In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
```

```
C:\Users\patil\anaconda3\lib\site-packages\pandas\core\computation\expressions.py:21: UserWarning: Pandas requires vers
ion '2.8.4' or newer of 'numexpr' (version '2.8.3' currently installed).
  from pandas.core.computation.check import NUMEXPR_INSTALLED
C:\Users\patil\anaconda3\lib\site-packages\pandas\core\arrays\masked.py:61: UserWarning: Pandas requires version '1.3.
6' or newer of 'bottleneck' (version '1.3.5' currently installed).
  from pandas.core import (
```

In [2]:
```
df = pd.read_csv("ifood_df.csv")
```

In [3]:
```
print("Shape:", df.shape)
print("\nColumns:", df.columns.tolist())
print("\nMissing values:\n", df.isnull().sum())
```

```
Shape: (2205, 39)

Columns: ['Income', 'Kidhome', 'Teenhome', 'Recency', 'MntWines', 'MntFruits', 'MntMeatProducts', 'MntFishProducts', 'M
ntSweetProducts', 'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases', 'NumCatalogPurchases', 'NumStorePurchases',
'NumWebVisitsMonth', 'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1', 'AcceptedCmp2', 'Complain', 'Z_Cos
tContact', 'Z_Revenue', 'Response', 'Age', 'Customer_Days', 'marital_Divorced', 'marital_Married', 'marital_Single', 'm
arital_Together', 'marital_Widow', 'education_2n Cycle', 'education_Basic', 'education_Graduation', 'education_Master',
'education_PhD', 'MntTotal', 'MntRegularProds', 'AcceptedCmpOverall']

Missing values:
 Income                 0
Kidhome                0
Teenhome               0
Recency                0
MntWines               0
MntFruits              0
MntMeatProducts        0
MntFishProducts        0
MntSweetProducts       0
MntGoldProds           0
NumDealsPurchases      0
NumWebPurchases        0
NumCatalogPurchases    0
NumStorePurchases      0
NumWebVisitsMonth      0
AcceptedCmp3           0
AcceptedCmp4           0
AcceptedCmp5           0
AcceptedCmp1           0
AcceptedCmp2           0
Complain               0
Z_CostContact          0
Z_Revenue              0
Response               0
Age                    0
Customer_Days          0
marital_Divorced       0
marital_Married        0
marital_Single         0
marital_Together       0
marital_Widow          0
education_2n Cycle     0
education_Basic        0
education_Graduation   0
education_Master       0
```

```
education_PhD          0
MntTotal               0
MntRegularProds        0
AcceptedCmpOverall     0
dtype: int64
```

In [4]:
```python
df.head()
```

Out[4]:

	Income	Kidhome	Teenhome	Recency	MntWines	MntFruits	MntMeatProducts	MntFishProducts	MntSweetProducts	MntGoldProds	...
0	58138.0	0	0	58	635	88	546	172	88	88	...
1	46344.0	1	1	38	11	1	6	2	1	6	...
2	71613.0	0	0	26	426	49	127	111	21	42	...
3	26646.0	1	0	26	11	4	20	10	3	5	...
4	58293.0	1	0	94	173	43	118	46	27	15	...

5 rows × 39 columns

In [5]:
```python
df.drop_duplicates(inplace=True)
```

In [6]:
```python
df = df.fillna(df.median(numeric_only=True))
```

In [7]:
```python
print(df.dtypes)
```

```
Income                  float64
Kidhome                   int64
Teenhome                  int64
Recency                   int64
MntWines                  int64
MntFruits                 int64
MntMeatProducts           int64
MntFishProducts           int64
MntSweetProducts          int64
MntGoldProds              int64
NumDealsPurchases         int64
NumWebPurchases           int64
NumCatalogPurchases       int64
NumStorePurchases         int64
NumWebVisitsMonth         int64
AcceptedCmp3              int64
AcceptedCmp4              int64
AcceptedCmp5              int64
AcceptedCmp1              int64
AcceptedCmp2              int64
Complain                  int64
Z_CostContact             int64
Z_Revenue                 int64
Response                  int64
Age                       int64
Customer_Days             int64
marital_Divorced          int64
marital_Married           int64
marital_Single            int64
marital_Together          int64
marital_Widow             int64
education_2n Cycle        int64
education_Basic           int64
education_Graduation      int64
education_Master          int64
education_PhD             int64
MntTotal                  int64
MntRegularProds           int64
AcceptedCmpOverall        int64
dtype: object
```

In [8]:
```
df.describe().T
```

Out[8]:

	count	mean	std	min	25%	50%	75%	max
Income	2021.0	51687.258783	20713.046401	1730.0	35416.0	51412.0	68274.0	113734.0
Kidhome	2021.0	0.443345	0.536196	0.0	0.0	0.0	1.0	2.0
Teenhome	2021.0	0.509649	0.546393	0.0	0.0	0.0	1.0	2.0
Recency	2021.0	48.880752	28.950917	0.0	24.0	49.0	74.0	99.0
MntWines	2021.0	306.492331	337.603877	0.0	24.0	178.0	507.0	1493.0
MntFruits	2021.0	26.364671	39.776518	0.0	2.0	8.0	33.0	199.0
MntMeatProducts	2021.0	166.059871	219.869126	0.0	16.0	68.0	230.0	1725.0
MntFishProducts	2021.0	37.603662	54.892196	0.0	3.0	12.0	50.0	259.0
MntSweetProducts	2021.0	27.268679	41.575454	0.0	1.0	8.0	34.0	262.0
MntGoldProds	2021.0	43.921821	51.678211	0.0	9.0	25.0	56.0	321.0
NumDealsPurchases	2021.0	2.330035	1.892778	0.0	1.0	2.0	3.0	15.0
NumWebPurchases	2021.0	4.115289	2.753588	0.0	2.0	4.0	6.0	27.0
NumCatalogPurchases	2021.0	2.644730	2.799126	0.0	0.0	2.0	4.0	28.0
NumStorePurchases	2021.0	5.807521	3.230434	0.0	3.0	5.0	8.0	13.0
NumWebVisitsMonth	2021.0	5.340426	2.426319	0.0	3.0	6.0	7.0	20.0
AcceptedCmp3	2021.0	0.074715	0.262997	0.0	0.0	0.0	0.0	1.0
AcceptedCmp4	2021.0	0.076695	0.266172	0.0	0.0	0.0	0.0	1.0
AcceptedCmp5	2021.0	0.072241	0.258951	0.0	0.0	0.0	0.0	1.0
AcceptedCmp1	2021.0	0.065809	0.248009	0.0	0.0	0.0	0.0	1.0
AcceptedCmp2	2021.0	0.012865	0.112720	0.0	0.0	0.0	0.0	1.0
Complain	2021.0	0.009401	0.096527	0.0	0.0	0.0	0.0	1.0
Z_CostContact	2021.0	3.000000	0.000000	3.0	3.0	3.0	3.0	3.0
Z_Revenue	2021.0	11.000000	0.000000	11.0	11.0	11.0	11.0	11.0
Response	2021.0	0.153884	0.360927	0.0	0.0	0.0	0.0	1.0
Age	2021.0	51.117269	11.667616	24.0	43.0	50.0	61.0	80.0

	count	mean	std	min	25%	50%	75%	max
Customer_Days	2021.0	2511.613063	202.546762	2159.0	2337.0	2511.0	2688.0	2858.0
marital_Divorced	2021.0	0.105888	0.307771	0.0	0.0	0.0	0.0	1.0
marital_Married	2021.0	0.388422	0.487512	0.0	0.0	0.0	1.0	1.0
marital_Single	2021.0	0.219198	0.413806	0.0	0.0	0.0	0.0	1.0
marital_Together	2021.0	0.251856	0.434186	0.0	0.0	0.0	1.0	1.0
marital_Widow	2021.0	0.034636	0.182902	0.0	0.0	0.0	0.0	1.0
education_2n Cycle	2021.0	0.090549	0.287038	0.0	0.0	0.0	0.0	1.0
education_Basic	2021.0	0.024245	0.153848	0.0	0.0	0.0	0.0	1.0
education_Graduation	2021.0	0.502227	0.500119	0.0	0.0	1.0	1.0	1.0
education_Master	2021.0	0.165760	0.371957	0.0	0.0	0.0	0.0	1.0
education_PhD	2021.0	0.217219	0.412455	0.0	0.0	0.0	0.0	1.0
MntTotal	2021.0	563.789213	576.775749	4.0	55.0	343.0	964.0	2491.0
MntRegularProds	2021.0	519.867392	554.797857	-283.0	42.0	288.0	883.0	2458.0
AcceptedCmpOverall	2021.0	0.302326	0.680812	0.0	0.0	0.0	0.0	4.0

In [9]:
```
if 'Income' in df.columns:
    avg_income = df['Income'].mean()
    print(f"Average Income: ₹{avg_income:,.2f}")
```

```
Average Income: ₹51,687.26
```

In [10]:
```
purchase_cols = [col for col in df.columns if 'Mnt' in col]
df['Total_Spending'] = df[purchase_cols].sum(axis=1)

print("\nAverage Purchase Value:", df['Total_Spending'].mean())
print("Median Purchase Value:", df['Total_Spending'].median())
```

```
Average Purchase Value: 1691.367639782286
Median Purchase Value: 1029.0
```

In [11]:
```
freq_cols = [col for col in df.columns if 'Num' in col]
df['Total_Transactions'] = df[freq_cols].sum(axis=1)
```

```
df[['Total_Spending', 'Total_Transactions']].describe()
```

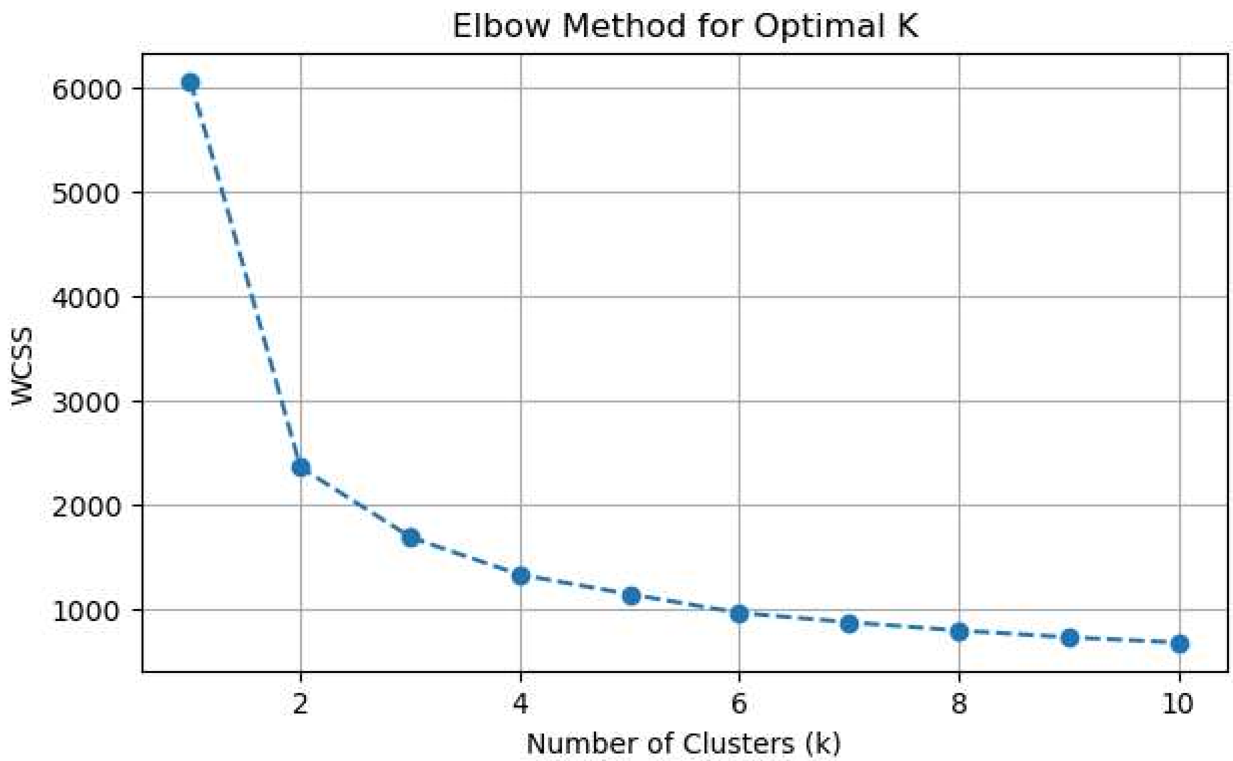
Out[11]:

	Total_Spending	Total_Transactions
count	2021.000000	2021.000000
mean	1691.367640	20.238001
std	1730.327247	7.220657
min	12.000000	6.000000
25%	165.000000	14.000000
50%	1029.000000	20.000000
75%	2892.000000	25.000000
max	7473.000000	46.000000

In [12]:

```
features = ['Total_Spending', 'Total_Transactions']
if 'Income' in df.columns:
    features.append('Income')

X = df[features]

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Compute WCSS
wcss = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10, algorithm='full')
    kmeans.fit(X_scaled)
    wcss.append(kmeans.inertia_)

plt.figure(figsize=(7, 4))
plt.plot(range(1, 11), wcss, marker='o', linestyle='--')
plt.title('Elbow Method for Optimal K')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('WCSS')
plt.grid(True)
plt.show()

# Apply K-Means
```

```
kmeans = KMeans(n_clusters=4, random_state=42, n_init=10, algorithm='elkan')
df['Cluster'] = kmeans.fit_predict(X_scaled)

df['Cluster'].value_counts()
```



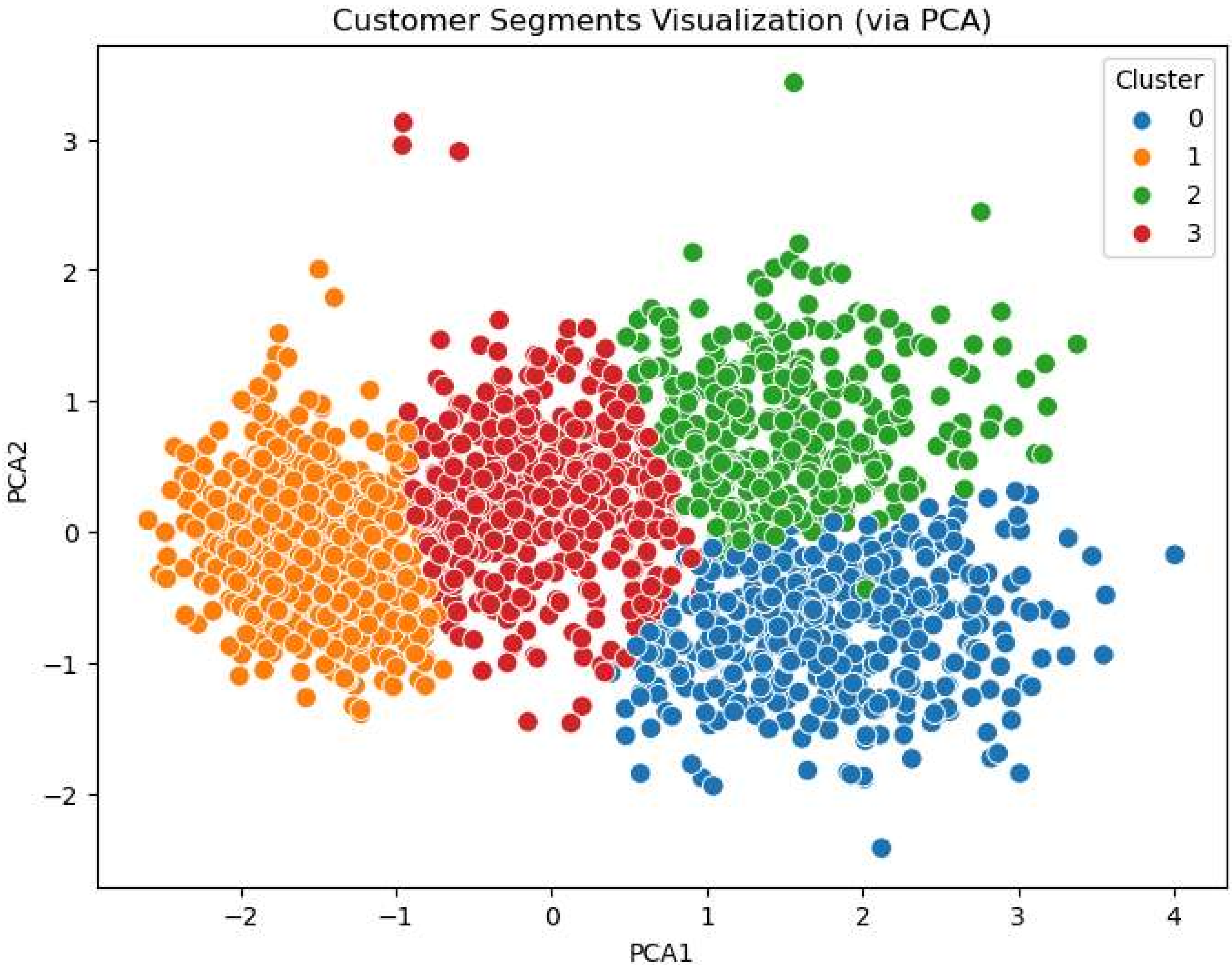
Out[12]:

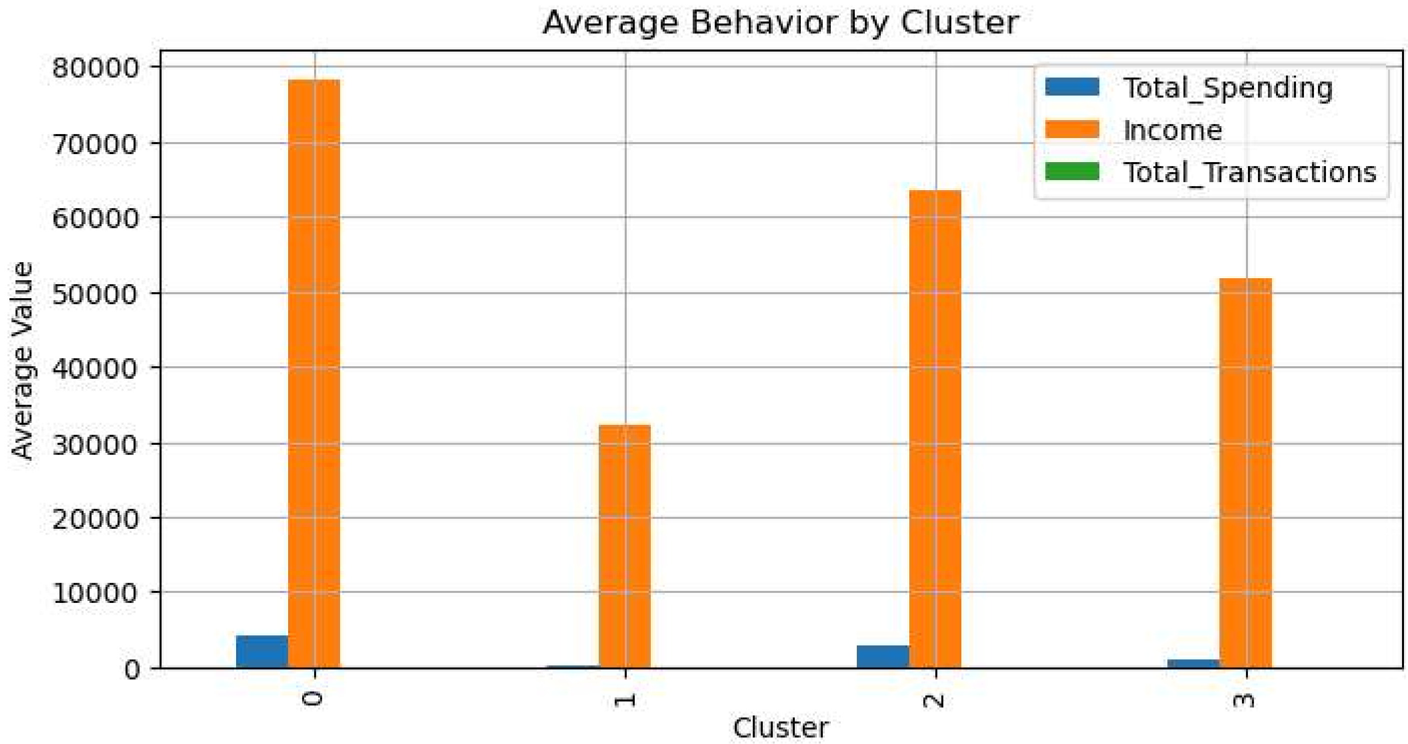
```
Cluster
1    796
3    455
0    415
2    355
Name: count, dtype: int64
```

In [13]:

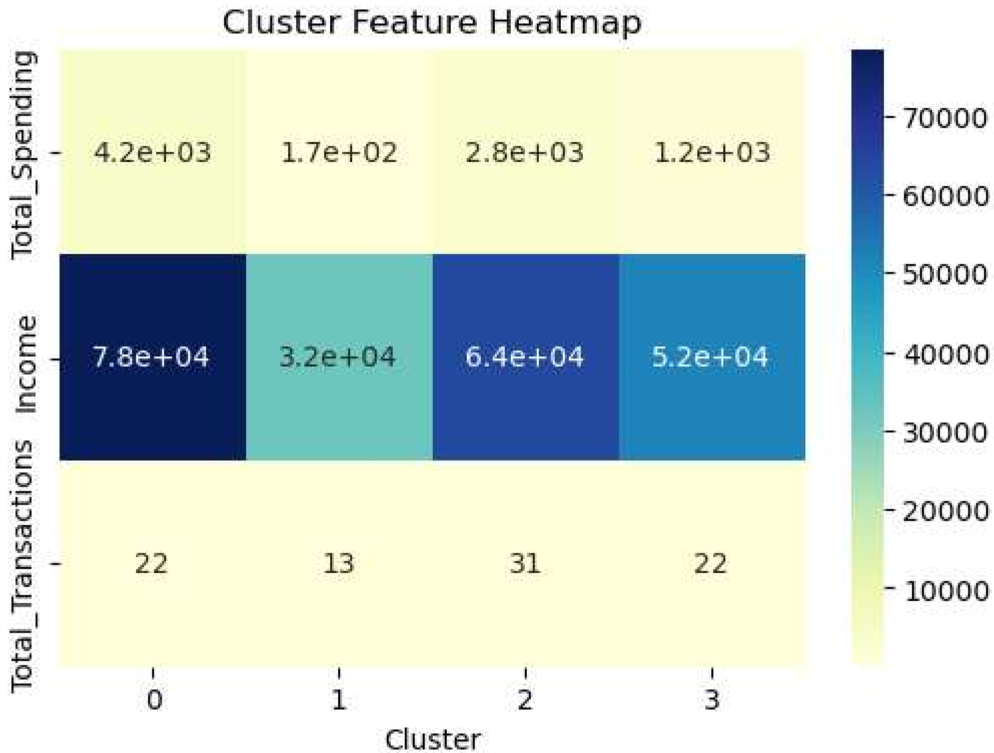
```
pca = PCA(n_components=2)
pca_components = pca.fit_transform(X_scaled)
df['PCA1'], df['PCA2'] = pca_components[:,0], pca_components[:,1]

plt.figure(figsize=(8,6))
sns.scatterplot(data=df, x='PCA1', y='PCA2', hue='Cluster', palette='tab10', s=70)
plt.title('Customer Segments Visualization (via PCA)')
plt.legend(title='Cluster')
plt.show()
```

```python
cluster_summary = df.groupby('Cluster')[['Total_Spending', 'Income', 'Total_Transactions']].mean()
cluster_summary.plot(kind='bar', figsize=(8,4))
plt.title('Average Behavior by Cluster')
plt.ylabel('Average Value')
plt.grid(True)
plt.show()

plt.figure(figsize=(6,4))
sns.heatmap(cluster_summary.T, annot=True, cmap='YlGnBu')
plt.title('Cluster Feature Heatmap')
plt.show()
```


Customer Segments Visualization (via PCA)
Cluster
0
1
2
3
PCA2
PCA1
3
2
1
0
−1
−2
−2
−1
0
1
2
3
4



Average Behavior by Cluster
Total_Spending
Income
Total_Transactions
80000
70000
60000
50000
40000
30000
20000
10000
0
Average Value
0
1
2
3
Cluster



Insights and Recommendations

Cluster Analysis Summary:

1.Cluster 0 (High Income & High Spending): Represents premium customers. Focus marketing campaigns and loyalty rewards here.

2.Cluster 1 (Moderate Income, Moderate Spending): Growth segment — target with combo offers or personalized promotions.

3.Cluster 2 (Low Income, Low Spending): Price-sensitive customers — push discounts or bundles.

4.Cluster 3 (High Income, Low Spending): Upsell opportunities — consider premium product exposure or luxury campaigns.

Recommendations:

Introduce loyalty programs for high-value clusters. Use targeted email marketing based on cluster profiles. Offer personalized product recommendations using behavioral data. Conduct churn analysis for low-engagement clusters.