Enhancing Sales for Big Basket

A Final report for the BDM capstone Project

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Executive Summary

BigBasket, among India's largest online grocery platforms, increasingly faces the pressure from fast delivery competitors like Zepto, Blinkit and Instamart. While BigBasket has the largest range of products compared to its competitors, BigBasket cannot always satisfy inventory issues and customer complaints—mainly regarding the quality of products. This report outlines dedicated knowledge and insights into the best practices of deal pricing (market prices and sale prices), with a customer ratings function and understanding the stock levels of goods.

The data, titled as "**Big Basket Entire Product List (~28k points)".** was obtained from Kaggle. The dataset features 27,555 data points against 10 features and features information about their products, including product name, category, market price, sale price, discount, customer rating, and brand. The dataset was cleaned, and exploratory data analysis (EDA) was performed using Python tools (Pandas, Matplotlib, Seaborn). Box plots were created to assess items for outliers, line graphs and bar charts were then created to assess trends. Descriptive statistics reported that the average sale price was ₹322.51, the average rating was 3.94, and the mean discount was 11.83%.

There are several key findings to highlight. Market prices are artificially inflated in order to create a larger discount value (50-60%); two categories that primarily represented this were Beauty and Hygiene and Gourmet Foods. High counts of dissatisfaction exist among products with ratings ≤ 2.5. Skin Care and Fragrances were two categories that contained the most dissatisfaction; however, in comparison Turmeric and Ghee showed high demand but consistently low stock levels.

My interpretation of these findings is that there should be improved pricing transparency into the marketplace, improved quality control in poorly scored categories, and better stock optimization for top-selling gross products. Improving stock management and genuine discount practices can help build customer trust and satisfaction and revenue performance.

Proof of Originality

This report, "Enhancing Sales for Big Basket" is secondary data collected from publicly available sources. The data is obtained from Kaggle and was analyzed. Kaggle is a widely recognized platform for open-access dataset used in research and data-driven projects. Comprehensive information on BigBasket's product listings, like product names, categories, brand, descriptions, pricing, and customer rating has been provided by the dataset.

Dataset details

- **Dataset Name:** Big Basket Entire Product List (~28K datapoints)
- **Dataset Link:** https://www.kaggle.com/datasets/surajjha101/bigbasket-entire-product-list-28k-datapoints/data
- **Dataset Source:** Kaggle
- **Data Analysis Colab Link:** https://colab.research.google.com/drive/1ClP7zoa2s24_RoFS6ZQUi_JwmlcpzXvq?usp=sharing

In the Python notebook provided includes exploratory data analysis of a BigBasket dataset and preprocessing, which involves reading in a CSV, manipulating the index, and calculating discount percentages. Data exploration is done as a matter of course (describe, info, null checks), and then graphs are used to highlight some of the insights that we found useful whether it be pricing, discount per category, or other useful trends.

Metadata and Descriptive Statistics

Metadata

In the workbook, there is 1 worksheet named "BigBasket Products", where the original dataset consists of **27,555 rows and 10 columns,** and their columns are

Column Name	Description	Data Type
Index	Every product is assigned a unique identifier to ensure accurate tracking and reference of products.	Integer
Product	Big Basket has listed the official name of the product, which is used for display and search on their site.	String
Category	The data has primary classifications of 'Beauty & Hygiene', 'Kitchen, Garden & Pets', 'Cleaning & Household', 'Gourmet & World Food', 'Foodgrains, Oil & Masala', 'Snacks & Branded Foods', 'Beverages', 'Bakery, Cakes & Dairy', 'Baby Care', 'Fruits & Vegetables', 'Eggs, Meat & Fish,' which gives the broad clarification.	String

Sub- Category	A detailed classification for each category, which gives a greater data analysis.	String
Brand	The brand performance insights are essential, which are associated with the manufacturer or brand of the product.	String
Sale price	The current selling prices on BigBasket are often adjusted according to the ongoing discounts.	Decimal (2)
Market price	The Maximum Retail Price (MRP), the price set by manufacturers.	Decimal (2)
Type	Type into which product falls into different category and sub category.	String
Rating	Rating the product has gotten from its consumers is between 1.0 and 5.0. Customer feedback metrics that indicate product quality and popularity.	Decimal (1)
Description	Supplementary information providing context and additional product features.	String
Discount	The percentage of the MRP deducted from the sale price indicates promotional offers.	Decimal (2)

Table -1 (Metadata)

Descriptive Statistics

The analysis begins by exploring the range of products, looking into pricing patterns, category distribution, and what makes certain items more popular. It follows a structured path starting with data preparation and data cleaning, followed by exploratory analysis, visualization, and finally drawing insights that highlight key trends and strategies. Table 2, shown below, summarizes the central tendency and dispersion for the dataset's key variables. For example, the product's average selling price is slightly lower than 140, whereas the actual MRP of the product is 150. The mean discount percentage is 11.83%, which gives the typical offer applied to products.

Sales price and market price value are available in the data for all 27,554 products, whereas ratings are available only for 18,929 products. According to the data, the average sales price is Rs. 322.51, whereas the market average price is Rs. 382.06. The average rating is 3.94, which indicates most products have good reviews. Rating ranges from 1.0 (worst) to 5.0 (best). High standard deviation in prices gives a large variation in product pricing. In this data, the cheapest product has a sales price of Rs. 2.45, while the expensive product costs Rs. 12,500.

Statistic	Sale Price (₹)	Market Price (₹)	Rating	Discount (%)
Count	27,554	27,554	18,929	27,554
Mean	322.51	382.06	3.94	11.83%
Std	486.86	581.87	0.61	14.62%
Min	2.45	3.00	1.0	0.00%
Max	12,500.00	12,500.00	5.0	83.67%
25%	95.00	100.00	3.94	0.00%
50%	190.00	220.00	3.94	5.00%
75%	359.00	425.00	4.20	20.00%

Table -2 (Descriptive Statistics)

25% of the sales price of the product is below ₹ 95, and the market price is below 100. Half of the products (50%) at least have a 5% discount and a median sales price of ₹ 190 and a median market price of ₹ 220. 75% of the products are below ₹ 359 with a market price of 425 and at least a 20% discount.

Detailed Explanation of Analysis Process/Method

Process of Data Analysis in Inventory Optimization

The journey of data analysis encompasses several crucial steps, each contributing to the overall understanding of inventory optimization. This process involves defining the problem, collecting and organizing data, cleaning and transforming it, applying analysis techniques, and ultimately drawing meaningful conclusions.

Data Loading and Preprocessing

This analysis is based on a dataset available on Kaggle. First, the dataset was extracted using the Pandas library in Python. After loading the dataset, the first few entries were fetched using the .head() function, which confirmed that the dataset was appended correctly. This was positive for a glimpse of the dataset's form and contents.

Now, the shape of the dataset has been confirmed using the shape command, which gives the total number of rows and columns and helps them understand the proportionate size of the data. In order to further supplement their understanding of the data, they executed the info() command, which offered an insight into the column data datatypes, enabling them to know whether they needed to adjust some column types in the preprocessing step.

As far as the current objective is concerned, it was vital to determine if there were any missing values across attributes, which was achieved with isnull().sum().

COLUMN NAME	DATA TYPE	NON-NULL VALUE	NULL VALUES
INDEX	Integer	27555	0
PRODUCT	String	27554	1
CATEGORY	String	27555	0
SUB- CATEGORY	String	27555	0
BRAND	String	27554	1
SALE PRICE	Decimal (2)	27555	0
MARKET PRICE	Decimal (2)	27555	0
TYPE	String	27555	0
RATING	Decimal (1)	18929	8626
DESCRIPTION	String	27440	115
DISCOUNT	Decimal (2)	27555	0

Table 3 (Data Info and No. of Null values)

Data Cleaning

1. **Handled Missing Values in the Rating Column:** Checked for missing values in the rating column by replacing the missing rating column by replacing the missing rating with the mean value of all existing ratings according to each category to ensure that no row is discarded mainly due to a missing rating and keeps the rating distribution balanced.
2. **Removed Incomplete (Empty) Rows in Description Column:** Identified rows with missing or null values in the Description column and dropped 115 rows which lacks

description because missing descriptions reduce data quality and textual data is important for product context.

3. **Few column data consolidate into "Others":** Common label "Others" has been used for the grouped infrequent values for multiple categorical features such as
    - **a.** Product items appearing less than 4 times.
    - **b.** Sub-category with less than 400 occurrences.
    - **c.** Any brand with fewer than 50 entries.
    - **d.** Types with fewer than 20 entries.

    It helps to reduce noise in a data set and make analysis/charts more stable.

4. **Ensured Consistency Across Categorical Columns:** Columns like Brand, Product, etc. have been standardized by text format like consistent casing and spacing with different spelling or formats.
5. **Verified Data Typers:** Numerical columns like Rating have been checked whether it is in the correct numeric formats and categorical columns were ensured to be in object string format and converted them appropriately.

Exploratory Data Analysis

Understanding the structure, quality and key patterns of the data set is the goal of Exploratory Data Analysis (EDA), which enables the identification of trends, correlationsand insights necessary for inventory and sales strategy decisions both numerical and categorical feature of the data set has been included in the analysis using basic statistical and visualization tools from python libraries such as pandas, matplotlib and seaborn.

➢ **Data Analysis and Feature Details:**

The data set consists of 27,555 records and 10 primary features such as product name (string), category and sub-category (string), brand (string), sale price and market price (decimal), rating (1.0–5.0 scale), description (text/string), discount (%) and types (string).

➢ **Handling Outliers:**

Using a boxplot, outlier detection was performed primarily on the rating column, which helped to visualize the distribution and detect unusually low ratings, which are different from the rest of the data.

- The rating range is from 0.0 to 5.0, with a mean of 3.94 and a standard deviation of 0.61.
- The box plot showed a concentration of ratings between 3.5 and 4.5, while ratings ≤ 2.5 were identified as potential outliers.
- The low-rated products show customer dissatisfaction and were further analyzed to identify those product categories and sub-categories.

Extreme values in rating are business-relevant indicators and not data errors, unlike pricing features. They were retained and used for quality improvement and customer satisfaction strategies.

- **Univariate and Bivariate Analysis:**

To compute the summary statistics for numerical variables such as sale_price, market_price, discount and rating, .describe() method has been used. This provided insights into the measures of mean, median, standard deviation and quantile.

Sales prices ranged from ₹ 2.45 to ₹ 12,500, with an average of around ₹ 322.51, while the mean of the market price is ₹ 382.06. The overall average rating was 3.94 out of 5.

To detect price outliers and to understand the spread of ratings and discounts, boxplots and histograms were created.

- **Categorical Data Analysis:**

To evaluate the frequency distribution in columns such as category, sub-category and brand, the .value_counts() method was used.

Using Bar charts and pie charts, these distributions were visualized, which shows Dominant product categories (e.g Beauty & Hygiene had 7856 products)

This helped with deeper analysis by highlighting where BigBasket has a concentrated product presence which needed to consolidate inventory.

- **Checking Mutual Information:**

I performed a proxy analysis using grouped statistical summaries

- Grouped mean ratings by category, sub-category - calculated average ratings with each category which shows possible issues in product quality or rating.

- Grouped discount patterns by category—helped by revealing categories consistently applying high discounts.

This grouping analysis is a basis substitute for mutual information, which helps to identify the categories that have the most shared variability features.

Results and Findings

Key insights learned through analysis of data:

Correlation Analysis Overview

The correlation matrix has been calculated and visualized using a heatmap, which help to understand the linear relationships between the numerical variables of the Big Basket dataset The strength and direction of associations between the variables has been identified by this technique. The Pearson correlation coefficient has been used to measure the degree of linear correlation ranging from -1 (perfect negative correlation) to +1 (perfect positive correlation), with 0 indication no linear correlation.

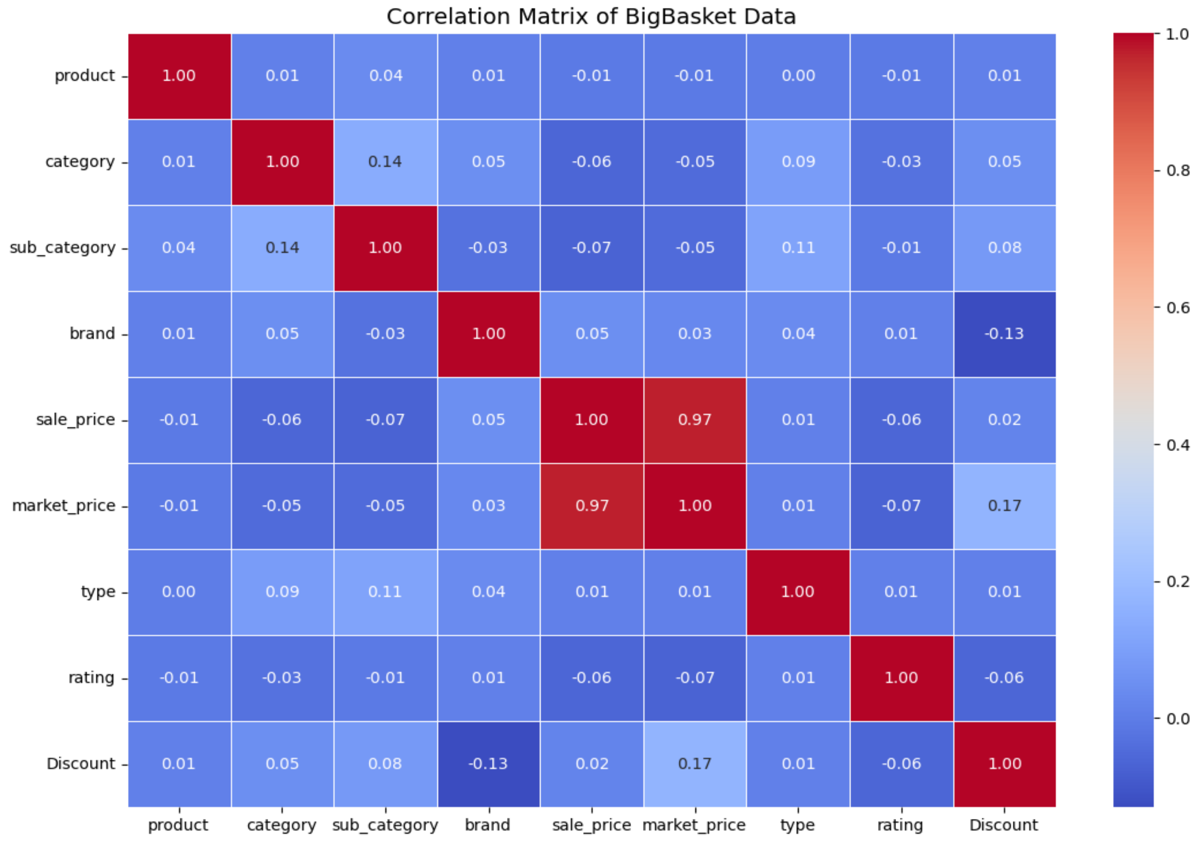

Figure- 1 (Heat Map)

- Sales price and market price: Very strong positive correlation (0.97). These two prices are always very close together and are the strong link between the two.
- Discount and market price: Moderate correlation (0.17). This is typically where not high-end products can be afforded but not pricing at the level, you'd expect the market price to be.
- Type and sales price: Some very weak correlations that aren't interesting. Zero to positive relationships with almost type and sales price.

We didn't find any strong correlation between the attributes, except for market price and sales price, which isn't useful for our analysis but the comprehensive visual summary of how various product attributes interact, particularly those related to pricing, branding, categorization, and discounting has been provided by the heatmap.

1. Overpriced products with heavy discounts:

The topic Overpriced Products with Heavy Discounts examines an ingrained pricing scam that involves trying to convince consumers that a product has been discounted when price discounting was actually factored into the unlikely higher ticket price. This issue encompasses marketing manipulation and pricing psychology, which also fit very well into a discussion of e-commerce pricing strategy and e-commerce discount patterns.

Discounting Patterns and Price Manipulation in Big Basket: A Category-Level Analysis

This analysis is directly related to the issue when it comes to the difference between market price and sale price, and it specifically relates to the possibility of inflated market prices being used to create the impression of large discounts.

The discount has been calculated by a simple formula:

Discount (%) = ((market_price - sale_price) / market_price) * 100

Category	Market Price (₹)	Sale Price (₹)	Estimated Discount (%)
Gourmet & World Food	~1722	~778	~54.81%
Foodgrains, Oil & Masala	~1061	~449	~57.69%
Beauty & Hygiene	~975	~360	~63.08%

Kitchen, Garden & Pets	~898	~350	~61.02%
Cleaning & Household	~358	~164	~54.19%
Beverages	~290	~125	~56.90%
Snacks & Branded Foods	~224	~90	~59.82%
Bakery, Cakes & Dairy	~150	~66	~56.00%
Eggs, Meat & Fish	~126	~56	~55.56%
Fruits & Vegetables	~37	~16	~56.76%

Table-4

A review of several discounted products that are over 50% off across a variety of categories (Table-4) reveals an established price system where products are typically marked considerably above the competitive market price and usually reduced in connection with sales. This is illustrated by the average market price and sale price data.

- Gourmet and World Food exhibit the highest average market price of ~₹1722 and a sale price of ~₹778 (approximately 54.81% off); the steep drop shows a strong likelihood that the item was intentionally marked up.

- The two items in Food grains, Oil & Masala and Beauty & Hygiene show significant markdowns (approximately 57.69% and 63.08%). Both are stable product categories that typically should not exhibit extreme discounting.

- Kitchen, Garden & Pets (~61.02% off) and Cleaning & Household (~54.19% off) are similar examples of price inconsistency. Products probably were listed at an artificially inflated base price to justify the "sale" price during the markdown. Of interest, Kitchen, Garden & Pets had the greatest estimated markdown, which can imply perhaps the aggressiveness of a price markdown.

- Each category reviewed had markdowns between 54%-63% regardless of original product type or commodity value reinforcing the notion of standard overpricing. Even basic and perishable categories, Fruits & Vegetables (~₹37 to ~₹16), listed pricing 56.76% off, which is not typical of fresh produce.

According to the analysis of the figure-2, it suggests that the categories, which are reviewed likely to have overpriced items with artificially inflated markdowns. Retailers may have been taking advantage of a perceived "higher" market price in order to induce a value metric, particularly in premium and essential product categories. Pricing professionalism and accountability may be warranted to protect consumer interests.

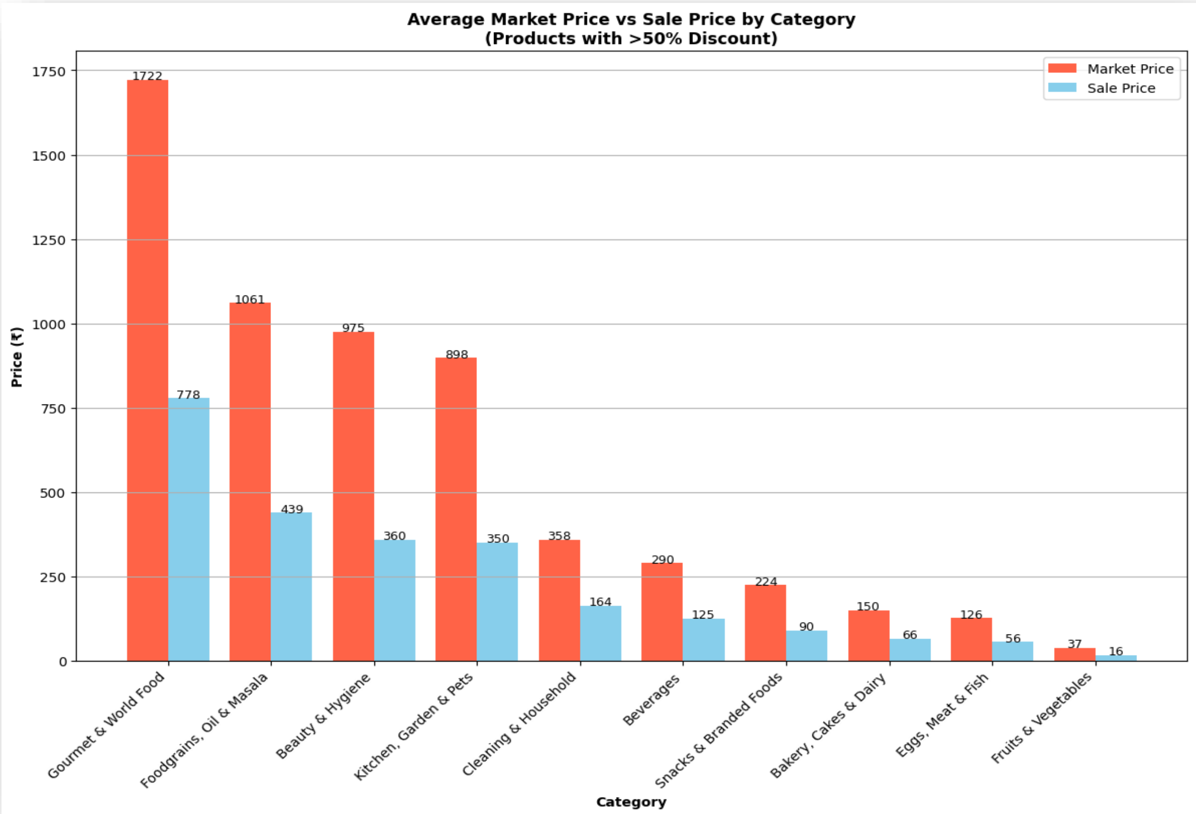

Figure-2 (Bar chart)

The price analysis has been exhibited with the line chart (figure-3) to present the divergence between market price and sales price across these different categories. This organized, side-by-side comparison can show what products are overpriced and provide insight into price strategy, demand, and category performance.

➢ The data show that categories like Body Care (₹596.88 vs ₹535.17) and Kitchen, Garden & Pets (₹660.23 vs ₹507.86) display a heavy markup, which is then followed by a sizeable discount, which indicates artificially inflated price endings to provide a false sense of savings, increasing sales in these categories.

- Fruits & Vegetables (₹64.45 vs ₹50.90) and Bakery, Cakes & Dairy (₹157.88 vs ₹142.80) have low sales, which may result from short shelf life, perishability, and other logistical issues, increasing potential for waste from both markdown and processes in the supply chain, even with reasonable pricing.

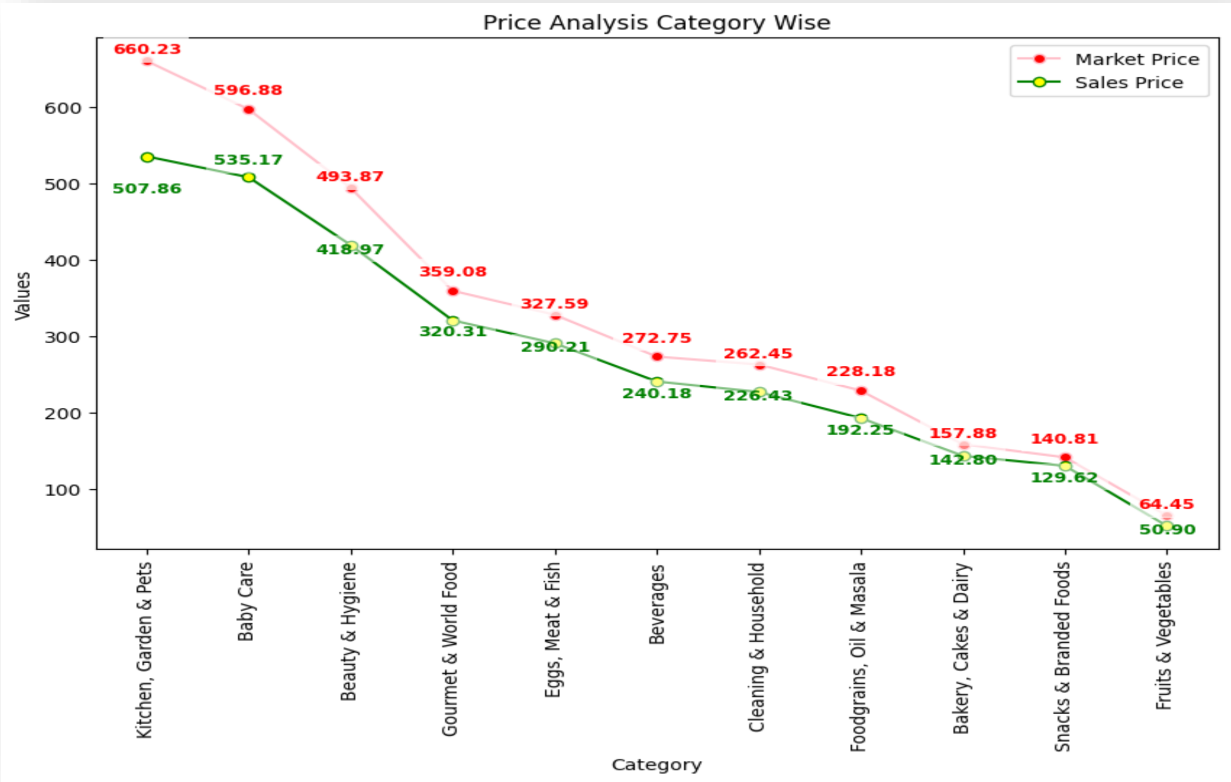

Figure-3 (Line chart)

- The categories Foodgrains, Oil, and Masala (₹228.18 vs ₹192.25) and Snacks & Branded Food (₹140.81 vs ₹129.62) have moderate price differences while experiencing low sales, which is likely a combination of poor price/perceived value and/or inefficient pricing of some sort.

- The smaller price difference that Gourmet & World Food (₹359.08 vs ₹320.31) and Eggs, Meat, & Fish (₹327.59 vs ₹290.21) suggest that the pricing gap is less artificial and more prices reflect willingness to pay, representing more stable consumer demand. These categories are more representative of greater balance across ideal pricing without heavy discounts.

2. Low-Rated Products in Key Categories:

The topic Low-Rated Products in Key Categories focuses on finding out which product types have the most negative feedback. The count of low-rated products per category helps identify which main categories have the highest number of poorly rated items. Low-Rated Products in Key Sub-Categories gives a deeper look into specific areas where product quality might be a common issue.

a) **Count of Low-Rated Products per Category:** The number of low-rated products (rating <= 2.5) across different categories has been displayed by the bar chart (figure-4) categories with low-rated products along with their numbers can be identified through the chart. The bar chart is effective for ranking categories with low-rated products, making it easy to compare customer dissatisfaction levels across categories.

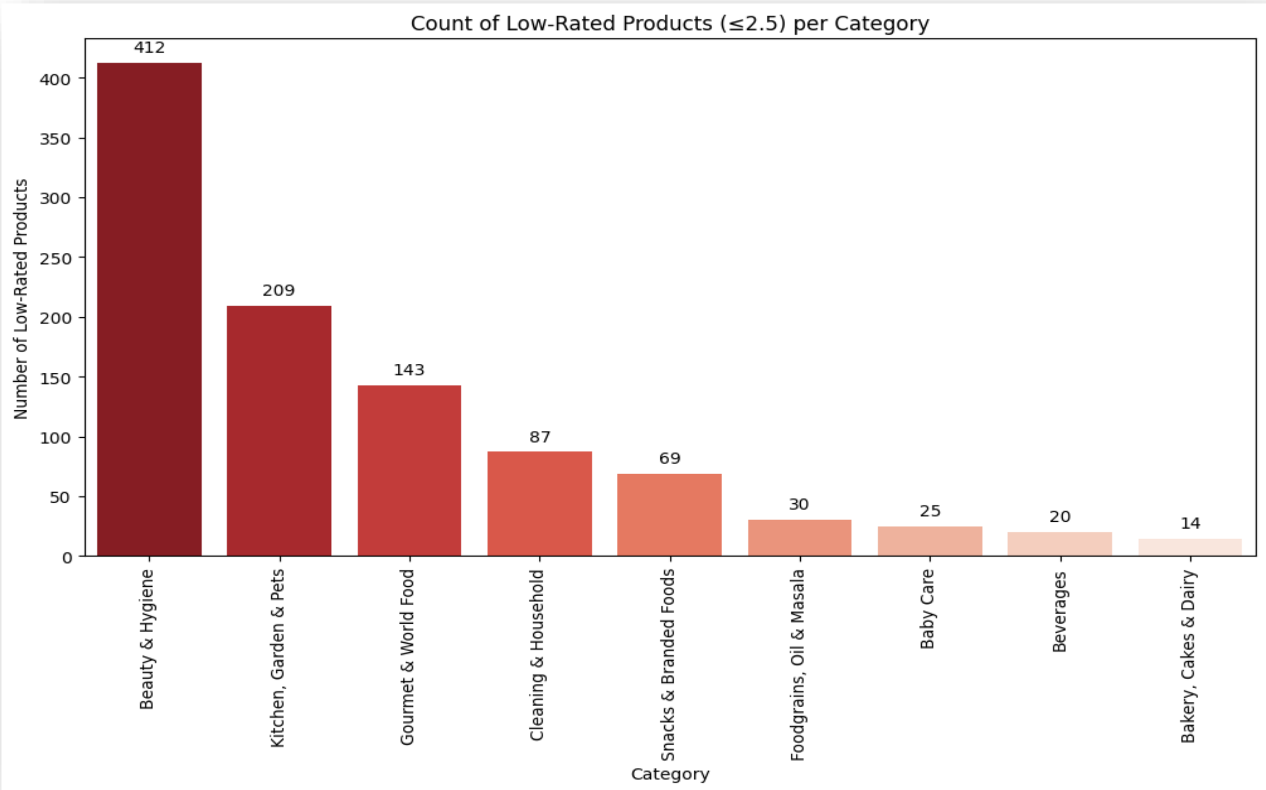

Figure-4 (Bar chart)

- Beauty and hygiene category has the highest number of low-rated products, which shows the possible problem with misleading claims, product quality or negative customer experience. Out of 7856 products in the Beauty and Hygiene category, 412 products have a low rating of 2.5 or below.
- Kitchen, garden and pet category follows with 209 low-rated products out of 3562, showing a significant number of dissatisfied customers possibly due to damaged or different a expired products in household and pet-related items.
- Possibly due to taste preferences, quality concerns or ineffective cleaning products, gourmet and world food and cleaning and household categories have a noticeable amount of low-rated products.
- The rating of bakery, cakes and dairy and beverages shows that these categories imply better quality control and customer satisfaction and have the least number of poorly rated products.

The possible reasons for low ratings might be due to reposted poor-quality products in categories like Beauty and hygiene and kitchen essentials and misleading marketing. High-priced items with unworthy products and might be due to difficulty in returns and warranty claims in some categories.

b) **Low-Rated Products in Key Sub-Categories:** The horizontal bar chart helps to visualize the top 10 sub categories of low rated products with the help of chart (figure-5) it's easy to identify the low rated sub categories along with their counts. A horizontal bar chart is useful for ranking sub-categories based on customer dissatisfaction levels, making it easy to identify problem areas.

- **Skin Care** is the first most affected sub category which has around 141 low-rated products out of 2291 that show mixed reviews due to personal preferences, skin reactions, or effectiveness issues. These categories need better product quality, customer education or improved descriptions.
    a. **Fragrances and Deos** follows with 75 low-rated products out of 1000, and the ratings are mainly based on scent longevity and preferences, inaccurate product descriptions, or customer expectations not being met.
- In other sub-category, **storage and accessories** and **crockery and cutlery** receive low ratings due to material quality, durability, and product design. **Men's grooming,**

Chocolates and Biscuits and **Hair care** dissatisfaction could be linked to product effectiveness, taste or packaging.

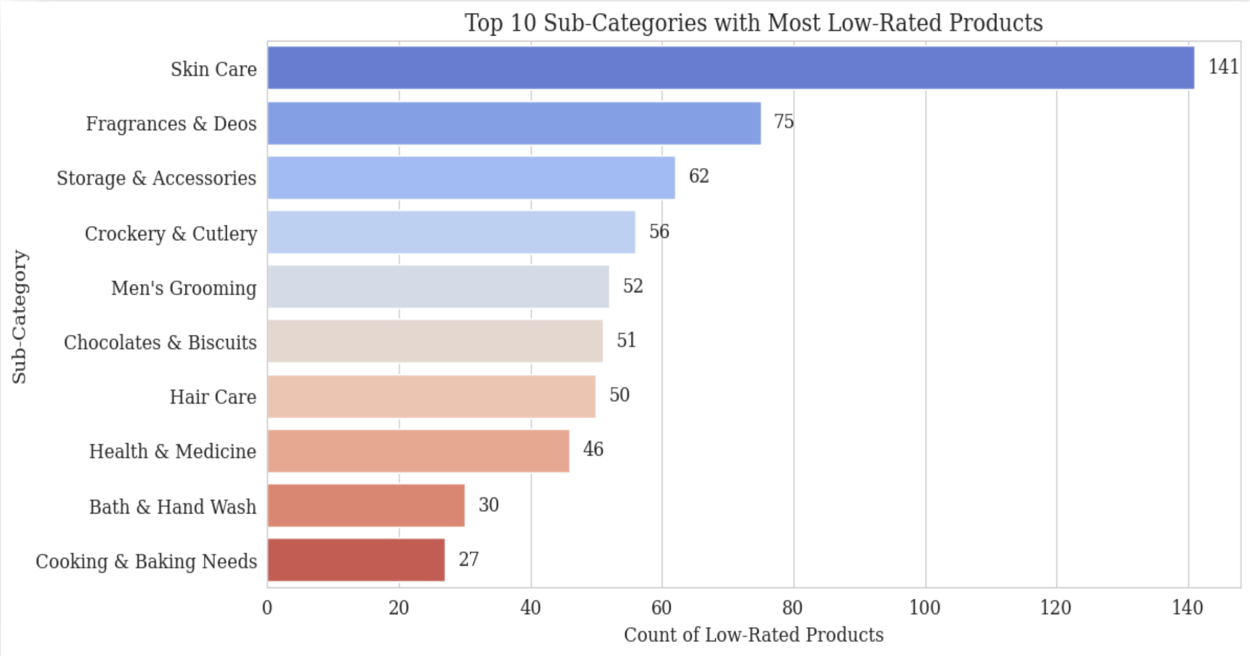

Figure-5 (Bar chart)

3. Inventory Management Issues:

The analysis deals with inventory optimization by matching product accessibility to customer expectations and category performance. The content allows one to analyze the number of accessible products, customer ratings and reviews, and category product sub-movements to identify inventory accessibility and enable better thinking involved in inventory managing decisions to limit overstock and understock situations and improve customer experience and operational efficiencies.

a) **Optimizing Inventory through Analysis of Customer Preferences and Product Distribution:** This analysis focuses on inventory management by analyzing product count, customer preferences and ratings of different categories which helps to identify demanded products and to optimize the stock for better customer satisfaction.

- According to the figure-6, Turmeric Powder/Arisina Pudi shows the highest sales compared to other products and products like Extra Virgin Olive Oil, Cow Ghee/Tuppa and Soft Drink also exhibit consistent demand, which shows their important role in daily customer demand.
- The presence of both food items like ghee, oil, spices and non-food items like Hair color and

hand sanitizer among the top-selling products shows a broad customer preference spectrum. Inventory should monitor these categories separately to fine-tune stock levels based on category-specific movement patterns.

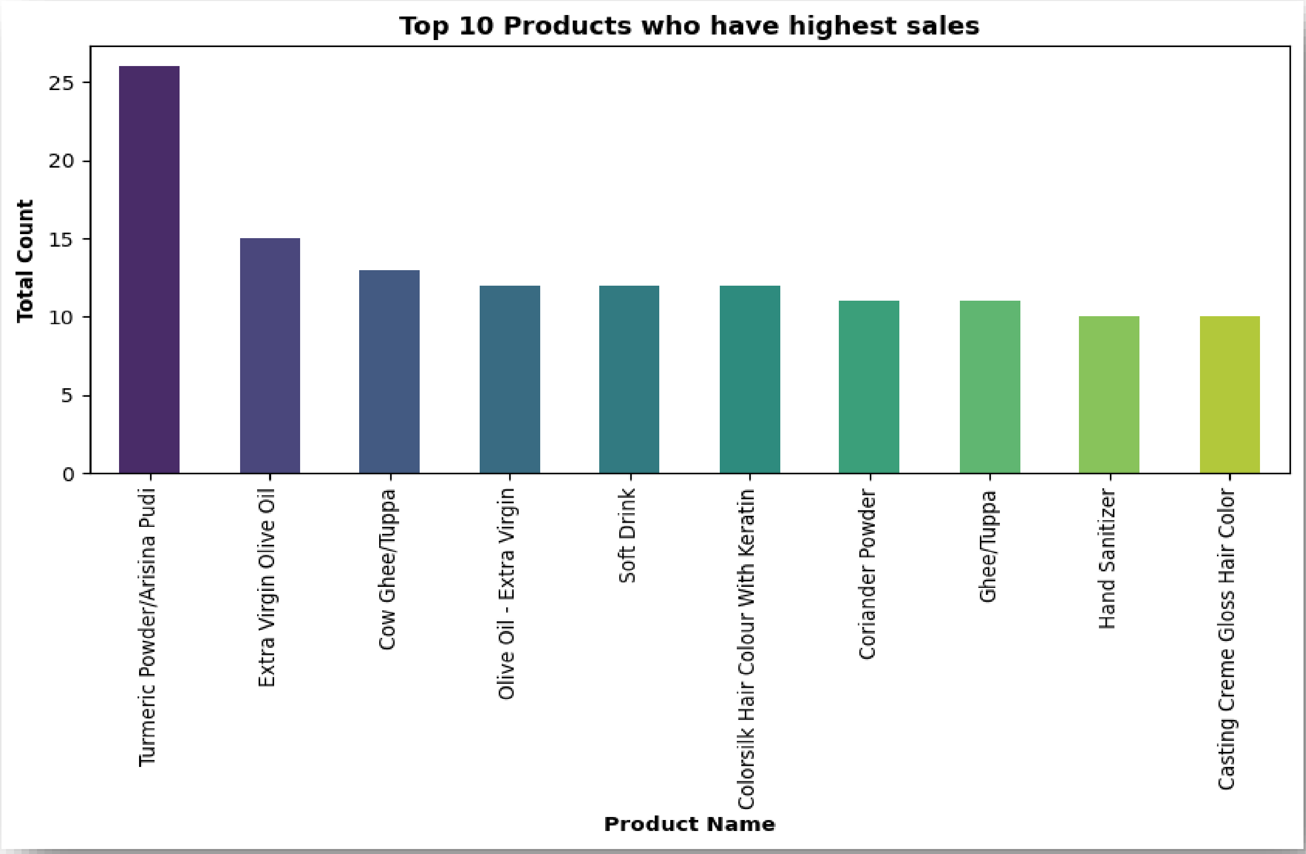

Figure-6 (Bar chart)

- Figure 7 shows that the Beauty & Hygiene and Gourmet & World Food categories received the highest number of customer ratings, and categories like Kitchen, Garden & Pets and Snacks & Branded Foods also received substantial ratings, suggesting stable demand and high customer satisfaction.
- The low rating has been received by categories such as Eggs, Meat & Fish and Fruits & Vegetables which shows low customer interaction or dissatisfaction. Product offerings, shelf-life management, or marketing strategies should be improved in these segments to improve its sales

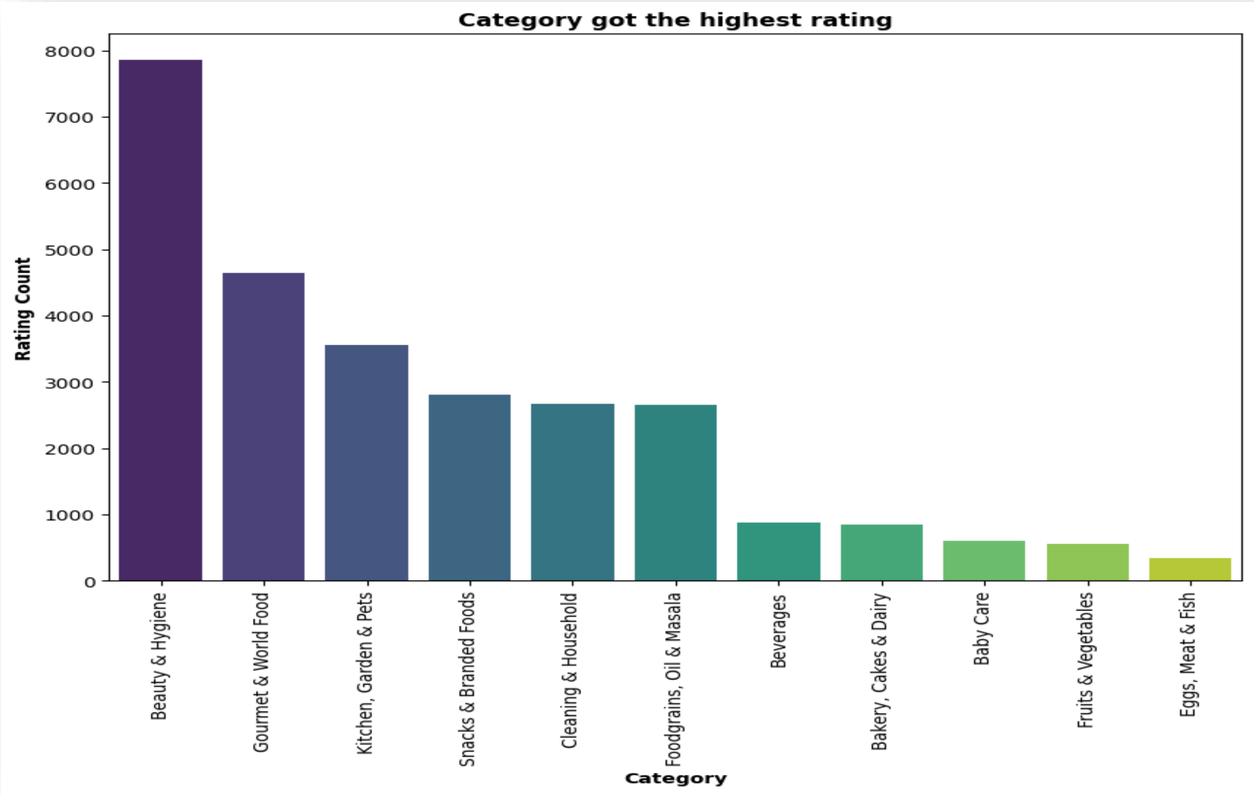

Figure-7 (Bar chart)

- By analyzing the figure 8, we can figure out that the Skin Care sub category has a higher number of ratings and subcategories like Health & Medicine, Hair Care, Storage & Accessories, and Fragrances & Deos show similar, moderate engagement levels, which shows a strong and consistent customer demand.
- Minimal ratings have been received by the Kitchen Accessories, Biscuits & Cookies, and Spreads, Sauces & Ketchup subcategories, which suggests limited customer interest. Stock Keeping Unit rationalization and discounting seasonally to optimize shelf space of the products of above subcategory can help to maintain the inventory

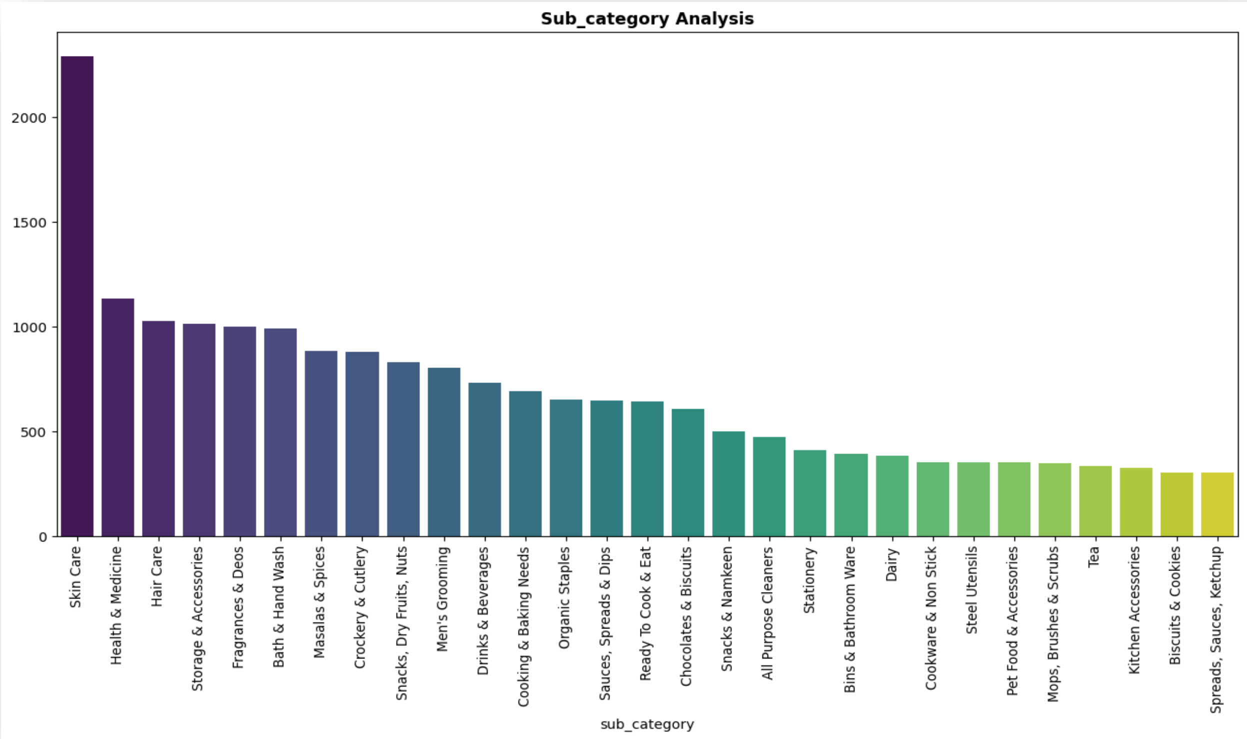

Figure-8 (Bar chart)

Interpretation of results

1. **Overpriced Products with Heavy Discounts:**

   - In a variety of categories, large overriding discounts (50%–60% off) are regularly observed, however these prices are most likely not real. When the original prices are likely intentionally inflated, this creates the illusion of a discount.
   - With regard to fruits, vegetables, dairy products, and baked goods, there is a smaller gap between the original and sale prices. This is possibly due to perishability and limited opportunities to mark up prices or increase them too much.

2. **Low-Rated Products in Key Categories:**

   - The Beauty & Hygiene category has the highest number of low-rated products (412), which suggests potential issues with product quality, misleading marketing claims, or overall poor customer experience. Likewise, Kitchen, Garden & Pets has a significant number of low ratings (209), which indicates latent dissatisfaction that could stem from product condition, expiration, or unreasonable expectations. Meanwhile, the lowest degree of customer dissatisfaction is seen in Bakery, Cakes & Dairy, and

Beverages, which correlate to a higher business trust mark alongside the low rate of low-rated products.

- The Skin Care sub-category contains the greatest number of products rated poorly (141), indicating that customers, for some reason, seem to be disappointed, either because of their personal skin reaction, the lack of efficacy of the product, or the product description being rather deceptive. Other sub-categories like Fragrances & Deos, Storage & Accessories, and Hair Care also indicate remarkable dissatisfaction, mostly because of expectation, product value, or preference issues.
- Customers have a low rating for the productivity of these categories, Fruits & Vegetables and Eggs, Meat & Fish. This might indicate understocking or inefficient management, which definitely has a negative impact on sales and customer satisfaction.

3. **Inventory Management Issues:**
   - A high demand essential product, Turmeric Powder/Arisina Pudi and other products like Olive Oil, Cow Ghee, and Soft Drinks shows steady sales. A diverse demand pattern across multiple categories has been indicated by the mix of food and non-food items among top sellers.
   - Categories like Beauty & Hygiene, Snacks & Beverages and Personal Care should be evaluated and it should be noted that products had ample stock levels and were well-received by customers. This indicates that popular sellers are fulfilling customer demand and stocking up as well.
   - The consistent high-performing subcategory with a large margin is Skin Care. Sub categories like Hair Care and Health & Medicine show steady but moderate interest, which shows a strong and consistent customer demand.

Recommendations

1. **Correct Discount Strategy and Improve pricing Transparency:** Revaluation the pricing strategy in BigBasket ensures the authenticity in market pricing. To build trust and retain customers over time, transparent and real discoun,especially in heavily discounted categories like Beauty & Hygiene will be helpful.

2. **Eliminate or Improve Low-Rated Products:** Categories with low ratings (e.g: Skin Care, Fragrance, Storage and Accessories needed focused quality checks and verified customer feedback loops. To resolve the quality issues, replacing the consistently underperforming SKU or working with suppliers is necessary.

3. **Ensure Steady Inventory for High-Demand Items:** The importance of essential products such as Turmeric Powder, Cow ghee and Olive Oil in daily usage makes them ideal for promotions, bundles and subscriptions. It’s necessary for the products to be consistently available with optimal stock levels.

4. **Category-Based Inventory Optimization:** Inventory should be aligned with customer interest. Popular ones like Health medicine and Hair Care should be restocked more frequently whereas categories and sub-categories with low engagement can be offered in bundles or in limited-time sales.

5. **Improve Strategy for Perishable Goods:** Enhancing cold storage, faster delivery timelines and reduced pricing for near-expiry stock can reduce wastage and improve customer satisfaction for categories like Fruits & Vegetables.

THANK YOU