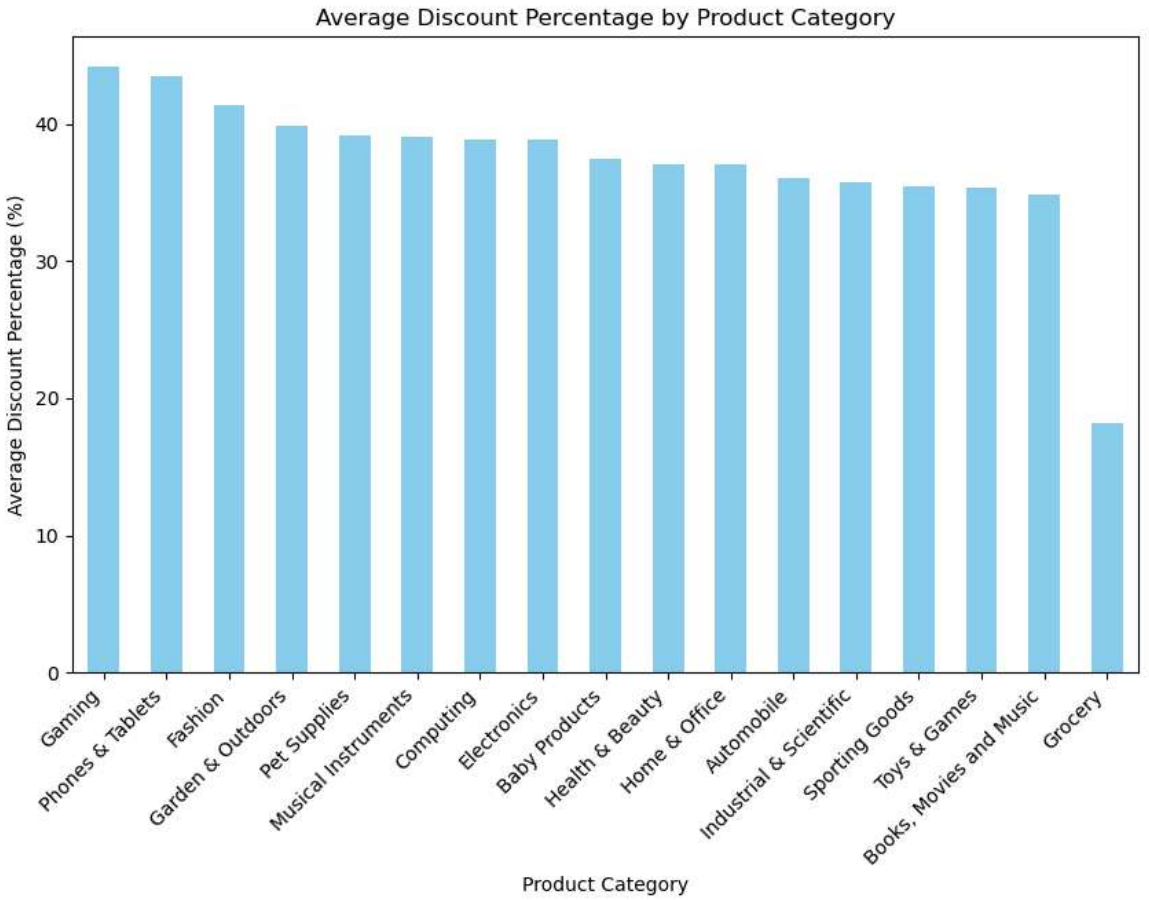
The analysis of the relationship between product prices and discount percentages

The analysis of the relationship between product prices and discount percentages revealed a very weak positive correlation of 0.0758. This suggests that there is no strong linear relationship between higher product prices and the discount percentage offered. In other words, higher-priced products are not necessarily associated with higher discounts, and the discounting strategy appears to be relatively independent of product pricing in this dataset.

Discounts by Product Category

In [110…

```
# Grouping by 'main_category' and calculating the average discount percentage
category_discount = df.groupby('main_category')['discount_percentage'].mean().

# Plotting the results
plt.figure(figsize=(10, 6))
category_discount.plot(kind='bar', color='skyblue')
plt.title("Average Discount Percentage by Product Category")
plt.xlabel("Product Category")
plt.ylabel("Average Discount Percentage (%)")
plt.xticks(rotation=45, ha="right")
plt.show()
```



Gaming and Phones & Tablets are the categories with the highest average discount percentages, both slightly above 40%. This suggests that retailers might offer higher discounts in these categories, possibly due to competition or product lifecycle considerations (e.g., clearance of older models or new releases).

Grocery stands out as having a much lower discount percentage, which is typical, as grocery items generally have lower profit margins and are less likely to have significant discounts compared to electronics or fashion products.

The remaining categories, such as Fashion, Computing, and Health & Beauty, all show moderate discount percentages, ranging from 20% to 40%. This suggests a similar discounting strategy across these common consumer product categories.

Discounts by Price Range

In [111…

```
# Define price ranges (e.g., Low: < 1000, Mid: 1000-5000, High: > 5000)
bins = [0, 1000, 5000, 10000, float('inf')]
labels = ['Low', 'Mid', 'High', 'Very High']
df['price_range'] = pd.cut(df['original_price_numeric'], bins=bins, labels=lab

# Grouping by price range and calculating the average discount percentage
price_range_discount = df.groupby('price_range')['discount_percentage'].mean()

# Plotting the results
plt.figure(figsize=(10, 6))
price_range_discount.plot(kind='bar', color='lightcoral')
plt.title("Average Discount Percentage by Price Range")
plt.xlabel("Price Range")
plt.ylabel("Average Discount Percentage (%)")
plt.xticks(rotation=0)
plt.show()
```

```
C:\Users\user\AppData\Local\Temp\ipykernel_37676\2681739294.py:7: FutureWarnin
g: The default of observed=False is deprecated and will be changed to True in a
future version of pandas. Pass observed=False to retain current behavior or obs
erved=True to adopt the future default and silence this warning.
  price_range_discount = df.groupby('price_range')['discount_percentage'].mean
()
```

This suggests that discounts are relatively consistent across all price ranges. In other words, products of different price levels (low, mid, high) do not show significant variation in discount percentages, which is contrary to the expectation that higher-priced products would necessarily receive higher discounts.

Discounts by Ratings

In [112…

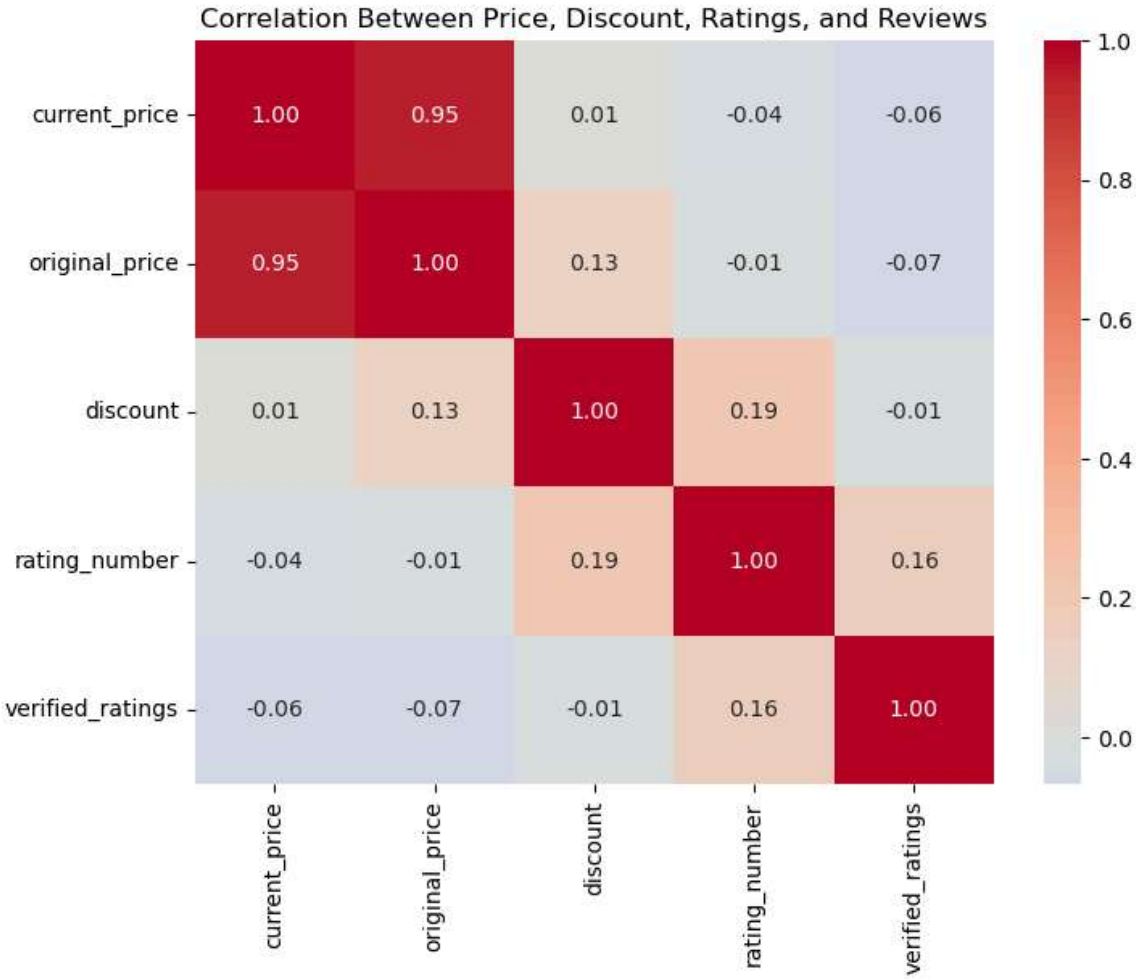
```
# First, ensure the 'rating_number' is numeric (it may have been read as a str
df['rating_number'] = pd.to_numeric(df['rating_number'], errors='coerce')

# Grouping by 'rating_number' and calculating the average discount percentage
rating_discount = df.groupby('rating_number')['discount_percentage'].mean()

# Plotting the results
plt.figure(figsize=(10, 6))
rating_discount.plot(kind='line', marker='o', color='purple')
plt.title("Average Discount Percentage by Product Rating")
plt.xlabel("Rating Number")
plt.ylabel("Average Discount Percentage (%)")
plt.grid(True)
plt.show()
```

Numeric columns & Correlations computation

In [113…

```
# Select relevant numeric columns
num_cols = ['current_price', 'original_price', 'discount', 'rating_number', '
```

```
corr = data[num_cols].corr()

# Heatmap
plt.figure(figsize=(8,6))
sns.heatmap(corr, annot=True, cmap="coolwarm", center=0, fmt=".2f")
plt.title("Correlation Between Price, Discount, Ratings, and Reviews")
plt.show()
```



This shows which features are positively/negatively correlated with current_price.

- High positive correlation with original_price : current price is usually derived from the original price (discounted).
- Correlation with discount : Discounts don't strongly drive prices. This matches what we saw in scatterplots — discounts are more about marketing than actual price level.
- Correlations with ratings or reviews : More expensive products don't necessarily get higher ratings or more reviews. In fact, popularity tends to be for cheaper items, confirming what we saw earlier.
- Discount vs Ratings / Reviews : Slight tendency for discounted products to attract more ratings, but the effect is very small

more ratings, but the effect is very small.

- Ratings vs Reviews : Makes sense, products with many reviews tend to also have higher rating averages, though not strongly.

% of Competitive Products per Category

In [114…

```
# Compute median price per category
category_medians = data.groupby('main_category')['current_price'].median()

# Define competitive product
data['competitive'] = data.apply(
    lambda row: 1 if (row['current_price'] <= category_medians[row['main_categ
                   and (row['rating_number'] >= 4.0)
                else 0, axis=1
)
```

In [115…

```
competitive_summary = data.groupby('main_category')['competitive'].mean() * 10
print(competitive_summary.sort_values(ascending=False))
```

```
main_category
Grocery                    47.058824
Computing                  32.673267
Sporting Goods             31.250000
Automobile                 29.729730
Gaming                     28.571429
Home & Office              28.165375
Health & Beauty            26.506024
Industrial & Scientific    26.086957
Baby Products              23.076923
Toys & Games               19.512195
Electronics                18.539326
Pet Supplies               18.181818
Garden & Outdoors          16.279070
Fashion                    14.245014
Phones & Tablets           13.636364
Books, Movies and Music    12.280702
Musical Instruments         0.000000
Name: competitive, dtype: float64
```

We needed to know how products are well priced and rated compared to others in the same category.

- For the price, median is a good measure of a "typical" price in each category. Using category-specific medians allows us to normalize comparisons across categories.
- For rating we choose a high rate (≥ 4.0) to count as competitive. This combination balances **value for money** and **customer satisfaction.**

This is what the results mean for Grocery, Phones & Tablets, and Musical Instruments:

Grocery (47%)

- Nearly half of grocery items meet the competitive criteria.
- This reflects a price-sensitive, crowded market where many sellers offer affordable, well-rated items.

Phones & Tablets (14%)

- Very few products are competitive.
- This market is premium-driven: many devices are above median price, and only a small fraction combine affordability with strong ratings.

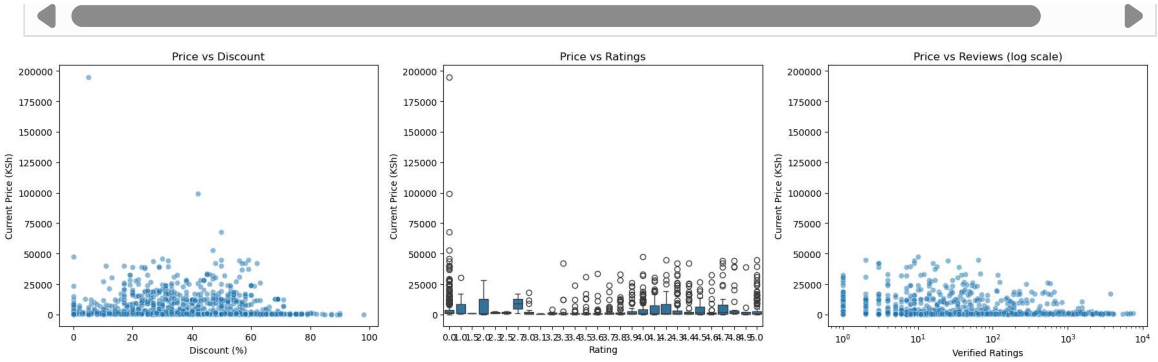
Musical Instruments (0%)

- No products met the competitive definition.
- Likely because this is a specialized niche market with high prices and fewer ratings.

Relationship Between Price and Discount, Ratings, & Reviews Using Graph

In [116…

```
# Ensure numeric types
data['discount'] = pd.to_numeric(data['discount'], errors='coerce')
data['current_price'] = pd.to_numeric(data['current_price'], errors='coerce')
data['verified_ratings'] = pd.to_numeric(data['verified_ratings'], errors='coe
data['rating_number'] = pd.to_numeric(data['rating_number'], errors='coerce')

import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(18,5))

# 1. Price vs Discount
plt.subplot(1,3,1)
sns.scatterplot(data=data, x='discount', y='current_price', alpha=0.5)
plt.title("Price vs Discount")
plt.xlabel("Discount (%)")
plt.ylabel("Current Price (KSh)")

# 2. Price vs Ratings
plt.subplot(1,3,2)
sns.boxplot(data=data, x='rating_number', y='current_price')
plt.title("Price vs Ratings")
plt.xlabel("Rating")
plt.ylabel("Current Price (KSh)")

# 3. Price vs Reviews
plt.subplot(1,3,3)
sns.scatterplot(data=data, x='verified_ratings', y='current_price', alpha=0.5)
plt.xscale("log")   # reviews are often skewed
plt.title("Price vs Reviews (log scale)")
plt.xlabel("Verified Ratings")
plt.ylabel("Current Price (KSh)")

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



We did the visualizations because we wanted to understand the relationships between Price and other key factors:

- Discount (% off from original price)
- Ratings (quality perception from customers)
- Reviews (Verified Ratings) (popularity or trust from customer activity) The relationship help us know if:
- bigger discounts actually lower prices.
- higher-rated products are priced differently
- popular items with many reviews sell at higher or lower prices This is critical for modeling & business insights, since price is central to competitiveness.

Interpretation of the graphs

- Discounts are mostly applied to low/mid-priced products; discounts don't directly correlate with higher prices.
- Price doesn't strongly depend on the rating score. A highly rated product isn't necessarily more expensive; cheap products can also get high ratings.
- Products with many reviews are usually affordable and accessible items, not premium/high-price ones. Popularity tends to go hand-in-hand with affordability.

Pricing vs Ratings.

Why it matters.

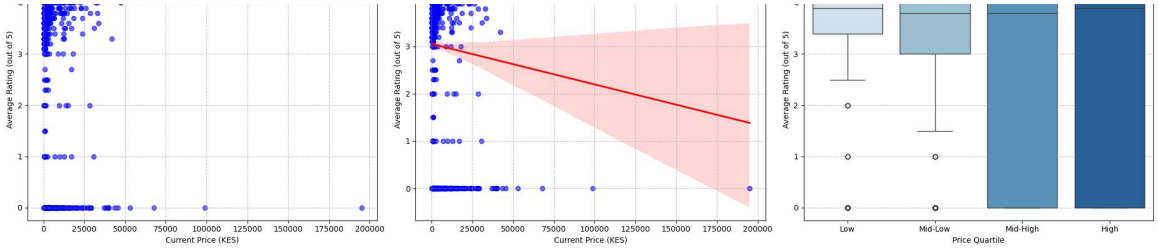
It is crucial because it shows whether higher prices actually translate into higher customer satisfaction. In E-commerce, this insight helps sellers balance competitive pricing with perceived value — proving that success isn't just about lowering prices, but about finding the sweet spot where customers feel they're getting both quality and affordability.

In [117…

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

# --- Correlation ---
correlation = data["current_price"].corr(data["rating_number"])
print(f"Correlation between price and rating: {correlation:.2f}")
```

```
# --- Create price quartiles ---
data["price_quartile"] = pd.qcut(
    data["current_price"],
    q=4,
    labels=["Low", "Mid-Low", "Mid-High", "High"]
)

# --- Setup subplots (3 side by side) ---
fig, axes = plt.subplots(1, 3, figsize=(21,6))

# 1️⃣ Scatter only all products
axes[0].scatter(data["current_price"], data["rating_number"], alpha=0.6, color
axes[0].set_title("Scatter: Price vs Rating")
axes[0].set_xlabel("Current Price (KES)")
axes[0].set_ylabel("Average Rating (out of 5)")
axes[0].grid(True, linestyle="--", alpha=0.7)

# 2️⃣ Scatter + Regression Line
sns.regplot(
    x="current_price",
    y="rating_number",
    data=data,
    scatter_kws={"alpha":0.6, "color":"blue"},
    line_kws={"color":"red"},
    ax=axes[1]
)
axes[1].set_title("Scatter + Trendline")
axes[1].set_xlabel("Current Price (KES)")
axes[1].set_ylabel("Average Rating (out of 5)")
axes[1].grid(True, linestyle="--", alpha=0.7)

# 3️⃣ Boxplot by Price Quartiles
sns.boxplot(
    x="price_quartile",
    y="rating_number",
    data=data,
    palette="Blues",
    ax=axes[2]
)
axes[2].set_title("Ratings Across Price Quartiles")
axes[2].set_xlabel("Price Quartile")
axes[2].set_ylabel("Average Rating (out of 5)")
axes[2].grid(axis="y", linestyle="--", alpha=0.7)

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

```
Correlation between price and rating: -0.04
C:\Users\user\AppData\Local\Temp\ipykernel_37676\1790915775.py:40: FutureWarnin
g:

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 e
ffect.

  sns.boxplot(
```



Findings: Price vs Ratings

- The **correlation is near zero (~-0.04)**, showing that **price and ratings have almost no meaningful relationship** in our dataset.
- **Premium products** (e.g., smartphones) do earn solid ratings, but this isn't consistent enough to prove that higher prices guarantee better reviews.
- **Budget products** (like fashion items) also perform well in ratings, proving that affordability and value-for-money matter just as much as price.
- **Mid-range items** still hover around average ratings, suggesting that shoppers can be more critical in this tier.

The scatter showed **no clear upward or downward trend** → ratings are spread across all price points, meaning customers do not base their satisfaction primarily on price. From our data set, 5-star products cluster more in the **mid and lower price ranges** rather than at the very top. Premium products can get good ratings, but affordable items often achieve 5 stars too, since buyers love value-for-money.

Recommendations

- **Do not rely on pricing alone** as a driver for higher ratings — quality, durability, and user experience matter more.
- **Invest in product quality and customer service** across all tiers, as both budget and premium buyers reward value-for-money.
- **Highlight customer value in marketing** for affordable and mid-range items, since they have strong potential to earn top ratings.
- **For premium products**, focus on showcasing unique features and after-sales support, which could justify higher prices and improve satisfaction.

Conclusion

The analysis shows that **price has little to no influence on customer ratings**. While higher-end products can receive good reviews, **affordable and mid-range items are just as likely to achieve 5-star ratings** when they deliver strong value. This suggests that to boost customer satisfaction and ratings, the company should prioritize **quality, perceived value, and customer experience** over pricing strategies alone.

Price Landscape (Category-level Pricing)

Purpose

Turn an **already-cleaned** product table (`data`) into **category-level price context** that is easy to use in analysis, dashboards, and machine-learning features.

What the function does

`build_price_landscape_simple(df, price_col="current_price", category_col="main_category", out_dir="price_landscape_outputs")` :

- **Validates & filters**: keeps rows with a non-null, positive price and a category.
- **Aggregates**: computes **median price** and **count** per category.
- **Visualizes**:
  - **Bar chart** — Top 15 categories by median price.
  - **Histogram** — distribution of prices (tail clipped for readability).
  - **Boxplots** — price spread for Top 10 categories by item count.
- **Exports**:
  - `median_price_by_category.csv`
  - Three PNG charts for quick sharing.
- **Returns**: a dictionary with the median table, file paths, and quick summary stats (top-5 expensive/cheap categories, distribution quantiles).

Why this is useful for modeling

- **Category priors**: raw prices aren't comparable across categories (e.g., Electronics vs Grocery). Per-category medians provide a stable baseline.
- **Feature engineering (drop-in)**:
  - `price_to_cat_median = current_price / median_category_price`
  - `is_below_cat_median = 1[current_price < median_category_price]`
    These give the model **relative price** context and often outperform raw price.
- **Robust to skew**: medians reduce sensitivity to outliers, improving stability.
- **Interpretable**: medians/spreads are easy to explain and help debug anomalies.
- **Leakage-safe**: built from current cleaned data, aggregated **by category only** (no future labels).

How it works (pipeline steps)

1. **Select & coerce** `price_col` to numeric; drop invalid or non-positive prices.
2. **Group & aggregate** by `category_col` → median price + item count.
3. **Save** the aggregation to CSV for downstream usage.
4. **Plot** bar/hist/box charts for fast EDA and reporting.
5. **Summarize** high/low categories and distribution stats (min, quartiles, p90/p95,

max).

In [118…

```
PL_PRICE_COL = 'current_price'
PL_CATEGORY_COL = 'main_category'
PL_OUT_DIR = 'price_landscape_outputs'
```

In [119…

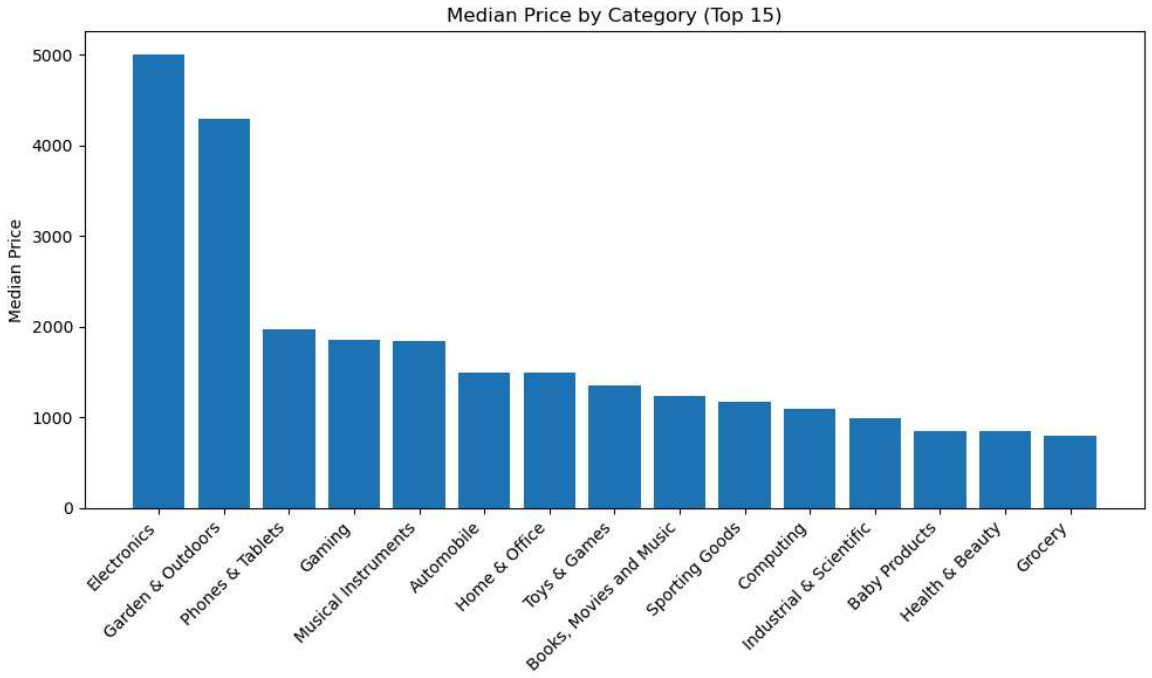
```
def build_price_landscape_simple(
    df: pd.DataFrame,
    price_col: str = "current_price",      # numeric (or coercible)
    category_col: str = "main_category",   # cleaned category
    out_dir: str = "price_landscape_outputs",
    hist_clip_pct: float = 0.99            # clip extreme tail for nicer hist
):
    """
    Minimal Price Landscape for already-cleaned data.
    - Computes median price by category (+count)
    - Exports CSV + bar (top-15), histogram, boxplot (top-10 by count)
    - Robust to empty categories; uses Matplotlib 3.9+ tick_labels

    Returns:
        dict with {median_by_cat, paths, rows_used}
    """
    os.makedirs(out_dir, exist_ok=True)

    # 1) Ensure expected columns and light numeric coercion
    if price_col not in df.columns:
        raise ValueError(f"Price column '{price_col}' not in DataFrame.")
    if category_col not in df.columns:
        raise ValueError(f"Category column '{category_col}' not in DataFrame.'

    work = df[[category_col, price_col]].copy()
    work[price_col] = pd.to_numeric(work[price_col], errors="coerce")
    work = work.dropna(subset=[category_col, price_col])
    work = work[work[price_col] > 0]
    work = work.rename(columns={category_col: "_main_category", price_col: "_c

    rows_used = int(len(work))
    if rows_used == 0:
        raise RuntimeError("No rows to plot after filtering. Check your cleane

    # 2) Median by category (+count)
    median_by_cat = (
        work.groupby("_main_category", as_index=False)
            .agg(median_price=("_current_price_num", "median"),
                 count=("_current_price_num", "size"))
            .sort_values("median_price", ascending=False)
    )
    medians_path = os.path.join(out_dir, "median_price_by_category.csv")
    median_by_cat.to_csv(medians_path, index=False)

    # 3) Bar chart (Top 15 by median)
    top = median_by_cat.head(15)
    plt.figure(figsize=(10, 6))
    plt.bar(top["_main_category"], top["median_price"])
    plt.xticks(rotation=45, ha="right")
    plt.ylabel("Median Price")
    plt.title("Median Price by Category (Top 15)")
    plt.tight_layout()
```

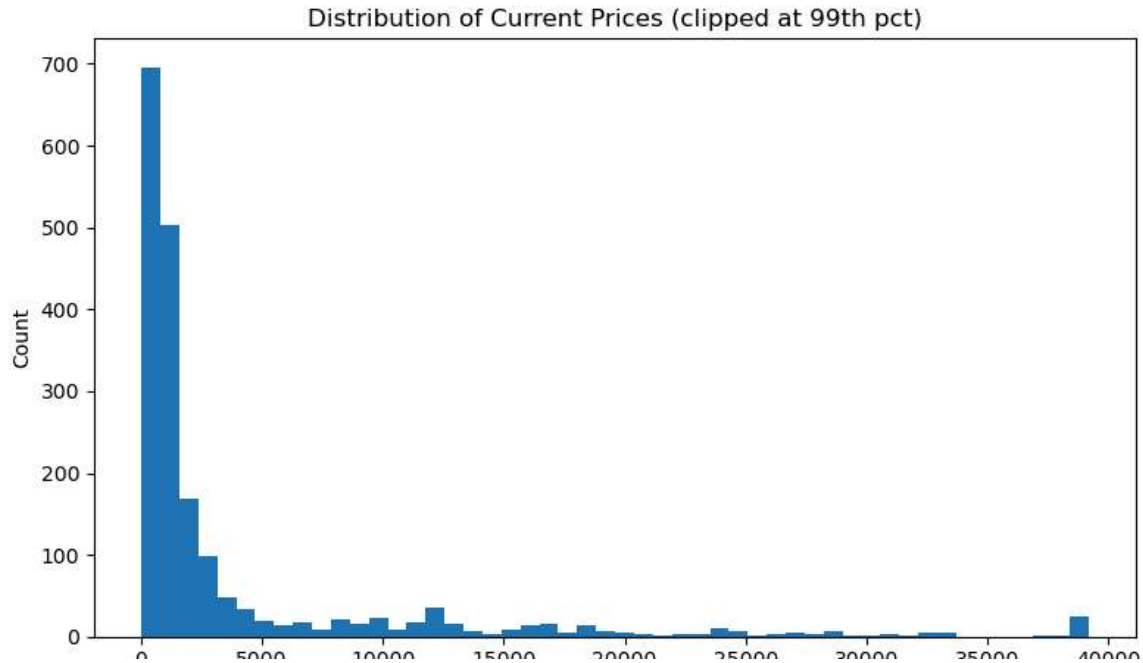
```
    bar_path = os.path.join(out_dir, "median_price_by_category_top15.png")
    plt.savefig(bar_path, dpi=150)
    plt.show()

    # 4) Histogram (clip tail for readability)
    vals = work["_current_price_num"].dropna().to_numpy()
    if vals.size:
        cap = np.quantile(vals, hist_clip_pct)
        vals = np.clip(vals, a_min=0, a_max=cap)
    plt.figure(figsize=(8, 5))
    plt.hist(vals, bins=50)
    plt.xlabel("Current Price")
    plt.ylabel("Count")
    plt.title(f"Distribution of Current Prices (clipped at {int(hist_clip_pct*
    plt.tight_layout()
    hist_path = os.path.join(out_dir, "price_distribution_hist.png")
    plt.savefig(hist_path, dpi=150)
    plt.show()

    # 5) Boxplots (Top 10 by count) — robust to empties + Matplotlib 3.9 param
    top10 = work["_main_category"].value_counts().head(10).index.tolist()
    box_df = work[work["_main_category"].isin(top10)]
    data_to_plot, labels_to_plot = [], []
    for c in top10:
        arr = box_df.loc[box_df["_main_category"] == c, "_current_price_num"].
        arr = arr[~np.isnan(arr)]
        if arr.size > 0:
            data_to_plot.append(arr)
            labels_to_plot.append(c)

    if data_to_plot:
        plt.figure(figsize=(10, 6))
        plt.boxplot(data_to_plot, tick_labels=labels_to_plot, showfliers=False
        plt.xticks(rotation=45, ha="right")
        plt.ylabel("Current Price")
        plt.title("Price Range by Category (Top 10 by count)")
        plt.tight_layout()
        box_path = os.path.join(out_dir, "boxplot_price_by_category_top10.png"
        plt.savefig(box_path, dpi=150)
        plt.show()
    else:
        box_path = None
        print("[WARN] No non-empty categories for boxplot; skipping.")

    # 6) Quick answers for report
    answers = {
        "top5_highest_median": median_by_cat.head(5).to_dict(orient="records")
        "top5_lowest_median": median_by_cat.sort_values("median_price").head(5
        "distribution": {
            "min": float(work["_current_price_num"].min()),
            "q25": float(work["_current_price_num"].quantile(0.25)),
            "median": float(work["_current_price_num"].median()),
            "q75": float(work["_current_price_num"].quantile(0.75)),
            "p90": float(work["_current_price_num"].quantile(0.90)),
            "p95": float(work["_current_price_num"].quantile(0.95)),
            "max": float(work["_current_price_num"].max()),
        },
    }

    return {
```

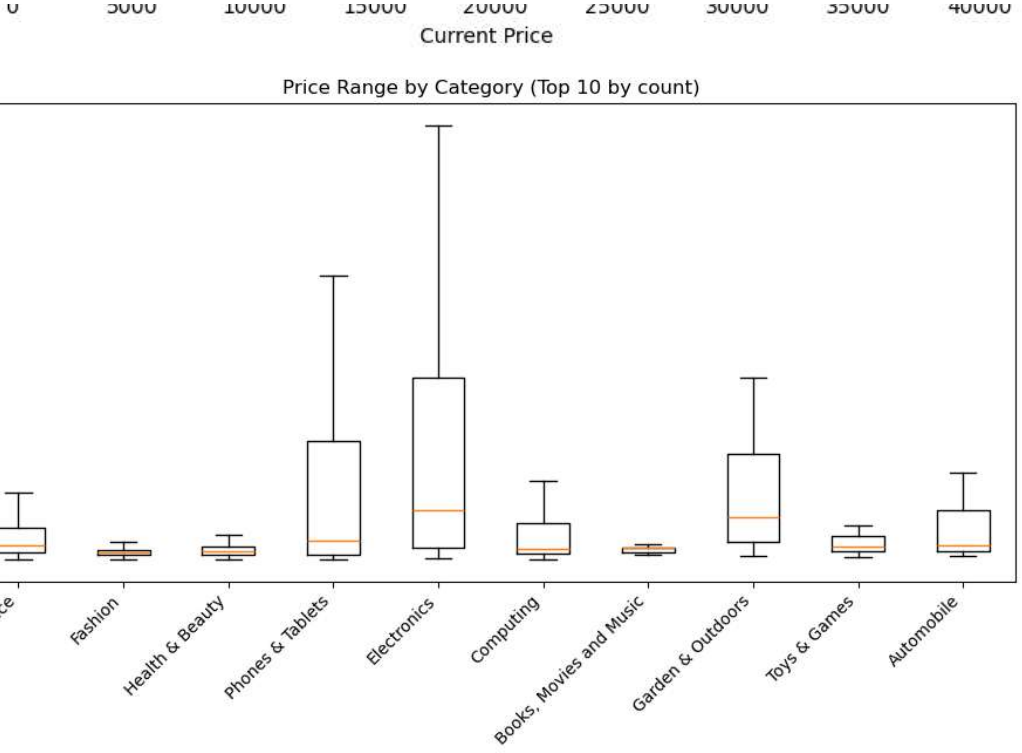
```
        "rows_used": rows_used,
        "median_by_cat": median_by_cat,
        "paths": {"medians_csv": medians_path, "bar": bar_path, "hist": hist_p
        "answers": answers,
    }
```

In [120…

```
pl = build_price_landscape_simple(
    data,                       # cleaned DataFrame
    price_col="current_price", # already numeric/cleaned
    category_col="main_category",
    out_dir=PL_OUT_DIR
)

pl["paths"], pl["answers"]
pl["median_by_cat"].head()
```







Out[120…

	_main_category	median_price	count
4	Electronics	5009.5	178
7	Garden & Outdoors	4300.0	43
14	Phones & Tablets	1974.5	264
6	Gaming	1852.0	7
12	Musical Instruments	1850.0	11

1) Bar chart — "Median Price by Category (Top 15)"

the middle (median) price for each category, sorted high → low.

- Electronics sits highest (≈ 5k KSh median), then Garden & Outdoors, then Phones & Tablets.
- Mid-tier medians: Gaming, Musical Instruments, Automobile, Home & Office.
- Lower medians: Computing, Industrial & Scientific, Baby Products, Health & Beauty, Grocery.

Significance; Categories naturally live at very different price levels. Raw price alone confuses models; use relative price features, e.g. price / median_category_price and a flag price_below_cat_median.

2) Histogram — "Distribution of Current Prices"

counts of items across the entire price range.

- Extremely right-skewed (long tail). Most products cluster at low prices; a small

number reach very high prices (tens of thousands to ~200k KSh).

Significance; Use log(price) or rank/quantile within category for analysis and modeling. For dashboards, consider a log x-axis or clip/winsorize (e.g., cap at 99th percentile) to make the bulk visible.

3) Boxplots — "Price Range by Category (Top 10 by count)"

per-category spread (median line, IQR box, whiskers, outliers).

- Electronics and Garden & Outdoors: wide spread and high upper whiskers → many premium items and big variation.
- Phones & Tablets: median below Electronics but still a broad range (budget → flagship).
- Home & Office, Fashion, Health & Beauty: lower medians and tighter spreads → more uniformly priced.
- Several categories show outliers (dots/long whiskers) → a few very expensive products.

Significance; When comparing prices, always compare within category. Outlier handling matters: cap or model them separately if they're legit luxury SKUs.

Pratical Steps for preparing modelling

1. Relative features

In [121…

```
# Join medians back for feature engineering
cat_medians = pl["median_by_cat"].rename(columns={"_main_category":"main_categ
model_df = data.merge(cat_medians, on="main_category", how="left")

model_df["price_to_cat_median"] = model_df["current_price"] / model_df["median
model_df["is_below_cat_median"] = (model_df["price_to_cat_median"] < 1.0).asty
```

Price Watchlist (≤ 90% of Category Median)

- Identifing products priced at or below 90% of their category's median price to flag potential deals. filters, compares, and highlights the best-priced products within each category for easy deal monitoring.

1. Defining output folder and key parameters — threshold (90%), top 50 overall, and top 5 per category.
2. Automatically find relevant columns like price, category, title, and URL.
3. Keeping only valid prices and categories, and convert prices to numeric values.
4. Computing the median price for each category.
5. Comparing each product's price to its category median; keep those ≤ 90%.

6. Reattaching titles and URLs for readability.
7. Saving top 50 overall deals and top 5 per category as CSV files.
8. Showing the top results directly in the notebook.

In [122…

```
# Watchlist (≤ 90% of category median) for an already-cleaned `data`
OUT_DIR = "price_landscape_outputs"
os.makedirs(OUT_DIR, exist_ok=True)

WATCH_THRESHOLD = 0.90   # deal threshold (≤ 90% of category median)
TOPN_OVERALL    = 50     # how many rows to keep overall
TOPN_PER_CAT    = 5      # top rows per category

# 0) Column detection on cleaned frame
cols = list(data.columns)
low  = {c: c.lower() for c in cols}

price_col = next((c for c in cols if low[c] == "current_price"), None) \
        or next((c for c in cols if "price" in low[c]), None)
cat_col   = "main_category" if any(c.lower() == "main_category" for c in cols)
title_col = next((c for c in cols if any(k in low[c] for k in ["title","name"
url_col   = next((c for c in cols if any(k in low[c] for k in ["url","link"]))
key_col   = next((c for c in cols if any(k in low[c] for k in ["sku","product_
        or title_col or url_col or cols[0]

if price_col is None:
    raise ValueError("Could not find a price column (e.g., 'current_price').")
if cat_col is None:
    raise ValueError("Cleaned data must include 'main_category'.")

# 1) Ensure numeric price in `price_num`
watch = data[[key_col, cat_col, price_col]].copy()
watch.columns = ["key", "main_category", "price_num"]
watch["price_num"] = pd.to_numeric(watch["price_num"], errors="coerce")
watch = watch.dropna(subset=["main_category", "price_num"])
watch = watch[watch["price_num"] > 0]

# 2) Get category medians (prefer the one you already computed; else compute r
try:
    med_df = pl["median_by_cat"].copy()  # from build_price_landscape_simple(.
    if "_main_category" in med_df.columns:
        med_df = med_df.rename(columns={"_main_category": "main_category"})
except Exception:
    med_df = (watch.groupby("main_category", as_index=False)
                   .agg(median_price=("price_num","median")))

# 3) Attach medians via map (avoids duplicate 'key' merge problems)
median_map = med_df.set_index("main_category")["median_price"]
watch["median_price"] = watch["main_category"].map(median_map)

# 4) Compute ratio and filter by threshold
watch["price_to_cat_median"] = watch["price_num"] / watch["median_price"]
watch = watch.dropna(subset=["price_to_cat_median"])
watch_deals = watch[watch["price_to_cat_median"] <= WATCH_THRESHOLD].copy()
watch_deals.sort_values("price_to_cat_median", inplace=True)

# 5) Optional enrichments (title/url) via safe map lookups
def attach_map(df_left, df_src, key, value_col, new_name):
    if (value_col is None) or (value_col == key) or (value_col not in df_src.c
        return df_left
```

```
    # unique key → value mapping
    lut = (df_src[[key, value_col]]
           .dropna(subset=[key])
           .astype({key: str})
           .drop_duplicates(subset=[key])
           .set_index(key)[value_col])
    df_left = df_left.copy()
    df_left["key"] = df_left["key"].astype(str)
    df_left[new_name] = df_left["key"].map(lut)
    return df_left

watch_deals = attach_map(watch_deals, data, key_col, title_col, "title")
watch_deals = attach_map(watch_deals, data, key_col, url_col,   "url")

# 6) Select columns to show/export
cols_show = ["key", "main_category", "price_num", "median_price", "price_to_ca
if "title" in watch_deals.columns: cols_show.insert(1, "title")
if "url"   in watch_deals.columns: cols_show.append("url")

watch_overall = watch_deals[cols_show].head(TOPN_OVERALL)

watch_per_cat = (watch_deals.sort_values("price_to_cat_median")
                 .groupby("main_category", group_keys=False)
                 .head(TOPN_PER_CAT))[cols_show]

# 7) Save
path_overall = os.path.join(OUT_DIR, "watchlist_top50_overall.csv")
path_per_cat = os.path.join(OUT_DIR, "watchlist_top5_per_category.csv")
watch_overall.to_csv(path_overall, index=False)
watch_per_cat.to_csv(path_per_cat, index=False)

print({
    "saved": {"overall": path_overall, "per_category": path_per_cat},
    "counts": {"overall": len(watch_overall), "per_category_rows": len(watch_p
})

# Peek (in notebooks)
try:
    display(watch_overall.head(10))
    display(watch_per_cat.head(10))
except NameError:
    print(watch_overall.head(10))
    print(watch_per_cat.head(10))
```

```
{'saved': {'overall': 'price_landscape_outputs\\watchlist_top50_overall.csv',
'per_category': 'price_landscape_outputs\\watchlist_top5_per_category.csv'}, 'c
ounts': {'overall': 50, 'per_category_rows': 81}}
```

	key	main_category	price_num	median_price	price_to_
1557	https://www.jumia.co.ke/generic-7pcs-silicone-...	Home & Office	26.0	1499.0	
1344	https://www.jumia.co.ke/generic-powder-extensi...	Health & Beauty	23.0	848.5	
14	https://www.jumia.co.ke/rashnik-tv-wall-mount-...	Electronics	200.0	5009.5	
	https://www.jumia.co.ke/generic-	Phones &			

1900	cable-with-mag...	Tablets	81.0	1974.5
1287	https://www.jumia.co.ke/generic-6-in-1-bottle-...	Home & Office	73.0	1499.0
393	https://www.jumia.co.ke/rashnik-tv-wall-mount-...	Electronics	268.0	5009.5
926	https://www.jumia.co.ke/generic-power-adaptor-...	Electronics	270.0	5009.5
1396	https://www.jumia.co.ke/tv-guard-or-fridge-gua...	Electronics	299.0	5009.5
1488	https://www.jumia.co.ke/generic-6a-66w-usb-typ...	Electronics	330.0	5009.5
1668	https://www.jumia.co.ke/generic-10pcs-ag13-a76...	Electronics	335.0	5009.5

	key	main_category	price_num	median_price	price_to_
1557	https://www.jumia.co.ke/generic-7pcs-silicone-...	Home & Office	26.0	1499.0	
1344	https://www.jumia.co.ke/generic-powder-extensi...	Health & Beauty	23.0	848.5	
14	https://www.jumia.co.ke/rashnik-tv-wall-mount-...	Electronics	200.0	5009.5	
1900	https://www.jumia.co.ke/generic-cable-with-mag...	Phones & Tablets	81.0	1974.5	
1287	https://www.jumia.co.ke/generic-6-in-1-bottle-...	Home & Office	73.0	1499.0	
393	https://www.jumia.co.ke/rashnik-tv-wall-mount-...	Electronics	268.0	5009.5	
926	https://www.jumia.co.ke/generic-power-adaptor-...	Electronics	270.0	5009.5	
1396	https://www.jumia.co.ke/tv-guard-or-fridge-gua...	Electronics	299.0	5009.5	
1488	https://www.jumia.co.ke/generic-6a-66w-usb-typ...	Electronics	330.0	5009.5	
1300	https://www.jumia.co.ke/generic-fashion-ladies...	Fashion	57.0	793.0	

Preprocessing and Basic Modelling

In [123…

```
X = data.drop(columns=['current_price'])
y = data['current_price']
```

```
y = data['current_price']
```

In [124…

```
# Redefine features after dropping the target
numeric_features = X.select_dtypes(include=['int64', 'float64']).columns.tolis
categorical_features = X.select_dtypes(include=['object']).columns.tolist()
```

Regression

- Regression Pipeline that preprocesses data and trains a regression model in one step that :
  - Fills missing values of numeric features with the median, then scaled.
  - Converts categorical features into numeric form using one-hot encoding.
  - Combines preprocessing and linear regression modeling into a single, automated workflow for cleaner and more consistent training.

In [126…

```
regression_preprocessor = ColumnTransformer(
    transformers=[
        ("num", Pipeline([
            ("imputer", SimpleImputer(strategy="median")),
            ("scaler", StandardScaler())
        ]), numeric_features),
        ("cat", OneHotEncoder(handle_unknown="ignore"), categorical_features)
    ]
)

regression_pipeline = Pipeline(steps=[
    ("preprocessor", regression_preprocessor),
    ("model", LinearRegression())
])
```

- Model Training and Evaluation Summary :
  - Splits the data into training (80%) and testing (20%) sets.
  - Trains the regression pipeline on the training data.
  - Generates predictions on the test set (X_test).
- Evaluates model performance using:
  - MAE (Mean Absolute Error): average absolute difference between predictions and actual values.
  - MSE (Mean Squared Error): penalizes larger errors more heavily.
  - R^2 Score: measures how well the model explains variance in the target variable (closer to 1 = better fit).

In [127…

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randc

regression_pipeline.fit(X_train, y_train)
```

```
y_pred = regression_pipeline.predict(X_test)

print("Mean Absolute Error (MAE):", mean_absolute_error(y_test, y_pred))
print("Mean Squared Error (MSE):", mean_squared_error(y_test, y_pred))
print("R-squared (R2):", r2_score(y_test, y_pred))
```

```
Mean Absolute Error (MAE): 1004.6303253853312
Mean Squared Error (MSE): 3780680.765871122
R-squared (R2): 0.9596534966559391
```

- The regression model performed very well on the test data.
  - Mean Absolute Error (MAE): On average, the model's predictions differ from the actual values by about 1,005 units, which is relatively small given the overall price scale (depending on your dataset's range).
  - While the MSE seems large numerically, it's expected since errors are squared, what matters more is the strong R^2 score. The model explains approximately 96% of the variance in the target variable, indicating an excellent fit and strong predictive accuracy.
- In summary:
  - The model generalizes well and captures most of the relationship between the input features and the target variable. The low MAE and high R^2 suggest that the pipeline including preprocessing and linear regression is performing effectively, with minimal room for improvement unless finer optimization or additional features are introduced.

KNN

- using KNN to make predictions based on similarity between data points.

In [128…

```
knn_preprocessor = ColumnTransformer(
    transformers=[
        ("num", Pipeline([
            ("imputer", SimpleImputer(strategy="median")),
            ("scaler", StandardScaler())
        ]), numeric_features),
        ("cat", OneHotEncoder(handle_unknown="ignore"), categorical_features)
    ]
)

knn_pipeline = Pipeline(steps=[
    ("preprocessor", knn_preprocessor),
    ("model", KNeighborsRegressor(n_neighbors=5))
])
```

In [129…

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randc

knn_pipeline.fit(X_train, y_train)
```

```
y_pred = knn_pipeline.predict(X_test)

print("Mean Absolute Error (MAE):", mean_absolute_error(y_test, y_pred))
print("Mean Squared Error (MSE):", mean_squared_error(y_test, y_pred))
print("R-squared (R2):", r2_score(y_test, y_pred))
```

```
Mean Absolute Error (MAE): 1366.0207349081363
Mean Squared Error (MSE): 8188042.5534120705
R-squared (R2): 0.9126192062432879
```

- KNN Model Training and Evaluation Summary
  - The dataset is divided into 80% training and 20% testing sets.
  - The knn_pipeline is trained on the training data (X_train, y_train).
  - The trained model predicts target values for the test set (X_test).
- Evaluation Metrics:
  - MAE: 1366.02 — average prediction error of about 1,366 units.
  - MSE: 8,188,042.55 — squared error measure, indicating some large deviations.
  - R^2: 0.91 — the model explains about 91% of the variance in the target variable.
- In summary the KNN model performs well with strong predictive accuracy (R^2 = 0.91), though it's slightly less precise than the linear regression model (R^2 = 0.96). This suggests the regression model generalizes slightly better, while KNN still provides solid performance.

Decision Tree

In [130…

```
dt_preprocessor = ColumnTransformer(
    transformers=[
        ("num", SimpleImputer(strategy="median"), numeric_features),
        ("cat", OneHotEncoder(handle_unknown="ignore"), categorical_features)
    ]
)

dt_pipeline = Pipeline(steps=[
    ("preprocessor", dt_preprocessor),
    ("model", DecisionTreeRegressor(random_state=42, max_depth=10))
])
```

In [131…

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randc

dt_pipeline.fit(X_train, y_train)

y_pred = dt_pipeline.predict(X_test)

print("Mean Absolute Error (MAE):", mean_absolute_error(y_test, y_pred))
print("Mean Squared Error (MSE):", mean_squared_error(y_test, y_pred))
print("R-squared (R2):", r2_score(y_test, y_pred))
```

```
Mean Absolute Error (MAE): 525.0234476842035
Mean Squared Error (MSE): 11029059.003085462
R-squared (R2): 0.8823005713767791
```

- A DecisionTreeRegressor with max_depth=10 and a fixed random_state=42 is used to prevent overfitting and ensure reproducibility.
- Training & Testing:
  - Data is split into 80% training and 20% testing.
  - The pipeline is fitted on training data and predictions are made on the test set.
- Performance Metrics:
  - MAE: 525.02 — average prediction error of about 525 units
  - MSE: 11,029,059.00 — captures some larger deviations.
  - R^2: 0.88 — the model explains 88% of the variance in the target variable.
- In summary the Decision Tree performs reasonably well (R^2 = 0.88), but slightly less accurate than the KNN model (R^2 = 0.91) and the Linear Regression model (R^2 = 0.96). It may capture non-linear patterns but could benefit from tuning depth or ensemble methods for better generalization.

Random Forest

In [132…

```
rf_preprocessor = ColumnTransformer(
    transformers=[
        ("num", SimpleImputer(strategy="median"), numeric_features),
        ("cat", OneHotEncoder(handle_unknown="ignore"), categorical_features)
    ]
)

rf_pipeline = Pipeline(steps=[
    ("preprocessor", rf_preprocessor),
    ("model", RandomForestRegressor(n_estimators=100, random_state=42))
])
```

In [133…

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando

rf_pipeline.fit(X_train, y_train)

y_pred = rf_pipeline.predict(X_test)

print("Mean Absolute Error (MAE):", mean_absolute_error(y_test, y_pred))
print("Mean Squared Error (MSE):", mean_squared_error(y_test, y_pred))
print("R-squared (R2):", r2_score(y_test, y_pred))
```

```
Mean Absolute Error (MAE): 374.9784514435695
Mean Squared Error (MSE): 5298348.901190814
R-squared (R2): 0.9434573123471215
```

- A RandomForestRegressor with 100 decision trees (n_estimators=100) and a fixed random_state=42 ensures consistent and stable results.Random forests reduce overfitting and improve prediction accuracy by averaging multiple trees.

- Performance Metrics:

  - MAE: 374.98 — on average, predictions deviate from actual values by about 375 units.
  - MSE: 5,298,348.90 — shows moderate variance in prediction errors.
  - R^2: 0.94 — the model explains 94% of the variance in the target variable.
- In summary the Random Forest demonstrates strong predictive power and generalization (R^2 = 0.94), outperforming the Decision Tree (R^2 = 0.88) and KNN (R^2 = 0.91), though still slightly below Linear Regression (R^2 = 0.96). Its ensemble approach provides a good balance between bias and variance, making it a robust and reliable model for this dataset.

Neural Networks

In [134…

```
nn_preprocessor = ColumnTransformer(
    transformers=[
        ("num", Pipeline([
            ("imputer", SimpleImputer(strategy="median")),
            ("scaler", StandardScaler())
        ]), numeric_features),
        ("cat", OneHotEncoder(handle_unknown="ignore"), categorical_features)
    ]
)

nn_pipeline = Pipeline(steps=[
    ("preprocessor", nn_preprocessor),
    ("model", MLPRegressor(hidden_layer_sizes=(100,50), max_iter=500, random_s
])
```

In [135…

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randc

nn_pipeline.fit(X_train, y_train)

y_pred = nn_pipeline.predict(X_test)

print("Mean Absolute Error (MAE):", mean_absolute_error(y_test, y_pred))
print("Mean Squared Error (MSE):", mean_squared_error(y_test, y_pred))
print("R-squared (R2):", r2_score(y_test, y_pred))
```

```
Mean Absolute Error (MAE): 2189.1147741680406
Mean Squared Error (MSE): 12194656.414946878
R-squared (R2): 0.8698615999883393
c:\Users\user\anaconda3\envs\clean_env\Lib\site-packages\sklearn\neural_network
\_multilayer_perceptron.py:781: ConvergenceWarning: Stochastic Optimizer: Maxim
um iterations (500) reached and the optimization hasn't converged yet.
```

```
warnings.warn(
```

- The model uses an MLPRegressor (Multi-Layer Perceptron) with two hidden layers:
  - Layer 1: 100 neurons
  - Layer 2: 50 neurons
  - The model runs for up to 500 iterations with a fixed random_state=42 for reproducibility. .
- Training & Testing:
  - Data split into 80% training and 20% testing sets.
  - The neural network learns complex non-linear relationships during training and makes predictions on unseen test data.
- Performance Metrics:
  - MAE: 2189.11 — the model's average absolute prediction error is relatively high.
  - MSE: 12,194,656.41 — reflects large squared errors due to poor convergence.
  - R^2: 0.87 — the model explains 87% of the variance, lower than Random Forest (0.94) and Linear Regression (0.96).

In summary the Neural Network model underperforms compared to other regressors, likely due to incomplete convergence and potential overfitting or suboptimal hyperparameters. With better tuning (e.g., more iterations, adjusted learning rate, or regularization), its performance could improve. However, in its current state, it's less efficient and less accurate than the other models tested.

Fine tuning the models.

- Objective:
  - Fine-tune and compares three regression models (Ridge Regression, Lasso Regression, and Random Forest) — to identify the best-performing model for predicting the target variable.
- Data Preparation:
  - Data is split into 80% training and 20% testing sets.
  - Numeric features → imputed with median values and standardized using StandardScaler.
  - Categorical features → encoded using OneHotEncoder to handle non-numeric variables.
- Model Tuning (GridSearchCV):
  - Each model is wrapped in a Pipeline and tuned using GridSearchCV (3-fold cross-validation, scoring="r2")

cross-validation, scoring='r2').

- Search ranges:
  - Ridge Regression: alpha values from 0.01 to 100.
  - Lasso Regression: alpha values from 0.001 to 10.
  - Random Forest: combinations of tree depth, number of estimators, and split/leaf parameters.

- Result Overview:

Model	MAE	MSE	RMSE	R^2
Random Forest	285.90	721,254	849.27	0.9923
Ridge Regression	1001.57	3,691,000	1921.20	0.9606
Lasso Regression	815.11	3,692,944	1921.70	0.9606

- Interpretation:
  - Random Forest achieved the highest R^2 (0.99), indicating exceptional predictive accuracy and a strong ability to capture non-linear relationships.
  - Both Ridge and Lasso regressions performed similarly, with $R^2 \approx 0.96$, showing solid linear modeling capability but less flexibility than Random Forest.

Overall, Random Forest stands out as the best-performing model after hyperparameter tuning, offering the lowest error and highest explanatory power.

In [136…

```
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import Ridge, Lasso
# ----------------------------
# Train/test split
# ----------------------------
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando

# ----------------------------
# Preprocessor
# ----------------------------
regression_preprocessor = ColumnTransformer(
    transformers=[
        ("num", Pipeline([
            ("imputer", SimpleImputer(strategy="median")),
            ("scaler", StandardScaler())
        ]), numeric_features),
        ("cat", OneHotEncoder(handle_unknown="ignore"), categorical_features)
    ]
)

# ----------------------------
# Define models & params
# ----------------------------
models = {
    "Ridge Regression": Ridge(random_state=42),
    "Lasso Regression": Lasso(random_state=42),
    "Random Forest": RandomForestRegressor(random_state=42)
}

param grids = {
```

```
    "Ridge Regression": {
        "model__alpha": [0.01, 0.1, 1.0, 10.0, 100.0]
    },
    "Lasso Regression": {
        "model__alpha": [0.001, 0.01, 0.1, 1.0, 10.0]
    },
    "Random Forest": {
        "model__n_estimators": [100, 200],
        "model__max_depth": [None, 10, 20],
        "model__min_samples_split": [2, 5],
        "model__min_samples_leaf": [1, 2]
    }
}

# ----------------------------
# Training & Evaluation
# ----------------------------
results = []

for name, model in models.items():
    pipe = Pipeline(steps=[
        ("preprocessor", regression_preprocessor),
        ("model", model)
    ])

    # Fine-tune
    search = GridSearchCV(
        pipe, param_grids[name],
        cv=3, scoring="r2",
        n_jobs=-1, verbose=1
    )
```