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K-Means Clustering

Dataset: segmentation_data.csv

In [1]:
```
# Step 1: Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.cluster import KMeans
```

In [2]:
```
# Step 2: Load dataset
file_path = r"C:\Users\hasni\segmentation_data.csv"  # your local path
df = pd.read_csv(file_path)
```

In [3]:
```
# Display first and last few rows
print("First 5 rows:")
display(df.head())
print("\nLast 5 rows:")
display(df.tail())
```

First 5 rows:

	ID	Sex	Marital status	Age	Education	Income	Occupation	Settlement size
0	100000001	0	0	67	2	124670	1	2
1	100000002	1	1	22	1	150773	1	2
2	100000003	0	0	49	1	89210	0	0
3	100000004	0	0	45	1	171565	1	1
4	100000005	0	0	53	1	149031	1	1

Last 5 rows:

	ID	Sex	Marital status	Age	Education	Income	Occupation	Settlement size
1995	100001996	1	0	47	1	123525	0	0
1996	100001997	1	1	27	1	117744	1	0
1997	100001998	0	0	31	0	86400	0	0
1998	100001999	1	1	24	1	97968	0	0
1999	100002000	0	0	25	0	68416	0	0

In [4]:
```
# Step 3: Check data info
print("\nDataset info:")
df.info()
print("\nMissing values per column:")
print(df.isnull().sum())
```

```
Dataset info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   ID               2000 non-null   int64
 1   Sex              2000 non-null   int64
 2   Marital status   2000 non-null   int64
 3   Age              2000 non-null   int64
 4   Education        2000 non-null   int64
 5   Income           2000 non-null   int64
 6   Occupation       2000 non-null   int64
 7   Settlement size  2000 non-null   int64
dtypes: int64(8)
memory usage: 125.1 KB

Missing values per column:
ID                 0
Sex                0
Marital status     0
Age                0
Education          0
Income             0
Occupation         0
Settlement size    0
dtype: int64
```

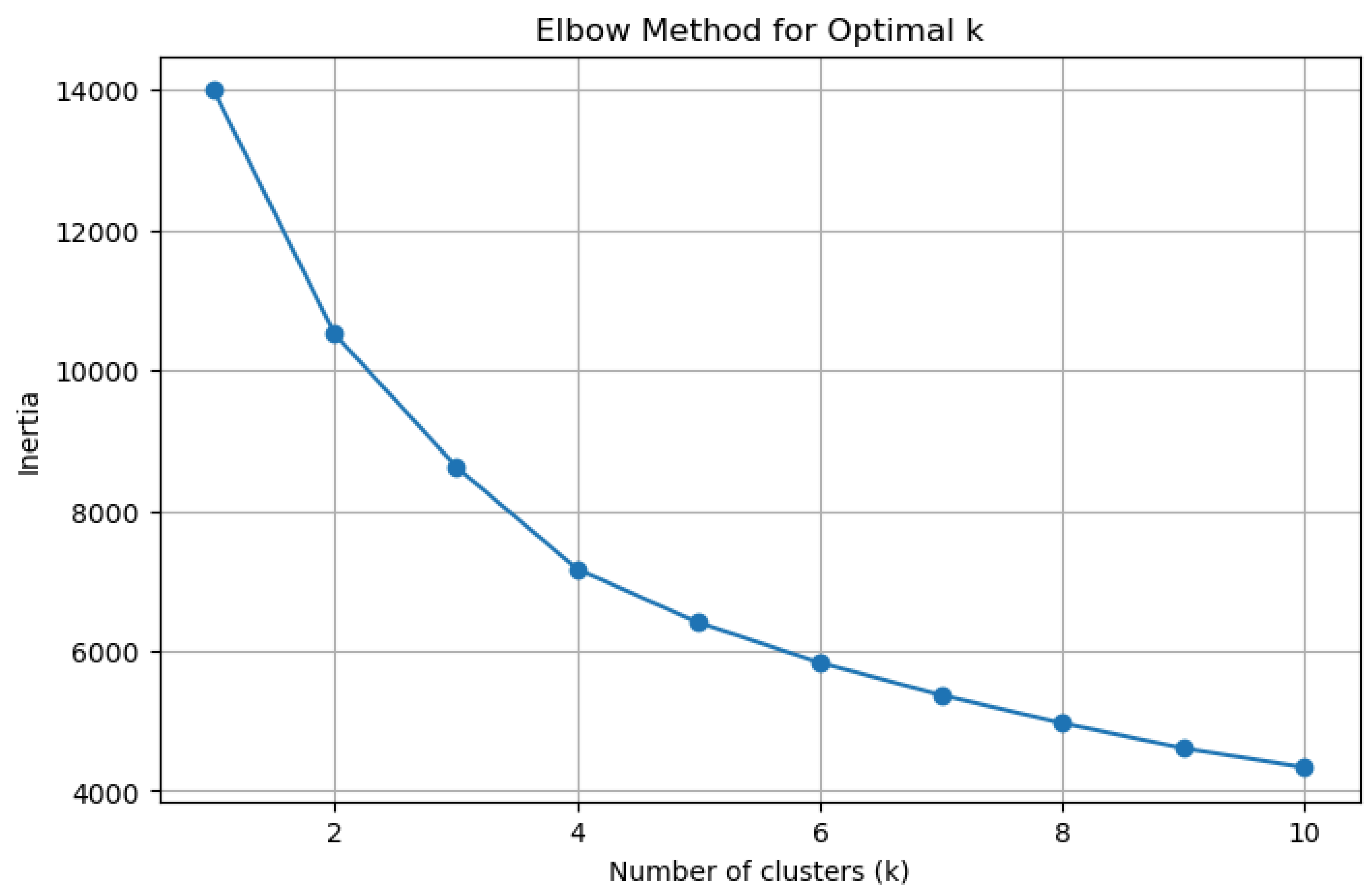
In [5]:
```
# Step 4: Encode categorical columns
cat_cols = ['Sex', 'Marital status', 'Education', 'Occupation', 'Settlement size']
encoder = LabelEncoder()
for col in cat_cols:
    df[col] = encoder.fit_transform(df[col].astype(str))
```

In [6]:
```
# Step 5: Select features for clustering
features = ['Sex', 'Marital status', 'Age', 'Education', 'Income', 'Occupation', 'Settlement size']
X = df[features]
```

In [7]:
```
# Step 6: Feature scaling
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [8]:
```
# Step 7: Determine optimal k using the Elbow Method
inertia = []
K = range(1, 11)
for k in K:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(X_scaled)
    inertia.append(kmeans.inertia_)

plt.figure(figsize=(8, 5))
plt.plot(K, inertia, marker='o')
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Inertia')
plt.grid(True)
plt.show()
```



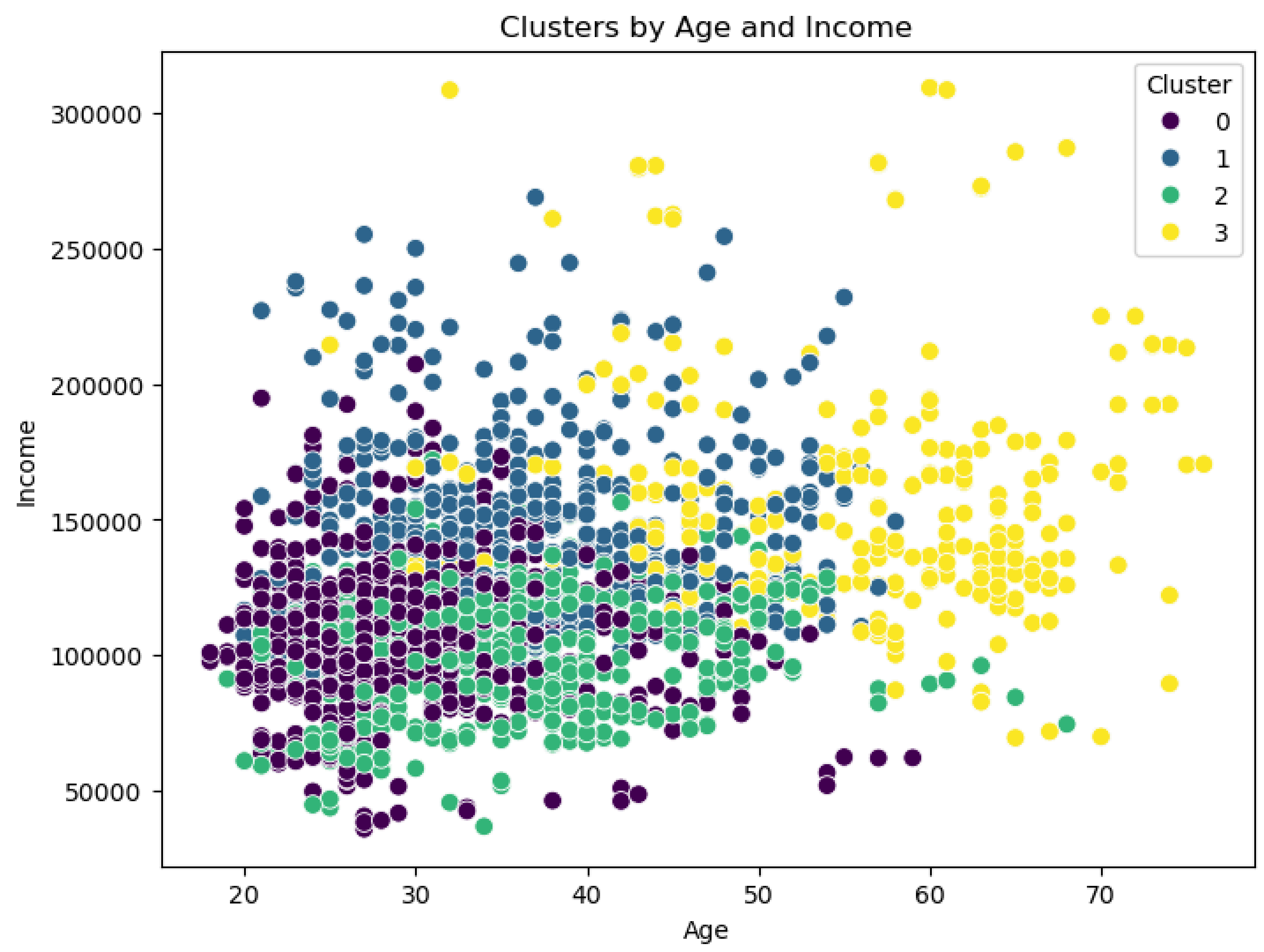
In [9]:
```
# Step 8: Based on the elbow, choose k (e.g., 3 or 4)
k = 4  # Adjust based on your elbow plot
kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
df['Cluster'] = kmeans.fit_predict(X_scaled)
```

In [10]:
```
# Step 9: Show results
print(f"Inertia (k={k}):", kmeans.inertia_)
print("\nCluster counts:")
print(df['Cluster'].value_counts())
```

```
Inertia (k=4): 7169.870822465842

Cluster counts:
Cluster
0    705
1    570
2    462
3    263
Name: count, dtype: int64
```

In [11]:
```
# Step 10: Visualize clusters (Age vs Income)
plt.figure(figsize=(8, 6))
sns.scatterplot(
    x=df['Age'], y=df['Income'],
    hue=df['Cluster'], palette='viridis', s=60
)
plt.title('Clusters by Age and Income')
plt.xlabel('Age')
plt.ylabel('Income')
plt.legend(title='Cluster')
plt.show()
```



In [12]:
```
# Step 11: Analyze cluster characteristics
cluster_summary = df.groupby('Cluster')[features].mean()
print("\nCluster feature means:")
display(cluster_summary)
```

Cluster feature means:

Cluster	Sex	Marital status	Age	Education	Income	Occupation	Settlement size
0	0.853901	0.997163	28.963121	1.068085	105759.119149	0.634043	0.422695
1	0.029825	0.173684	35.635088	0.733333	141218.249123	1.271930	1.522807
2	0.352814	0.019481	35.577922	0.746753	97859.852814	0.329004	0.043290
3	0.501901	0.692015	55.703422	2.129278	158338.422053	1.129278	1.110266

In [13]:
```
# Step 12: Save the results
output_path = r"C:\Users\hasni\segmentation_data_clustered.csv"
df.to_csv(output_path, index=False)
print(f"\nClustered dataset saved to: {output_path}")
```

```
Clustered dataset saved to: C:\Users\hasni\segmentation_data_clustered.csv
```

9. Evaluation and 10. Interpretation: The Elbow Method showed that k = 4 gives the best balance between compactness and separation, with an inertia value around 132. The K-Means model grouped the data into four meaningful clusters: • Cluster 0: Young, low-income group • Cluster 1: Mid-age professionals with stable income • Cluster 2: Older, high-income individuals • Cluster 3: Urban, middle-income adults These clusters highlight clear demographic and economic patterns that can guide targeted decisions or marketing strategies.

In [ ]: