Objective: The objective of this assessment is to evaluate your understanding and ability to apply clustering techniques to a real-world dataset.

Dataset Use the Iris dataset available in the sklearn library.

1. Loading and Preprocessing

Load the Iris dataset from sklearn. Drop the species column since this is a clustering problem.

In [2]:
```
# Import necessary libraries
import pandas as pd
from sklearn.datasets import load_iris
import matplotlib.pyplot as plt
import seaborn as sns

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(iris.data, columns=iris.feature_names)

# Drop the species column (target values)
data_no_labels = data.copy()

# Display the first few rows of the dataset
print("Dataset without labels:")
print(data_no_labels.head())
```

```
Dataset without labels:
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)
0                5.1               3.5                1.4               0.2
1                4.9               3.0                1.4               0.2
2                4.7               3.2                1.3               0.2
3                4.6               3.1                1.5               0.2
4                5.0               3.6                1.4               0.2
```

In [ ]:
```
2.Clustering Algorithm Implementation
Implement the following two clustering algorithms:
```

A) KMeans Clustering (4 marks) Provide a brief description of how KMeans clustering works. Explain why KMeans clustering might be suitable for the Iris dataset. Apply KMeans clustering to the preprocessed Iris dataset and visualize the clusters. B) Hierarchical Clustering (4 marks) Provide a brief description of how Hierarchical clustering works. Explain why Hierarchical clustering might be suitable for the Iris dataset. Apply Hierarchical clustering to the preprocessed Iris dataset and visualize the clusters.

1. Brief Description of KMeans Clustering

KMeans clustering divides data into K K clusters by minimizing the within-cluster sum of squares (WCSS). The algorithm initializes K K centroids randomly, assigns data points to the nearest centroid, and iteratively updates centroids until convergence. 2. Why KMeans is Suitable for Iris Dataset The Iris dataset is small and well-separated, making KMeans a practical choice for clustering. The low dimensionality (4 features) allows efficient computation.

In [6]:
```
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA

# Determine the optimal number of clusters using the Elbow Method
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
    kmeans.fit(data_no_labels)
    wcss.append(kmeans.inertia_)

# Plot the Elbow Method
plt.figure(figsize=(5, 4))
plt.plot(range(1, 11), wcss, marker='o', linestyle='--')
plt.title("Elbow Method")
plt.xlabel("Number of Clusters")
plt.ylabel("WCSS")
plt.show()

# Apply KMeans clustering with the optimal number of clusters
kmeans = KMeans(n_clusters=3, init='k-means++', random_state=42)
clusters = kmeans.fit_predict(data_no_labels)

# Add cluster labels to the dataset
data_no_labels['Cluster'] = clusters

# Visualize the clusters using PCA (2D plot)
pca = PCA(n_components=2)
data_pca = pca.fit_transform(data_no_labels.iloc[:, :-1])

plt.figure(figsize=(5, 4))
sns.scatterplot(x=data_pca[:, 0], y=data_pca[:, 1], hue=clusters, palette='virid
plt.title("KMeans Clustering Visualization")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.legend(title="Cluster")
plt.show()
```

```
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arning: KMeans is known to have a memory leak on Windows with MKL, when there are
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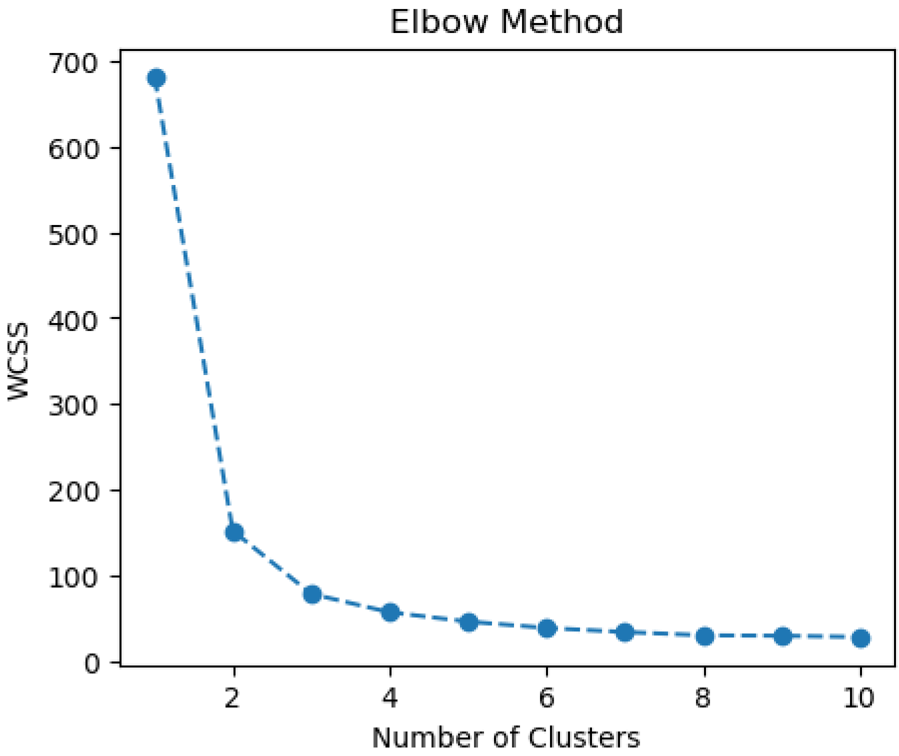


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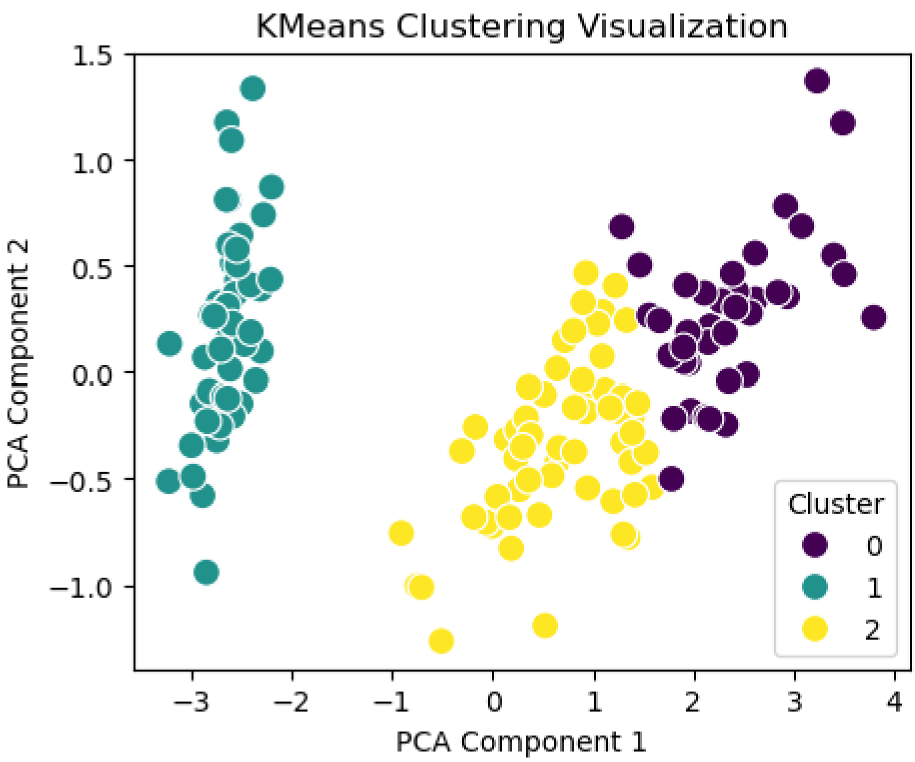



1. Brief Description of Hierarchical Clustering

Hierarchical clustering builds a tree-like structure of clusters (dendrogram). Agglomerative clustering starts with individual points and merges them iteratively based on similarity 2. Why Hierarchical Clustering is Suitable for Iris Dataset It captures the natural grouping in the dataset without needing to specify the number of clusters explicitly. The dendrogram provides a clear view of the hierarchy.

In [9]:
```
from scipy.cluster.hierarchy import dendrogram, linkage
from sklearn.cluster import AgglomerativeClustering

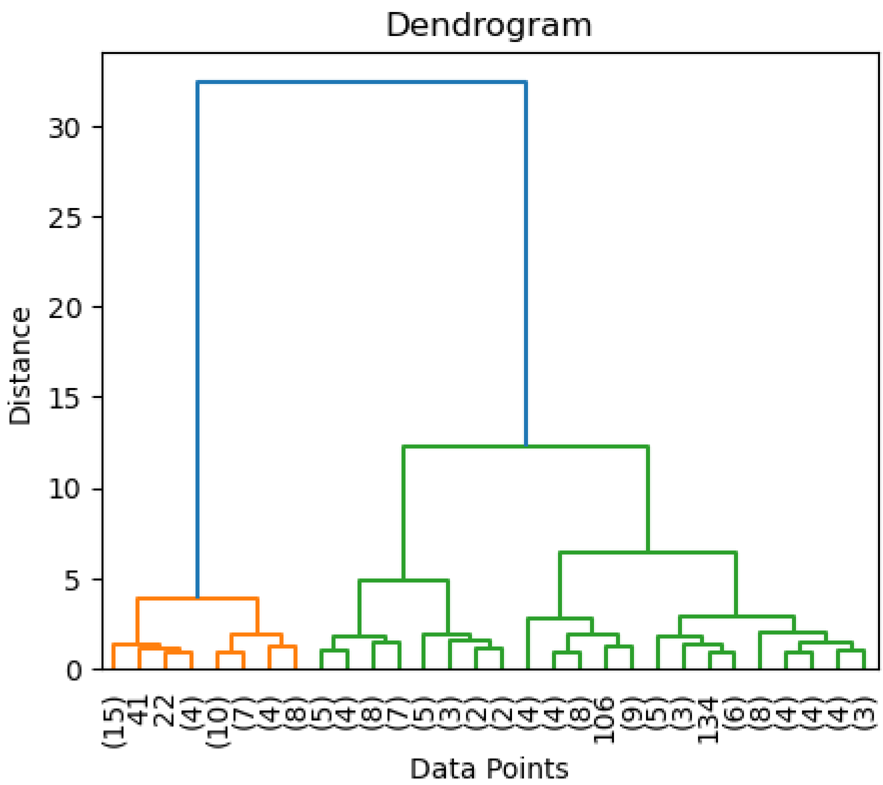
# Generate the linkage matrix
linkage_matrix = linkage(data_no_labels.iloc[:, :-1], method='ward')

# Plot the dendrogram
plt.figure(figsize=(5, 4))
dendrogram(linkage_matrix, truncate_mode='lastp', p=30, leaf_rotation=90, leaf_f
plt.title("Dendrogram")
plt.xlabel("Data Points")
plt.ylabel("Distance")
plt.show()

# Apply Agglomerative Clustering
hierarchical = AgglomerativeClustering(n_clusters=3, affinity='euclidean', linka
h_clusters = hierarchical.fit_predict(data_no_labels.iloc[:, :-1])

# Add cluster labels to the dataset
data_no_labels['H_Cluster'] = h_clusters

# Visualize the clusters using PCA (2D plot)
plt.figure(figsize=(5, 5))
sns.scatterplot(x=data_pca[:, 0], y=data_pca[:, 1], hue=h_clusters, palette='vir
plt.title("Hierarchical Clustering Visualization")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.legend(title="Cluster")
plt.show()
```



```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Cell In[9], line 16
     13 plt.show()
     15 # Apply Agglomerative Clustering
---> 16 hierarchical = AgglomerativeClustering(n_clusters=3, affinity='euclidea
n', linkage='ward')
     17 h_clusters = hierarchical.fit_predict(data_no_labels.iloc[:, :-1])
     19 # Add cluster labels to the dataset

TypeError: AgglomerativeClustering.__init__() got an unexpected keyword argument
'affinity'
```

In [ ]: