```
The dataset includes information on Nike shoes sold across a variety of
platforms, including Nike's own website, Amazon, and other retailers.
It contains data on the shoe model, colorway, size, price, and the
number of reviews and ratings. Additionally, the dataset contains text
data on customer reviews, allowing for a detailed analysis of consumer
opinions and feedback.

By analyzing this dataset, researchers and analysts can gain insight
into which Nike shoes are most popular among consumers, as well as the
features and characteristics that customers value most in a shoe. This
information could be used to inform future product design and marketing
strategies for Nike and other shoe brands.

Furthermore, consumers and shoe enthusiasts can benefit from this
dataset to make more informed decisions about purchasing Nike shoes
based on the experiences of other customers. The dataset may also be
used by retailers to optimize their inventory and marketing strategies
based on popular models, sizes, and colorways. Overall, this dataset
has the potential to provide valuable insights for both the industry
and consumers, shedding light on the factors that contribute to the
success of Nike's shoes.
```

In [114]:
```
#SIMRAT KAUR ANAND
#Hierarchical Clustering
#Visualization: Dendrogram with Truncation
#Apply KMeans clustering
```

In [115]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.cluster import AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram, linkage
from sklearn.preprocessing import StandardScaler, LabelEncoder
import matplotlib.pyplot as plt
```

In [116]:
```
df = pd.read_csv('nike_shoes_sales.csv')
```

In [117]:
```
df.head()
```

Out[117]:

	product_name	product_id	listing_price	sale_price	discount	brand	description	rating	review
0	Nike Air Force 1 '07 Essential	CJ1646-600	0	7495	0	Nike	Let your shoe game shimmer in the Nike Air For...	0.0	
1	Nike Air Force 1 '07	CT4328-101	0	7495	0	Nike	The legend lives on in the Nike Air Force 1 '0...	0.0	
2	Nike Air Force 1 Sage Low LX	CI3482-200	0	9995	0	Nike	Taking both height and craft to new levels, th...	0.0	
3	Nike Air Max Dia SE	CD0479-200	0	9995	0	Nike	Designed for a woman's foot, the Nike Air Max ...	0.0	
4	Nike Air Max Verona	CZ6156-101	0	9995	0	Nike	Pass on the good vibes in the Nike Air Max Ver...	0.0	

In [118]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 643 entries, 0 to 642
Data columns (total 10 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   product_name   643 non-null    object 
 1   product_id     643 non-null    object 
 2   listing_price  643 non-null    int64  
 3   sale_price     643 non-null    int64  
 4   discount       643 non-null    int64  
 5   brand          643 non-null    object 
 6   description    640 non-null    object 
 7   rating         643 non-null    float64
 8   reviews        643 non-null    int64  
 9   images         572 non-null    object 
dtypes: float64(1), int64(4), object(5)
memory usage: 50.4+ KB
```

In [119]:
```
df.describe()
```

Out[119]:

	listing_price	sale_price	discount	rating	reviews
count	643.000000	643.000000	643.0	643.000000	643.000000
mean	3875.762053	10213.676516	0.0	2.734837	7.181960
std	5889.947172	4513.289512	0.0	2.137756	15.968315
min	0.000000	1595.000000	0.0	0.000000	0.000000
25%	0.000000	6995.000000	0.0	0.000000	0.000000
50%	0.000000	9597.000000	0.0	3.800000	1.000000
75%	8495.000000	12797.000000	0.0	4.600000	6.000000
max	19995.000000	36500.000000	0.0	5.000000	223.000000

In [120]:
```
#Drop discount column as it is constant and all 0 and also images as we w
df.drop(['discount', 'images'], axis=1, inplace=True)
```

In [121]:
```
df.isnull().sum()
```

Out[121]:
```
product_name     0
product_id       0
listing_price    0
sale_price       0
brand            0
description      3
rating           0
reviews          0
dtype: int64
```

In [122]:
```
# Handle missing values
df['description'].fillna('', inplace=True)
```

In [123]:
```
sns.displot(data=df, x="listing_price", kde=True)
```

Out[123]: <seaborn.axisgrid.FacetGrid at 0x7fdc00617040>

In [124]:
```
sns.displot(data=df, x="sale_price", kde=True)
```

Out[124]: <seaborn.axisgrid.FacetGrid at 0x7fdc51ca1700>

In [125]:
```
#Convert to $ as sales numbers are not reflecting the true values
df['sale_price'] = df['sale_price'] / 100
df['listing_price'] = df['listing_price'] / 100
```

In [126]:
```
sns.displot(data=df, x="sale_price", kde=True)
```

Out[126]: <seaborn.axisgrid.FacetGrid at 0x7fdc31e3a070>

In [127]:
```
sns.displot(data=df, x="listing_price", kde=True)
```

Out[127]: <seaborn.axisgrid.FacetGrid at 0x7fdc31ea4e80>

In [128]:
```
#For each product with a listing_price of zero, we'll find a similar prod
#Then, we'll impute the listing_price of our target product with the sale


from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import linear_kernel

# 1. Vectorize product names using TF-IDF
tfidf = TfidfVectorizer(stop_words='english')
tfidf_matrix = tfidf.fit_transform(df['product_name'])

# Function to get the index of the most similar product
def get_similar_product(idx):
    cosine_similarities = linear_kernel(tfidf_matrix[idx], tfidf_matrix)
    # We ignore the product itself by setting its similarity to -1
    cosine_similarities[idx] = -1
    return cosine_similarities.argmax()

# 2. For each product with a listing_price of zero, find the most simila
zero_price_indices = df[df['listing_price'] == 0].index

for idx in zero_price_indices:
    similar_idx = get_similar_product(idx)
    # Impute with the sale_price of the most similar product
    df.at[idx, 'listing_price'] = df.at[similar_idx, 'sale_price']
```

In [129]:
```
df
```

Out[129]:

	product_name	product_id	listing_price	sale_price	brand	description	rating	reviews
0	Nike Air Force 1 '07 Essential	CJ1646-600	55.97	74.95	Nike	Let your shoe game shimmer in the Nike Air For...	0.0	0
1	Nike Air Force 1 '07	CT4328-101	74.95	74.95	Nike	The legend lives on in the Nike Air Force 1 '0...	0.0	0
2	Nike Air Force 1 Sage Low LX	CI3482-200	89.95	99.95	Nike	Taking both height and craft to new levels, th...	0.0	0
3	Nike Air Max Dia SE	CD0479-200	59.97	99.95	Nike	Designed for a woman's foot, the Nike Air Max ...	0.0	0
4	Nike Air Max Verona	CZ6156-101	99.95	99.95	Nike	Pass on the good vibes in the Nike Air Max Ver...	0.0	0
...	...	...	...	...	...	...	...	...
638	Air Jordan 8 Retro	CI1236-100	159.95	127.97	Nike	The Air Jordan 8 Retro recaptures the memorabl...	5.0	1
639	Nike Phantom Venom Club IC	AO0578-717	49.95	34.97	Nike	The Nike Phantom Venom Club IC is engineered f...	0.0	0
640	Nike Mercurial Superfly 7 Academy TF	AT7978-414	84.95	59.47	Nike	The soft upper of the Nike Mercurial Superfly ...	5.0	1
641	Nike Air Max 98	AH6799-300	169.95	169.95	Nike	The Nike Air Max 98 features the OG design lin...	4.0	4
642	Nike P-6000 SE	CJ9585-600	89.95	62.97	Nike	A mash-up of Pegasus' past, the Nike P-6000 SE...	0.0	0

643 rows × 8 columns

In [130]:
```
sns.displot(data=df, x="listing_price", kde=True)
```

Out[130]:
```
<seaborn.axisgrid.FacetGrid at 0x7fdc31eae070>
```

In [131]:
```
#Exclude 0 ratings as it means there are no current ratings for that prod
sns.displot(data=df[df["rating"] != 0], x="rating", kde=True)
```

Out[131]: <seaborn.axisgrid.FacetGrid at 0x7fdc31e609a0>

In [132]:
```
sns.pairplot(df)
```

Out[132]: <seaborn.axisgrid.PairGrid at 0x7fdc31cffa00>

In [133]:
```
df['price_difference'] = df['listing_price'] - df['sale_price']
```

If we consider listing_price as the original or recommended retail price of the product and sale_price as the price at which it's actually being sold: then IF

Listing Price > Sale Price indicates product is being sold at a discount i.e. clear out old inventory, compute with other sellers

Listing Price < Sale Price indicates if demand is high, prices might surge above the original listing price. could be part of collector's item dynamic pricing

In [134]:
```
sns.displot(data=df, x="price_difference", kde=True)
```

Out[134]: <seaborn.axisgrid.FacetGrid at 0x7fdc519aef70>

In [135]:
```
df['price_ratio'] = df['sale_price'] / df['listing_price']
```

In [136]:
```
sns.heatmap(df.corr(), vmin=-1, vmax=1, annot=True);
```

In [137]:
```
#  price_ratio
df['price_ratio'] = df['sale_price'] / df['listing_price']

# price_category
quantiles = df['sale_price'].quantile([0.33, 0.66]).values
df['price_category'] = pd.cut(df['sale_price'],
                              bins=[0] + list(quantiles) + [float('inf')
                              labels=['low', 'medium', 'high'])

df[['price_ratio', 'price_category']].head()
```

Out[137]:

	price_ratio	price_category
0	1.339110	low
1	1.000000	low
2	1.111173	medium
3	1.666667	medium
4	1.000000	medium

In [138]:
```
df.head(5)
```

Out[138]:

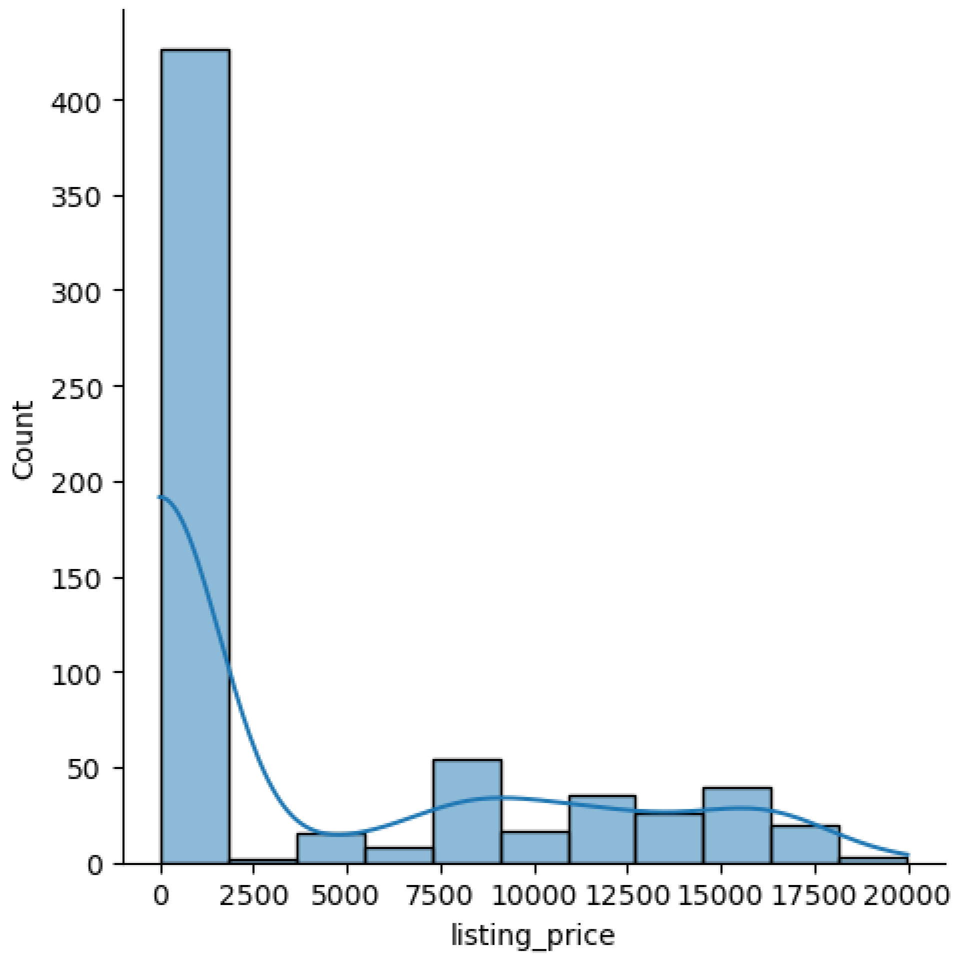
	product_name	product_id	listing_price	sale_price	brand	description	rating	reviews	price_d
0	Nike Air Force 1 '07 Essential	CJ1646-600	55.97	74.95	Nike	Let your shoe game shimmer in the Nike Air For...	0.0	0	
1	Nike Air Force 1 '07	CT4328-101	74.95	74.95	Nike	The legend lives on in the Nike Air Force 1 '0...	0.0	0	
2	Nike Air Force 1 Sage Low LX	CI3482-200	89.95	99.95	Nike	Taking both height and craft to new levels, th...	0.0	0	
3	Nike Air Max Dia SE	CD0479-200	59.97	99.95	Nike	Designed for a woman's foot, the Nike Air Max ...	0.0	0	
4	Nike Air Max Verona	CZ6156-101	99.95	99.95	Nike	Pass on the good vibes in the Nike Air Max Ver...	0.0	0	

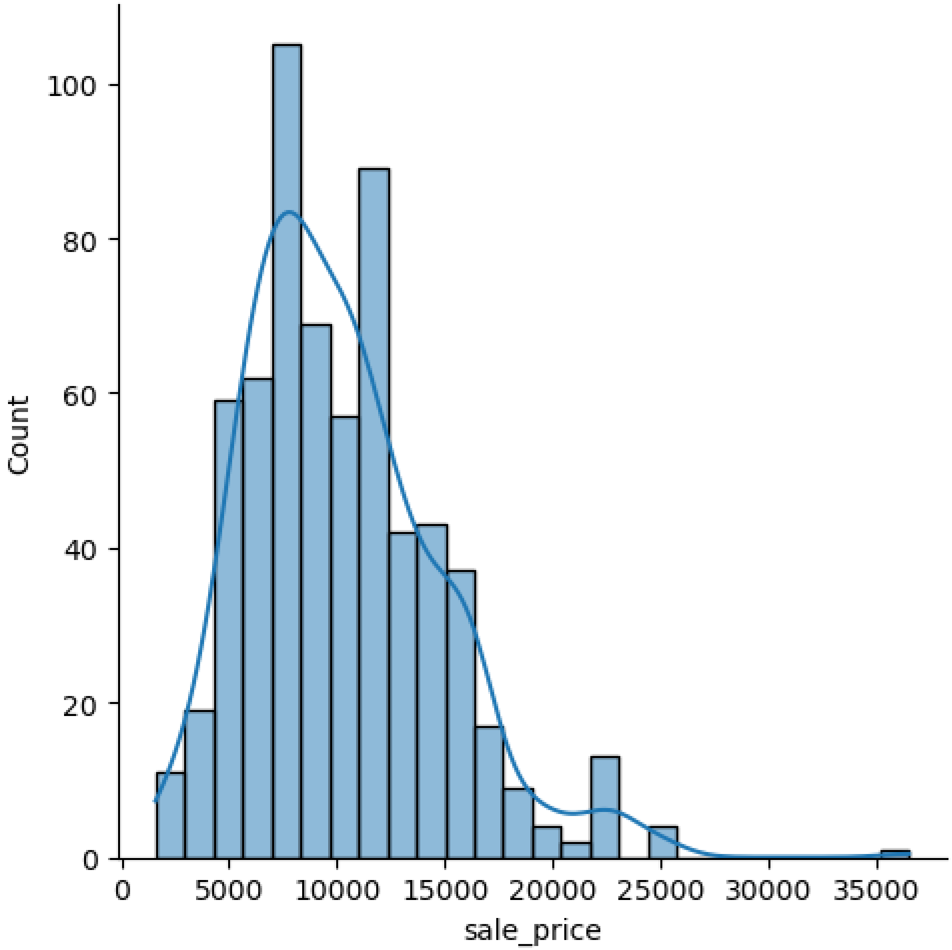
In [139]:
```
df.info()
```

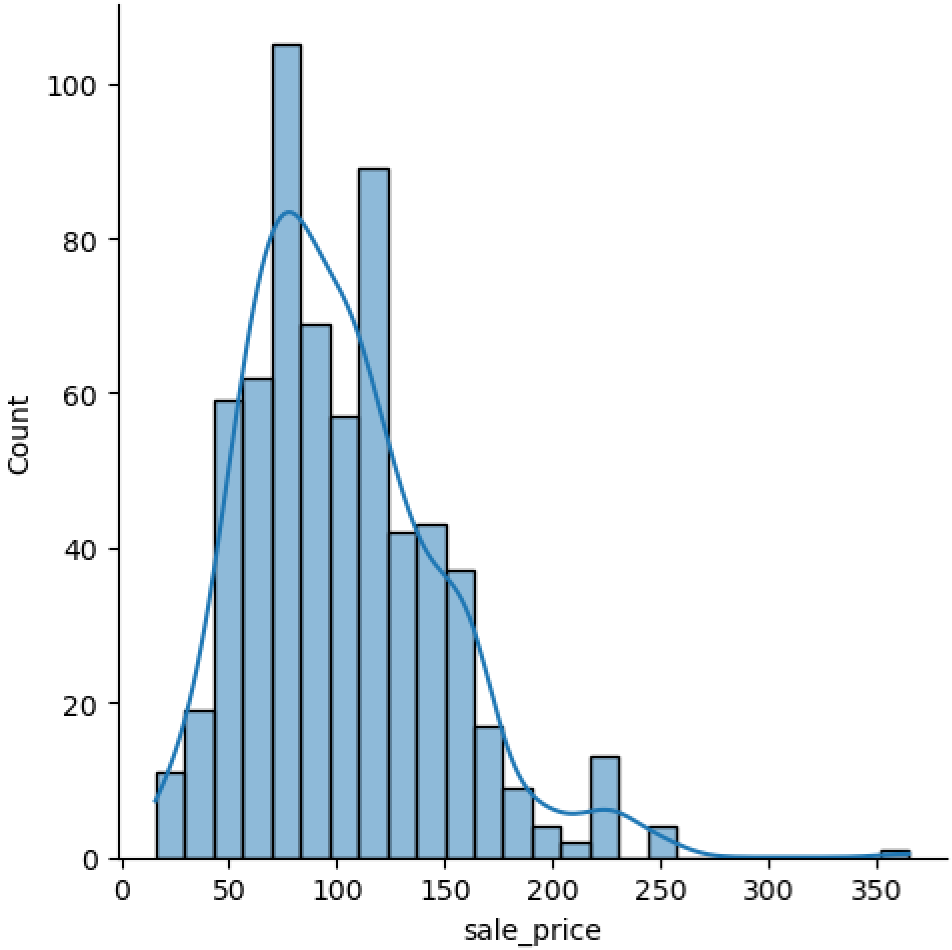
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 643 entries, 0 to 642
Data columns (total 11 columns):
 #   Column            Non-Null Count  Dtype   
---  ------            --------------  -----   
 0   product_name      643 non-null    object  
 1   product_id        643 non-null    object  
 2   listing_price     643 non-null    float64 
 3   sale_price        643 non-null    float64 
 4   brand             643 non-null    object  
 5   description       643 non-null    object  
 6   rating            643 non-null    float64 
 7   reviews           643 non-null    int64   
 8   price_difference  643 non-null    float64 
 9   price_ratio       643 non-null    float64 
 10  price_category    643 non-null    category
dtypes: category(1), float64(5), int64(1), object(4)
memory usage: 51.1+ KB
```

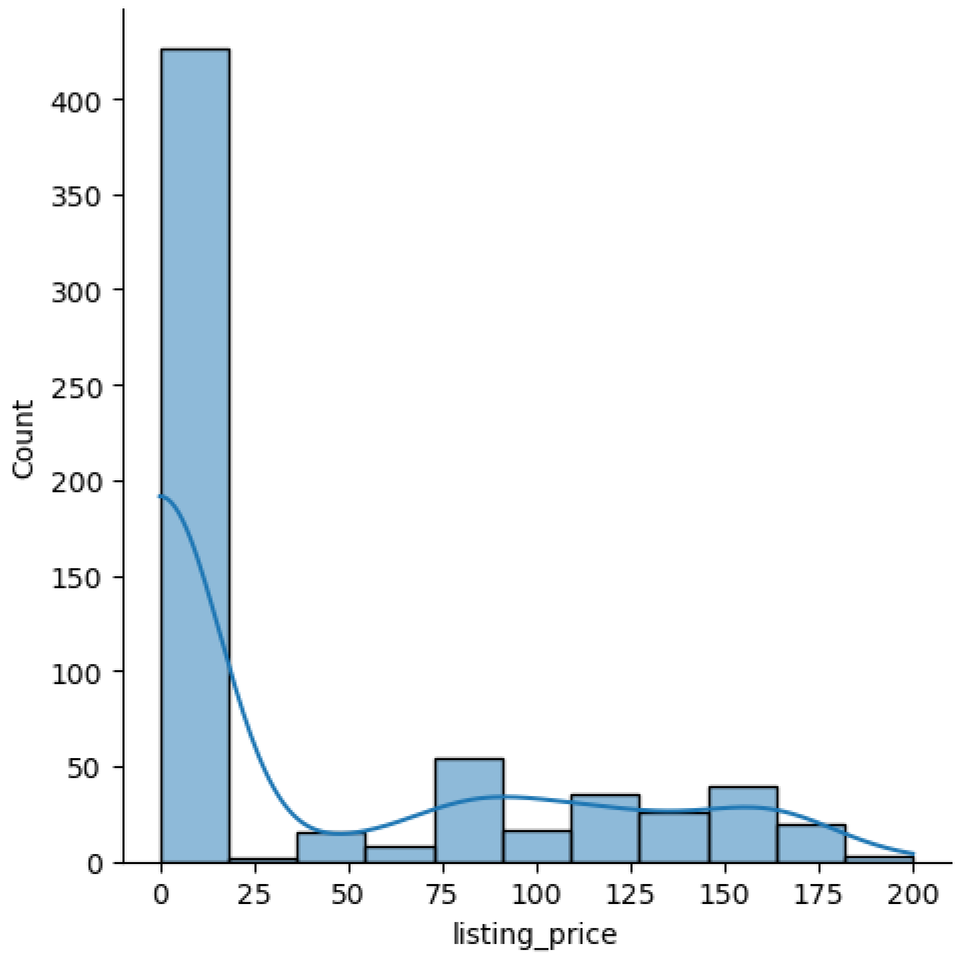
In [140]:
```
label_encoder = LabelEncoder()
# Convert 'price_category' to numeric using label encoding
df['price_category_encoded'] = label_encoder.fit_transform(df['price_cat
# Standardizing the data
features = ['listing_price', 'sale_price', 'rating', 'reviews', 'price_d
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df[features])
# Hierarchical Clustering
linked = linkage(scaled_data, 'ward')
```

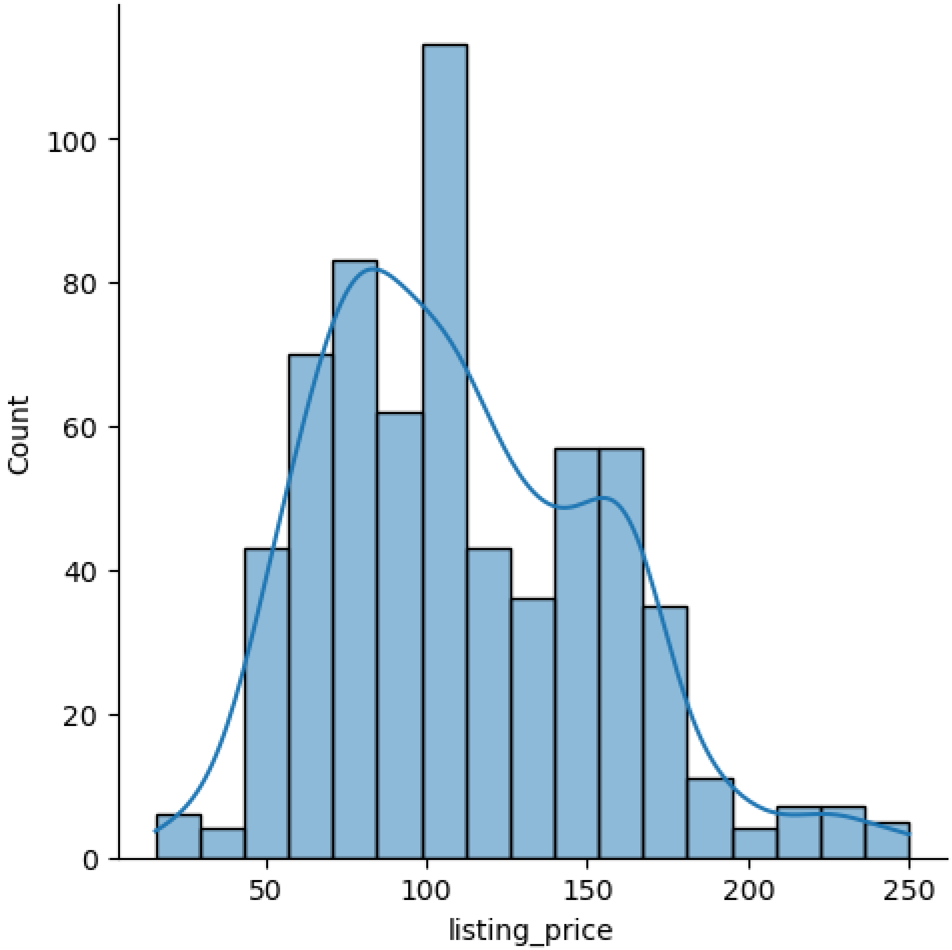
In [141]:
```
# Visualization: Dendrogram with Truncation
plt.figure(figsize=(15, 7))
dendrogram(linked,
           truncate_mode='lastp',  # Show only the last 'p' merged clust
           p=10,  # Show only the last 10 merged clusters
           show_contracted=True,  # To give a summarized view
           orientation='top',
           distance_sort='descending',
           show_leaf_counts=True)
plt.title("Truncated Hierarchical Clustering Dendrogram")
plt.xlabel("Cluster size")
plt.ylabel("Ward's distance")
plt.show()
```

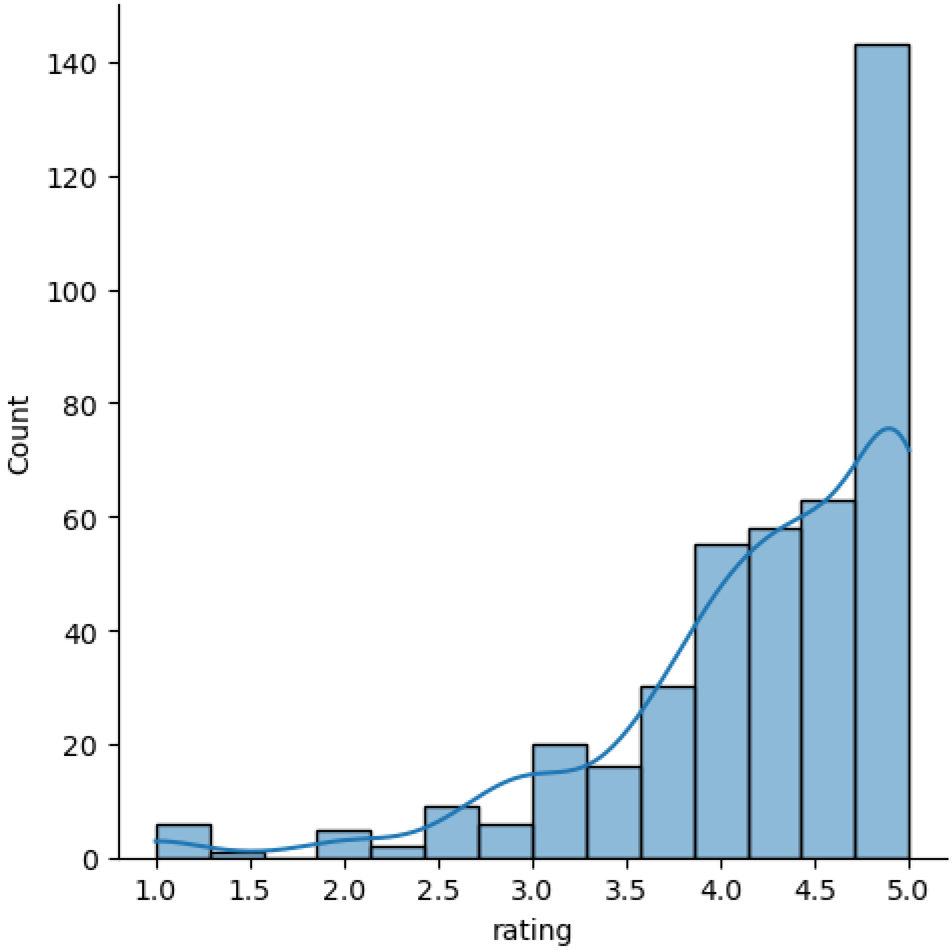


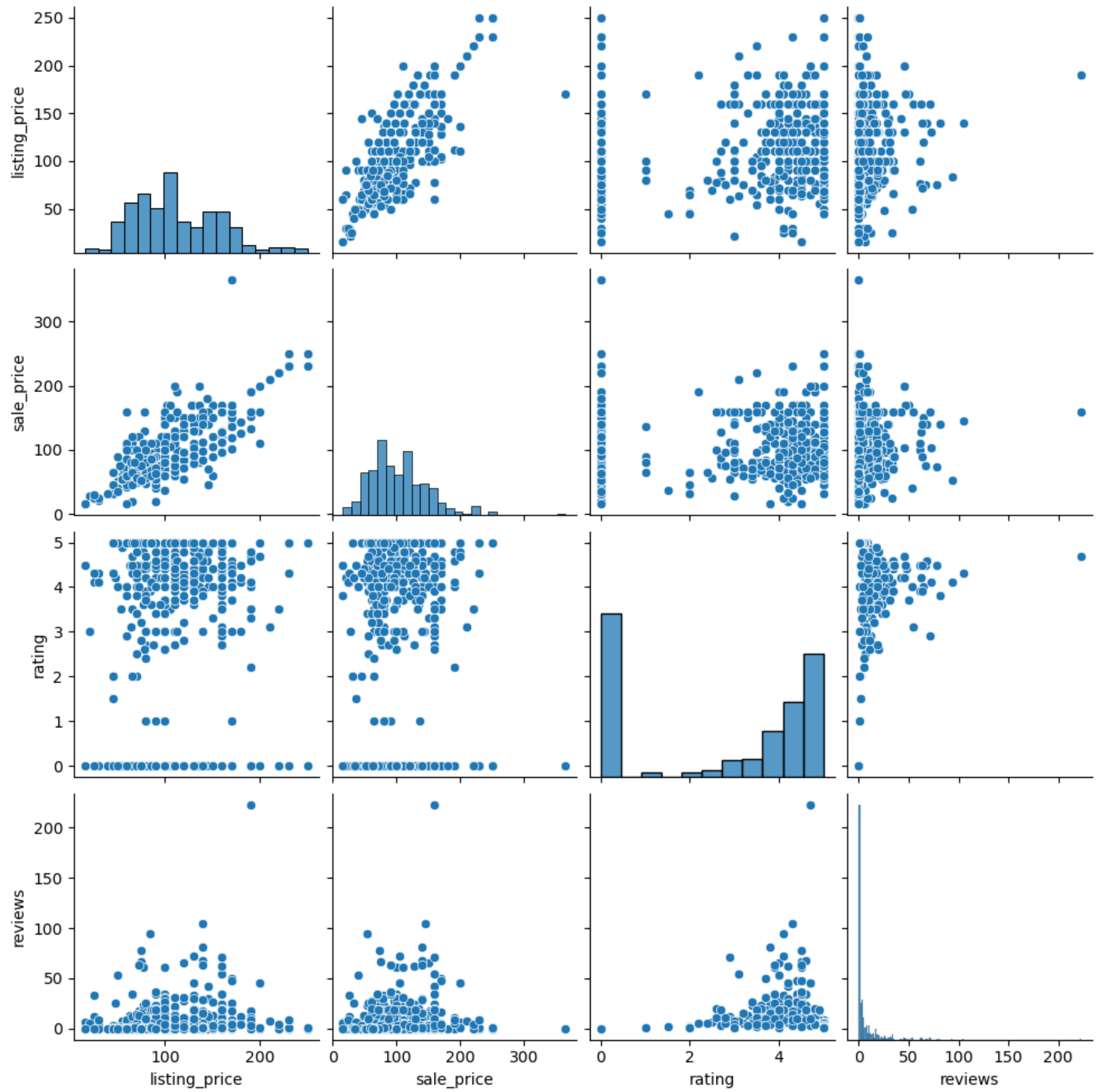

Count
sale_price
0
20
40
60
80
100
0
5000
10000
15000
20000
25000
30000
35000

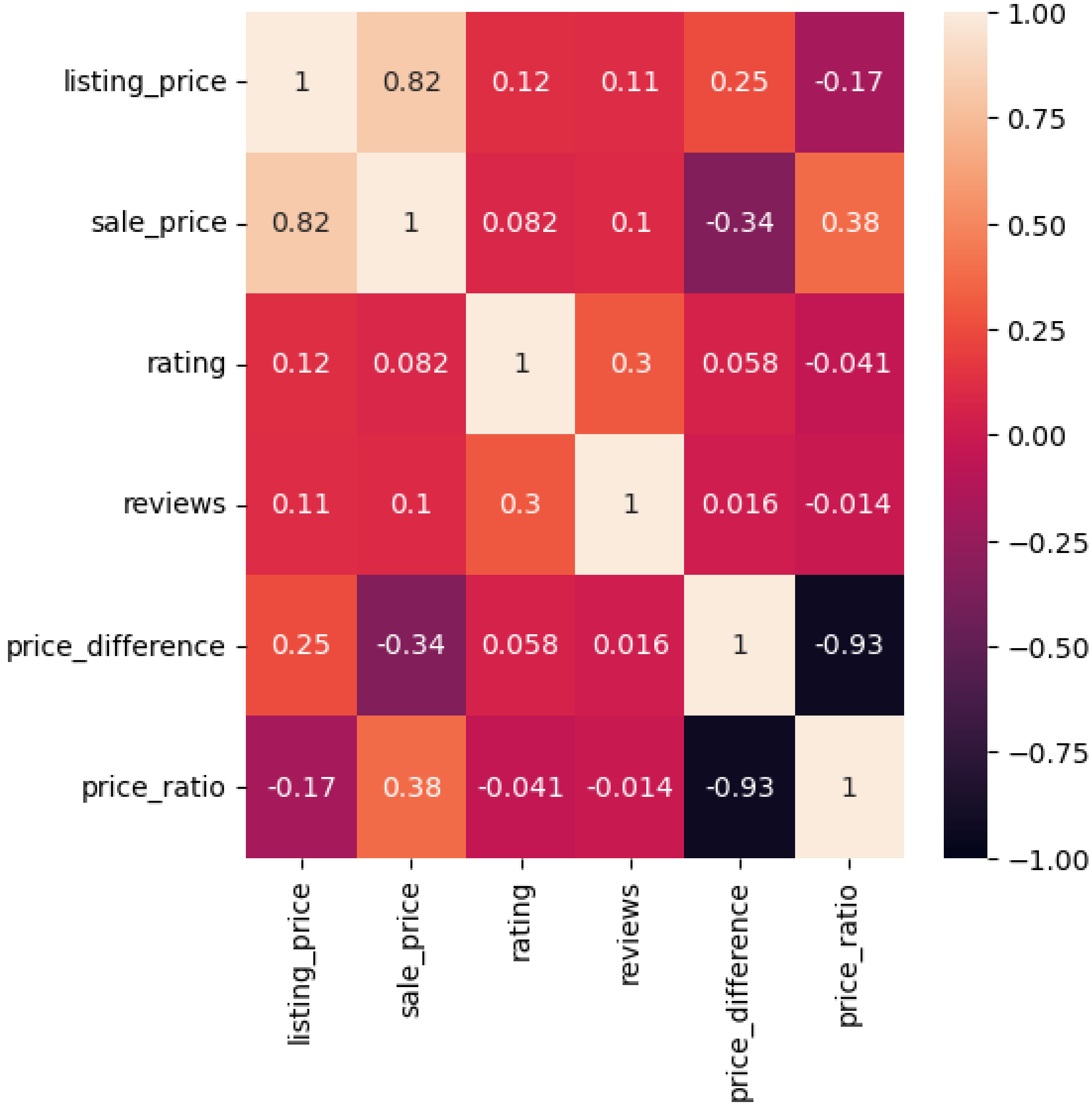

Count
sale_price
0
20
40
60
80
100
0
50
100
150
200
250
300
350

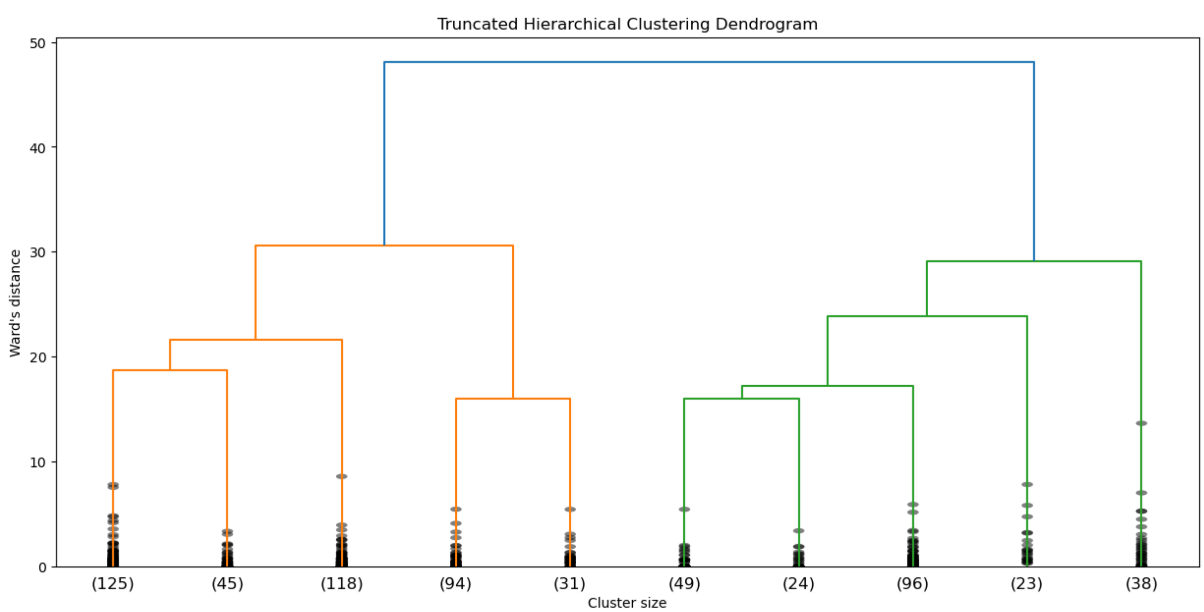

Count
400
350
300
250
200
150
100
50
0
0
25
50
75
100
125
150
175
200
listing_price


Count
listing_price
0
20
40
60
80
100
50
100
150
200
250


140
120
100
80
60
40
20
0
Count
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
rating


listing_price
sale_price
rating
reviews
listing_price
sale_price
rating
reviews


listing_price
sale_price
rating
reviews
price_difference
price_ratio
1 0.82 0.12 0.11 0.25 -0.17
0.82 1 0.082 0.1 -0.34 0.38
0.12 0.082 1 0.3 0.058 -0.041
0.11 0.1 0.3 1 0.016 -0.014
0.25 -0.34 0.058 0.016 1 -0.93
-0.17 0.38 -0.041 -0.014 -0.93 1
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Truncated Hierarchical Clustering Dendrogram
Ward's distance
Cluster size
(125) (45) (118) (94) (31) (49) (24) (96) (23) (38)
0
10
20
30
40
50

In [142]:
```
scaled_df = pd.DataFrame(scaled_data, columns=features)
for col in df.columns:
    if col not in features:
        scaled_df[col] = df[col]
```

In [143]:
```
scaled_df
```

Out[143]:

	listing_price	sale_price	rating	reviews	price_difference	price_ratio	price_category_enc
0	-1.250013	-0.602840	-1.280299	-0.450113	-1.037481	1.567450	-0.0
1	-0.816728	-0.602840	-1.280299	-0.450113	-0.323246	0.235658	-0.0
2	-0.474300	-0.048489	-1.280299	-0.450113	-0.699555	0.672268	1.1
3	-1.158699	-0.048489	-1.280299	-0.450113	-1.827730	2.853867	1.1
4	-0.246015	-0.048489	-1.280299	-0.450113	-0.323246	0.235658	1.1
...	...	...	...	...	...	...	
638	1.123695	0.572827	1.060424	-0.387441	0.880191	-0.549560	-1.2
639	-1.387441	-1.489358	-1.280299	-0.450113	0.240465	-0.942143	-0.0
640	-0.588443	-0.946094	1.060424	-0.387441	0.635590	-0.942305	-0.0
641	1.351980	1.503693	0.592279	-0.199422	-0.323246	0.235658	-1.2
642	-0.474300	-0.868485	-1.280299	-0.450113	0.692036	-0.942318	-0.0

643 rows × 12 columns

In [144]:
```
# 6 clusters at Ward's distance 20
cluster = AgglomerativeClustering(n_clusters=6, affinity='euclidean', li
df['cluster_labels'] = cluster.fit_predict(scaled_df[features])
```

In [145]:
```
df[df["cluster_labels"] == 1]
```

Out[145]:

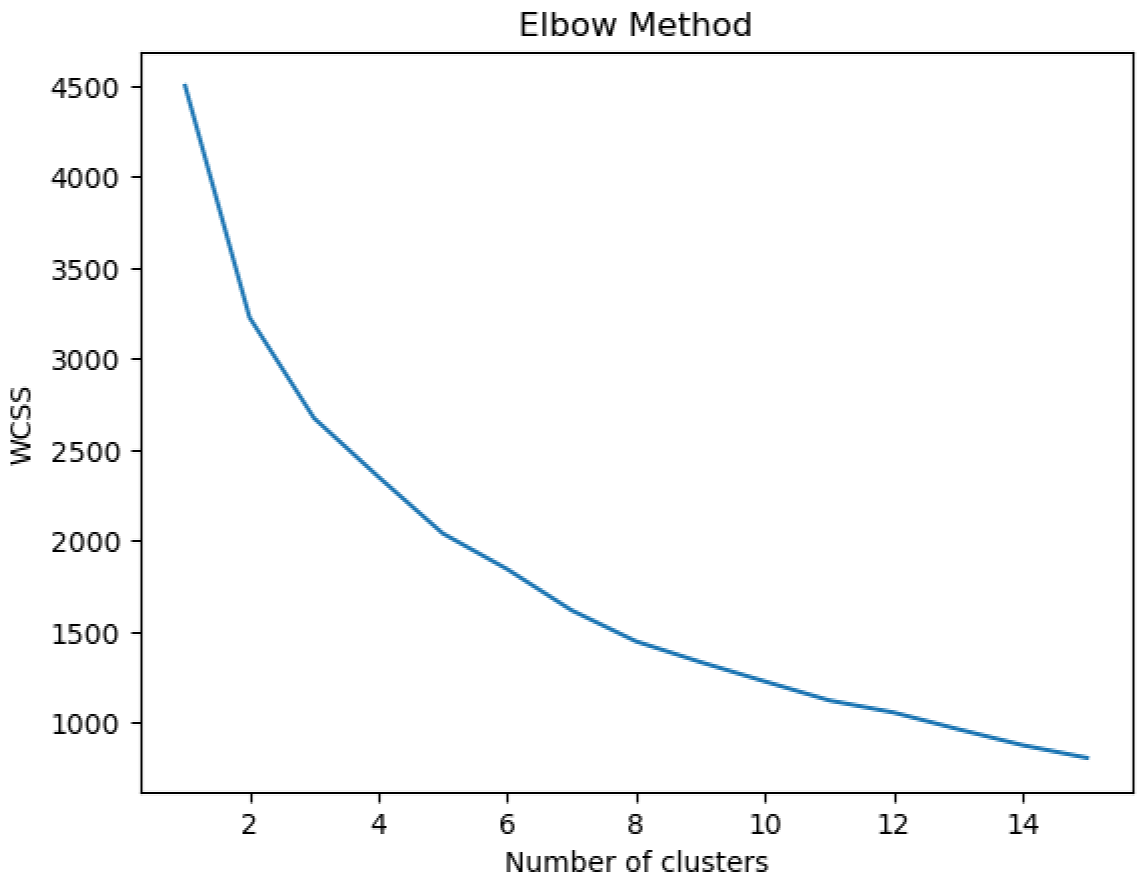
	product_name	product_id	listing_price	sale_price	brand	description	rating	reviews	price
8	Nike Zoom Pegasus Turbo 2	AT8242-009	159.95	159.95	Nike	The Nike Zoom Pegasus Turbo 2 is updated with ...	2.7	14	
9	Nike Air Max 270 React ENG	CK2595-500	149.95	149.95	Nike	The Nike Air Max 270 React ENG combines a full...	5.0	2	
16	Nike Air Max 270 React ENG	CK2608-100	149.95	149.95	Nike	Refresh your step in the Nike Air Max 270 Reac...	0.0	0	
17	Nike Air Max 97	921733-104	159.95	169.95	Nike	The Nike Air Max 97 keeps a sneaker icon going...	4.3	16	
20	Nike Air Max 97	CT4525-001	169.95	159.95	Nike	Remastered from the OG that shook up the runni...	0.0	0	
...	...	...	...	...	...	...	...	...	
631	Nike Metcon 5 AMP	CN5455-160	119.95	119.95	Nike	The Nike Metcon 5 AMP arms you with stability ...	4.5	2	
632	Air Jordan 5 Retro	CD2722-001	189.95	159.95	Nike	The Air Jordan 5 Retro for women gives a colou...	3.3	3	
637	Nike React Metcon AMP	CT9155-063	139.95	139.95	Nike	The Nike React Metcon AMP takes the stability ...	3.0	1	
638	Air Jordan 8 Retro	CI1236-100	159.95	127.97	Nike	The Air Jordan 8 Retro recaptures the memorabl...	5.0	1	
641	Nike Air Max 98	AH6799-300	169.95	169.95	Nike	The Nike Air Max 98 features the OG design lin...	4.0	4	

169 rows × 13 columns

In [146]:
```
from sklearn.cluster import KMeans

# Using the Elbow method to find the optimal number of clusters
wcss = []
for i in range(1, 16):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init
    kmeans.fit(scaled_data)
    wcss.append(kmeans.inertia_)

# Plot the Elbow method
plt.plot(range(1, 16), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```

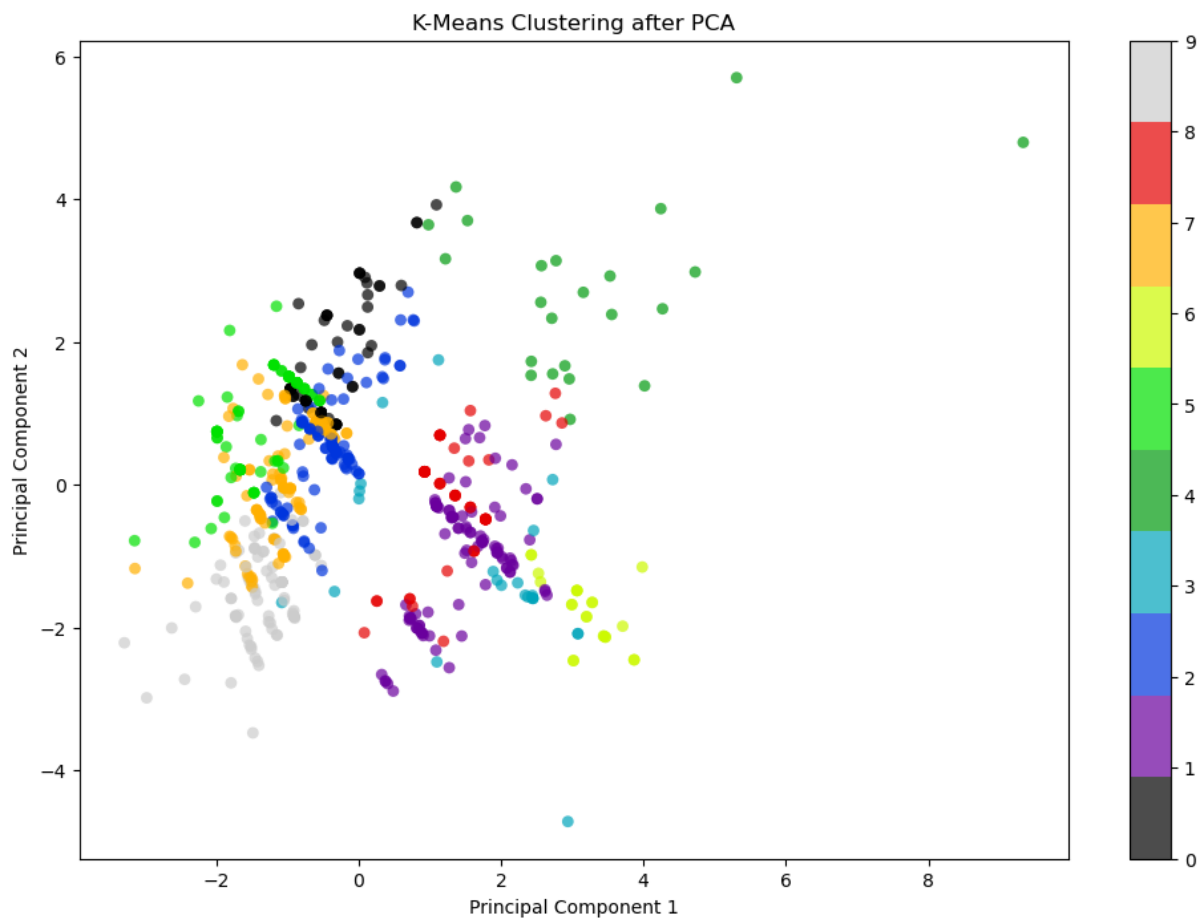


In [147]:
```
# Apply KMeans clustering
optimal_clusters = 10
kmeans = KMeans(n_clusters=optimal_clusters, init='k-means++', max_iter=
df['kmeans_cluster_labels'] = kmeans.fit_predict(scaled_data)
```

In [148]:
```
om sklearn.decomposition import PCA

a = PCA(n_components=2)
incipalComponents = pca.fit_transform(scaled_data)

.figure(figsize=(12, 8))
.scatter(principalComponents[:, 0], principalComponents[:, 1], c=df['kmea
         cmap=plt.cm.get_cmap('nipy_spectral', 10))
.colorbar()
.title('K-Means Clustering after PCA')
.xlabel('Principal Component 1')
.ylabel('Principal Component 2')
.show()
```



In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: