Capstone Project (SEPHORA)

Enhancing Customer Experience: Unraveling Sephora’s Skincare Reviews

Product Dataset Overview

Feature	Description
product_id	The unique identifier for the product from the site
product_name	The full name of the product
brand_id	The unique identifier for the product brand from the site
brand_name	The full name of the product brand
loves_count	The number of people who have marked this product as a favorite
rating	The average rating of the product based on user reviews
reviews	The number of user reviews for the product
size	The size of the product, which may be in oz, ml, g, packs, or other units depending on the product type
variation_type	The type of variation parameter for the product (e.g. Size, Color)
variation_value	The specific value of the variation parameter for the product (e.g. 100 mL, Golden Sand)
variation_desc	A description of the variation parameter for the product (e.g. tone for fairest skin)
ingredients	A list of ingredients included in the product, for example: ['Product variation 1:', 'Water, Glycerin', 'Product variation 2:', 'Talc, Mica'] or if no variations ['Water, Glycerin']
price_usd	The price of the product in US dollars
value_price_usd	The potential cost savings of the product, presented on the site next to the regular price
sale_price_usd	The sale price of the product in US dollars
limited_edition	Indicates whether the product is a limited edition or not (1-true, 0-false)
new	Indicates whether the product is new or not (1-true, 0-false)
online_only	Indicates whether the product is only sold online or not (1-true, 0-false)
out_of_stock	Indicates whether the product is currently out of stock or not (1 if true, 0 if false)
sephora_exclusive	Indicates whether the product is exclusive to Sephora or not (1 if true, 0 if false)
highlights	A list of tags or features that highlight the product's attributes (e.g. ['Vegan', 'Matte Finish'])
primary_category	First category in the breadcrumb section
secondary_category	Second category in the breadcrumb section
tertiary_category	Third category in the breadcrumb section
child_count	The number of variations of the product available
child_max_price	The highest price among the variations of the product
child_min_price	The lowest price among the variations of the product

This table organizes the various features and their descriptions in a clear tabular format. Each row represents a specific feature, and the corresponding descriptions are provided in the adjacent cell.

In [37]:
```
# importing necessary libraries

import pandas as pd
import numpy as np

# loading in products data

data = pd.read_csv(r"C:\Users\logeshwar\OneDrive\Documents\Sephora\product_info.csv")
data.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8494 entries, 0 to 8493
Data columns (total 27 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   product_id          8494 non-null   object 
 1   product_name        8494 non-null   object 
 2   brand_id            8494 non-null   int64  
 3   brand_name          8494 non-null   object 
 4   loves_count         8494 non-null   int64  
 5   rating              8216 non-null   float64
 6   reviews             8216 non-null   float64
 7   size                6863 non-null   object 
 8   variation_type      7050 non-null   object 
 9   variation_value     6896 non-null   object 
 10  variation_desc      1250 non-null   object 
 11  ingredients         7549 non-null   object 
 12  price_usd           8494 non-null   float64
 13  value_price_usd     451 non-null    float64
 14  sale_price_usd      270 non-null    float64
 15  limited_edition     8494 non-null   int64  
 16  new                 8494 non-null   int64  
 17  online_only         8494 non-null   int64  
 18  out_of_stock        8494 non-null   int64  
 19  sephora_exclusive   8494 non-null   int64  
 20  highlights          6287 non-null   object 
 21  primary_category    8494 non-null   object 
 22  secondary_category  8486 non-null   object 
 23  tertiary_category   7504 non-null   object 
 24  child_count         8494 non-null   int64  
 25  child_max_price     2754 non-null   float64
 26  child_min_price     2754 non-null   float64
dtypes: float64(7), int64(8), object(12)
memory usage: 1.7+ MB
```

From this, we gather that the products dataset contains 27 columns and 8,494 rows of data. The columns vary in data types, and there is missing data within the dataframe.

Review Dataset Overview

Feature	Description
author_id	The unique identifier for the author of the review on the website
rating	The rating given by the author for the product on a scale of 1 to 5
is_recommended	Indicates if the author recommends the product or not (1-true, 0-false)
helpfulness	The ratio of all ratings to positive ratings for the review: helpfulness = total_pos_feedback_count / total_feedback_count
total_feedback_count	Total number of feedback (positive and negative ratings) left by users for the review
total_neg_feedback_count	The number of users who gave a negative rating for the review
total_pos_feedback_count	The number of users who gave a positive rating for the review
submission_time	Date the review was posted on the website in the 'yyyy-mm-dd' format
review_text	The main text of the review written by the author
review_title	The title of the review written by the author
skin_tone	Author's skin tone (e.g. fair, tan, etc.)
eye_color	Author's eye color (e.g. brown, green, etc.)
skin_type	Author's skin type (e.g. combination, oily, etc.)
hair_color	Author's hair color (e.g. brown, auburn, etc.)
product_id	The unique identifier for the product on the website

This table presents the various features related to the review data in a tabular format. Each row corresponds to a specific feature, and the descriptions are provided in the adjacent cell, making it easy to read and understand the details of each feature.

For the datasets related to the reviews, it will be helpful to join them all into one dataframe, which we can do with the following:

In [38]:
```python
# getting the files

import pandas as pd

t1 = pd.read_csv(r"C:\Users\logeshwar\OneDrive\Documents\Sephora\reviews_0_250.csv", low_memory=False)
t2 = pd.read_csv(r"C:\Users\logeshwar\OneDrive\Documents\Sephora\reviews_250_500.csv", low_memory=False)
t3 = pd.read_csv(r"C:\Users\logeshwar\OneDrive\Documents\Sephora\reviews_500_750.csv", low_memory=False)
t4 = pd.read_csv(r"C:\Users\logeshwar\OneDrive\Documents\Sephora\reviews_750_1000.csv", low_memory=False)
t5 = pd.read_csv(r"C:\Users\logeshwar\OneDrive\Documents\Sephora\reviews_1000_1500.csv", low_memory=False)
t6 = pd.read_csv(r"C:\Users\logeshwar\OneDrive\Documents\Sephora\reviews_1500_end.csv", low_memory=False)

# combining the dfs
```

```
texta = pd.concat([t1,t2,t3,t4,t5,t6])
texta.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1301136 entries, 0 to 49976
Data columns (total 19 columns):
 #   Column                    Non-Null Count    Dtype  
---  ------                    --------------    -----  
 0   Unnamed: 0                1301136 non-null  int64  
 1   author_id                 1301136 non-null  object 
 2   rating                    1301136 non-null  int64  
 3   is_recommended            1107162 non-null  float64
 4   helpfulness               631670 non-null   float64
 5   total_feedback_count      1301136 non-null  int64  
 6   total_neg_feedback_count  1301136 non-null  int64  
 7   total_pos_feedback_count  1301136 non-null  int64  
 8   submission_time           1301136 non-null  object 
 9   review_text               1299520 non-null  object 
 10  review_title              930754 non-null   object 
 11  skin_tone                 1103798 non-null  object 
 12  eye_color                 1057734 non-null  object 
 13  skin_type                 1172830 non-null  object 
 14  hair_color                1037824 non-null  object 
 15  product_id                1301136 non-null  object 
 16  product_name              1301136 non-null  object 
 17  brand_name                1301136 non-null  object 
 18  price_usd                 1301136 non-null  float64
dtypes: float64(3), int64(5), object(11)
memory usage: 198.5+ MB
```

We gather that there are around 1.3 million reviews with varying amounts of missing data across 19 columns of the 6 datasets.

It can also be helpful to view the numeric and non-numeric columns of both dataframes. We can do so with the following:

Numeric Columns

In [39]:
```
numeric_cols = data.select_dtypes(include = ['number']).columns
print(numeric_cols)
print(f'{len(numeric_cols)} Numeric Columns in Products Dataset')
```

```
Index(['brand_id', 'loves_count', 'rating', 'reviews', 'price_usd',
       'value_price_usd', 'sale_price_usd', 'limited_edition', 'new',
       'online_only', 'out_of_stock', 'sephora_exclusive', 'child_count',
       'child_max_price', 'child_min_price'],
      dtype='object')
15 Numeric Columns in Products Dataset
```

In [40]:
```
numeric_cols_reviews = texta.select_dtypes(include = ['number']).columns
print(numeric_cols_reviews)
print(f'{len(numeric_cols_reviews)} Numeric Columns in Reviews Dataset')
```

```
Index(['Unnamed: 0', 'rating', 'is_recommended', 'helpfulness',
       'total_feedback_count', 'total_neg_feedback_count',
       'total_pos_feedback_count', 'price_usd'],
      dtype='object')
8 Numeric Columns in Reviews Dataset
```

Non-Numeric Columns

In [41]:
```
non_numeric_cols = data.select_dtypes(exclude=['number']).columns
print(non_numeric_cols)
print(f'{len(non_numeric_cols)} Non-Numeric Columns in Products Dataset')
```

```
Index(['product_id', 'product_name', 'brand_name', 'size', 'variation_type',
       'variation_value', 'variation_desc', 'ingredients', 'highlights',
       'primary_category', 'secondary_category', 'tertiary_category'],
      dtype='object')
12 Non-Numeric Columns in Products Dataset
```

In [42]:
```
non_numeric_rev_cols = texta.select_dtypes(exclude=['number']).columns
print(non_numeric_rev_cols)
print(f'{len(non_numeric_rev_cols)} Non-Numeric Columns in Reviews Dataset')
```

```
Index(['author_id', 'submission_time', 'review_text', 'review_title',
       'skin_tone', 'eye_color', 'skin_type', 'hair_color', 'product_id',
       'product_name', 'brand_name'],
      dtype='object')
11 Non-Numeric Columns in Reviews Dataset
```

Data Cleaning

Data Cleaning on product Dataset

Next, we need to clean the products dataset by performing the following tasks:

Assessing missing data and determining its extent. Removing unnecessary data that is not relevant to our analysis. Identifying and handling outliers, if present. Reformatting the data if required.

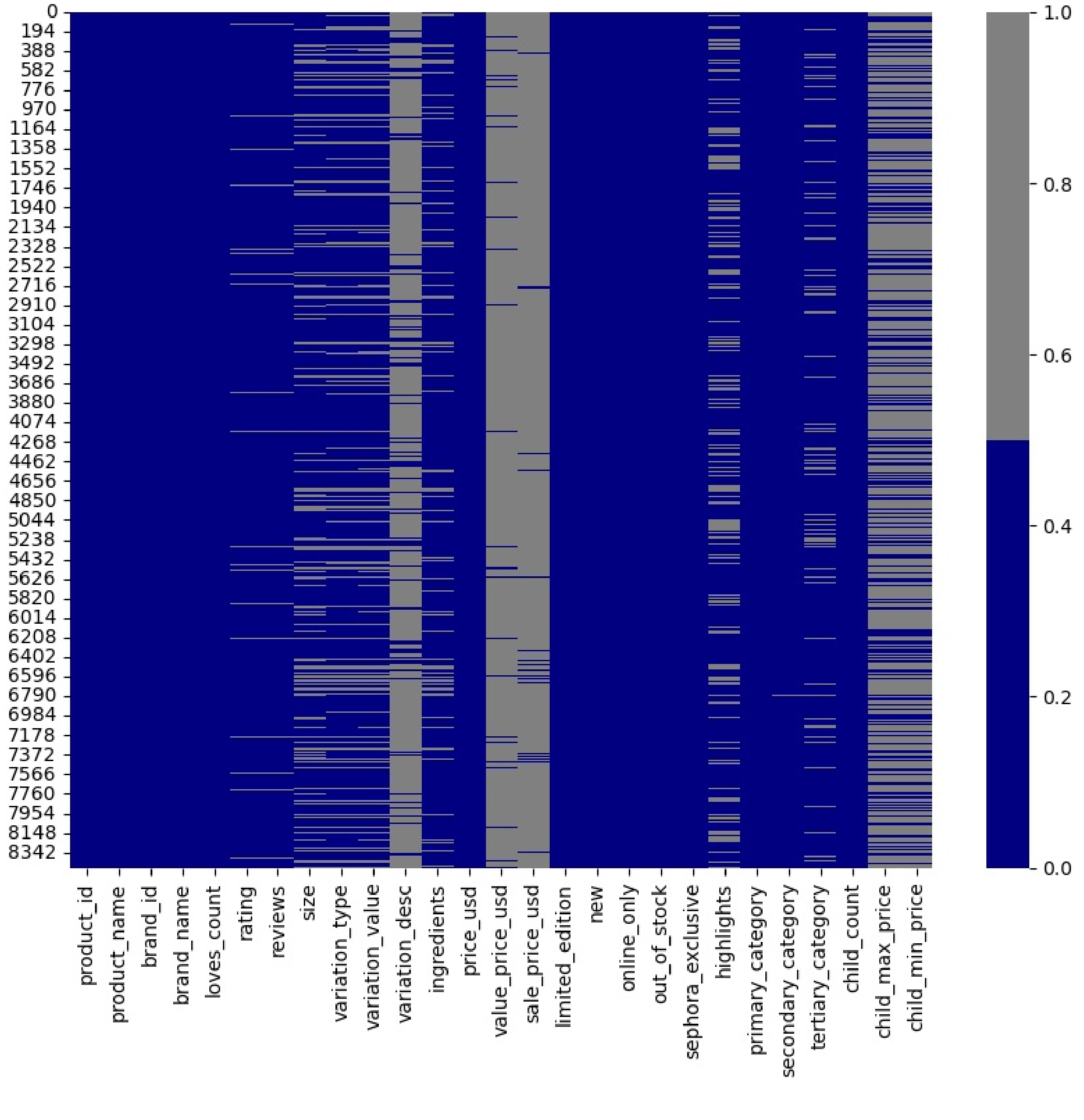
Here we use the following code to see the amount of nulls by column within the dataset:

In [43]:
```
num_missing = data.isna().sum()
num_missing
```

Out[43]:
```
product_id              0
product_name            0
brand_id                0
brand_name              0
loves_count             0
rating                278
reviews               278
size                 1631
variation_type       1444
variation_value      1598
variation_desc       7244
ingredients           945
price_usd               0
value_price_usd      8043
sale_price_usd       8224
limited_edition         0
new                     0
online_only             0
out_of_stock            0
sephora_exclusive       0
highlights           2207
primary_category        0
secondary_category      8
tertiary_category     990
child_count             0
child_max_price      5740
child_min_price      5740
dtype: int64
```

In [44]:
```
# heatmap to visualize missing data (products)

import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(10,8))

cols= data.columns
colors=['navy','grey']
sns.heatmap(data[cols].isna(),cmap=sns.color_palette(colors))
```

Out[44]:
```
<AxesSubplot:>
```

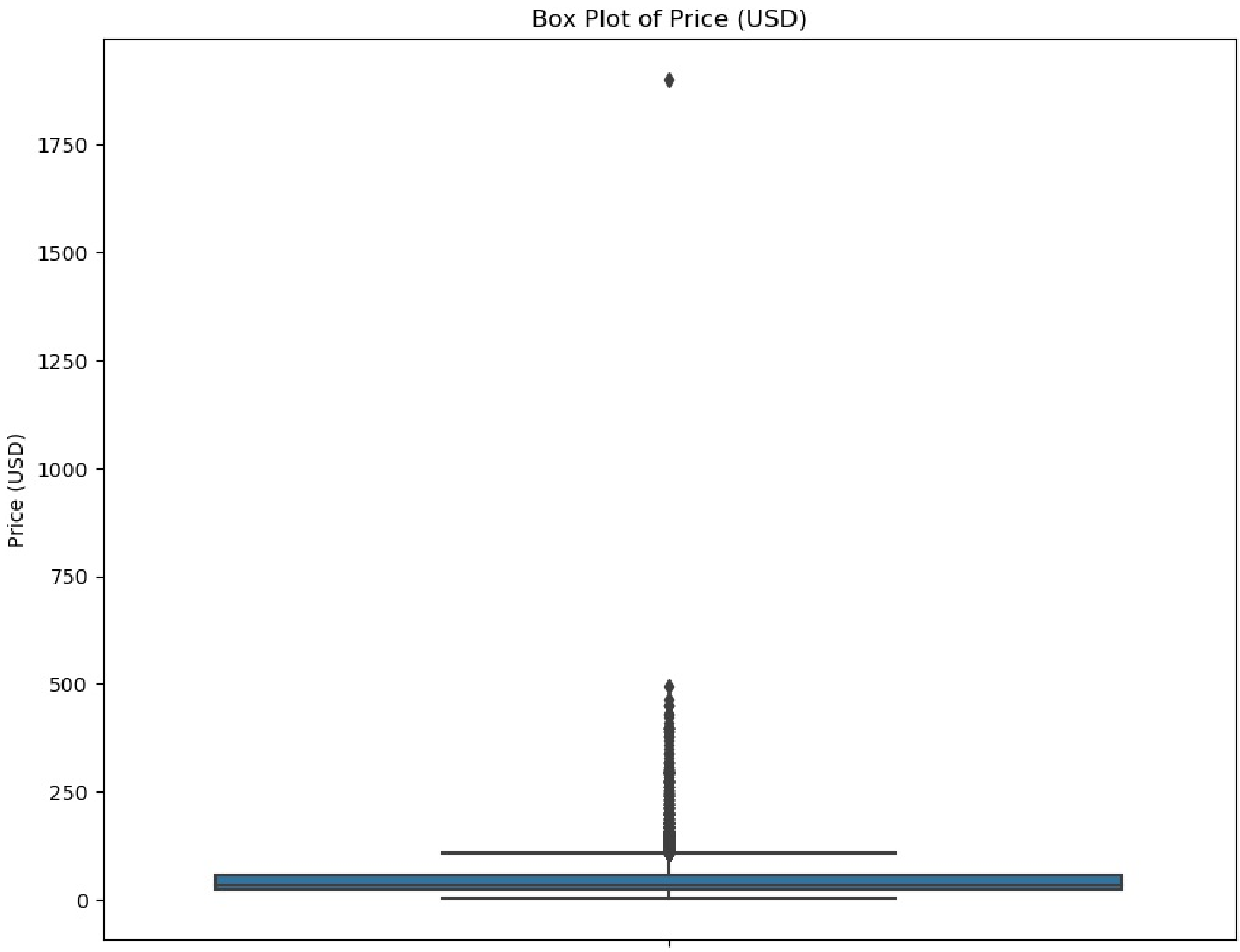


0
194
388
582
776
970
1164
1358
1552
1746
1940
2134
2328
2522
2716
2910
3104
3298
3492
3686
3880
4074
4268
4462
4656
4850
5044
5238
5432
5626
5820
6014
6208
6402
6596
6790
6984
7178
7372
7566
7760
7954
8148
8342
product_id
product_name
brand_id
brand_name
loves_count
rating
reviews
size
variation_type
variation_value
variation_desc
ingredients
price_usd
value_price_usd
sale_price_usd
limited_edition
new
online_only
out_of_stock
sephora_exclusive
highlights
primary_category
secondary_category
tertiary_category
child_count
child_max_price
child_min_price
1.0
0.8
0.6
0.4
0.2
0.0

INTERPRETATIONS:

From this, we can make note of the columns with a high percentage of missing data for when we assess which columns to remove from our dataset

In [45]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Assuming 'data' is the DataFrame containing the data
# Replace 'data' with the actual DataFrame name

plt.figure(figsize=(10, 8))
sns.boxplot(data=data, y='price_usd')
plt.title('Box Plot of Price (USD)')
plt.ylabel('Price (USD)')
plt.show()
```



Explanation:

By creating a box plot of the 'price_usd' column, we can quickly observe the spread and central tendency of the prices in the dataset. It allows us to identify potential outliers, understand the range of prices, and assess the overall distribution of the prices in terms of quartiles.

INTERPRETATION:

In summary, the box plot provides an effective and concise visual summary of the distribution of the 'price_usd' column in the 'data' DataFrame, helping us better understand the pricing patterns and any potential outliers in the dataset.

In [46]:
```
data.loc[data['price_usd']>1750]
```

Out[46]:

	product_id	product_name	brand_id	brand_name	loves_count	rating	reviews	size	variation_type	variation_value	...	online_only
6802	P502216	Shani Darden by Déesse PRO LED Light Mask	6314	Shani Darden Skin Care	4154	3.75	4.0	NaN	NaN	NaN	...	1

1 rows × 27 columns

INTERPRETATIONS:

The code data.loc[data['price_usd']>1750] retrieves rows from the data DataFrame where the value in the 'price_usd' column is greater than to 1750.

After doing some digging on Sephora's site, we can confirm that the price of the product above is legitimate. However, we will still exclude the outlier from the data to better gauge the price distribution later on.

Dropping the outlier

In [47]:
```
import pandas as pd

# Assuming your DataFrame is stored in a variable called "data"
# Replace "data" with the actual name of your DataFrame if different.

# Code to filter and drop the rows
data.drop(data[data['price_usd'] > 1750].index, inplace=True)

# The above code will drop the rows where 'price_usd' is greater than 1750.
```

In [48]:
```
import pandas as pd

# Assuming your dataset is stored in a variable called "data"
# Replace "data" with the actual name of your DataFrame if different.

# Your code to read or import the dataset goes here...
# For example: data = pd.read_csv('your_dataset.csv')

# Drop the specified columns
columns_to_drop = [
    'loves_count',
    'tertiary_category',
    'highlights',
    'child_count',
    'child_max_price',
    'child_min_price',
    'sale_price_usd',
    'value_price_usd',
    'variation_value',
    'variation_desc'
]
data_edited = data.drop(columns=columns_to_drop)

# After dropping the columns, you can use "data_edited" instead of "data" for the updated dataset.
```

INTERPRETATIONS:

We are dropping certain columns from the original dataset to create a new DataFrame called "data_edited." The reason for doing this is to remove unnecessary or irrelevant columns that are not needed for the analysis or that contain a large number of missing values. By dropping these columns, we can create a more focused and compact dataset that only contains the relevant information, making it easier to work with and potentially improving the efficiency of any subsequent data analysis or modeling tasks.

In [49]:
```
data_edited.info()
```

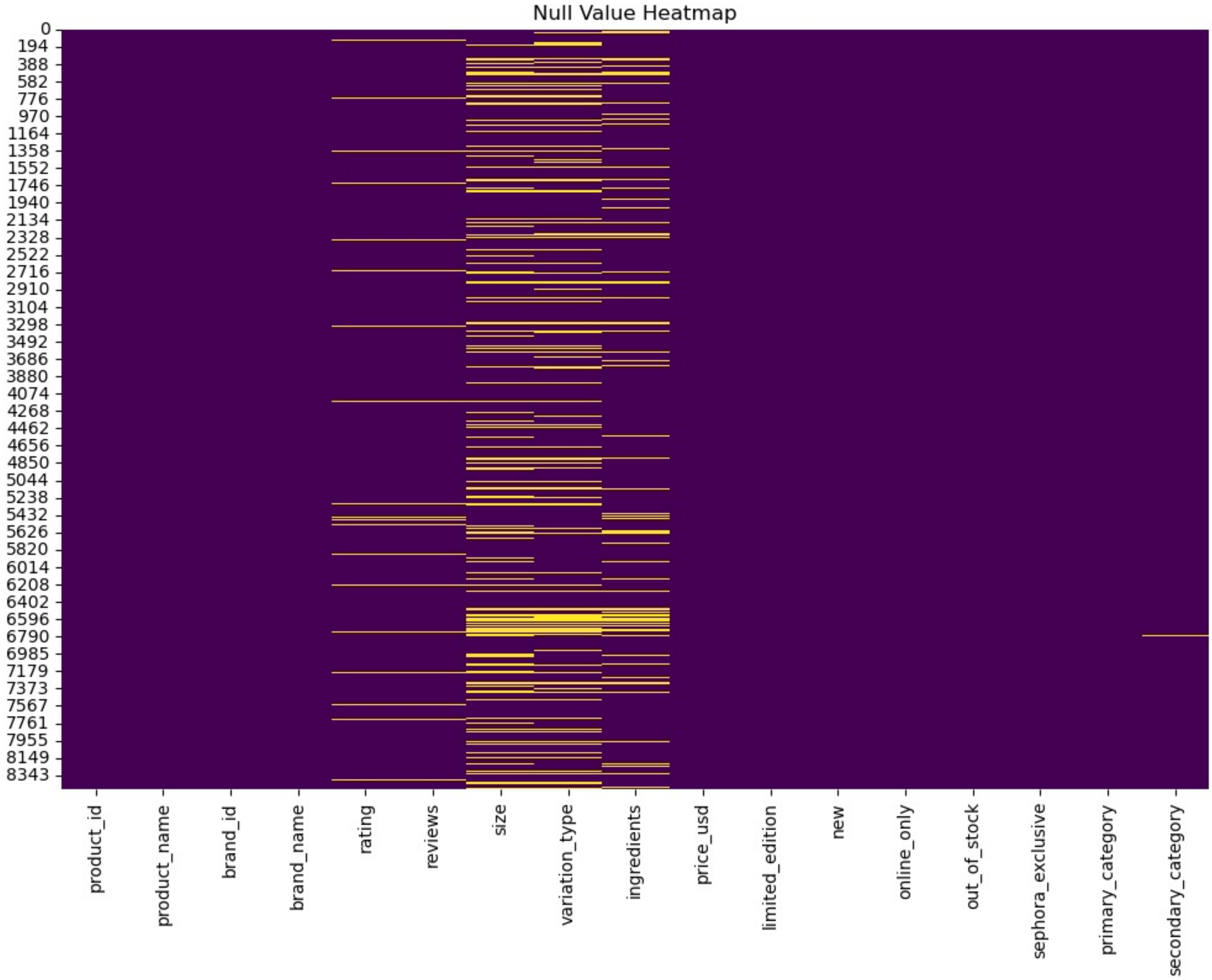
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8493 entries, 0 to 8493
Data columns (total 17 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   product_id          8493 non-null   object 
 1   product_name        8493 non-null   object 
 2   brand_id            8493 non-null   int64  
 3   brand_name          8493 non-null   object 
 4   rating              8215 non-null   float64
 5   reviews             8215 non-null   float64
 6   size                6863 non-null   object 
 7   variation_type      7050 non-null   object 
 8   ingredients         7549 non-null   object 
 9   price_usd           8493 non-null   float64
 10  limited_edition     8493 non-null   int64  
 11  new                 8493 non-null   int64  
 12  online_only         8493 non-null   int64  
 13  out_of_stock        8493 non-null   int64  
 14  sephora_exclusive   8493 non-null   int64  
 15  primary_category    8493 non-null   object 
 16  secondary_category  8485 non-null   object 
dtypes: float64(3), int64(6), object(8)
memory usage: 1.2+ MB
```

In [50]:
```
data_edited.shape
```

Out[50]:
```
(8493, 17)
```

We are creating a heatmap of null values in the "data_edited" DataFrame to visualize and understand the presence of missing data within the dataset.

In [51]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Assuming your DataFrame is stored in a variable called "data_edited"
# Replace "data_edited" with the actual name of your DataFrame if different.

# Create a DataFrame to store information about null values
null_heatmap_data = data_edited.isnull()

# Create the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(null_heatmap_data, cbar=False, cmap='viridis')
plt.title('Null Value Heatmap')
plt.show()
```



INTERPRETATIONS:

By visualizing the null values using a heatmap, we can make informed decisions on how to handle missing data, such as imputing missing values, removing rows or columns with too many missing values, or applying specific data cleaning techniques.

In [52]:
```
import pandas as pd

# Assuming your DataFrame is stored in a variable called "data_edited"
# Replace "data_edited" with the actual name of your DataFrame if different.

# Calculate the mode for 'rating' and 'reviews'
rating_mode = data_edited['rating'].mode().iloc[0]
reviews_mode = data_edited['reviews'].mode().iloc[0]

# Fill the null values with the calculated modes
data_edited['rating'].fillna(rating_mode, inplace=True)
data_edited['reviews'].fillna(reviews_mode, inplace=True)
```

INTERPRETATIONS:

Filling missing values with the mode is a common data imputation technique used when dealing with missing data in a dataset. By using the mode, we are essentially replacing the missing values with the most frequently occurring values in the respective columns

In [53]:
```
import pandas as pd
```

```
In [53]: import pandas as pd

# Assuming your DataFrame is stored in a variable called "data_edited"
# Replace "data_edited" with the actual name of your DataFrame if different.

# Get unique values in the 'variation_type' column
unique_variation_types = data_edited['variation_type'].unique()

# Print the unique values
print(unique_variation_types)
```

```
[nan 'Size + Concentration + Formulation' 'Scent' 'Size' 'Color'
 'Size + Concentration' 'Type' 'Formulation']
```

```
In [54]: import pandas as pd

# Assuming your DataFrame is stored in a variable called "data_edited"
# Replace "data_edited" with the actual name of your DataFrame if different.

# Get unique values in the 'size' column
unique_sizes = data_edited['size'].unique()

# Print the unique values
print(unique_sizes)
```

```
[nan '3.4 oz/ 100 mL' '0.25 oz/ 7.5 mL' ... '0.25 oz/ 7.5 ml' '2.6 oz'
 '.11 oz / 3.2 mL']
```

```
In [55]: data.isnull().sum()
```

```
Out[55]:
product_id               0
product_name             0
brand_id                 0
brand_name               0
loves_count              0
rating                 278
reviews                278
size                  1630
variation_type        1443
variation_value       1597
variation_desc        7243
ingredients            944
price_usd                0
value_price_usd       8042
sale_price_usd        8223
limited_edition          0
new                      0
online_only              0
out_of_stock             0
sephora_exclusive        0
highlights            2207
primary_category         0
secondary_category       8
tertiary_category      990
child_count              0
child_max_price       5739
child_min_price       5739
dtype: int64
```

```
In [56]: import pandas as pd

# Assuming your DataFrame is stored in a variable called "data_edited"
# Replace "data_edited" with the actual name of your DataFrame if different.

# Calculate the mode for 'secondary_category'
secondary_category_mode = data_edited['secondary_category'].mode().iloc[0]

# Fill null values with the calculated mode for 'secondary_category'
data_edited['secondary_category'].fillna(secondary_category_mode, inplace=True)

# Fill null values in 'size' and 'variation_type' with 'Not Available'
data_edited['size'].fillna('Not Available', inplace=True)
data_edited['variation_type'].fillna('Not Available', inplace=True)
```

```
In [57]: import pandas as pd

# Assuming your DataFrame is stored in a variable called "data_edited"
# Replace "data_edited" with the actual name of your DataFrame if different.

# Get unique values in the 'size' column
unique_sizes = data_edited['size'].unique()

# Print the unique values
print(unique_sizes)
```

```
['Not Available' '3.4 oz/ 100 mL' '0.25 oz/ 7.5 mL' ... '0.25 oz/ 7.5 ml'
 '2.6 oz' '.11 oz / 3.2 mL']
```

```
In [58]: import pandas as pd
```

```
# Assuming your DataFrame is stored in a variable called "data_edited"
# Replace "data_edited" with the actual name of your DataFrame if different.

# Get unique values in the 'variation_type' column
unique_variation_types = data_edited['variation_type'].unique()

# Print the unique values
print(unique_variation_types)
```

```
['Not Available' 'Size + Concentration + Formulation' 'Scent' 'Size'
 'Color' 'Size + Concentration' 'Type' 'Formulation']
```

In [59]:
```
import pandas as pd

# Assuming your DataFrame is stored in a variable called "data_edited"
# Replace "data_edited" with the actual name of your DataFrame if different.

# Fill null values in 'ingredients' column with 'Not available'
data_edited['ingredients'].fillna('Not available', inplace=True)
```

In [60]:
```
data_edited.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8493 entries, 0 to 8493
Data columns (total 17 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   product_id          8493 non-null   object 
 1   product_name        8493 non-null   object 
 2   brand_id            8493 non-null   int64  
 3   brand_name          8493 non-null   object 
 4   rating              8493 non-null   float64
 5   reviews             8493 non-null   float64
 6   size                8493 non-null   object 
 7   variation_type      8493 non-null   object 
 8   ingredients         8493 non-null   object 
 9   price_usd           8493 non-null   float64
 10  limited_edition     8493 non-null   int64  
 11  new                 8493 non-null   int64  
 12  online_only         8493 non-null   int64  
 13  out_of_stock        8493 non-null   int64  
 14  sephora_exclusive   8493 non-null   int64  
 15  primary_category    8493 non-null   object 
 16  secondary_category  8493 non-null   object 
dtypes: float64(3), int64(6), object(8)
memory usage: 1.2+ MB
```

In [61]:
```
# Assuming you have already defined the variable data_edited with the edited dataset
numeric_cols = data_edited.select_dtypes(include=['number']).columns
print(numeric_cols)
print(f'{len(numeric_cols)} Numeric Columns in Products Dataset')
```

```
Index(['brand_id', 'rating', 'reviews', 'price_usd', 'limited_edition', 'new',
       'online_only', 'out_of_stock', 'sephora_exclusive'],
      dtype='object')
9 Numeric Columns in Products Dataset
```

In [62]:
```
# Assuming you have already defined the variable data_edited with the edited dataset
numeric_cols = data_edited.select_dtypes(include=['number']).columns
print(numeric_cols)
print(f'{len(numeric_cols)} Numeric Columns in Products Dataset')
```

```
Index(['brand_id', 'rating', 'reviews', 'price_usd', 'limited_edition', 'new',
       'online_only', 'out_of_stock', 'sephora_exclusive'],
      dtype='object')
9 Numeric Columns in Products Dataset
```

In [63]:
```
# Assuming you have a DataFrame named 'data_edited'

# Columns to convert from numeric (int64) to object (string)
columns_to_convert = ['limited_edition', 'new', 'online_only', 'out_of_stock', 'sephora_exclusive']

# Convert the selected columns to object (string) dtype
data_edited[columns_to_convert] = data_edited[columns_to_convert].astype(str)

# Verify the new dtypes of the selected columns
print(data_edited.dtypes)
```

```
product_id             object
product_name           object
brand_id                int64
brand_name             object
rating                float64
reviews               float64
size                   object
variation_type         object
ingredients            object
price_usd             float64
limited_edition        object
new                    object
online_only            object
out_of_stock           object
sephora_exclusive      object
primary_category       object
secondary_category     object
dtype: object
```

In [64]:
```python
data_edited.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8493 entries, 0 to 8493
Data columns (total 17 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   product_id          8493 non-null   object 
 1   product_name        8493 non-null   object 
 2   brand_id            8493 non-null   int64  
 3   brand_name          8493 non-null   object 
 4   rating              8493 non-null   float64
 5   reviews             8493 non-null   float64
 6   size                8493 non-null   object 
 7   variation_type      8493 non-null   object 
 8   ingredients         8493 non-null   object 
 9   price_usd           8493 non-null   float64
 10  limited_edition     8493 non-null   object 
 11  new                 8493 non-null   object 
 12  online_only         8493 non-null   object 
 13  out_of_stock        8493 non-null   object 
 14  sephora_exclusive   8493 non-null   object 
 15  primary_category    8493 non-null   object 
 16  secondary_category  8493 non-null   object 
dtypes: float64(3), int64(1), object(13)
memory usage: 1.2+ MB
```

In [65]:
```python
data_edited.head(10)
```

Out[65]:

	product_id	product_name	brand_id	brand_name	rating	reviews	size	variation_type	ingredients	price_usd	limited_edition	new
0	P473671	Fragrance Discovery Set	6342	19-69	3.6364	11.0	Not Available	Not Available	['Capri Eau de Parfum:', 'Alcohol Denat. (SD A...	35.0	0	0
1	P473668	La Habana Eau de Parfum	6342	19-69	4.1538	13.0	3.4 oz/ 100 mL	Size + Concentration + Formulation	['Alcohol Denat. (SD Alcohol 39C), Parfum (Fra...	195.0	0	0
2	P473662	Rainbow Bar Eau de Parfum	6342	19-69	4.2500	16.0	3.4 oz/ 100 mL	Size + Concentration + Formulation	['Alcohol Denat. (SD Alcohol 39C), Parfum (Fra...	195.0	0	0
3	P473660	Kasbah Eau de Parfum	6342	19-69	4.4762	21.0	3.4 oz/ 100 mL	Size + Concentration + Formulation	['Alcohol Denat. (SD Alcohol 39C), Parfum (Fra...	195.0	0	0
4	P473658	Purple Haze Eau de Parfum	6342	19-69	3.2308	13.0	3.4 oz/ 100 mL	Size + Concentration + Formulation	['Alcohol Denat. (SD Alcohol 39C), Parfum (Fra...	195.0	0	0
5	P473661	Kasbah Eau de Parfum Travel Spray	6342	19-69	4.4762	21.0	0.25 oz/ 7.5 mL	Size + Concentration + Formulation	['Alcohol Denat. (SD Alcohol 39C), Parfum (Fra...	30.0	0	0
6	P473659	Purple Haze Eau de Parfum Travel Spray	6342	19-69	3.2308	13.0	0.25 oz/ 7.5 mL	Size + Concentration + Formulation	['Alcohol Denat. (SD Alcohol 39C), Parfum (Fra...	30.0	0	0
7	P473666	Invisible Post Eau de Parfum	6342	19-69	3.6250	8.0	3.4 oz/ 100 mL	Size + Concentration + Formulation	['Alcohol Denat. (SD Alcohol 39C), Parfum (Fra...	195.0	0	0
8	P472300	Capri Eau de Parfum	6342	19-69	3.5714	7.0	3.4 oz/ 100 mL	Size + Concentration + Formulation	['Alcohol Denat. (SD Alcohol 39C), Parfum (Fra...	195.0	0	0
9	P473667	Invisible Post Eau de Parfum Travel Spray	6342	19-69	3.6250	8.0	0.25 oz/ 7.5 mL	Size + Concentration + Formulation	['Alcohol Denat. (SD Alcohol 39C), Parfum (Fra...	30.0	0	0

In [66]:

```
data_edited
```

Out[66]:

	product_id	product_name	brand_id	brand_name	rating	reviews	size	variation_type	ingredients	price_usd	limited_edit
0	P473671	Fragrance Discovery Set	6342	19-69	3.6364	11.0	Not Available	Not Available	['Capri Eau de Parfum:', 'Alcohol Denat. (SD A...	35.0	
1	P473668	La Habana Eau de Parfum	6342	19-69	4.1538	13.0	3.4 oz/ 100 mL	Size + Concentration + Formulation	['Alcohol Denat. (SD Alcohol 39C), Parfum (Fra...	195.0	
2	P473662	Rainbow Bar Eau de Parfum	6342	19-69	4.2500	16.0	3.4 oz/ 100 mL	Size + Concentration + Formulation	['Alcohol Denat. (SD Alcohol 39C), Parfum (Fra...	195.0	
3	P473660	Kasbah Eau de Parfum	6342	19-69	4.4762	21.0	3.4 oz/ 100 mL	Size + Concentration + Formulation	['Alcohol Denat. (SD Alcohol 39C), Parfum (Fra...	195.0	
4	P473658	Purple Haze Eau de Parfum	6342	19-69	3.2308	13.0	3.4 oz/ 100 mL	Size + Concentration + Formulation	['Alcohol Denat. (SD Alcohol 39C), Parfum (Fra...	195.0	
...	...	...	...	...	...	...	...	...	...	...	
8489	P467659	Couture Clutch Eyeshadow Palette	1070	Yves Saint Laurent	4.4286	7.0	Not Available	Not Available	['Talc, Synthetic Fluorphlogopite, Triethylhex...	150.0	
8490	P500874	L'Homme Eau de Parfum	1070	Yves Saint Laurent	4.6367	556.0	2 oz / 60 mL	Size + Concentration + Formulation	['Alcohol, Aqua / Water / Eau, Parfum / Fragra...	106.0	
8491	P504428	Mon Paris Eau de Parfum Gift Set	1070	Yves Saint Laurent	5.0000	2.0	Not Available	Not Available	['Mon Paris Eau de Parfum:', 'Alcohol, Parfum/...	134.0	
8492	P504448	Y Eau de Parfum Gift Set	1070	Yves Saint Laurent	5.0000	2.0	Not Available	Not Available	['Alcohol, Parfum/Fragrance, Aqua/Water, Limon...	167.0	
8493	P505461	Candy Glaze Lip Gloss Stick Duo with Hyaluroni...	1070	Yves Saint Laurent	5.0000	2.0	.11 oz / 3.2 mL	Color	['Diisostearyl Malate, Bis-Behenyl/Isostearyl/...	50.0	

8493 rows × 17 columns

In [67]:
```python
data_edited.to_csv("C:\\Users\\logeshwar\\Downloads\\Sephora Product dataset.csv",index=False)
```

Data Cleaning on Reviews Dataset

Here we use the following code to see the amount of nulls by column within the dataset:

In [68]:
```python
texta.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1301136 entries, 0 to 49976
Data columns (total 19 columns):
 #   Column                    Non-Null Count    Dtype  
---  ------                    --------------    -----  
 0   Unnamed: 0                1301136 non-null  int64  
 1   author_id                 1301136 non-null  object 
 2   rating                    1301136 non-null  int64  
 3   is_recommended            1107162 non-null  float64
 4   helpfulness               631670 non-null   float64
 5   total_feedback_count      1301136 non-null  int64  
 6   total_neg_feedback_count  1301136 non-null  int64  
 7   total_pos_feedback_count  1301136 non-null  int64  
 8   submission_time           1301136 non-null  object 
 9   review_text               1299520 non-null  object 
 10  review_title              930754 non-null   object 
 11  skin_tone                 1103798 non-null  object 
 12  eye_color                 1057734 non-null  object 
 13  skin_type                 1172830 non-null  object 
 14  hair_color                1037824 non-null  object 
 15  product_id                1301136 non-null  object 
 16  product_name              1301136 non-null  object 
 17  brand_name                1301136 non-null  object 
 18  price_usd                 1301136 non-null  float64
dtypes: float64(3), int64(5), object(11)
memory usage: 198.5+ MB
```

In [69]:
```python
texta.shape
```

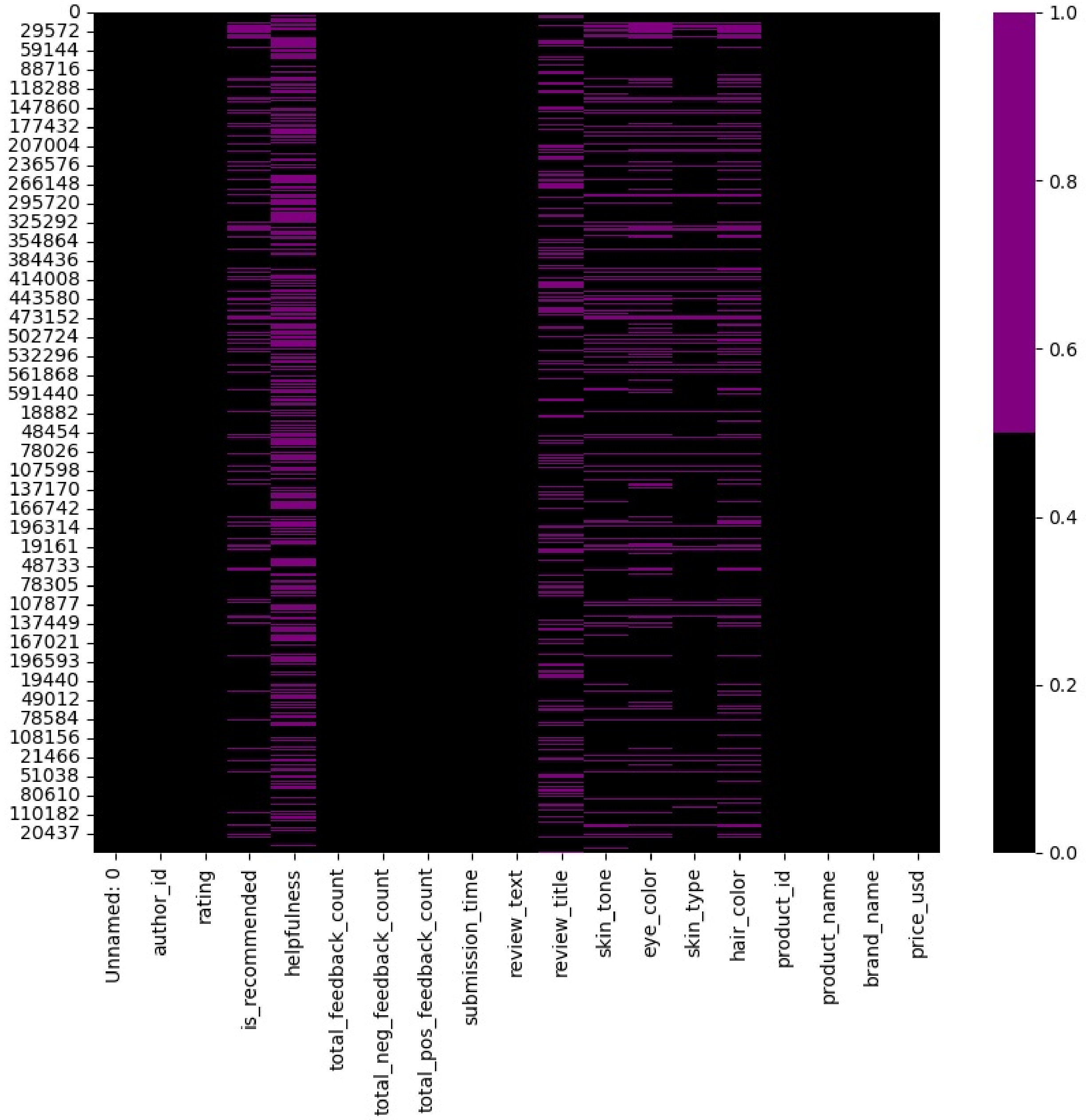
Out[69]:
```
(1301136, 19)
```

In [70]:
```python
# heatmap to visualize missing data (reviews)

import seaborn as sns
```

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10,8))

cols= texta.columns
colors=['black','purple']
sns.heatmap(texta[cols].isna(),cmap=sns.color_palette(colors))
```

Out[70]:

```
<AxesSubplot:>
```



INTERPRETATIONS:

From this, we can make note of the columns with a high percentage of missing data for when we assess which columns to remove from our dataset

In [71]:

```
import pandas as pd

# Assuming your DataFrame is stored in a variable called "texta"
# Replace "texta" with the actual name of your DataFrame if different.

# Get unique values in the 'helpfulness' column
unique_helpfulness = texta['helpfulness'].unique()

# Print the unique values
print(unique_helpfulness)
```

```
[1.                nan 0.25       ... 0.182927   0.265625   0.90131599]
```

Dropping the unnecessary columns

In [72]:

```
import pandas as pd

# Assuming your DataFrame is stored in a variable called "text_edited"
```

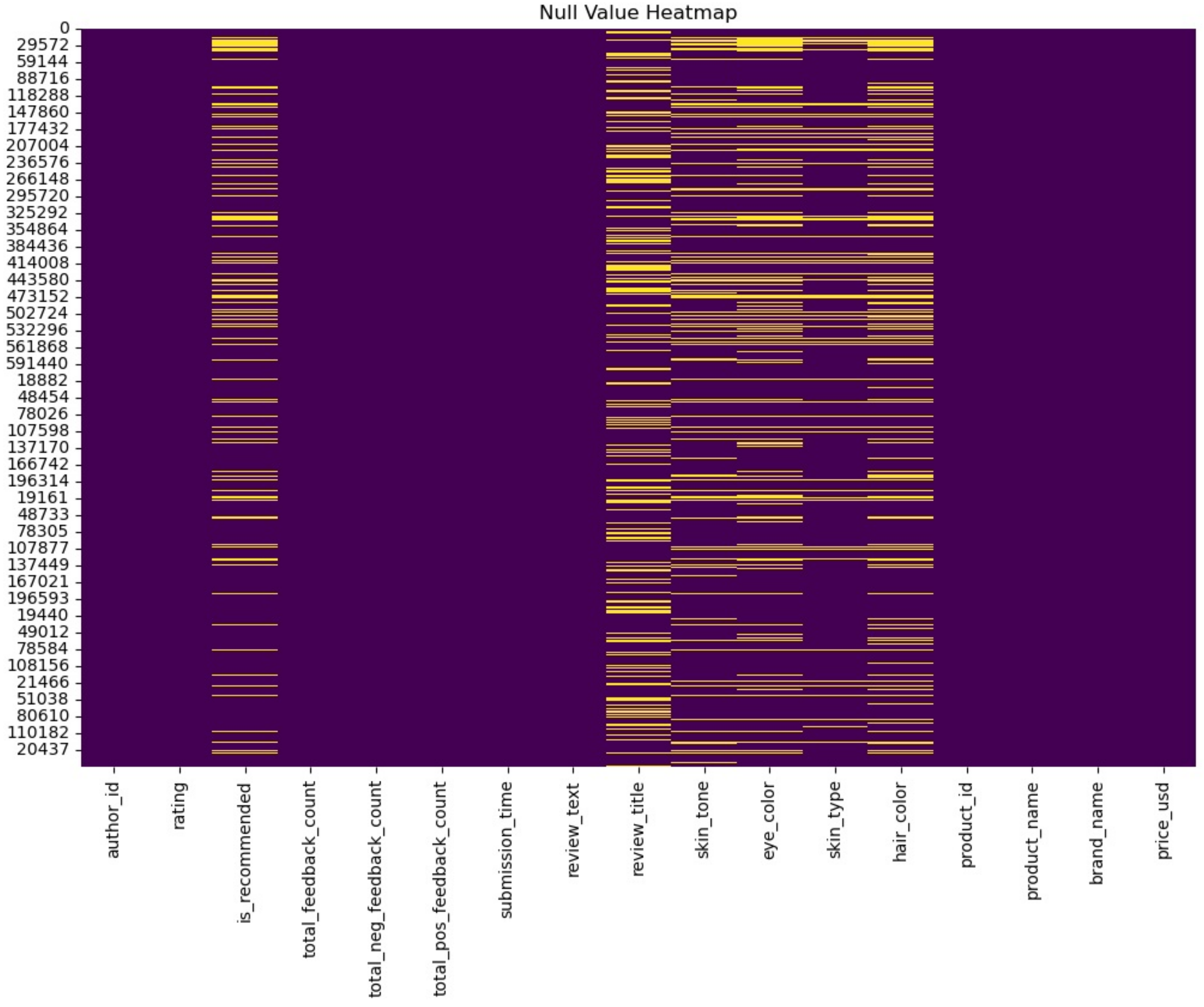
```
# Replace "text_edited" with the actual name of your DataFrame if different.

# Drop the 'helpfulness' column and the 'Unnamed: 0' column
texta = texta.drop(['helpfulness', 'Unnamed: 0'], axis=1)

# After dropping the columns, 'helpfulness' and 'Unnamed: 0', you can use "text_edited" for the updated dataset
```

In [73]:

```
# Change the DataFrame name from "texta" to "text_edited"
text_edited = texta
```

In [74]:

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

# Assuming your DataFrame is stored in a variable called "text_edited"
# Replace "text_edited" with the actual name of your DataFrame if different.

# Create a DataFrame to store information about null values
null_heatmap_data = text_edited.isnull()

# Create the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(null_heatmap_data, cbar=False, cmap='viridis')
plt.title('Null Value Heatmap')
plt.show()
```



In [75]:

```
import pandas as pd

# Assuming your DataFrame is stored in a variable called "text_edited"
# Replace "text_edited" with the actual name of your DataFrame if different.

# Calculate the modes for 'eye_color', 'skin_type', 'hair_color', and 'skin_tone'
eye_color_mode = text_edited['eye_color'].mode().iloc[0]
skin_type_mode = text_edited['skin_type'].mode().iloc[0]
hair_color_mode = text_edited['hair_color'].mode().iloc[0]
skin_tone_mode = text_edited['skin_tone'].mode().iloc[0]

# Fill null values with the calculated modes
text_edited['eye_color'].fillna(eye_color_mode, inplace=True)
text_edited['skin_type'].fillna(skin_type_mode, inplace=True)
text_edited['hair_color'].fillna(hair_color_mode, inplace=True)
```

```
text_edited['skin_tone'].fillna(skin_tone_mode, inplace=True)
```

In [76]:
```
import pandas as pd

# Assuming your DataFrame is stored in a variable called "text_edited"
# Replace "text_edited" with the actual name of your DataFrame if different.

# Fill null values in 'review_text' and 'review_title' with "Not Available"
text_edited['review_text'].fillna("Not Available", inplace=True)
text_edited['review_title'].fillna("Not Available", inplace=True)
```

In [77]:
```
import pandas as pd

# Assuming your DataFrame is stored in a variable called "text_edited"
# Replace "text_edited" with the actual name of your DataFrame if different.

# Get unique values in the 'is_recommended' column
unique_is_recommended = text_edited['is_recommended'].unique()

# Print the unique values
print(unique_is_recommended)
```

```
[ 1.  0. nan]
```

In [78]:
```
 text_edited['is_recommended'].value_counts()
```

Out[78]:
```
1.0    929476
0.0    177686
Name: is_recommended, dtype: int64
```

In [79]:
```
import pandas as pd

# Assuming your DataFrame is stored in a variable called "text_edited"
# Replace "text_edited" with the actual name of your DataFrame if different.

# Calculate the mode for 'is_recommended'
is_recommended_mode = text_edited['is_recommended'].mode().iloc[0]

# Fill null values in 'is_recommended' with the calculated mode
text_edited['is_recommended'].fillna(is_recommended_mode, inplace=True)
```

In [80]:
```
import pandas as pd

# Assuming your DataFrame is stored in a variable called "text_edited"
# Replace "text_edited" with the actual name of your DataFrame if different.

# Get unique values in the 'is_recommended' column
unique_is_recommended = text_edited['is_recommended'].unique()

# Print the unique values
print(unique_is_recommended)
```

```
[1. 0.]
```

In [81]:
```
# Assuming you have already defined the variable text_edited with the edited dataset
numeric_cols_reviews = text_edited.select_dtypes(include=['number']).columns
print(numeric_cols_reviews)
print(f'{len(numeric_cols_reviews)} Numeric Columns in Reviews Dataset')
```

```
Index(['rating', 'is_recommended', 'total_feedback_count',
       'total_neg_feedback_count', 'total_pos_feedback_count', 'price_usd'],
      dtype='object')
6 Numeric Columns in Reviews Dataset
```

In [82]:
```
import pandas as pd

# Assuming you have a DataFrame named 'text_edited'

# Convert 'is_recommended' column from float64 to object (string)
text_edited['is_recommended'] = text_edited['is_recommended'].astype(str)

# Convert 'submission_time' column to datetime64[ns]
text_edited['submission_time'] = pd.to_datetime(text_edited['submission_time'])

# Verify the new dtypes of the columns
print(text_edited.dtypes)
```

```
author_id                             object
rating                                 int64
is_recommended                        object
total_feedback_count                   int64
total_neg_feedback_count               int64
total_pos_feedback_count               int64
submission_time               datetime64[ns]
review_text                           object
review_title                          object
skin_tone                             object
eye_color                             object
skin_type                             object
hair_color                            object
product_id                            object
product_name                          object
brand_name                            object
price_usd                            float64
dtype: object
```

In [83]:
```python
text_edited.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1301136 entries, 0 to 49976
Data columns (total 17 columns):
 #   Column                    Non-Null Count    Dtype
---  ------                    --------------    -----
 0   author_id                 1301136 non-null  object
 1   rating                    1301136 non-null  int64
 2   is_recommended            1301136 non-null  object
 3   total_feedback_count      1301136 non-null  int64
 4   total_neg_feedback_count  1301136 non-null  int64
 5   total_pos_feedback_count  1301136 non-null  int64
 6   submission_time           1301136 non-null  datetime64[ns]
 7   review_text               1301136 non-null  object
 8   review_title              1301136 non-null  object
 9   skin_tone                 1301136 non-null  object
 10  eye_color                 1301136 non-null  object
 11  skin_type                 1301136 non-null  object
 12  hair_color                1301136 non-null  object
 13  product_id                1301136 non-null  object
 14  product_name              1301136 non-null  object
 15  brand_name                1301136 non-null  object
 16  price_usd                 1301136 non-null  float64
dtypes: datetime64[ns](1), float64(1), int64(4), object(11)
memory usage: 178.7+ MB
```

In [84]:
```python
text_edited.head()
```

Out[84]:

	author_id	rating	is_recommended	total_feedback_count	total_neg_feedback_count	total_pos_feedback_count	submission_time	review_
0	1741593524	5	1.0	2	0	2	2023-02-01	I us wit Nuc “(Clean
1	31423088263	1	0.0	0	0	0	2023-03-21	I bo th mask readin re
2	5061282401	5	1.0	0	0	0	2023-03-21	My re title s all! I g excit
3	6083038851	5	1.0	0	0	0	2023-03-20	I’ve al love formu a ti
4	47056667835	5	1.0	0	0	0	2023-03-20	If you dry cra lips, thi mus

In [85]:
```python
text_edited
```

Out[85]:

	author_id	rating	is_recommended	total_feedback_count	total_neg_feedback_count	total_pos_feedback_count	submission_time	re
0	1741593524	5	1.0	2	0	2	2023-02-01	C
1	31423088263	1	0.0	0	0	0	2023-03-21	r
2	5061282401	5	1.0	0	0	0	2023-03-21	a
3	6083038851	5	1.0	0	0	0	2023-03-20	I f
4	47056667835	5	1.0	0	0	0	2023-03-20	I d lip
...	...	...	...	...	...	...	...	
49972	2276253200	5	1.0	0	0	0	2023-03-13	
49973	28013163278	5	1.0	0	0	0	2023-03-13	a r
49974	1539813076	5	1.0	0	0	0	2023-03-13	it
49975	5595682861	5	1.0	0	0	0	2023-03-13	I a
49976	27666075558	5	1.0	0	0	0	2023-03-13	r

1301136 rows × 17 columns

EXPLORATORY DATA ANALYSIS

EDA on Product Dataset

In [86]:

```
# Display basic information about the dataset
print(data_edited.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8493 entries, 0 to 8493
Data columns (total 17 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   product_id          8493 non-null   object 
 1   product_name        8493 non-null   object 
 2   brand_id            8493 non-null   int64  
 3   brand_name          8493 non-null   object 
 4   rating              8493 non-null   float64
 5   reviews             8493 non-null   float64
 6   size                8493 non-null   object 
 7   variation_type      8493 non-null   object 
 8   ingredients         8493 non-null   object 
 9   price_usd           8493 non-null   float64
 10  limited_edition     8493 non-null   object 
 11  new                 8493 non-null   object 
 12  online_only         8493 non-null   object 
 13  out_of_stock        8493 non-null   object 
 14  sephora_exclusive   8493 non-null   object 
 15  primary_category    8493 non-null   object 
 16  secondary_category  8493 non-null   object 
dtypes: float64(3), int64(1), object(13)
memory usage: 1.2+ MB
None
```

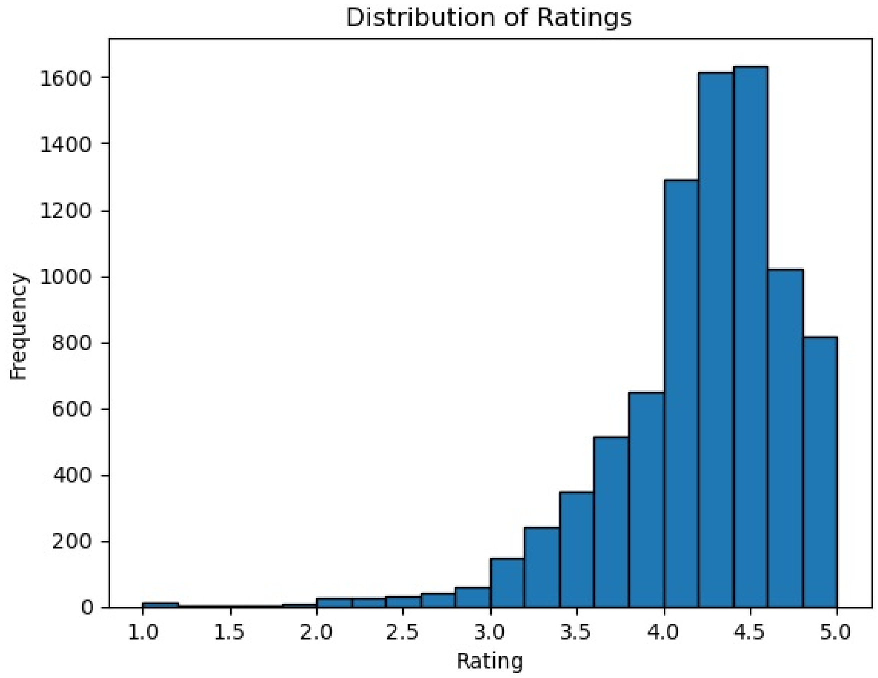
In [87]:

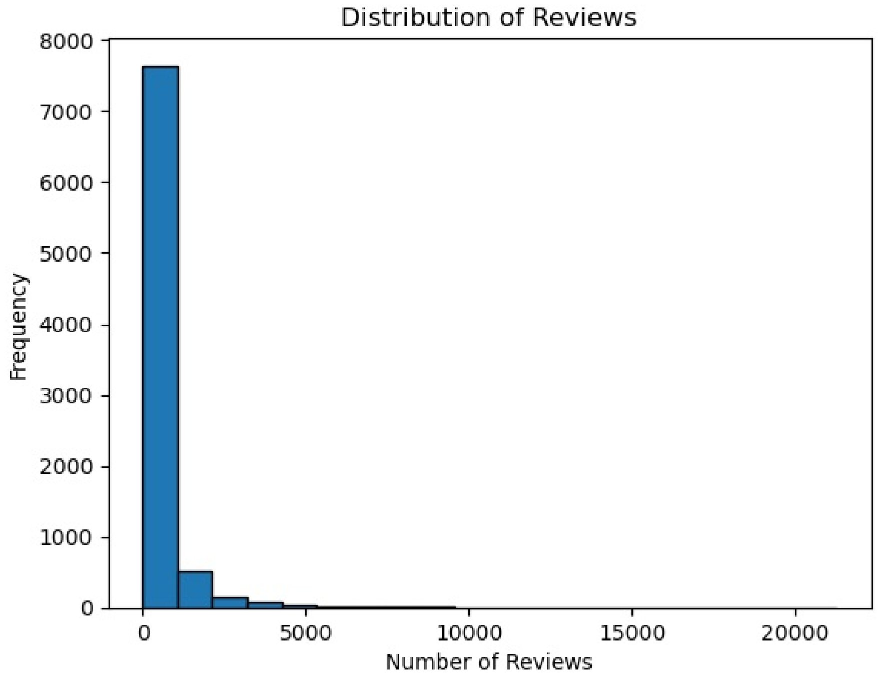
```
# Summary statistics of numeric columns
print(data_edited.describe())
```

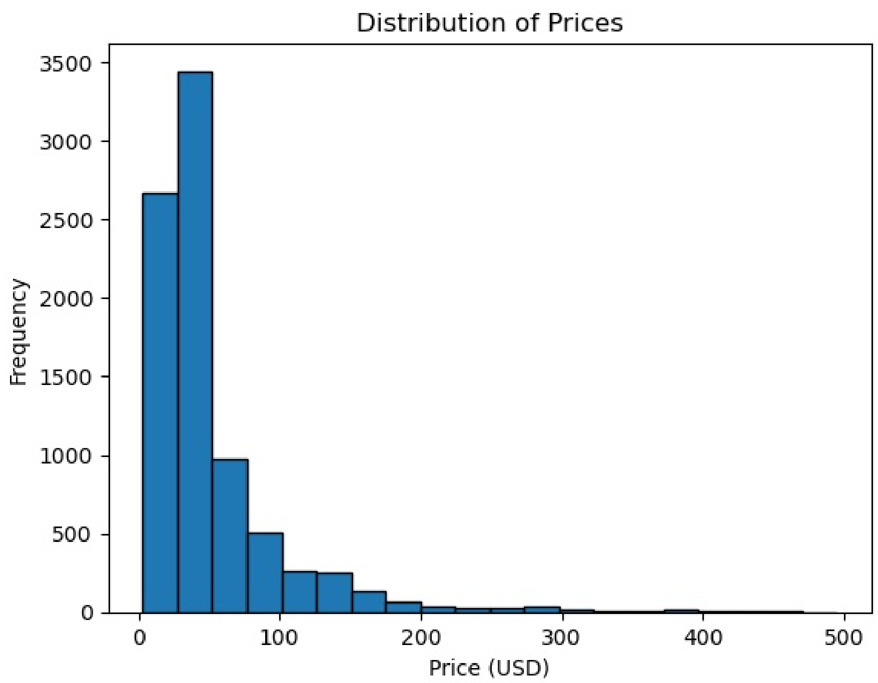
```
          brand_id       rating       reviews    price_usd
count  8493.000000  8493.000000   8493.000000  8493.000000
mean   5422.335570     4.220931    433.981161    51.437963
std    1709.669236     0.527999   1086.759660    49.783262
min    1063.000000     1.000000      1.000000     3.000000
25%    5333.000000     4.000000     22.000000    25.000000
50%    6156.000000     4.308800    112.000000    35.000000
75%    6328.000000     4.558400    402.000000    58.000000
max    8020.000000     5.000000  21281.000000   495.000000
```

In [88]:

```
# Distribution of numerical features

# Histogram of 'rating' column
plt.hist(data_edited['rating'], bins=20, edgecolor='black')
plt.xlabel('Rating')
plt.ylabel('Frequency')
plt.title('Distribution of Ratings')
plt.show()

# Histogram of 'reviews' column
plt.hist(data_edited['reviews'], bins=20, edgecolor='black')
plt.xlabel('Number of Reviews')
plt.ylabel('Frequency')
plt.title('Distribution of Reviews')
plt.show()

# Histogram of 'price_usd' column
plt.hist(data_edited['price_usd'], bins=20, edgecolor='black')
plt.xlabel('Price (USD)')
plt.ylabel('Frequency')
plt.title('Distribution of Prices')
plt.show()
```

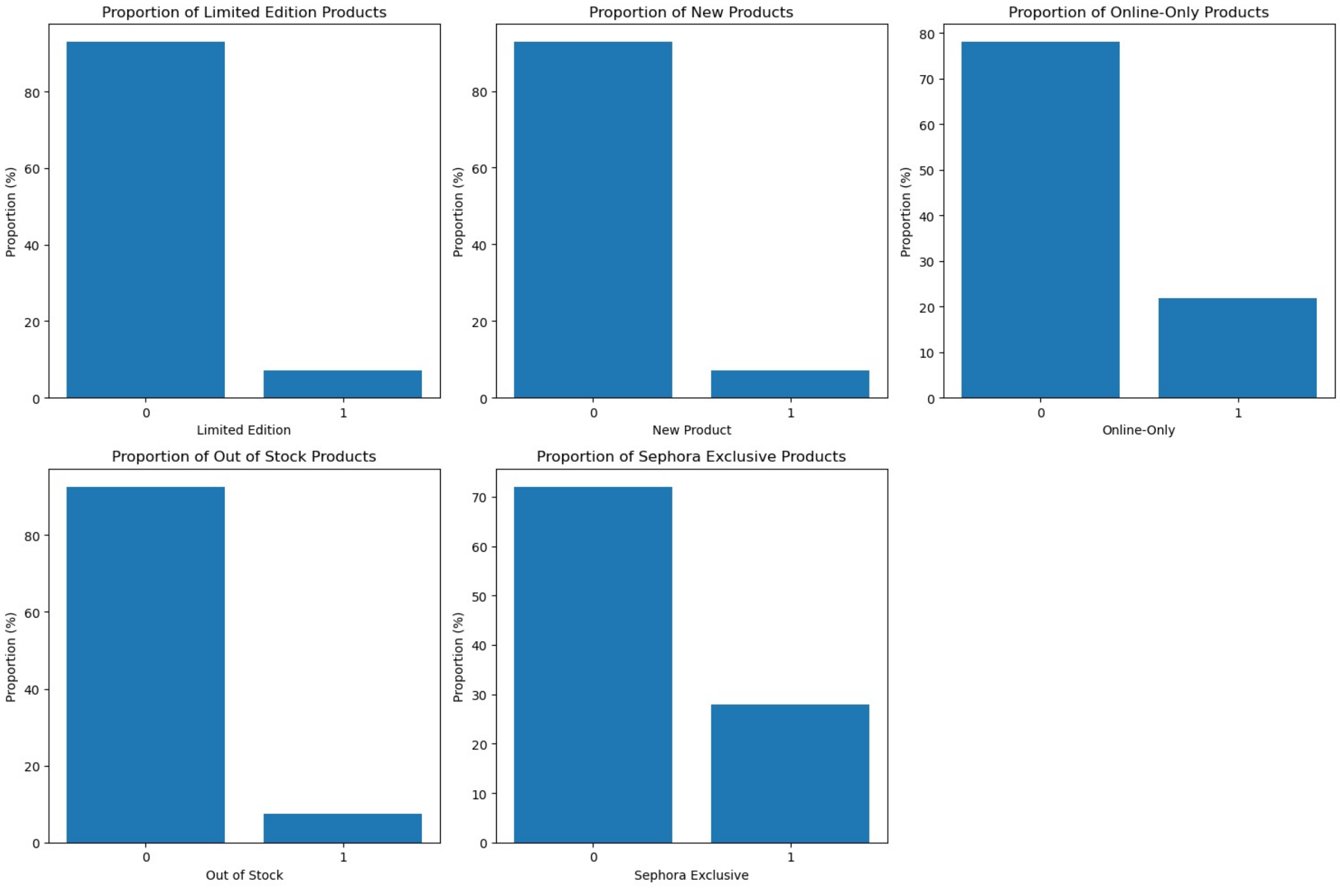






In [89]:
```
import pandas as pd
import matplotlib.pyplot as plt
```

```python
# Assuming your DataFrame is stored in a variable called "data_edited"
# Replace "data_edited" with the actual name of your DataFrame if different.

# Proportion of limited edition, new, online-only, out of stock, and Sephora exclusive products
limited_edition_counts = data_edited['limited_edition'].value_counts(normalize=True) * 100
new_counts = data_edited['new'].value_counts(normalize=True) * 100
online_only_counts = data_edited['online_only'].value_counts(normalize=True) * 100
out_of_stock_counts = data_edited['out_of_stock'].value_counts(normalize=True) * 100
sephora_exclusive_counts = data_edited['sephora_exclusive'].value_counts(normalize=True) * 100

# Plotting the proportions as bar plots
fig, axs = plt.subplots(2, 3, figsize=(15, 10))

# Bar plot for limited edition
axs[0, 0].bar(limited_edition_counts.index, limited_edition_counts.values)
axs[0, 0].set_title("Proportion of Limited Edition Products")
axs[0, 0].set_xlabel("Limited Edition")
axs[0, 0].set_ylabel("Proportion (%)")

# Bar plot for new products
axs[0, 1].bar(new_counts.index, new_counts.values)
axs[0, 1].set_title("Proportion of New Products")
axs[0, 1].set_xlabel("New Product")
axs[0, 1].set_ylabel("Proportion (%)")

# Bar plot for online-only products
axs[0, 2].bar(online_only_counts.index, online_only_counts.values)
axs[0, 2].set_title("Proportion of Online-Only Products")
axs[0, 2].set_xlabel("Online-Only")
axs[0, 2].set_ylabel("Proportion (%)")

# Bar plot for out of stock products
axs[1, 0].bar(out_of_stock_counts.index, out_of_stock_counts.values)
axs[1, 0].set_title("Proportion of Out of Stock Products")
axs[1, 0].set_xlabel("Out of Stock")
axs[1, 0].set_ylabel("Proportion (%)")

# Bar plot for Sephora exclusive products
axs[1, 1].bar(sephora_exclusive_counts.index, sephora_exclusive_counts.values)
axs[1, 1].set_title("Proportion of Sephora Exclusive Products")
axs[1, 1].set_xlabel("Sephora Exclusive")
axs[1, 1].set_ylabel("Proportion (%)")

# Removing the empty subplot
fig.delaxes(axs[1, 2])

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



INTERPRETATION:

Most products aren't "Limited Edition" or "New".

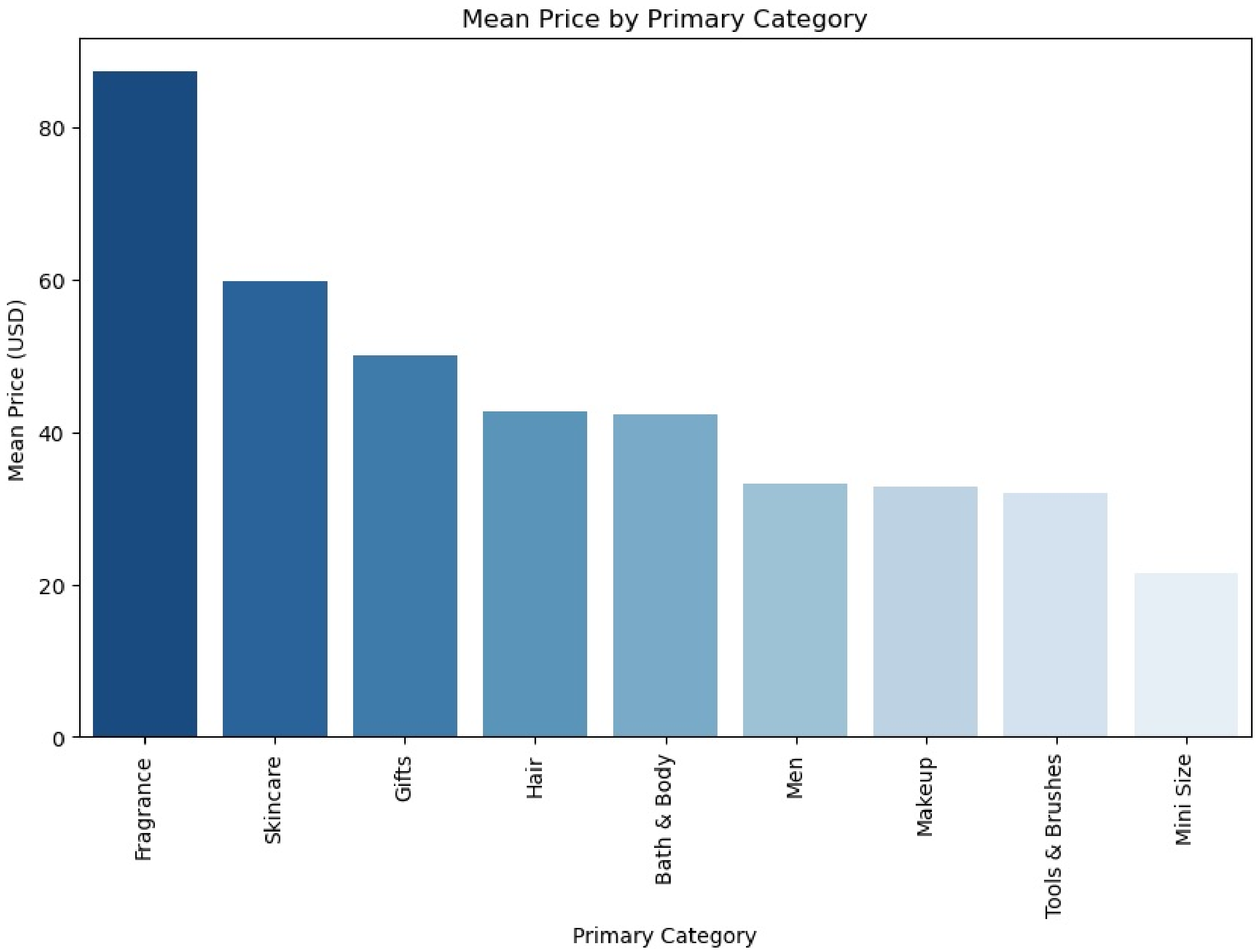
About 1 in 5 products are "Out of Stock".

Roughly 1 in 3 products are "Sephora Exclusive".

A quarter of the products are sold "Online-Only".

In short, most products are regular items, with a few being exclusive to Sephora or online-only.

In [90]:
```
mean_price_by_category = data_edited.groupby('primary_category')['price_usd'].mean().sort_values(ascending=Fals
plt.figure(figsize=(10, 6))
sns.barplot(x=mean_price_by_category.index, y=mean_price_by_category.values, palette='Blues_r')
plt.xlabel('Primary Category')
plt.ylabel('Mean Price (USD)')
plt.title('Mean Price by Primary Category')
plt.xticks(rotation=90)
plt.show()
```

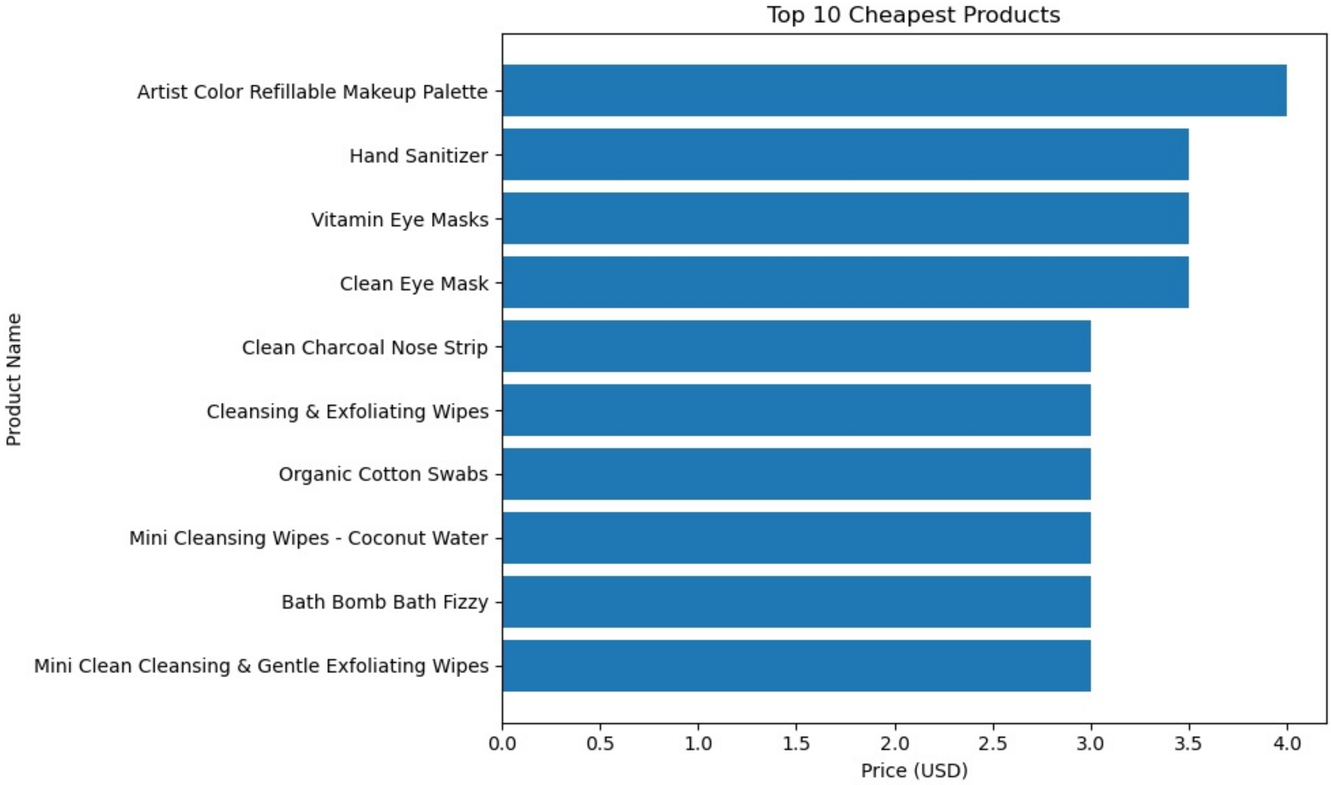


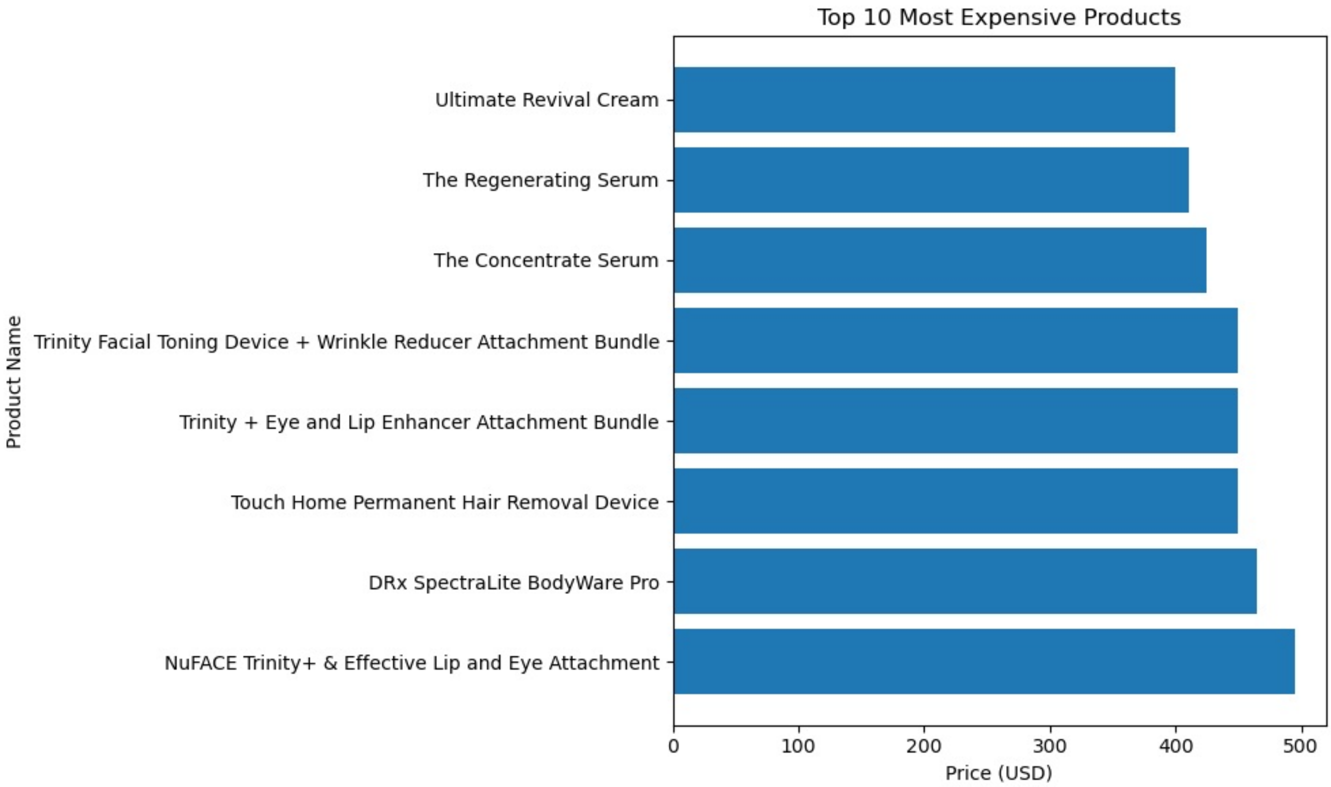
INTERPRETATION:

The graph shows the average price of products for different categories at Sephora. "Fragrance" has the highest average price, while "Mini Size" items have the lowest average price.

In [91]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Assuming you have a DataFrame named 'data_edited'

# Sort the DataFrame by 'price_usd' in ascending order to get cheapest products first
cheapest_products = data_edited.sort_values(by='price_usd').head(10)

# Sort the DataFrame by 'price_usd' in descending order to get most expensive products first
expensive_products = data_edited.sort_values(by='price_usd', ascending=False).head(10)

# Create a bar chart for the top 10 cheapest products
plt.figure(figsize=(10, 6))
plt.barh(cheapest_products['product_name'], cheapest_products['price_usd'])
plt.title('Top 10 Cheapest Products')
plt.xlabel('Price (USD)')
plt.ylabel('Product Name')
plt.tight_layout()
plt.show()
```

```
# Create a bar chart for the top 10 most expensive products
plt.figure(figsize=(10, 6))
plt.barh(expensive_products['product_name'], expensive_products['price_usd'])
plt.title('Top 10 Most Expensive Products')
plt.xlabel('Price (USD)')
plt.ylabel('Product Name')
plt.tight_layout()
plt.show()
```





INTERPRETATION:

The graphs display the top 10 cheapest and most expensive products at Sephora.

Cheapest Products: Items like "Hand Sanitizer" and "Clean Eye Mask" are among the least expensive, with prices under $4. Most Expensive Products: Products like "Ultimate Revival Cream" and "The Regenerating Serum" are among the priciest, costing several hundred dollars each. In essence, Sephora offers a wide price range, from very affordable items to premium-priced products.

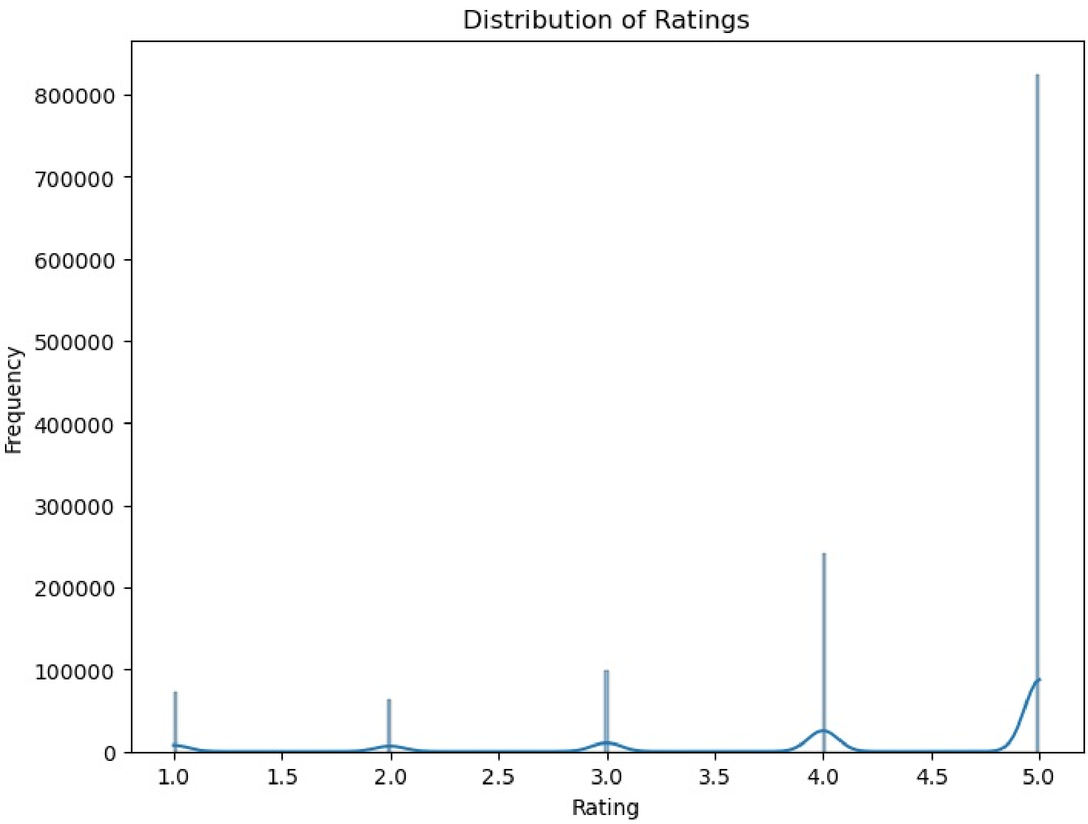
EDA on Reviews Dataset

In [92]:

```
text_edited.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1301136 entries, 0 to 49976
Data columns (total 17 columns):
 #   Column                    Non-Null Count    Dtype
---  ------                    --------------    -----
 0   author_id                 1301136 non-null  object
 1   rating                    1301136 non-null  int64
 2   is_recommended            1301136 non-null  object
 3   total_feedback_count      1301136 non-null  int64
 4   total_neg_feedback_count  1301136 non-null  int64
 5   total_pos_feedback_count  1301136 non-null  int64
 6   submission_time           1301136 non-null  datetime64[ns]
 7   review_text               1301136 non-null  object
 8   review_title              1301136 non-null  object
 9   skin_tone                 1301136 non-null  object
 10  eye_color                 1301136 non-null  object
 11  skin_type                 1301136 non-null  object
 12  hair_color                1301136 non-null  object
 13  product_id                1301136 non-null  object
 14  product_name              1301136 non-null  object
 15  brand_name                1301136 non-null  object
 16  price_usd                 1301136 non-null  float64
dtypes: datetime64[ns](1), float64(1), int64(4), object(11)
memory usage: 178.7+ MB
```

In [93]:
```
# Distribution plot of 'rating' column
plt.figure(figsize=(8, 6))
sns.histplot(text_edited['rating'], kde=True)
plt.xlabel('Rating')
plt.ylabel('Frequency')
plt.title('Distribution of Ratings')
plt.show()
```

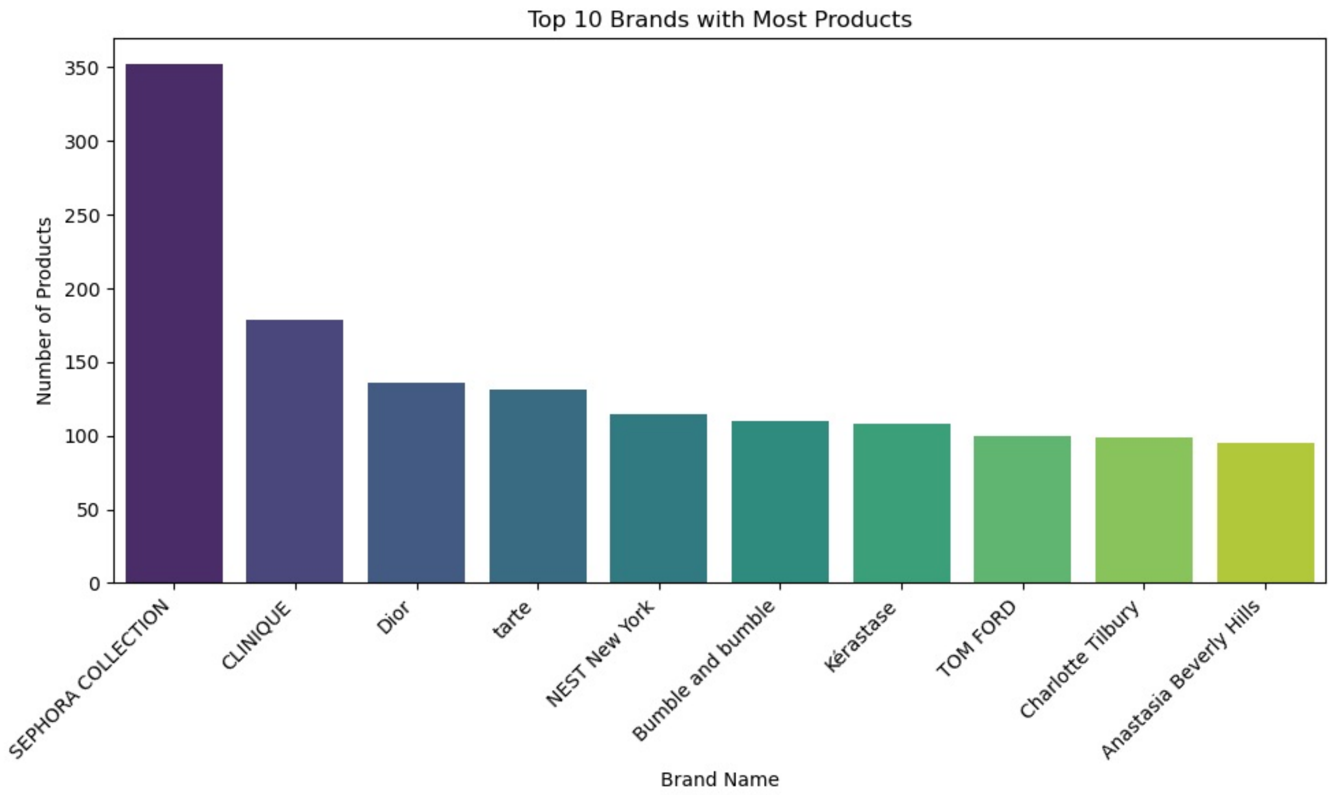


INTERPRETATION:

The graph showcases the distribution of product ratings:

A very small number of products received ratings around 1.0 to 3.0. The majority of products received the highest rating of 5.0. In essence, most products at Sephora have been highly rated by customers.

In [94]:
```
top_brands = data['brand_name'].value_counts().nlargest(10)

plt.figure(figsize=(10, 6))
sns.barplot(x=top_brands.index, y=top_brands.values, palette='viridis')
plt.xticks(rotation=45, ha='right')
plt.xlabel('Brand Name')
plt.ylabel('Number of Products')
plt.title('Top 10 Brands with Most Products')
plt.tight_layout()
plt.show()
```



INTERPRETATION:

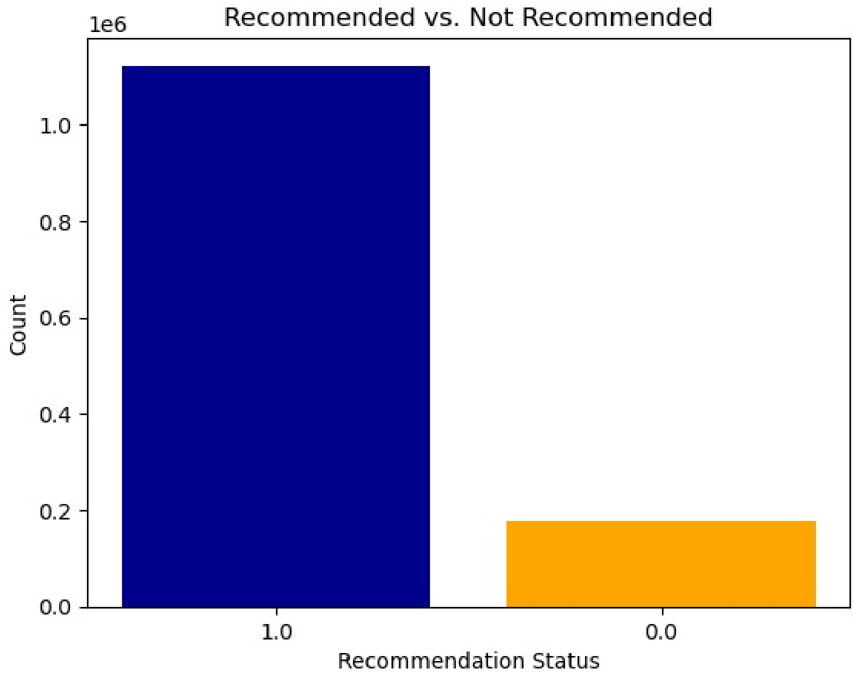
The chart showcases the top 10 brands with the most products on Sephora.

SEPHORA COLLECTION has the highest number, over 300 products. CLINIQUE comes second with around 250 products. Brands like Dior, tarte, and NEST New York have between 100 to 200 products. The remaining brands, including TOM FORD and Charlotte Tilbury, offer 50 to 100 products each.

In essence, SEPHORA COLLECTION dominates in product variety, but several other brands also have a strong presence.

In [95]:

```
import matplotlib.pyplot as plt
import pandas as pd

# Assuming your dataset is stored in a DataFrame called 'text_edited'
# If your dataset is in a CSV file, you can read it using pd.read_csv('filename.csv')

# Step 1: Count occurrences of each value in 'is_recommended' column
recommended_counts = text_edited['is_recommended'].value_counts()

# Step 2: Create the bar chart
plt.bar(recommended_counts.index, recommended_counts.values, color=['darkblue', 'orange'])

plt.xlabel('Recommendation Status')
plt.ylabel('Count')
plt.title('Recommended vs. Not Recommended')
plt.show()
```



The visualization titled "Recommended vs. Not Recommended" provides a clear comparison of the count of products that have been recommended versus those that haven't.

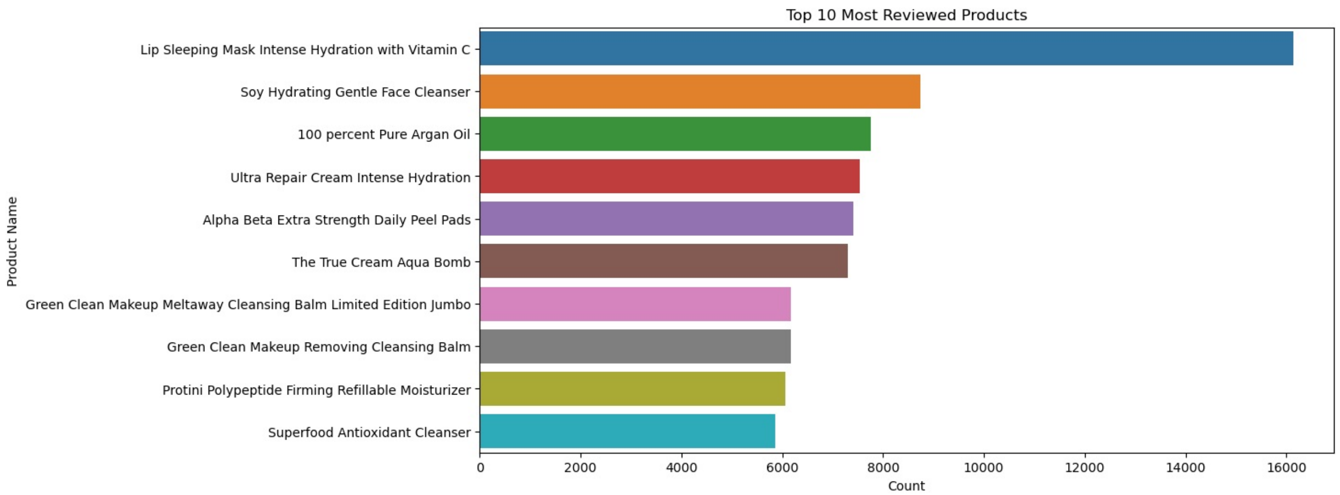
INTERPRETATION:

A vast majority of products have been recommended, as indicated by the tall blue bar. This suggests that most users or reviewers had a positive experience with the products and found them satisfactory.

A significantly smaller number of products were not recommended, as shown by the shorter orange bar. This indicates that a lesser number of users had reservations or were not entirely satisfied with these products.

In summary, the visualization underscores a predominantly positive reception for products, with a small fraction not meeting the users' expectations or requirements.

In [96]:
```
# Count of products by 'product_name'
plt.figure(figsize=(12, 6))
sns.barplot(y=text_edited['product_name'].value_counts().nlargest(10).index, x=text_edited['product_name'].valu
plt.ylabel('Product Name')
plt.xlabel('Count')
plt.title('Top 10 Most Reviewed Products')
plt.show()
```

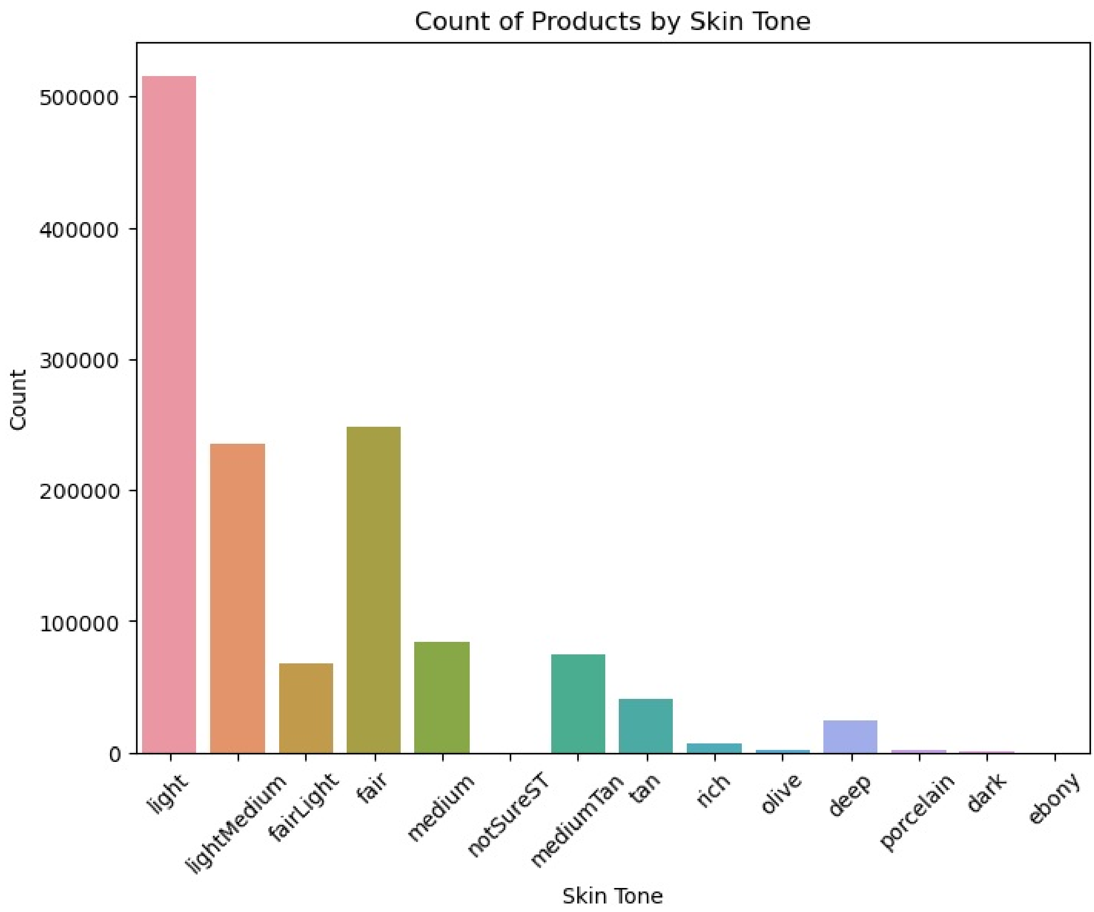


INTERPRETATION:

The graph displays the top 10 products with the highest number of reviews. The "Lip Sleeping Mask Intense Hydration with Vitamin C" has the most reviews, followed by other products in decreasing order.

In [97]:
```
# Count of Products by Skin Tone
plt.figure(figsize=(8, 6))
sns.countplot(x='skin_tone', data=text_edited)
plt.xlabel('Skin Tone')
plt.ylabel('Count')
plt.title('Count of Products by Skin Tone')
```

```
plt.xticks(rotation=45)
plt.show()
```



INTERPRETATION:

The graph illustrates the count of products based on different skin tones. "Light" skin tone products have the highest count, followed by "light/medium" and "medium" skin tones. Other skin tones have comparatively fewer products.

STATISTICAL TESTS:

Test for Collinearity:

In [118…

```
import warnings
warnings.filterwarnings('ignore')
```

In [117…

```
import pandas as pd

# Load the dataset
data = pd.read_csv(r"C:\Users\logeshwar\Downloads\Sephora Reviews Dataset.csv")

# Calculate Pearson correlation coefficients for numerical variables
numerical_vars = ['rating', 'total_feedback_count', 'total_neg_feedback_count', 'total_pos_feedback_count', 'pr
correlation_matrix = data[numerical_vars].corr()
print("Correlation Matrix:")
print(correlation_matrix)
```

```
Correlation Matrix:
                           rating  total_feedback_count  \
rating                   1.000000             -0.080300   
total_feedback_count    -0.080300              1.000000   
total_neg_feedback_count -0.182179             0.674619   
total_pos_feedback_count -0.049147             0.984976   
price_usd               -0.002616              0.008143   

                          total_neg_feedback_count  total_pos_feedback_count  \
rating                                   -0.182179                 -0.049147   
total_feedback_count                      0.674619                  0.984976   
total_neg_feedback_count                  1.000000                  0.537009   
total_pos_feedback_count                  0.537009                  1.000000   
price_usd                                 0.007682                  0.007508   

                          price_usd  
rating                    -0.002616  
total_feedback_count       0.008143  
total_neg_feedback_count   0.007682  
total_pos_feedback_count   0.007508  
price_usd                  1.000000  
```

INTERPRETATION:

Products with higher ratings tend to have fewer negative feedbacks.

Products with more total feedback also have more positive and negative feedback.

Price doesn't show a clear relationship with ratings or feedback counts.

Basically, well-rated products get fewer negative comments, and popular products (with lots of feedback) have both more likes and dislikes. Product prices don’t seem to affect ratings or the number of comments much.

Chi-Square Test:

In [100…

```
from scipy.stats import chi2_contingency

# Create a contingency table for two categorical variables
contingency_table = pd.crosstab(data['is_recommended'], data['skin_type'])

# Perform the chi-square test
chi2_stat, p_value, dof, expected = chi2_contingency(contingency_table)
print("Chi-Square Test - Chi2-statistic:", chi2_stat)
print("Chi-Square Test - P-value:", p_value)
```

```
Chi-Square Test - Chi2-statistic: 1923.860016218833
Chi-Square Test - P-value: 0.0
```

INTERPRETATION:

The Chi-Square test was performed to check if there's a relationship between the recommendation status ('is_recommended') of a product and the skin type of users ('skin_type').

With a Chi2-statistic value of 1923.86 and a p-value of 0.0, the results are statistically significant. This suggests that there is a strong association between whether a product is recommended and the skin type of the users. In other words, the likelihood of a product being recommended may vary depending on the skin type of the user.

Chi-square Test for Independence:

In [102…

```
from scipy.stats import chi2_contingency

# List of categorical predictors including 'rating'
categorical_predictors = ['rating', 'skin_tone', 'eye_color', 'skin_type', 'hair_color']

# Running chi-square test for each predictor against 'is_recommended'
for predictor in categorical_predictors:
    crosstab = pd.crosstab(data[predictor], data['is_recommended'])
    chi2, p, _, _ = chi2_contingency(crosstab)
    print(f"P-value for {predictor} vs. is_recommended:", p)
```

```
P-value for rating vs. is_recommended: 0.0
P-value for skin_tone vs. is_recommended: 0.0
P-value for eye_color vs. is_recommended: 0.0
P-value for skin_type vs. is_recommended: 0.0
P-value for hair_color vs. is_recommended: 0.0
```

INTERPRETATION:

All the p-values are 0.0, which means:

Rating, skin_tone, eye_color, skin_type, and hair_color each have a relationship with whether a product is recommended or not.

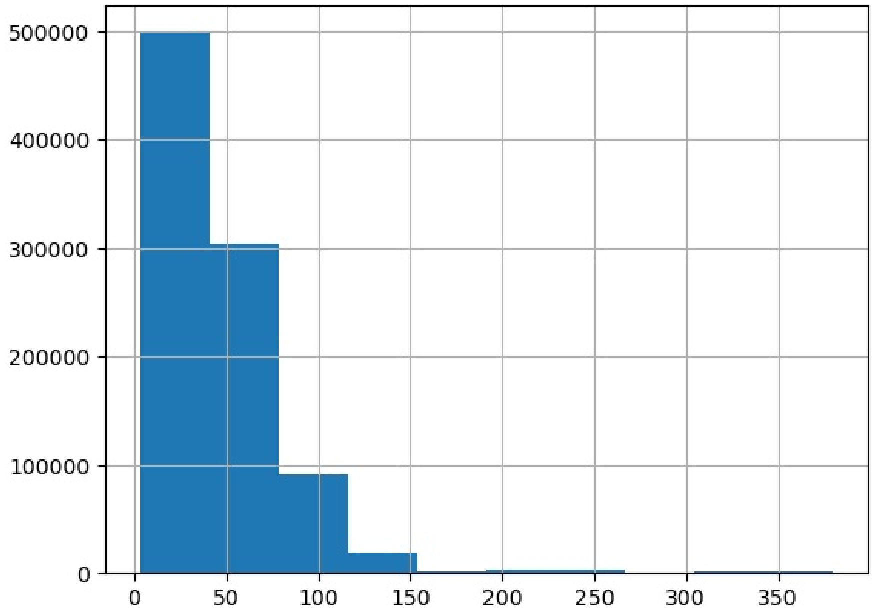
It's not just by random chance; there's a real association.

For example, products with higher ratings are more likely to be recommended. Similarly, people with different skin tones, eye colors, etc., might have varying preferences.

In short, all these factors play a role in whether a product gets recommended.

Descriptive Statistics and Visualization:

In [103…
```python
import matplotlib.pyplot as plt

data['price_usd'].hist()
plt.show()

print(data['is_recommended'].value_counts())
```




```
1.0    799381
0.0    124076
Name: is_recommended, dtype: int64
```

INTERPRETATION:

The histogram shows how product prices are spread out.

Most products, around 86.5%, are recommended by customers, while the rest are not.

In short, the majority of products get a thumbs-up from customers, and the histogram shows their pricing distribution.

T-Test:

In [104…
```python
print(data['is_recommended'].unique())
print(data['is_recommended'].dtype)
```

```
[1. 0.]
float64
```

In [105…
```python
from scipy.stats import ttest_ind

# Split the data into two groups: recommended and not recommended
recommended_prices = data[data['is_recommended'] == 1]['price_usd']
not_recommended_prices = data[data['is_recommended'] == 0]['price_usd']

# Perform the t-test
t_stat, p_value = ttest_ind(recommended_prices, not_recommended_prices)

print("T-statistic:", t_stat)
print("P-value:", p_value)
```

```
T-statistic: -2.9337376064389415
P-value: 0.0033491543629176807
```

INTERPRETATION:

The T-statistic value of -2.9337 suggests that there's a difference between the two groups, with the average price of the not-recommended products being higher than the recommended ones (since the value is negative).

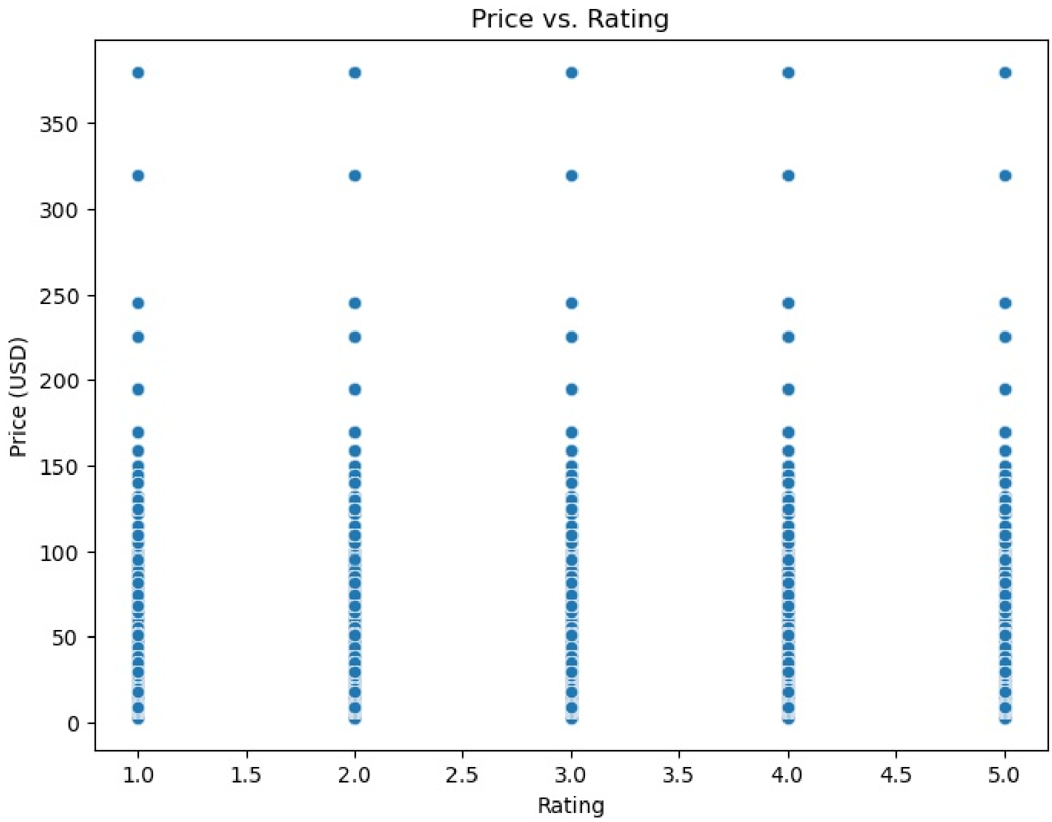
The P-value is 0.0033, which is less than the typical significance level of 0.05. This means that the difference between the average prices of recommended and not-recommended products is statistically significant. In other words, the observed difference in the averages is likely not due to random chance.

In simple terms: The average price of products that aren't recommended is statistically higher than those that are recommended. make it simple

Relationship between product prices (in USD) and their ratings.

In [107…

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

plt.figure(figsize=(8, 6))
sns.scatterplot(x='rating', y='price_usd', data=data, alpha=0.5)
plt.xlabel('Rating')
plt.ylabel('Price (USD)')
plt.title('Price vs. Rating')
plt.show()
```



The graph shows the relationship between product prices (in USD) and their ratings.

INTERPRETATIONS:

Most products, regardless of their price, have a high rating (around 4 to 5).

There are some products with low ratings (1 to 2), but they are fewer in number.

Products with a wide range of prices can have similar high ratings.

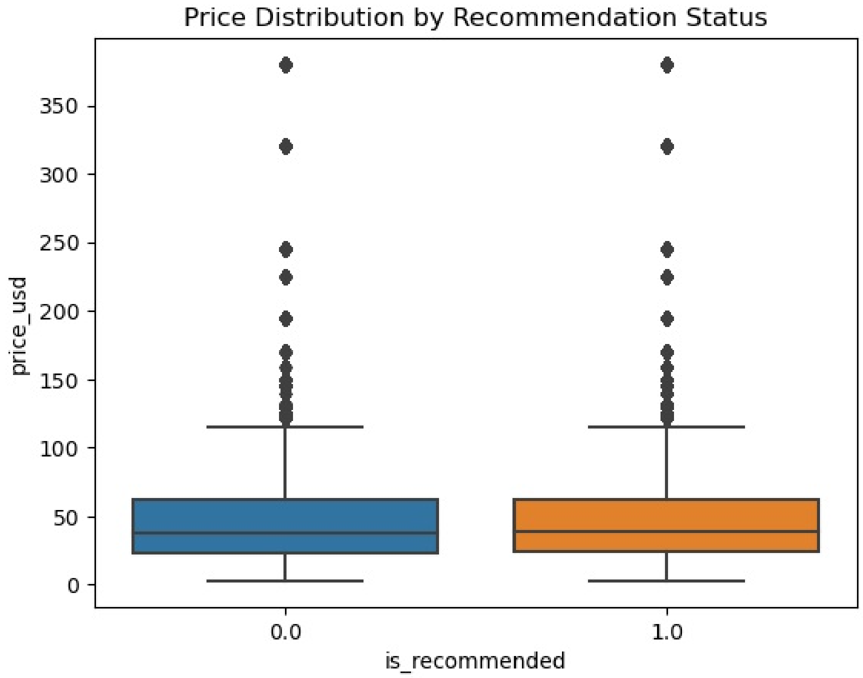
Overall, there's no clear trend that higher-priced products have higher or lower ratings.

Business Problem 1

Is there a significant difference in average product prices between products that are recommended and those that are not?

In [108…

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

# Create a boxplot to visualize price differences
sns.boxplot(x='is_recommended', y='price_usd', data=data)
plt.title("Price Distribution by Recommendation Status")
plt.show()
```



INTERPRETATION:

The boxplot displays the distribution of product prices based on their recommendation status. For products that are recommended (represented by 1.0), the price range appears broader, with both a higher median price and more outliers in the higher price range compared to products that are not recommended (represented by 0.0). The non-recommended products have a slightly lower median price, with fewer high-priced outliers.

Solution to the Business Problem:

Value for Money:

The wider range and slightly higher median price for recommended products suggest that customers are willing to pay a premium for products they perceive as valuable or of high quality. The brand should focus on emphasizing the value proposition and unique selling points of higher-priced products to maintain and even boost their recommendation status.

Price Sensitivity:

The non-recommended products' lower price range hints at possible issues other than just the price – perhaps quality, packaging, or efficacy. It might be beneficial to revisit these products and analyze negative feedback to understand the core concerns.

Review and Revise:

The presence of high-priced outliers in the non-recommended bracket suggests that there might be premium products that aren't meeting customer expectations. A deeper dive into the specific feedback for these products could offer insights into why they aren't resonating well with customers despite their high price point.

Customer Engagement:

Engage with customers to understand what improvements can be made to non-recommended products, especially those in the higher price range. Feedback can be invaluable in making necessary changes to the product or its positioning.

Pricing Strategy:

Consider periodic reviews of the pricing strategy, taking into account customer feedback and market trends. Offering promotions, discounts, or bundling options might help in improving the recommendation status of certain products.

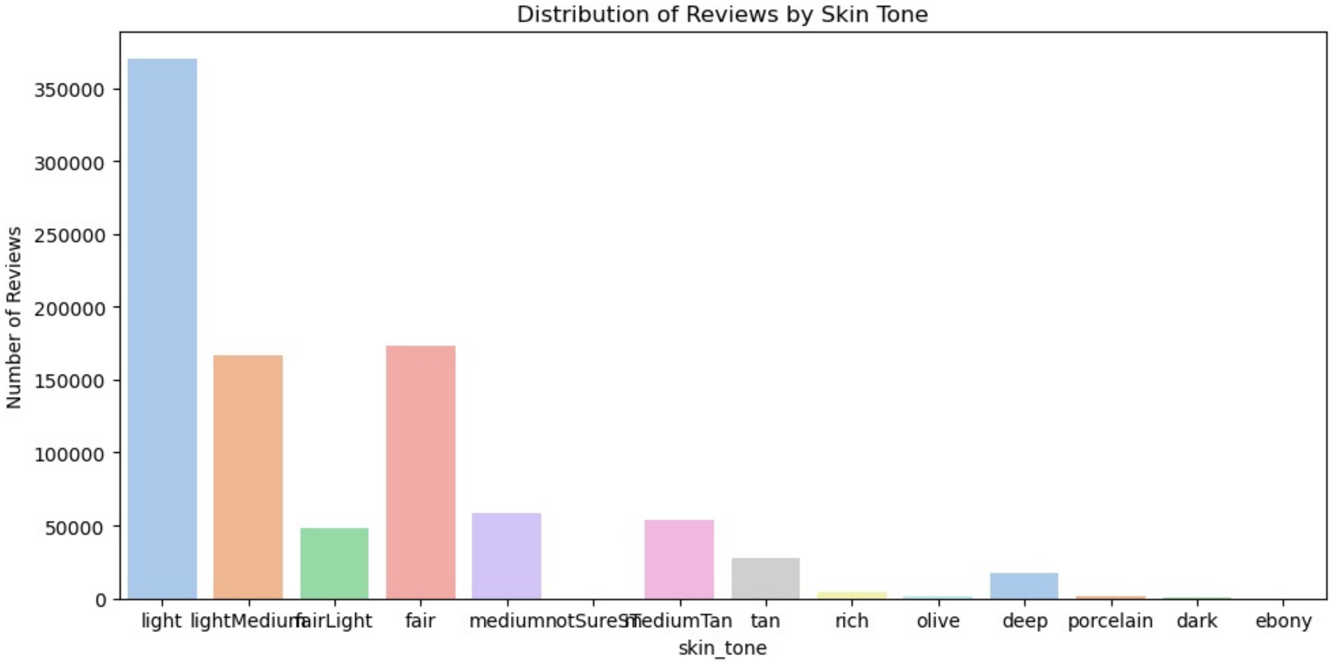
In conclusion, while price plays a role in a product's recommendation status, it's crucial to understand that customers value quality, efficacy, and overall satisfaction. Ensuring that products, whether low or high priced, meet or exceed customer expectations will positively impact their recommendation status.

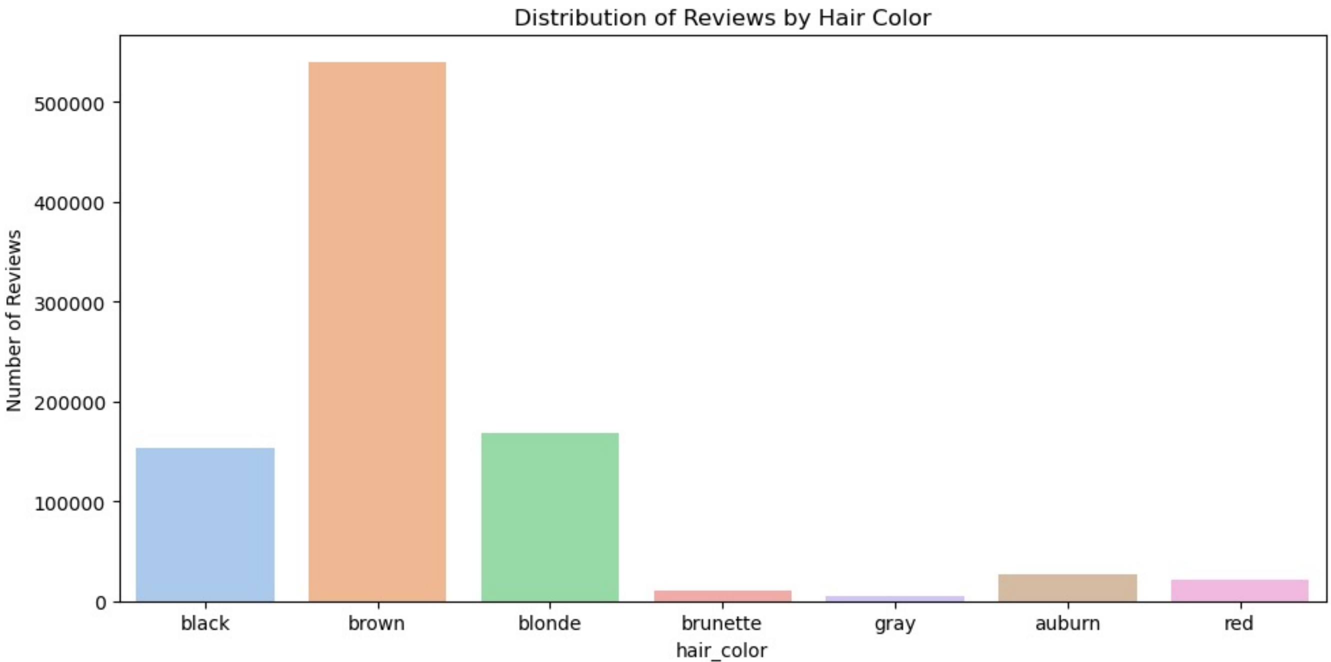
Business Problem 2

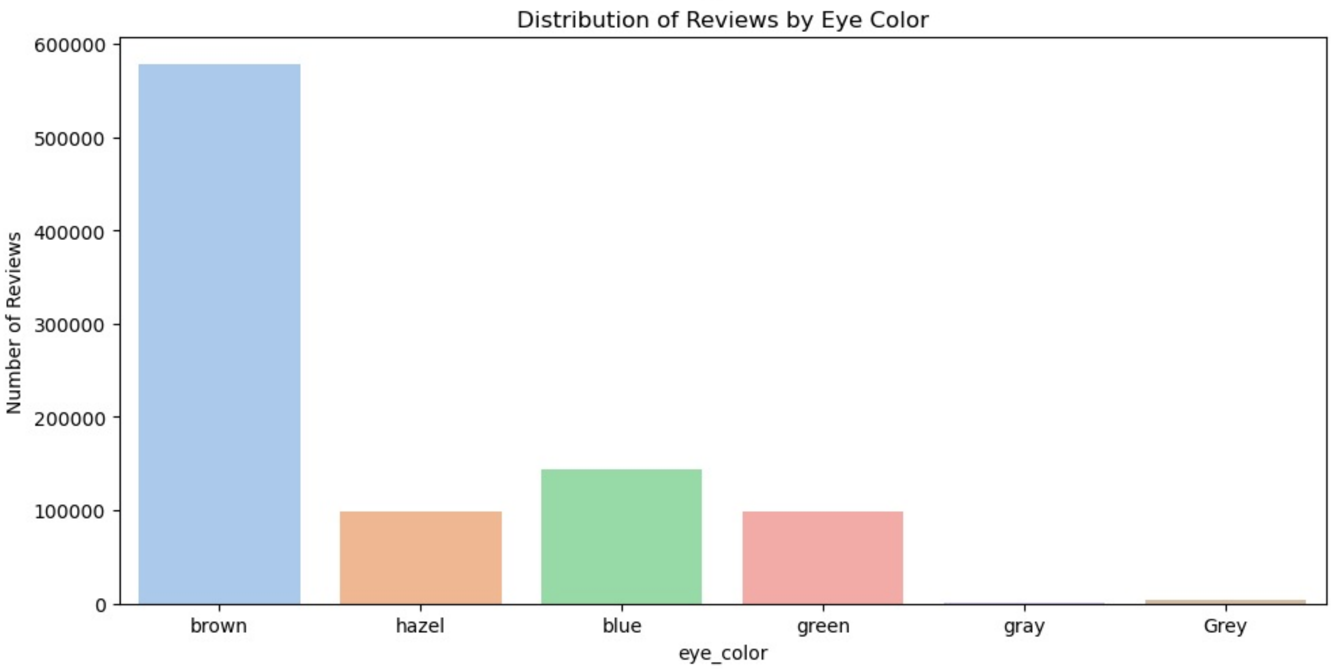
"To launch a new marketing campaign, we want to identify which customer segments (based on features like skin tone, hair color, eye color) might be underrepresented or overly dissatisfied in our reviews. Identifying these groups will allow us to tailor our campaigns to these segments, ensuring they feel represented and addressing their specific concerns."

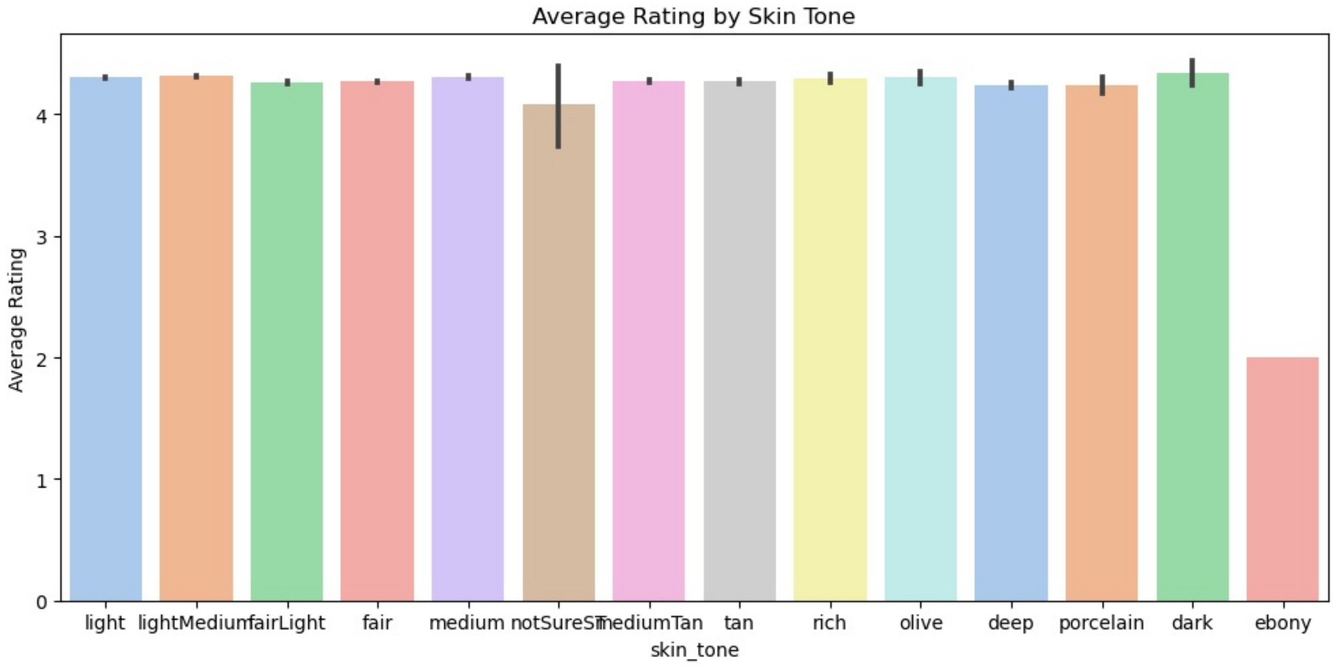
In [109…

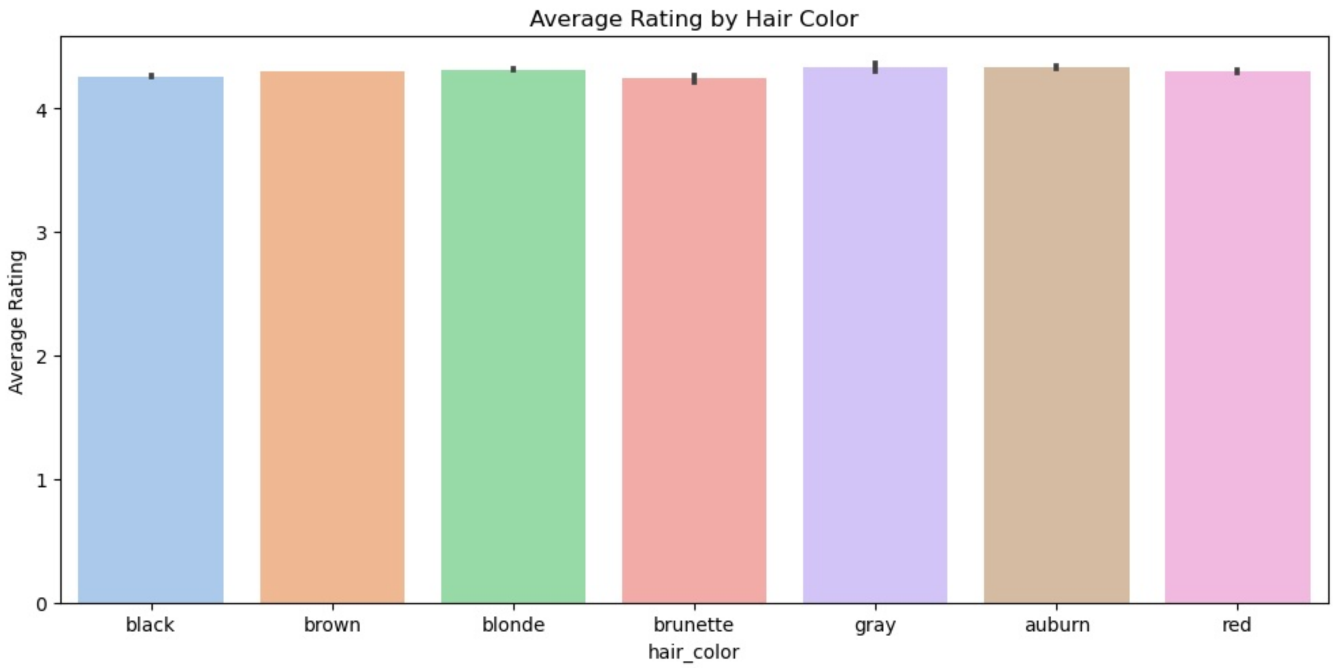
```
import matplotlib.pyplot as plt
import seaborn as sns

# Distribution of reviews based on skin tone, hair color, and eye color
fig, axes = plt.subplots(nrows=3, ncols=1, figsize=(10, 15))

sns.countplot(x='skin_tone', data=data, ax=axes[0], palette='pastel')
axes[0].set_title('Distribution of Reviews by Skin Tone')
axes[0].set_ylabel('Number of Reviews')

sns.countplot(x='hair_color', data=data, ax=axes[1], palette='pastel')
axes[1].set_title('Distribution of Reviews by Hair Color')
axes[1].set_ylabel('Number of Reviews')

sns.countplot(x='eye_color', data=data, ax=axes[2], palette='pastel')
axes[2].set_title('Distribution of Reviews by Eye Color')
axes[2].set_ylabel('Number of Reviews')

plt.tight_layout()
plt.show()

# Average satisfaction (rating) for each segment
fig, axes = plt.subplots(nrows=3, ncols=1, figsize=(10, 15))

sns.barplot(x='skin_tone', y='rating', data=data, ax=axes[0], palette='pastel')
axes[0].set_title('Average Rating by Skin Tone')
axes[0].set_ylabel('Average Rating')

sns.barplot(x='hair_color', y='rating', data=data, ax=axes[1], palette='pastel')
axes[1].set_title('Average Rating by Hair Color')
axes[1].set_ylabel('Average Rating')

sns.barplot(x='eye_color', y='rating', data=data, ax=axes[2], palette='pastel')
axes[2].set_title('Average Rating by Eye Color')
axes[2].set_ylabel('Average Rating')

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

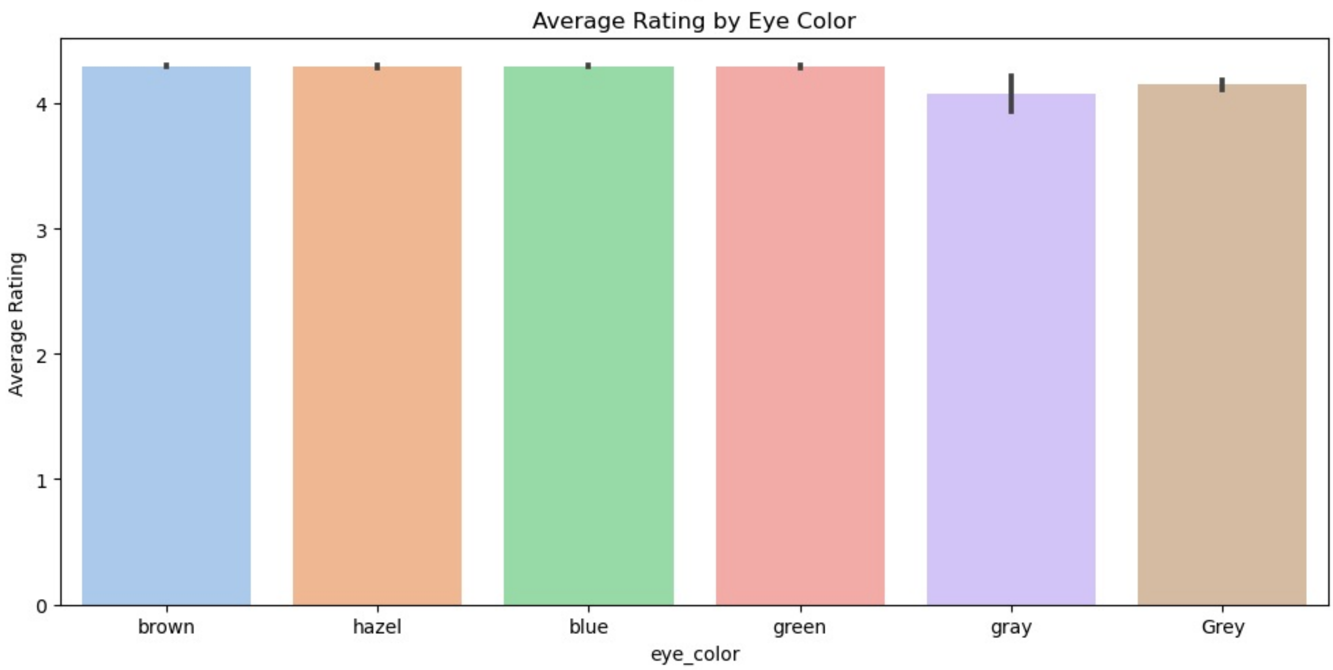

Distribution of Reviews by Skin Tone
Number of Reviews
0
50000
100000
150000
200000
250000
300000
350000
light
lightMedium
fairLight
fair
medium
notSureST
mediumTan
tan
rich
olive
deep
porcelain
dark
ebony
skin_tone


Distribution of Reviews by Hair Color
Number of Reviews
0
100000
200000
300000
400000
500000
black
brown
blonde
brunette
gray
auburn
red
hair_color


Distribution of Reviews by Eye Color
Number of Reviews
0
100000
200000
300000
400000
500000
600000
brown
hazel
blue
green
gray
Grey
eye_color


Average Rating by Skin Tone
Average Rating
0
1
2
3
4
light
lightMedium
fairLight
fair
medium
notSureSt
mediumTan
tan
rich
olive
deep
porcelain
dark
ebony
skin_tone


Average Rating by Hair Color
Average Rating
0
1
2
3
4
black
brown
blonde
brunette
gray
auburn
red
hair_color


Average Rating by Eye Color
Average Rating
0
1
2
3
4
brown
hazel
blue
green
gray
Grey
eye_color

INTERPRETATION:

Reviews by Skin Tone:

Most reviews come from individuals with "light" and "medium" skin tones, with fewer reviews from other tones. Reviews by Hair Color: A majority of the feedback is from users with "brown" hair, followed by those with "black" and "blonde" hair.

Reviews by Eye Color:

The majority of reviewers have "brown" eyes, followed by "blue" and "green."

Average Rating by Skin Tone:

All skin tones generally give consistent ratings, suggesting overall satisfaction across the board.

Average Rating by Hair and Eye Color:

Similarly, there is a consistent average rating across different hair and eye colors, indicating that products are perceived similarly across these categories.

Solution to the Business Problem:

Diversify Feedback Pool:

Enhance marketing campaigns targeting underrepresented skin, hair, and eye colors. Collaborations with influencers from these categories can help in acquiring diverse feedback.

Tailored Product Lines:

Consider introducing or refining products tailored to the unique needs and preferences of underrepresented categories. For instance, certain makeup colors might be more vibrant on specific skin tones or work best for a particular hair color.

Educational Initiatives:

Launch tutorials, guides, or workshops emphasizing the use of products for diverse skin, hair, and eye colors. This can help consumers make informed decisions and feel more represented.

Feedback Analysis:

Conduct deeper analyses of reviews, especially from underrepresented categories, to identify any product shortcomings and areas for improvement.

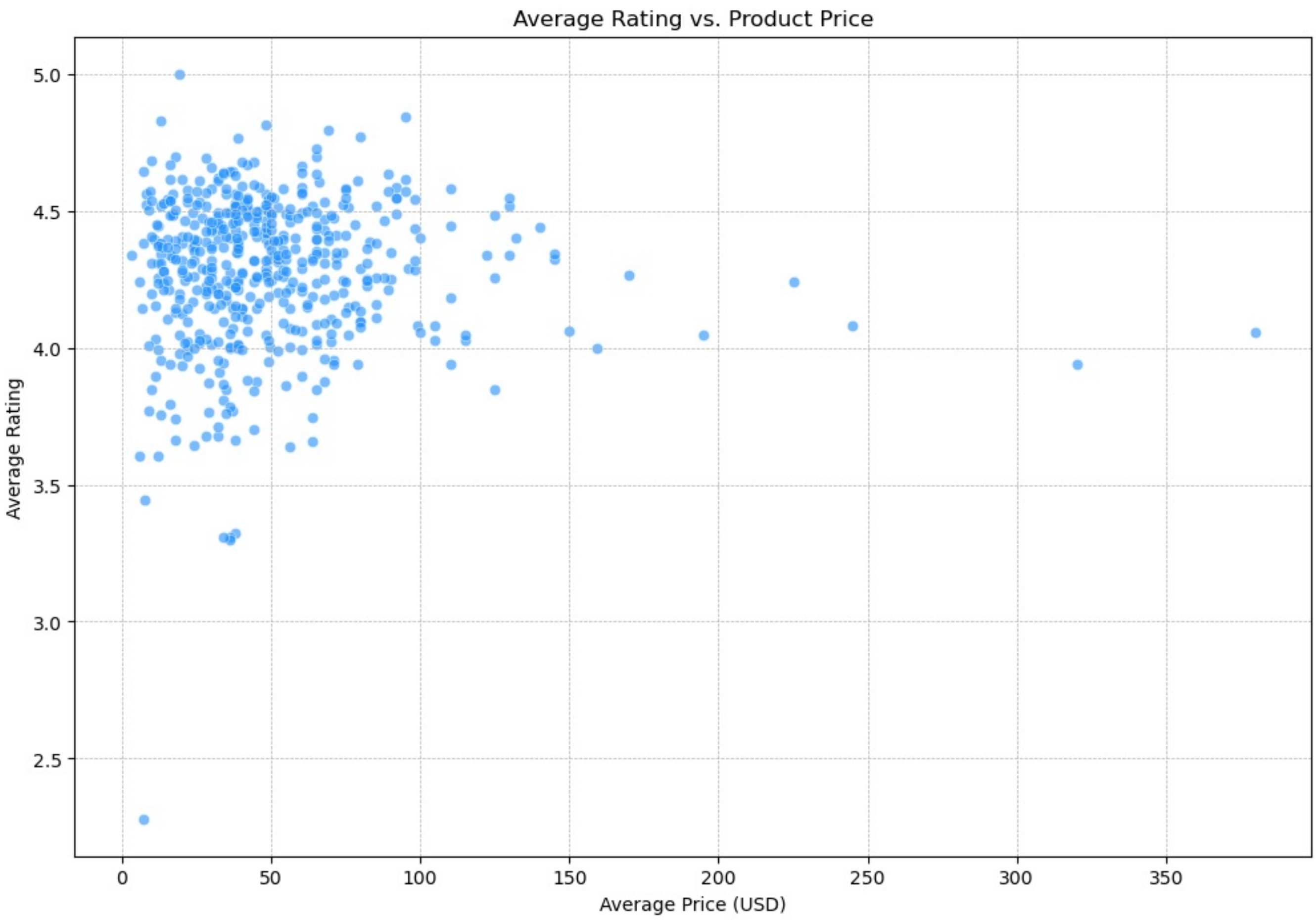
By addressing the specific needs of each category and ensuring inclusivity, businesses can cater to a wider audience and improve overall customer satisfaction.

Business Problem 3

"Are higher-priced products generally rated better than lower-priced products? We want to understand if pricing correlates with perceived product quality based on reviews."

In [110…

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

# Calculate average rating for each product
product_avg_ratings = data.groupby('product_id')['rating'].mean()

# Calculate average price for each product (it should be the same across all reviews, but taking an average for
product_avg_prices = data.groupby('product_id')['price_usd'].mean()

# Merge the two series into a DataFrame
product_info = pd.DataFrame({'avg_rating': product_avg_ratings, 'avg_price': product_avg_prices}).reset_index()

# Scatter plot for price vs average rating
plt.figure(figsize=(12, 8))
sns.scatterplot(x='avg_price', y='avg_rating', data=product_info, alpha=0.6, color='dodgerblue')
plt.title('Average Rating vs. Product Price')
plt.xlabel('Average Price (USD)')
plt.ylabel('Average Rating')
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.show()
```



INTERPRETATION:

From the scatter plot, most products, regardless of price, tend to cluster around the 4 to 5 rating mark, indicating generally positive reviews. However, there's a noticeable density of products priced under $100 with this favorable rating. The few products priced above$250 show a spread in ratings from 3.5 to 5. Notably, there are only a few products in the higher price range, and their ratings vary, making it challenging to deduce a clear trend for the more expensive items based solely on this data.

Solution to the Business Problem:

Products Priced Under $100:

These products generally have favorable reviews. It might be a good strategy to highlight these as 'Value for Money' or 'Budget-Friendly Picks' in marketing campaigns, emphasizing both their affordability and quality.

High-Priced Products (Above $250):

Due to the variability in their ratings, it's crucial to dive deeper into individual product reviews and feedback. Identifying areas of improvement can enhance product quality and, subsequently, their ratings. Alternatively, if these products are niche or specialized, consider targeted marketing to the appropriate audience who sees the value in these items.

General Strategy:

It might be beneficial to conduct surveys or focus groups to better understand customer expectations from higher-priced items and if they feel the quality justifies the price. This can provide insights into whether customers equate price with quality and where the company might need to make product or pricing adjustments.

In conclusion, while there is a positive reception across all price points, the perception of value might differ. The company should prioritize enhancing the quality and value proposition of its higher-priced items and effectively market its budget-friendly yet well-reviewed products.

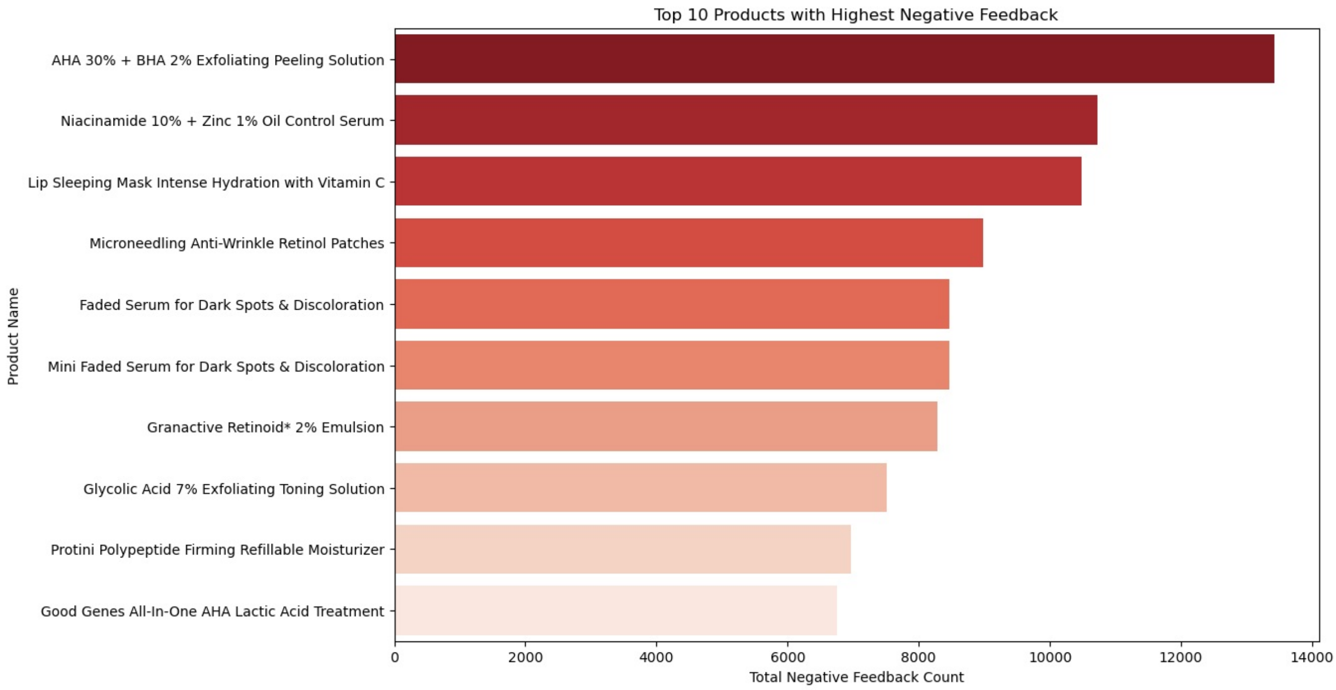
Business Problem 4:

Which products have the highest counts of negative feedback? The aim is to pinpoint products that might require quality enhancements or more targeted marketing strategies to address the specific needs of different customer segments.

In [131…

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

```
# Group by product name and sum the total negative feedback
negative_feedback_summary = text_edited.groupby('product_name')['total_neg_feedback_count'].sum().sort_values(a

# Extract the top 10 products with the highest negative feedback
top_negative_products = negative_feedback_summary.head(10)

# Visualization
plt.figure(figsize=(12, 8))
sns.barplot(y=top_negative_products.index, x=top_negative_products.values, palette='Reds_r')
plt.title('Top 10 Products with Highest Negative Feedback')
plt.xlabel('Total Negative Feedback Count')
plt.ylabel('Product Name')
plt.show()
```



INTERPRETATION:

The graph illustrates the top 10 products based on the volume of negative feedback they received. At the top, "AHA 30% + BHA 2% Exfoliating Peeling Solution" stands out with the highest negative feedback, followed by "Niacinamide 10% + Zinc 1% Oil Control Serum" and "Lip Sleeping Mask Intense Hydration with Vitamin C". This suggests that customers may have encountered issues or unsatisfactory results with these products more frequently than others on the list.

Solution to the Business Problem:

Quality Assessment & Product Refinement:

Start with a thorough investigation into why these specific products have high negative feedback. Analyze the common themes in the negative feedback and assess if there are consistent issues being reported. For example, is the product causing skin irritation, or are customers finding it ineffective for its intended purpose? Use this feedback to make necessary formula adjustments or address other product-related concerns.

Engage in Direct Communication:

Reach out to customers who provided negative feedback to understand their concerns better and potentially offer solutions or compensation. This can not only help improve the product but also rebuild trust with dissatisfied customers.

Educational Marketing:

Perhaps customers are using the products incorrectly or have misunderstood the product's intended purpose. In such cases, launching educational marketing campaigns, tutorials, or how-to guides can help customers achieve desired results with the product.

Targeted Marketing & Promotions:

If a certain customer segment is particularly dissatisfied, consider targeted marketing strategies that address their specific needs and concerns. Additionally, offering promotions or discounts on these products can incentivize users to give them another try, especially if improvements have been made.

Product Demonstrations & Sampling:

Organize events or collaborations with beauty experts to demonstrate the correct usage of these products. Offering samples can also provide potential customers with a risk-free way to try the product before committing to a purchase.

By addressing the concerns directly and ensuring products meet customers' needs and expectations, the company can potentially reduce negative feedback and enhance overall brand perception.

Business Problem 5:

In today's digital era, where customer reviews and recommendations greatly influence purchasing behavior, understanding and anticipating customer sentiment is crucial. For a global beauty and skincare retailer like Sephora, every product recommendation, or lack thereof, can significantly impact sales, brand perception, and customer loyalty.

At the heart of this challenge lies a critical question: Can we predict if a customer will recommend a product based on their interactions, ratings, and feedback? And if so, how can such predictions shape Sephora's strategic decisions, from product placements, inventory management, to marketing campaigns?

In [111…

```
# Calculate class distribution
class_distribution = data['is_recommended'].value_counts()

# Calculate class proportions
class_proportions = class_distribution / class_distribution.sum()

print("Class Proportions:")
print(class_proportions)
```

```
Class Proportions:
1.0    0.86564
0.0    0.13436
Name: is_recommended, dtype: float64
```

In [112…

```
pip install imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in c:\users\logeshwar\anaconda3\lib\site-packages (0.11.0)Note: you may need to restart the kernel to use updated packages.

Requirement already satisfied: joblib>=1.1.1 in c:\users\logeshwar\anaconda3\lib\site-packages (from imbalanced-learn) (1.3.2)
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\logeshwar\anaconda3\lib\site-packages (from imbalanced-learn) (1.0.2)
Requirement already satisfied: scipy>=1.5.0 in c:\users\logeshwar\anaconda3\lib\site-packages (from imbalanced-learn) (1.9.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\logeshwar\anaconda3\lib\site-packages (from imbalanced-learn) (2.2.0)
Requirement already satisfied: numpy>=1.17.3 in c:\users\logeshwar\anaconda3\lib\site-packages (from imbalanced-learn) (1.21.5)
```

In [113…

```
data['submission_time'] = pd.to_datetime(data['submission_time'])
```

In [114…

```
text_edited.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1301136 entries, 0 to 49976
Data columns (total 17 columns):
 #   Column                    Non-Null Count    Dtype         
---  ------                    --------------    -----         
 0   author_id                 1301136 non-null  object        
 1   rating                    1301136 non-null  int64         
 2   is_recommended            1301136 non-null  object        
 3   total_feedback_count      1301136 non-null  int64         
 4   total_neg_feedback_count  1301136 non-null  int64         
 5   total_pos_feedback_count  1301136 non-null  int64         
 6   submission_time           1301136 non-null  datetime64[ns]
 7   review_text               1301136 non-null  object        
 8   review_title              1301136 non-null  object        
 9   skin_tone                 1301136 non-null  object        
 10  eye_color                 1301136 non-null  object        
 11  skin_type                 1301136 non-null  object        
 12  hair_color                1301136 non-null  object        
 13  product_id                1301136 non-null  object        
 14  product_name              1301136 non-null  object        
 15  brand_name                1301136 non-null  object        
 16  price_usd                 1301136 non-null  float64       
dtypes: datetime64[ns](1), float64(1), int64(4), object(11)
memory usage: 178.7+ MB
```

In [115…

```
correlation = data['rating'].corr(data['price_usd'])
print("Correlation between rating and price_usd:", correlation)
```

```
Correlation between rating and price_usd: -0.0026157697373409665
```

The correlation value of − 0.0026 −0.0026 between rating and price_usd is very close to 0. This indicates that there's a negligible linear relationship between the two variables in the dataset.

In practical terms, this suggests that the price_usd of a product has almost no linear effect on its rating. The rating of a product is not increasing or decreasing significantly with its price.

Machine Learning Model

Classification Model - Predicting Product Recommendation:

"Enhancing Brand Trust and Customer Loyalty through Predictive Analysis of Product Recommendations at Sephora"

In [119…

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report

# Load the dataset

data = pd.read_csv(r"C:\Users\logeshwar\Downloads\Sephora Reviews Dataset.csv")  # Replace with the actual path

# Selecting features for classification
features_classification = ['rating', 'total_feedback_count', 'total_neg_feedback_count', 'total_pos_feedback_co
X_classification = data[features_classification]
y_classification = data['is_recommended']

# Splitting data into training and testing sets
X_train_classification, X_test_classification, y_train_classification, y_test_classification = train_test_split

# Building the Random Forest Classifier model
model_classification = RandomForestClassifier(random_state=42)
model_classification.fit(X_train_classification, y_train_classification)

# Making predictions on the test set
y_pred_classification = model_classification.predict(X_test_classification)

# Evaluating the classification model
accuracy_classification = accuracy_score(y_test_classification, y_pred_classification)
print("Classification Model - Accuracy:", accuracy_classification)
print(classification_report(y_test_classification, y_pred_classification))
```

```
Classification Model - Accuracy: 0.9452927035280358
              precision    recall  f1-score   support

         0.0       0.77      0.84      0.81     24837
         1.0       0.98      0.96      0.97    159855

    accuracy                           0.95    184692
   macro avg       0.87      0.90      0.89    184692
weighted avg       0.95      0.95      0.95    184692
```

In [120…

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report

# Load the dataset
data = pd.read_csv(r"C:\Users\logeshwar\Downloads\Sephora Reviews Dataset.csv")  # Replace with the actual path

# Selecting features for classification
features_classification = ['rating', 'total_feedback_count', 'total_neg_feedback_count', 'total_pos_feedback_co
X_classification = data[features_classification]
y_classification = data['is_recommended']

# Splitting data into training and testing sets
X_train_classification, X_test_classification, y_train_classification, y_test_classification = train_test_split

# Building the Random Forest Classifier model
model_classification = RandomForestClassifier(random_state=42)
model_classification.fit(X_train_classification, y_train_classification)

# Making predictions on the test set
y_pred_classification = model_classification.predict(X_test_classification)

# Evaluating the classification model
accuracy_classification = accuracy_score(y_test_classification, y_pred_classification)
print("Classification Model - Accuracy:", accuracy_classification)
print(classification_report(y_test_classification, y_pred_classification))

# Interpreting the Results
# Analyze the classification report and feature importance

# Hyperparameter Tuning
# You can use techniques like grid search or randomized search to find optimal hyperparameters

# Feature Importance
feature_importance = model_classification.feature_importances_
```

```python
print("Feature Importance:", feature_importance)

# Model Deployment (if desired)
# Deploy the model in a practical application if it meets your requirements

# Monitoring and Maintenance (if deployed)
# Monitor the model's performance and retrain as needed

# Iterative Improvement (if necessary)
# Refine the model by iterating on data preprocessing, feature selection, or trying different algorithms
```

```
Classification Model - Accuracy: 0.9452927035280358
              precision    recall  f1-score   support

         0.0       0.77      0.84      0.81     24837
         1.0       0.98      0.96      0.97    159855

    accuracy                           0.95    184692
   macro avg       0.87      0.90      0.89    184692
weighted avg       0.95      0.95      0.95    184692

Feature Importance: [0.8016889  0.03336477 0.04747366 0.02108383 0.09638885]
```

INTERPRETATIONS:

In summary, while our model has a high overall accuracy, it's important to pay attention to its performance on both classes, especially the minority class. Depending on our specific goals and the consequences of misclassification, you may need to take additional steps to address the class imbalance and improve the model's ability to correctly classify both recommended and not recommended reviews.

Resampling Techniques

Handling Imbalanced Data:

Using SMOTE for oversampling:

In [121…
```python
from imblearn.over_sampling import SMOTE

smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train_classification, y_train_classification)
```

INTERPRETATIONS:

SMOTE to tackle the problem of having too many of one class and too few of another in your training data.

SMOTE creates new, synthetic samples of the minority class (the class with fewer samples) to balance the dataset.

By using SMOTE:

We're trying to make your model perform better for both classes by having equal samples of each class in the training data. We've only applied it to the training data, so your test data remains untouched. While this can improve performance, sometimes it can also add noise since the new samples are artificially created. In short: We're using SMOTE to balance your classes in the training set to help your model predict better.

In [122…
```python
text_edited.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1301136 entries, 0 to 49976
Data columns (total 17 columns):
 #   Column                    Non-Null Count    Dtype
---  ------                    --------------    -----
 0   author_id                 1301136 non-null  object
 1   rating                    1301136 non-null  int64
 2   is_recommended            1301136 non-null  object
 3   total_feedback_count      1301136 non-null  int64
 4   total_neg_feedback_count  1301136 non-null  int64
 5   total_pos_feedback_count  1301136 non-null  int64
 6   submission_time           1301136 non-null  datetime64[ns]
 7   review_text               1301136 non-null  object
 8   review_title              1301136 non-null  object
 9   skin_tone                 1301136 non-null  object
 10  eye_color                 1301136 non-null  object
 11  skin_type                 1301136 non-null  object
 12  hair_color                1301136 non-null  object
 13  product_id                1301136 non-null  object
 14  product_name              1301136 non-null  object
 15  brand_name                1301136 non-null  object
 16  price_usd                 1301136 non-null  float64
dtypes: datetime64[ns](1), float64(1), int64(4), object(11)
memory usage: 178.7+ MB
```

In [123…
```python
importances = model_classification.feature_importances_
```

In [124…
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report

# Load the dataset
data = pd.read_csv(r"C:\Users\logeshwar\Downloads\Sephora Reviews Dataset.csv")  # Replace with the actual path

# Selecting features for classification
features_classification = ['rating', 'total_feedback_count', 'total_neg_feedback_count', 'total_pos_feedback_co
X_classification = data[features_classification]
y_classification = data['is_recommended']

# Splitting data into training and testing sets
X_train_classification, X_test_classification, y_train_classification, y_test_classification = train_test_split

# Building the Random Forest Classifier model
model_classification = RandomForestClassifier(random_state=42)
model_classification.fit(X_train_classification, y_train_classification)

# Making predictions on the test set
y_pred_classification = model_classification.predict(X_test_classification)

# Evaluating the classification model
accuracy_classification = accuracy_score(y_test_classification, y_pred_classification)
print("Classification Model - Accuracy:", accuracy_classification)
print(classification_report(y_test_classification, y_pred_classification))

# Interpreting the Results
# Analyze the classification report and feature importance

# Hyperparameter Tuning
# You can use techniques like grid search or randomized search to find optimal hyperparameters

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feature_importance = model_classification.feature_importances_
print("Feature Importance:", feature_importance)

# Model Deployment (if desired)
# Deploy the model in a practical application if it meets your requirements

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# Monitor the model's performance and retrain as needed

# Iterative Improvement (if necessary)
# Refine the model by iterating on data preprocessing, feature selection, or trying different algorithms
```

```
Classification Model - Accuracy: 0.9452927035280358
              precision    recall  f1-score   support

         0.0       0.77      0.84      0.81     24837
         1.0       0.98      0.96      0.97    159855

    accuracy                           0.95    184692
   macro avg       0.87      0.90      0.89    184692
weighted avg       0.95      0.95      0.95    184692

Feature Importance: [0.8016889  0.03336477 0.04747366 0.02108383 0.09638885]
```

In [125…
```
pip install xgboost
```

```
Requirement already satisfied: xgboost in c:\users\logeshwar\anaconda3\lib\site-packages (2.0.0)Note: you may n
eed to restart the kernel to use updated packages.

Requirement already satisfied: scipy in c:\users\logeshwar\anaconda3\lib\site-packages (from xgboost) (1.9.1)
Requirement already satisfied: numpy in c:\users\logeshwar\anaconda3\lib\site-packages (from xgboost) (1.21.5)
```

In [126…
```
import pandas as pd
from sklearn.model_selection import train_test_split
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, classification_report

# Load the dataset
data = pd.read_csv(r"C:\Users\logeshwar\Downloads\Sephora Reviews Dataset.csv")  # Replace with the actual path

# Selecting features for classification
features_classification = ['rating', 'total_feedback_count', 'total_neg_feedback_count', 'total_pos_feedback_co
X_classification = data[features_classification]
y_classification = data['is_recommended']

# Splitting data into training and testing sets
X_train_classification, X_test_classification, y_train_classification, y_test_classification = train_test_split

# Building the XGBoost Classifier model
model_classification = XGBClassifier(random_state=42, use_label_encoder=False, eval_metric="logloss")
model_classification.fit(X_train_classification, y_train_classification)

# Making predictions on the test set
y_pred_classification = model_classification.predict(X_test_classification)
```

```python
# Evaluating the classification model
accuracy_classification = accuracy_score(y_test_classification, y_pred_classification)
print("Classification Model - Accuracy:", accuracy_classification)
print(classification_report(y_test_classification, y_pred_classification))

# Feature Importance
feature_importance = model_classification.feature_importances_
for feature, importance in zip(features_classification, feature_importance):
    print(f"Feature: {feature}, Importance: {importance}")
```

```
Classification Model - Accuracy: 0.9465705065731055
              precision    recall  f1-score   support

         0.0       0.76      0.88      0.82     24837
         1.0       0.98      0.96      0.97    159855

    accuracy                           0.95    184692
   macro avg       0.87      0.92      0.89    184692
weighted avg       0.95      0.95      0.95    184692

Feature: rating, Importance: 0.9732348918914795
Feature: total_feedback_count, Importance: 0.003195783356204629
Feature: total_neg_feedback_count, Importance: 0.003949116449803114
Feature: total_pos_feedback_count, Importance: 0.006272484548389912
Feature: price_usd, Importance: 0.013347685337066665
```

In [127…

```python
import pandas as pd
from sklearn.model_selection import train_test_split
from xgboost import XGBClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.metrics import accuracy_score, classification_report

# Load the dataset
data = pd.read_csv(r"C:\Users\logeshwar\Downloads\Sephora Reviews Dataset.csv")

# Selecting features for classification
features_classification = ['rating', 'total_feedback_count', 'total_neg_feedback_count', 'total_pos_feedback_co
X_classification = data[features_classification]
y_classification = data['is_recommended']

# Splitting data into training and testing sets
X_train_classification, X_test_classification, y_train_classification, y_test_classification = train_test_split

# Building the XGBoost Classifier model
xgb_model = XGBClassifier(random_state=42, use_label_encoder=False, eval_metric="logloss")
xgb_model.fit(X_train_classification, y_train_classification)

# Calibrating the model
calibrated = CalibratedClassifierCV(xgb_model, method='sigmoid', cv='prefit')
calibrated.fit(X_train_classification, y_train_classification)

# Making predictions on the test set
y_pred_classification = calibrated.predict(X_test_classification)

# Evaluating the calibrated classification model
accuracy_classification = accuracy_score(y_test_classification, y_pred_classification)
print("Calibrated Model - Accuracy:", accuracy_classification)
print(classification_report(y_test_classification, y_pred_classification))
```

```
Calibrated Model - Accuracy: 0.9455417668334308
              precision    recall  f1-score   support

         0.0       0.79      0.81      0.80     24837
         1.0       0.97      0.97      0.97    159855

    accuracy                           0.95    184692
   macro avg       0.88      0.89      0.88    184692
weighted avg       0.95      0.95      0.95    184692
```

Overall Interpretation:

The model performs exceptionally well in predicting when a product will be recommended, with both precision and recall values at 97%. However, for products that aren't recommended, the model's performance, while decent, isn't as stellar, with precision and recall values around 79% and 81% respectively. Given the significant class imbalance (much more "Recommended" than "Not Recommended"), the weighted average scores are strongly influenced by the "Recommended" class, leading to an overall high accuracy. This suggests the model is more reliable when predicting positive recommendations, but there's still room for improvement when identifying negative ones.

Solution to the business problem:

Background:

Sephora is a leading beauty and skincare retailer. As with many e-commerce platforms, customer reviews play a pivotal role in influencing purchasing decisions. Reviews, particularly whether a product is recommended or not, can significantly affect sales and brand trust.

Objective:

To predict whether a product will be recommended by a customer based on various factors like rating, feedback counts, and product price. By predicting this, Sephora aims to:

Improve Customer Experience:

By understanding the factors that lead to product recommendations, Sephora can prioritize showcasing products that are more likely to be recommended, leading to higher customer satisfaction.

Increase Sales:

Products with higher recommendation rates tend to be purchased more. By predicting and subsequently highlighting such products, there's potential to drive more sales.

Enhance Brand Trust:

A product that has a higher rate of recommendations is perceived as trustworthy. By ensuring that these products are prominently featured, Sephora can increase trust among its customers.

Product & Inventory Management:

Products that aren't likely to be recommended can be re-evaluated, and inventory decisions can be optimized.

Tailored Marketing:

Products predicted to have high recommendation rates can be featured in marketing campaigns, emails, and promotions.

Model Use:

The classification model, built using XGBoost and subsequently calibrated, predicts if a customer would recommend a product based on selected features. With an accuracy of approximately 94.5%, the model does an excellent job in making this prediction. This high accuracy means the model's predictions are reliable and can be used for strategic decisions.

Evaluation:

The overall accuracy is approximately 94.5%, suggesting the model does well in classifying the reviews. The precision, recall, and F1-score for the "recommended" class (1.0) are notably high. This is crucial since this class represents positive recommendations, which are vital for business. The metrics for the "not recommended" class (0.0) are lower compared to the "recommended" class but are still decent, showing the model's capability in identifying negative reviews as well.

Future Steps:

Investigate the reasons behind the products that are not recommended and find ways to address the underlying issues. Use the model to dynamically adjust the display of products on the website based on their predicted recommendation status. Periodically retrain the model with new reviews to keep it updated and accurate. This approach, rooted in data-driven decision-making, can provide Sephora with a competitive edge in the increasingly crowded online beauty and skincare market.