In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans, AgglomerativeClustering, DBSCAN, SpectralCluste
from sklearn.mixture import GaussianMixture
from sklearn.manifold import TSNE
import umap
from sklearn.metrics import silhouette_score, calinski_harabasz_score, davies_bould
from sklearn.preprocessing import StandardScaler
import warnings
import os
from scipy.stats import ttest_ind
warnings.filterwarnings('ignore')
```

identify the best algorithms and optimal cluster numbers, aiming for clearer customer segmentation.

In [ ]:
```
plt.style.use('default')
sns.set_palette("husl")
```

In [3]:
```
scaled_data = pd.read_csv(r"data\03_scaled_proprocessed_marketing_campaign.csv", in
print(f"Data shape: {scaled_data.shape}")
print(f"Features: {scaled_data.columns.tolist()}")
print()
```

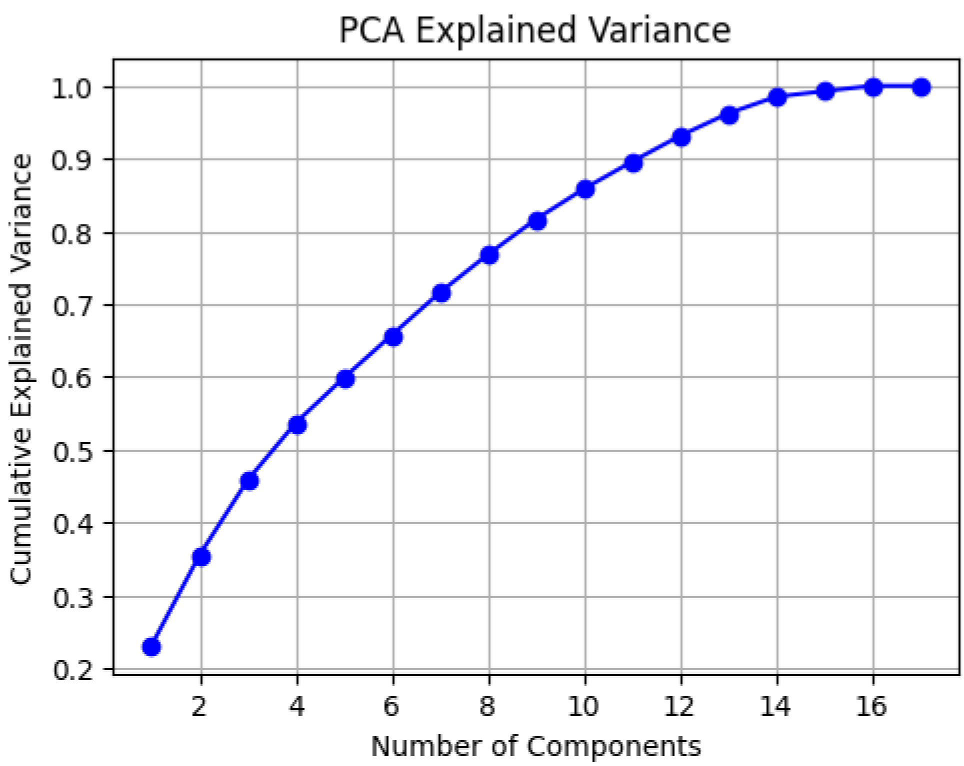
```
Data shape: (2184, 17)
Features: ['Education', 'Marital_Status', 'Income', 'Recency', 'Response', 'Age', 'C
ustomer_Since', 'Total_Spent', 'RatioWines', 'RatioFruits', 'RatioMeatProducts', 'Ra
tioFishProducts', 'RatioSweetProducts', 'RatioGoldProds', 'Total_Accepted_Campaign',
'Total_Purchase', 'Total_Web_Engagement']
```

In [4]:
```
# Prepare data for clustering
X = scaled_data.values
feature_names = scaled_data.columns.tolist()
```

In [5]:
```
# PCA Analysis
# Reduces the 17-dimensional dataset to a lower-dimensional space for clustering
# Identify patterns by projecting data onto axes that maximize variance
pca = PCA()
X_pca = pca.fit_transform(X)
```

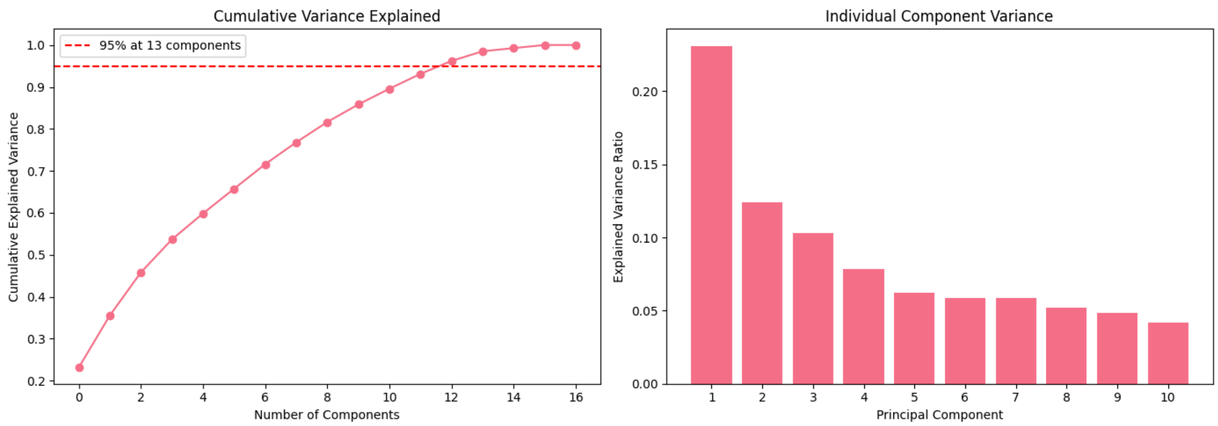
In [6]:
```
# Plot explained variance
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.plot(range(1, len(pca.explained_variance_ratio_) + 1),
         np.cumsum(pca.explained_variance_ratio_), 'bo-')
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')
plt.title('PCA Explained Variance')
```

```python
plt.savefig("plots/pca_explained_variance.png", dpi=300, bbox_inches='tight')
plt.grid(True)
```



In [7]:

```python
# Find number of components for 95% variance
n_components_95 = np.argmax(np.cumsum(pca.explained_variance_ratio_) >= 0.95) + 1

plt.figure(figsize=(14, 5))

# Cumulative variance plot with 95% line
plt.subplot(1, 2, 1)
plt.plot(np.cumsum(pca.explained_variance_ratio_), marker='o')
plt.axhline(y=0.95, color='r', linestyle='--', label=f'95% at {n_components_95} com
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')
plt.title('Cumulative Variance Explained')
plt.legend()

# Bar chart of first 10 components
plt.subplot(1, 2, 2)
plt.bar(range(1, min(11, len(pca.explained_variance_ratio_) + 1)),
        pca.explained_variance_ratio_[:10])
plt.xlabel('Principal Component')
plt.ylabel('Explained Variance Ratio')
plt.title('Individual Component Variance')
plt.xticks(range(1, min(11, len(pca.explained_variance_ratio_) + 1)))

plt.tight_layout()
plt.savefig("plots/pca_analysis.png", dpi=300, bbox_inches='tight')
plt.show()

print(f"Components needed for 95% variance: {n_components_95}")
print(f"First 5 components explain: {np.sum(pca.explained_variance_ratio_[:5]):.3f}
```




```
Components needed for 95% variance: 13
First 5 components explain: 0.598 of variance
```

Gradual decline in explained variance per component

In [8]:
```
pca_optimal = PCA(n_components=n_components_95)
X_pca_optimal = pca_optimal.fit_transform(X)
```

try out another alternative dimensionality reduction

In [9]:
```
# t-SNE
tsne = TSNE(n_components=2, random_state=42, perplexity=30)
X_tsne = tsne.fit_transform(X)
```

Clustering Algorithm Comparison

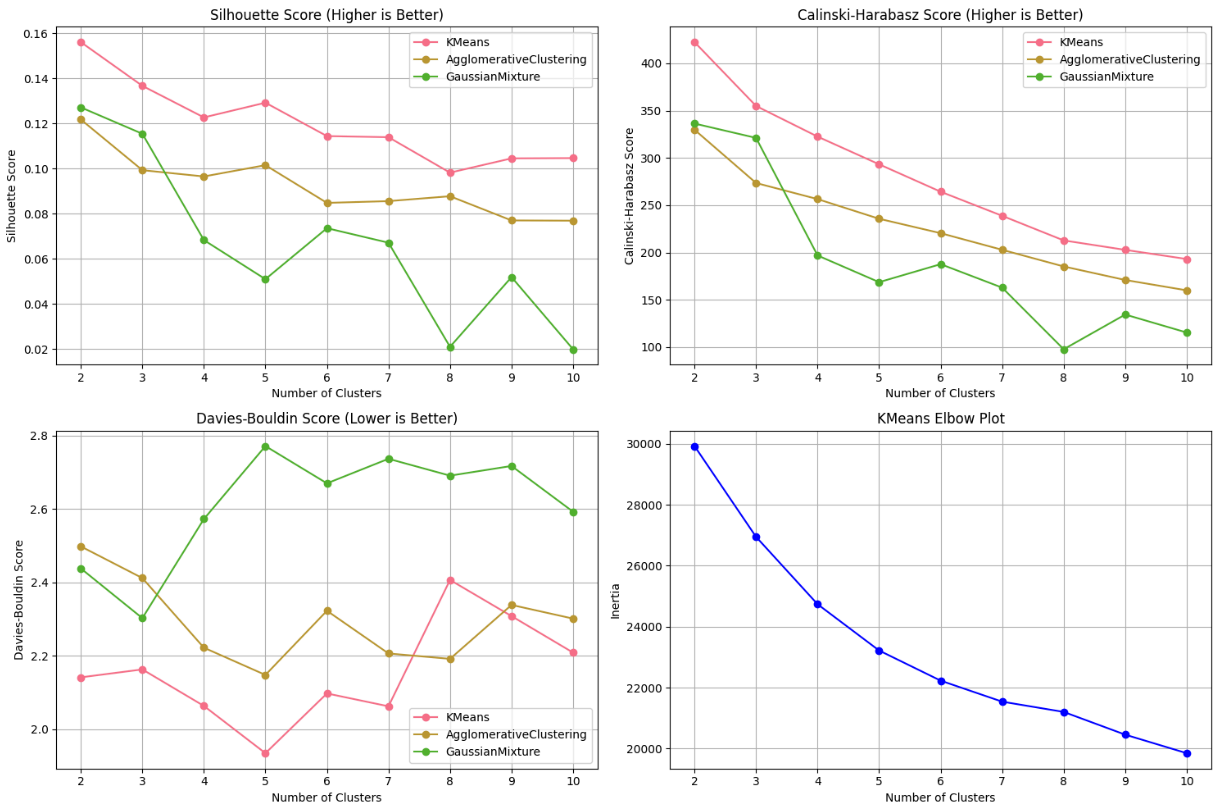
In [10]:
```
# Define range of cluster numbers to test
cluster_range = range(2, 11)
algorithms = {
    'KMeans': KMeans,
    'AgglomerativeClustering': AgglomerativeClustering,
    'GaussianMixture': GaussianMixture
}
```

In [14]:
```
# Store results
clustering_results = {}

for alg_name, alg_class in algorithms.items():
    print(f"Testing {alg_name}")
    clustering_results[alg_name] = {
        'silhouette': [],
        'calinski_harabasz': [],
        'davies_bouldin': [],
        'inertia': [] if alg_name == 'KMeans' else None
    }

    for n_clusters in cluster_range:
        if alg_name == 'GaussianMixture':
            model = alg_class(n_components=n_clusters, random_state=42)
            labels = model.fit_predict(X_pca_optimal)
        elif alg_name == 'AgglomerativeClustering':
```

```
            model = alg_class(n_clusters=n_clusters)
            labels = model.fit_predict(X_pca_optimal)
        else:
            model = alg_class(n_clusters=n_clusters, random_state=42)
            labels = model.fit_predict(X_pca_optimal)

        # Calculate metrics
        sil_score = silhouette_score(X_pca_optimal, labels)
        ch_score = calinski_harabasz_score(X_pca_optimal, labels)
        db_score = davies_bouldin_score(X_pca_optimal, labels)

        clustering_results[alg_name]['silhouette'].append(sil_score)
        clustering_results[alg_name]['calinski_harabasz'].append(ch_score)
        clustering_results[alg_name]['davies_bouldin'].append(db_score)

        if alg_name == 'KMeans':
            clustering_results[alg_name]['inertia'].append(model.inertia_)

    print(clustering_results)
```

```
Testing KMeans
{'KMeans': {'silhouette': [0.1559891203731964, 0.13661184620453445, 0.12261933508112
821, 0.1291405188248537, 0.1143420516702437, 0.11385099474271822, 0.0981409120876859
1, 0.10446788677425728, 0.1045862340494635], 'calinski_harabasz': [422.476422497865
6, 354.9651238739216, 322.57281985594256, 293.27323747491107, 264.29712441810716, 23
8.80752736853415, 212.7805210978872, 202.7959752094922, 193.09631677597886], 'davies
_bouldin': [2.140929480096599, 2.1625523900110877, 2.062931885795344, 1.934007203843
1537, 2.097036893809072, 2.0619349096038553, 2.4066311673107332, 2.3080015225425994,
2.2084517303011815], 'inertia': [29922.255527541693, 26944.948019975498, 24735.36465
674668, 23216.644801896105, 22228.561901660538, 21539.10033751105, 21202.52963472090
8, 20456.639991777338, 19848.75084282018]}}
Testing AgglomerativeClustering
{'KMeans': {'silhouette': [0.1559891203731964, 0.13661184620453445, 0.12261933508112
821, 0.1291405188248537, 0.1143420516702437, 0.11385099474271822, 0.0981409120876859
1, 0.10446788677425728, 0.1045862340494635], 'calinski_harabasz': [422.476422497865
6, 354.9651238739216, 322.57281985594256, 293.27323747491107, 264.29712441810716, 23
8.80752736853415, 212.7805210978872, 202.7959752094922, 193.09631677597886], 'davies
_bouldin': [2.140929480096599, 2.1625523900110877, 2.062931885795344, 1.934007203843
1537, 2.097036893809072, 2.0619349096038553, 2.4066311673107332, 2.3080015225425994,
2.2084517303011815], 'inertia': [29922.255527541693, 26944.948019975498, 24735.36465
674668, 23216.644801896105, 22228.561901660538, 21539.10033751105, 21202.52963472090
8, 20456.639991777338, 19848.75084282018]}, 'AgglomerativeClustering': {'silhouett
e': [0.12169586425363689, 0.09923218526653205, 0.09644749098524077, 0.10145339542917
677, 0.08473970694008581, 0.08551807935200742, 0.0876892011089052, 0.076960823715595
22, 0.07684679152778345], 'calinski_harabasz': [329.8184363943818, 273.509101510909
8, 256.4766439589112, 235.68298280789205, 220.44259261567086, 202.86087413574293, 18
5.2477379117445, 170.93804561268226, 159.97497716084672], 'davies_bouldin': [2.49812
90964039204, 2.411783965136237, 2.2218250006646643, 2.1475353605783787, 2.3225618791
655136, 2.206091037024968, 2.1913912857368407, 2.338475533792332, 2.30116277469346
7], 'inertia': None}}
Testing GaussianMixture
{'KMeans': {'silhouette': [0.1559891203731964, 0.13661184620453445, 0.12261933508112
821, 0.1291405188248537, 0.1143420516702437, 0.11385099474271822, 0.0981409120876859
1, 0.10446788677425728, 0.1045862340494635], 'calinski_harabasz': [422.476422497865
6, 354.9651238739216, 322.57281985594256, 293.27323747491107, 264.29712441810716, 23
8.80752736853415, 212.7805210978872, 202.7959752094922, 193.09631677597886], 'davies
_bouldin': [2.140929480096599, 2.1625523900110877, 2.062931885795344, 1.934007203843
1537, 2.097036893809072, 2.0619349096038553, 2.4066311673107332, 2.3080015225425994,
2.2084517303011815], 'inertia': [29922.255527541693, 26944.948019975498, 24735.36465
674668, 23216.644801896105, 22228.561901660538, 21539.10033751105, 21202.52963472090
8, 20456.639991777338, 19848.75084282018]}, 'AgglomerativeClustering': {'silhouett
e': [0.12169586425363689, 0.09923218526653205, 0.09644749098524077, 0.10145339542917
677, 0.08473970694008581, 0.08551807935200742, 0.0876892011089052, 0.076960823715595
22, 0.07684679152778345], 'calinski_harabasz': [329.8184363943818, 273.509101510909
8, 256.4766439589112, 235.68298280789205, 220.44259261567086, 202.86087413574293, 18
5.2477379117445, 170.93804561268226, 159.97497716084672], 'davies_bouldin': [2.49812
90964039204, 2.411783965136237, 2.2218250006646643, 2.1475353605783787, 2.3225618791
655136, 2.206091037024968, 2.1913912857368407, 2.338475533792332, 2.30116277469346
7], 'inertia': None}, 'GaussianMixture': {'silhouette': [0.12706540473418568, 0.1153
705517320746, 0.06824753387272954, 0.05092789932244002, 0.07352710420248955, 0.06708
997448033312, 0.020937701419985036, 0.05184100501279107, 0.019866809512639434], 'cal
inski_harabasz': [336.3786633744418, 321.2004189625554, 196.86628146382333, 168.6428
1820915446, 187.67701748196808, 162.8486361366568, 97.70119938544607, 134.3905790991
3365, 115.3710934383124], 'davies_bouldin': [2.438029684926626, 2.302391787920918,
2.5728425488858973, 2.771863856025493, 2.670231937272781, 2.737151442901761, 2.69115
98531645478, 2.7175915139751847, 2.5927526848991067], 'inertia': None}}
```

In [56]:
```
# Plot clustering evaluation metrics
fig, axes = plt.subplots(2, 2, figsize=(15, 10))

# Silhouette Score
axes[0, 0].set_title('Silhouette Score (Higher is Better)')
for alg_name in algorithms.keys():
    axes[0, 0].plot(cluster_range, clustering_results[alg_name]['silhouette'],
                    'o-', label=alg_name)
axes[0, 0].set_xlabel('Number of Clusters')
axes[0, 0].set_ylabel('Silhouette Score')
axes[0, 0].legend()
axes[0, 0].grid(True)

# Calinski-Harabasz Score
axes[0, 1].set_title('Calinski-Harabasz Score (Higher is Better)')
for alg_name in algorithms.keys():
    axes[0, 1].plot(cluster_range, clustering_results[alg_name]['calinski_harabasz'
                    'o-', label=alg_name)
axes[0, 1].set_xlabel('Number of Clusters')
axes[0, 1].set_ylabel('Calinski-Harabasz Score')
axes[0, 1].legend()
axes[0, 1].grid(True)

# Davies-Bouldin Score
axes[1, 0].set_title('Davies-Bouldin Score (Lower is Better)')
for alg_name in algorithms.keys():
    axes[1, 0].plot(cluster_range, clustering_results[alg_name]['davies_bouldin'],
                    'o-', label=alg_name)
axes[1, 0].set_xlabel('Number of Clusters')
axes[1, 0].set_ylabel('Davies-Bouldin Score')
axes[1, 0].legend()
axes[1, 0].grid(True)

# KMeans Elbow Plot
axes[1, 1].set_title('KMeans Elbow Plot')
axes[1, 1].plot(cluster_range, clustering_results['KMeans']['inertia'], 'o-', color
axes[1, 1].set_xlabel('Number of Clusters')
axes[1, 1].set_ylabel('Inertia')
axes[1, 1].grid(True)

plt.tight_layout()
plt.savefig('plots/clustering_evaluation.png', dpi=300, bbox_inches='tight')
plt.show()
```



KMeans: Best overall performance with highest silhouette scores

Agglomerative Clustering: Consistent but lower quality scores

Gaussian Mixture: Poor performance, unstable results

find the optimal # of clusters for each algo

In [57]:
```
for alg_name in algorithms.keys():
    sil_optimal = cluster_range[np.argmax(clustering_results[alg_name]['silhouette'
    ch_optimal = cluster_range[np.argmax(clustering_results[alg_name]['calinski_har
    db_optimal = cluster_range[np.argmin(clustering_results[alg_name]['davies_bould

    print(f"{alg_name}:")
    print(f"  Silhouette optimal: {sil_optimal}")
    print(f"  Calinski-Harabasz optimal: {ch_optimal}")
    print(f"  Davies-Bouldin optimal: {db_optimal}")
    print()
```

```
KMeans:
  Silhouette optimal: 2
  Calinski-Harabasz optimal: 2
  Davies-Bouldin optimal: 5

AgglomerativeClustering:
  Silhouette optimal: 2
  Calinski-Harabasz optimal: 2
  Davies-Bouldin optimal: 5

GaussianMixture:
  Silhouette optimal: 2
  Calinski-Harabasz optimal: 2
  Davies-Bouldin optimal: 3
```

find the best algo and # of clusters

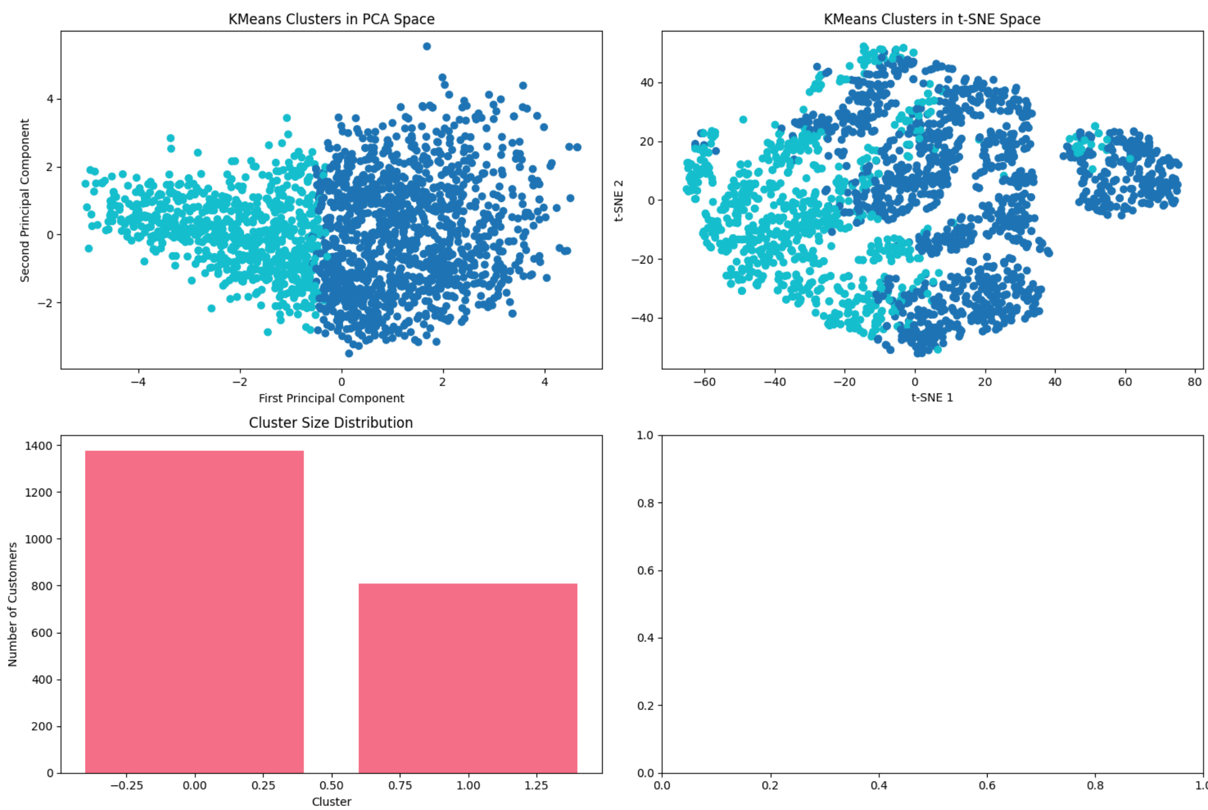
In [58]:
```python
avg_silhouette = {}
for alg_name in algorithms.keys():
    avg_silhouette[alg_name] = np.mean(clustering_results[alg_name]['silhouette'])

best_algorithm = max(avg_silhouette, key=avg_silhouette.get)
print(f"Best algorithm based on average silhouette score: {best_algorithm}")

# Find optimal clusters for best algorithm
best_n_clusters = cluster_range[np.argmax(clustering_results[best_algorithm]['silho
print(f"Optimal number of clusters: {best_n_clusters}")
```

```
Best algorithm based on average silhouette score: KMeans
Optimal number of clusters: 2
```

In [59]:
```python
# fit the best models with the best algo
if best_algorithm == 'GaussianMixture':
    best_model = GaussianMixture(n_components=best_n_clusters, random_state=42)
    best_labels = best_model.fit_predict(X_pca_optimal)
elif best_algorithm == 'AgglomerativeClustering':
    best_model = algorithms[best_algorithm](n_clusters=best_n_clusters)
    best_labels = best_model.fit_predict(X_pca_optimal)
else:
    best_model = algorithms[best_algorithm](n_clusters=best_n_clusters, random_stat
    best_labels = best_model.fit_predict(X_pca_optimal)
```

In [77]:
```python
# Visualize clusters in different spaces
fig, axes = plt.subplots(2, 2, figsize=(15, 10))

# PCA visualization
axes[0, 0].scatter(X_pca_optimal[:, 0], X_pca_optimal[:, 1], c=best_labels, cmap='t
axes[0, 0].set_title(f'{best_algorithm} Clusters in PCA Space')
axes[0, 0].set_xlabel('First Principal Component')
axes[0, 0].set_ylabel('Second Principal Component')

# t-SNE visualization
axes[0, 1].scatter(X_tsne[:, 0], X_tsne[:, 1], c=best_labels, cmap='tab10')
axes[0, 1].set_title(f'{best_algorithm} Clusters in t-SNE Space')
axes[0, 1].set_xlabel('t-SNE 1')
```

```
axes[0, 1].set_ylabel('t-SNE 2')

# Cluster size distribution
cluster_counts = np.bincount(best_labels)
axes[1, 0].bar(range(len(cluster_counts)), cluster_counts)
axes[1, 0].set_title('Cluster Size Distribution')
axes[1, 0].set_xlabel('Cluster')
axes[1, 0].set_ylabel('Number of Customers')

plt.tight_layout()
plt.savefig('plots/best_clustering_visualization.png', dpi=300, bbox_inches='tight'
plt.show()

print(f"Cluster sizes: {cluster_counts}")
```




```
Cluster sizes: [1375  809]
```

PCA shows 2 cluster clearly.

t-SNE shows the 2-cluster structure with distinct groups - one on the left (cyan) and one spread across the middle and right (blue).

Cluster Size Distribution shows an imbalanced split with Cluster 0 having ~1,400 customers and Cluster 1 having ~800 customers

In [78]:
```
os.makedirs('results/clustering', exist_ok=True)
scaled_data['Cluster'] = best_labels
scaled_data.to_csv('results/clustering/clustered_data_results.csv')

print(f"Best algorithm: {best_algorithm}")
print(f"Optimal clusters: {best_n_clusters}")
```

```
print(f"Silhouette score: {silhouette_score(X_pca_optimal, best_labels):.3f}")
```

```
Best algorithm: KMeans
Optimal clusters: 2
Silhouette score: 0.156
```

KMeans emerged as the best algorithm with two clusters and achieving a silhouette score of 0.156 and balanced group sizes. The analysis confirms clear customer segmentation. Now, I will start digging the result in clustered_data

In [82]:
```
cleaned_data = pd.read_csv("data/02_removed_outliers_redundant.csv", index_col=0)
clustered_data = pd.read_csv("results/clustering/clustered_data_results.csv", index
```

In [83]:
```
print(f"Data shape: {clustered_data.shape}")
print(f"Cluster distribution: {clustered_data['Cluster'].value_counts().sort_index(
print()
```

```
Data shape: (2184, 18)
Cluster distribution: Cluster
0    1375
1     809
Name: count, dtype: int64
```

In [87]:
```
# analyze cluster characteristics using original (non-scaled) data
cluster_profiles = {}
for cluster_id in sorted(clustered_data['Cluster'].unique()):
    cluster_mask = clustered_data['Cluster'] == cluster_id
    cluster_profiles[cluster_id] = cleaned_data[cluster_mask].describe()

for cluster_id, profile in cluster_profiles.items():
    print(f"\nCluster {cluster_id} (n={sum(clustered_data['Cluster'] == cluster_id)
    print(profile.loc[['mean', 'std']].round(2))
```

```
Cluster 0 (n=1375):
      Education  Marital_Status    Income  Recency  Response    Age  \
mean       0.53            0.65  61534.83    48.70      0.18  59.06
std        0.50            0.48  16099.54    29.15      0.38  11.20

      Customer_Since  Total_Spent  RatioWines  RatioFruits  RatioMeatProducts  \
mean          367.17       854.83        0.58         0.03               0.24
std           203.63       588.80        0.18         0.03               0.13

      RatioFishProducts  RatioSweetProducts  RatioGoldProds  \
mean               0.05                0.03            0.07
std                0.05                0.04            0.06

      Total_Accepted_Campaign  Total_Purchase  Total_Web_Engagement
mean                     0.43           24.27                 10.08
std                      0.80            6.59                  3.72

Cluster 1 (n=809):
      Education  Marital_Status    Income  Recency  Response    Age  \
mean       0.36            0.65  34475.75    49.66       0.1  51.12
std        0.48            0.48  15276.47    28.53       0.3  10.65

      Customer_Since  Total_Spent  RatioWines  RatioFruits  RatioMeatProducts  \
mean          330.23       163.52        0.26         0.08               0.26
std           198.53       243.86        0.16         0.07               0.11

      RatioFishProducts  RatioSweetProducts  RatioGoldProds  \
mean               0.12                0.08            0.20
std                0.10                0.07            0.12

      Total_Accepted_Campaign  Total_Purchase  Total_Web_Engagement
mean                     0.07           15.77                  8.27
std                      0.25            4.22                  2.58
```

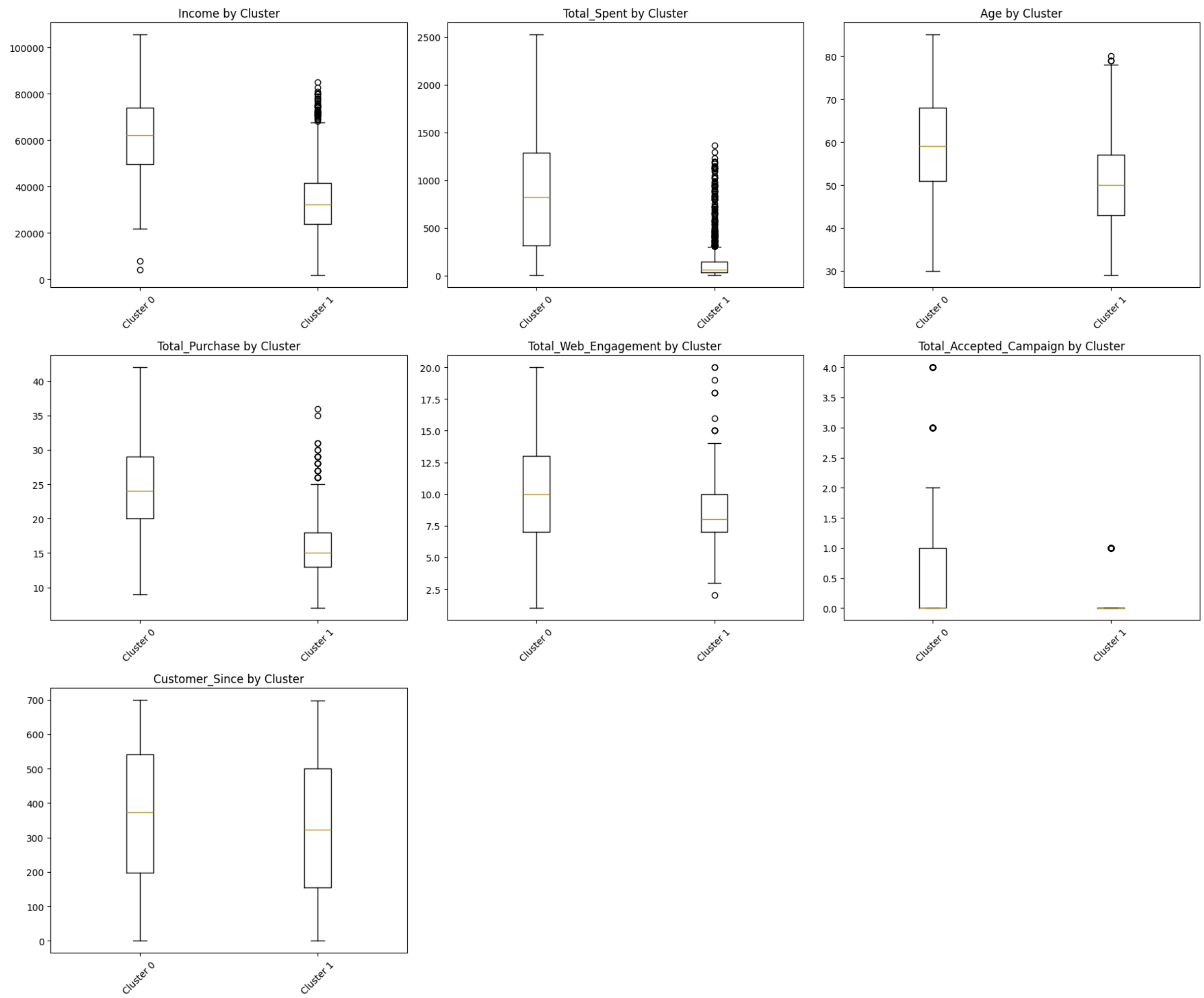
In [89]:

```python
# Compare clusters on key metrics
key_metrics = ['Income', 'Total_Spent', 'Age', 'Total_Purchase', 'Total_Web_Engagem
               'Total_Accepted_Campaign', 'Customer_Since']
```

In [91]:

```python
# Create comparison plots
fig, axes = plt.subplots(3, 3, figsize=(18, 15))
axes = axes.flatten()

for i, metric in enumerate(key_metrics):
    if metric in cleaned_data.columns:
        cluster_data = []
        cluster_labels = []

        for cluster_id in sorted(clustered_data['Cluster'].unique()):
            cluster_mask = clustered_data['Cluster'] == cluster_id
            cluster_data.append(cleaned_data[cluster_mask][metric])
            cluster_labels.append(f'Cluster {cluster_id}')

        axes[i].boxplot(cluster_data, labels=cluster_labels)
        axes[i].set_title(f'{metric} by Cluster')
        axes[i].tick_params(axis='x', rotation=45)
```

```
# Remove empty subplots
for j in range(len(key_metrics), len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
plt.savefig('plots/cluster_comparison.png', dpi=300, bbox_inches='tight')
plt.show()
```



show cleaner pattern for high and lower value customer

In [93]:
```
for metric in key_metrics:
    if metric in cleaned_data.columns:
        cluster_0_data = cleaned_data[clustered_data['Cluster'] == 0][metric]
        cluster_1_data = cleaned_data[clustered_data['Cluster'] == 1][metric]

        # T-test
        t_stat, p_value = ttest_ind(cluster_0_data, cluster_1_data)

        # Effect size (Cohen's d)
        pooled_std = np.sqrt(((len(cluster_0_data) - 1) * cluster_0_data.var() +
                              (len(cluster_1_data) - 1) * cluster_1_data.var()) /
                             (len(cluster_0_data) + len(cluster_1_data) - 2))
        cohens_d = (cluster_0_data.mean() - cluster_1_data.mean()) / pooled_std

        print(f"{metric}:")
```

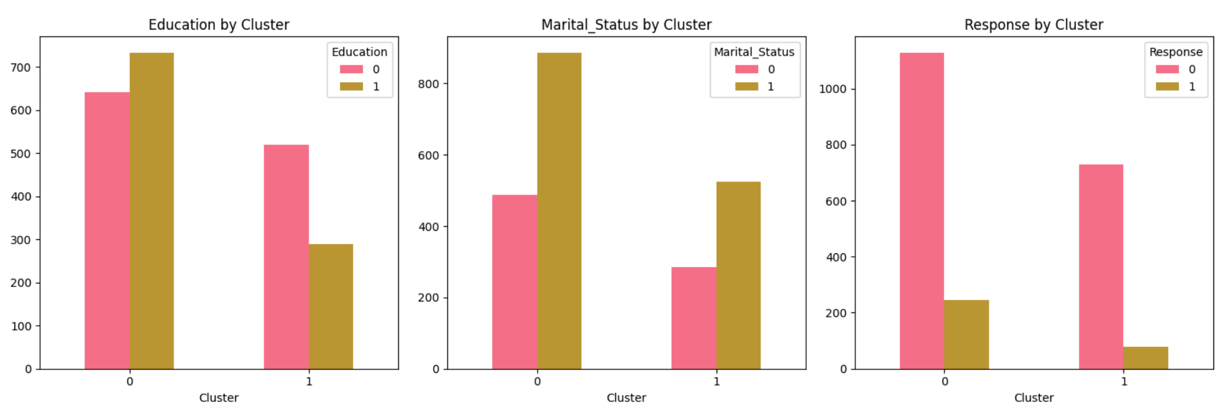
```
        print(f"  Cluster 0 mean: {cluster_0_data.mean():.2f}")
        print(f"  Cluster 1 mean: {cluster_1_data.mean():.2f}")
        print(f"  T-statistic: {t_stat:.3f}")
        print(f"  P-value: {p_value:.6f}")
        print(f"  Cohen's d: {cohens_d:.3f}")
        print(f"  Significant: {'Yes' if p_value < 0.05 else 'No'}")
        print()
```

```
Income:
  Cluster 0 mean: 61534.83
  Cluster 1 mean: 34475.75
  T-statistic: 38.651
  P-value: 0.000000
  Cohen's d: 1.713
  Significant: Yes

Total_Spent:
  Cluster 0 mean: 854.83
  Cluster 1 mean: 163.52
  T-statistic: 31.825
  P-value: 0.000000
  Cohen's d: 1.410
  Significant: Yes

Age:
  Cluster 0 mean: 59.06
  Cluster 1 mean: 51.12
  T-statistic: 16.309
  P-value: 0.000000
  Cohen's d: 0.723
  Significant: Yes

Total_Purchase:
  Cluster 0 mean: 24.27
  Cluster 1 mean: 15.77
  T-statistic: 32.896
  P-value: 0.000000
  Cohen's d: 1.458
  Significant: Yes

Total_Web_Engagement:
  Cluster 0 mean: 10.08
  Cluster 1 mean: 8.27
  T-statistic: 12.232
  P-value: 0.000000
  Cohen's d: 0.542
  Significant: Yes

Total_Accepted_Campaign:
  Cluster 0 mean: 0.43
  Cluster 1 mean: 0.07
  T-statistic: 12.628
  P-value: 0.000000
  Cohen's d: 0.560
  Significant: Yes

Customer_Since:
  Cluster 0 mean: 367.17
  Cluster 1 mean: 330.23
  T-statistic: 4.132
  P-value: 0.000037
  Cohen's d: 0.183
  Significant: Yes
```

In [94]:
```python
# Analyze categorical variables
categorical_vars = ['Education', 'Marital_Status', 'Response']

for var in categorical_vars:
    if var in cleaned_data.columns:
        print(f"\n{var} distribution by cluster:")
        crosstab = pd.crosstab(clustered_data['Cluster'], cleaned_data[var], normal
        print(crosstab.round(3))
```

```
Education distribution by cluster:
Education      0      1
Cluster
0          0.466  0.534
1          0.643  0.357

Marital_Status distribution by cluster:
Marital_Status      0      1
Cluster
0               0.355  0.645
1               0.352  0.648

Response distribution by cluster:
Response      0      1
Cluster
0         0.821  0.179
1         0.902  0.098
```

In [95]:
```python
fig, axes = plt.subplots(1, len(categorical_vars), figsize=(15, 5))

for i, var in enumerate(categorical_vars):
    if var in cleaned_data.columns:
        crosstab = pd.crosstab(clustered_data['Cluster'], cleaned_data[var])
        crosstab.plot(kind='bar', ax=axes[i], rot=0)
        axes[i].set_title(f'{var} by Cluster')
        axes[i].set_xlabel('Cluster')
        axes[i].legend(title=var)

plt.tight_layout()
plt.savefig('plots/categorical_comparison.png', dpi=300, bbox_inches='tight')
plt.show()
```



Education: Relatively balanced between clusters

Marital Status: Cluster 1 has proportionally more married customers

Response Rate: Cluster 0 has significantly higher campaign response rates

Try different numbers of clusters to see if we can find better segmentation

In [96]:
```
scaled_data = pd.read_csv(r"data\03_scaled_proprocessed_marketing_campaign.csv", in
X = scaled_data.values
```

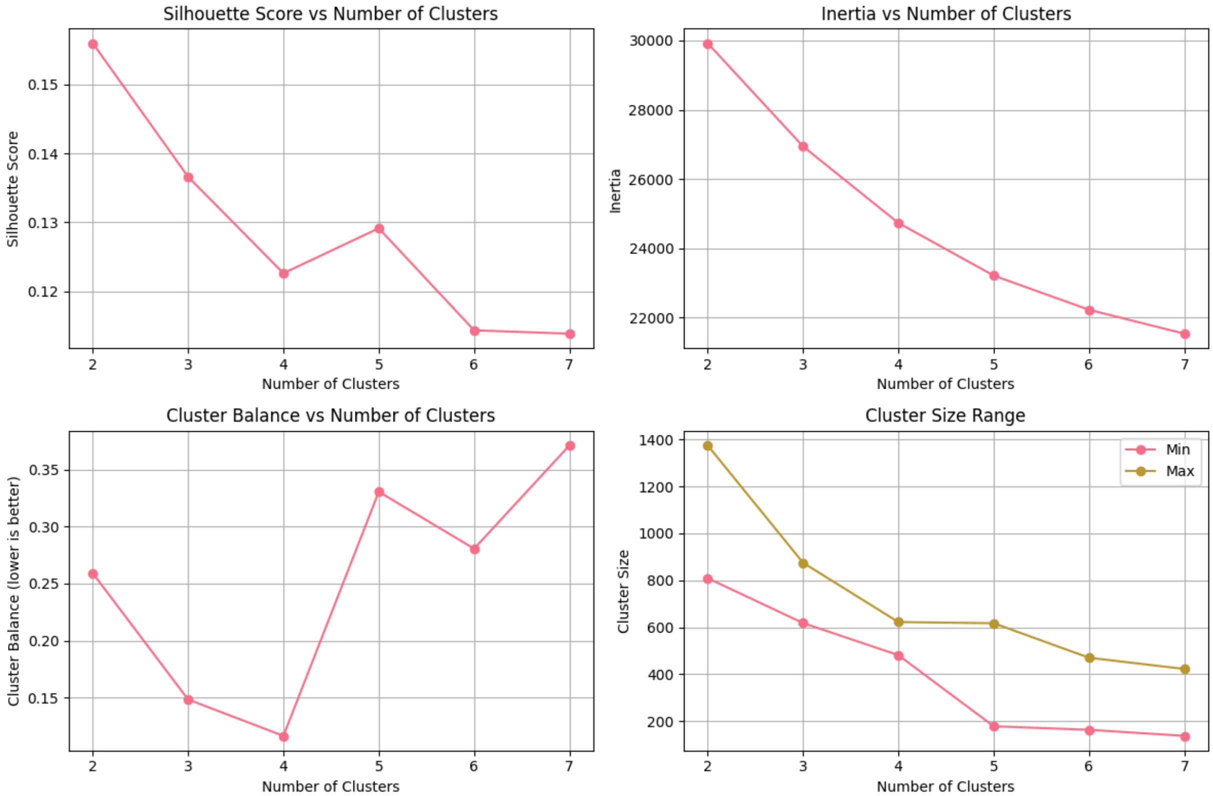
In [97]:
```
# Apply PCA
pca = PCA(n_components=13)  # Based on previous analysis
X_pca = pca.fit_transform(X)
```

In [98]:
```
# Test different cluster numbers
cluster_range = range(2, 8)
results = []

for n_clusters in cluster_range:
    kmeans = KMeans(n_clusters=n_clusters, random_state=42)
    labels = kmeans.fit_predict(X_pca)

    silhouette = silhouette_score(X_pca, labels)
    inertia = kmeans.inertia_

    # Calculate cluster balance (how evenly distributed the clusters are)
    cluster_counts = np.bincount(labels)
    cluster_balance = np.std(cluster_counts) / np.mean(cluster_counts)

    results.append({
        'n_clusters': n_clusters,
        'silhouette': silhouette,
        'inertia': inertia,
        'cluster_balance': cluster_balance,
        'min_cluster_size': min(cluster_counts),
        'max_cluster_size': max(cluster_counts)
    })

results_df = pd.DataFrame(results)
print(results_df.round(3))
```

```
   n_clusters  silhouette    inertia  cluster_balance  min_cluster_size  \
0           2       0.156  29922.256            0.259               809
1           3       0.137  26944.948            0.149               618
2           4       0.123  24735.365            0.117               481
3           5       0.129  23216.645            0.330               178
4           6       0.114  22228.562            0.281               163
5           7       0.114  21539.100            0.371               137

   max_cluster_size
0              1375
1               875
2               622
3               617
4               470
5               422
```

In [100…

```
fig, axes = plt.subplots(2, 2, figsize=(12, 8))

axes[0, 0].plot(results_df['n_clusters'], results_df['silhouette'], 'o-')
axes[0, 0].set_title('Silhouette Score vs Number of Clusters')
axes[0, 0].set_xlabel('Number of Clusters')
axes[0, 0].set_ylabel('Silhouette Score')
axes[0, 0].grid(True)

axes[0, 1].plot(results_df['n_clusters'], results_df['inertia'], 'o-')
axes[0, 1].set_title('Inertia vs Number of Clusters')
axes[0, 1].set_xlabel('Number of Clusters')
axes[0, 1].set_ylabel('Inertia')
axes[0, 1].grid(True)

axes[1, 0].plot(results_df['n_clusters'], results_df['cluster_balance'], 'o-')
axes[1, 0].set_title('Cluster Balance vs Number of Clusters')
axes[1, 0].set_xlabel('Number of Clusters')
axes[1, 0].set_ylabel('Cluster Balance (lower is better)')
axes[1, 0].grid(True)

axes[1, 1].plot(results_df['n_clusters'], results_df['min_cluster_size'], 'o-', lab
axes[1, 1].plot(results_df['n_clusters'], results_df['max_cluster_size'], 'o-', lab
axes[1, 1].set_title('Cluster Size Range')
axes[1, 1].set_xlabel('Number of Clusters')
axes[1, 1].set_ylabel('Cluster Size')
axes[1, 1].legend()
axes[1, 1].grid(True)

plt.tight_layout()
plt.savefig('plots/cluster_optimization.png', dpi=300, bbox_inches='tight')
plt.show()
```



For 2 clusters:

Silhouette Score: 0.156 (moderate separation)

Inertia: Shows elbow at k=3-4

Balance: Good at k=2 (0.26)

The optimal number of clusters appears to be 2 based on silhouette score. However, this creates very unbalanced clusters (1375 vs 809 customers). The silhouette score of 0.156 suggests weak cluster separation. It confirms that there is no clear segmentation. Characteristics reveal that Cluster 0 has higher income, spending, and engagement than Cluster 1, which indicates that customers in this dataset may not have very distinct segments.

The most clustering algorithms favor two clusters with weak separation (silhouette 0.156) The two groups differ significantly in income, spending, age, and purchase behavior, indicating meaningful, though weak, segmentation. This suggests customers are quite homogeneous, so for better interpretability, I will proceed to build supervised models using these clusters as labels to derive better insights.