In [18]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

# Disable scientific notation for large numbers
pd.options.display.float_format = '{:.0f}'.format

# Setting display options for Pandas to show three decimal places for floati
pd.set_option('display.float_format', lambda x: '%.2f' % x)
```

Data Loading

In [2]:
```
# import data
customer_df = pd.read_csv('/content/drive/MyDrive/Customer_data.csv')
```

Data Exploration

In [3]:
```
customer_df.info()  # Display information about the dataFrame, including dat
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   CustomerID          200 non-null    int64
 1   Genre               200 non-null    object
 2   Age                 200 non-null    int64
 3   Annual_Income_(k$)  200 non-null    int64
 4   Spending_Score      200 non-null    int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

In [4]:
```
customer_df.head()  # Display top 5 records
```

Out[4]:

	CustomerID	Genre	Age	Annual_Income_(k$)	Spending_Score
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

In [8]:
```
customer_df[['Annual_Income_(k$)','Spending_Score']].describe() # Display st
```

Out[8]:

	Annual_Income_(k$)	Spending_Score
count	200.00	200.00
mean	60.56	50.20
std	26.26	25.82
min	15.00	1.00
25%	41.50	34.75
50%	61.50	50.00
75%	78.00	73.00
max	137.00	99.00

Data Preprocessing

In [9]:
```
customer_df.isna().sum()  # Find sum of missing values
```

Out[9]:

	0
CustomerID	0
Genre	0
Age	0
Annual_Income_(k$)	0
Spending_Score	0

dtype: int64

Since, sum of missing values is zero, so there is no need to handle null values.

In [11]:
```
print(customer_df.duplicated().sum()) # Find sum of duplicate records
```

```
0
```

Since, sum of duplicated values is zero, so there is no need to drop duplicates.

Standardize the data using StandardScaler

In [12]:
```
# Select features to be scaled
features = customer_df[['Age', 'Annual_Income_(k$)', 'Spending_Score']]

# Initialize the StandardScaler
scaler = StandardScaler()

# Fit and transform the features
scaled_features = scaler.fit_transform(features)
```

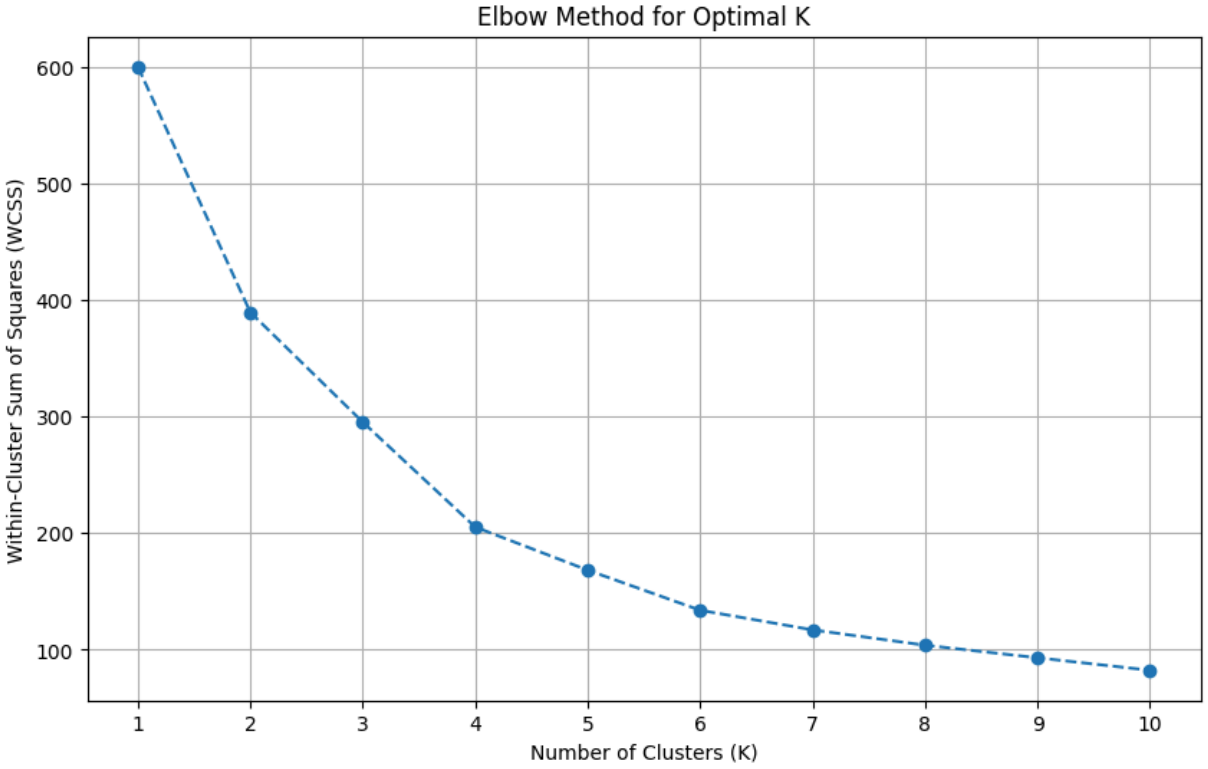
```
# Convert the scaled features back to a DataFrame
scaled_data = pd.DataFrame(scaled_features, columns=features.columns)
```

Clustering

Determine the optimal number of clusters using the Elbow Method.

In [13]:
```
from sklearn.cluster import KMeans
```

In [14]:
```
# Calculate WCSS for k=1 to 10
wcss = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, init='k-means++', random_state=42, n_init=
    kmeans.fit(scaled_features)
    wcss.append(kmeans.inertia_)  # inertia_ = WCSS

# Plot the Elbow curve
plt.figure(figsize=(10, 6))
plt.plot(range(1, 11), wcss, marker='o', linestyle='--')
plt.title('Elbow Method for Optimal K')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Within-Cluster Sum of Squares (WCSS)')
plt.xticks(range(1, 11))
plt.grid(True)
plt.show()
```



Apply K-Means Clustering and assign a cluster label to each customer.

In [15]:
```
n_clusters = 10

# Fit KMeans
kmeans = KMeans(n_clusters=n_clusters, init='k-means++', random_state=42, n_
clusters = kmeans.fit_predict(scaled_features)

# Assign cluster labels to the original data
customer_df['Cluster'] = clusters

# Output the result
print(customer_df[['CustomerID', 'Genre', 'Age', 'Annual_Income_(k$)', 'Sper
```

```
     CustomerID   Genre  Age  Annual_Income_(k$)  Spending_Score  Cluster
0             1    Male   19                  15              39        9
1             2    Male   21                  15              81        3
2             3  Female   20                  16               6        9
3             4  Female   23                  16              77        3
4             5  Female   31                  17              40        9
..          ...     ...  ...                 ...             ...      ...
195         196  Female   35                 120              79        8
196         197  Female   45                 126              28        2
197         198    Male   32                 126              74        8
198         199    Male   32                 137              18        2
199         200    Male   30                 137              83        8

[200 rows x 6 columns]
```

In [ ]:
```
# Save cleaned data
customer_df.to_csv('/content/drive/MyDrive/Customer_data_final.csv', index=F
```

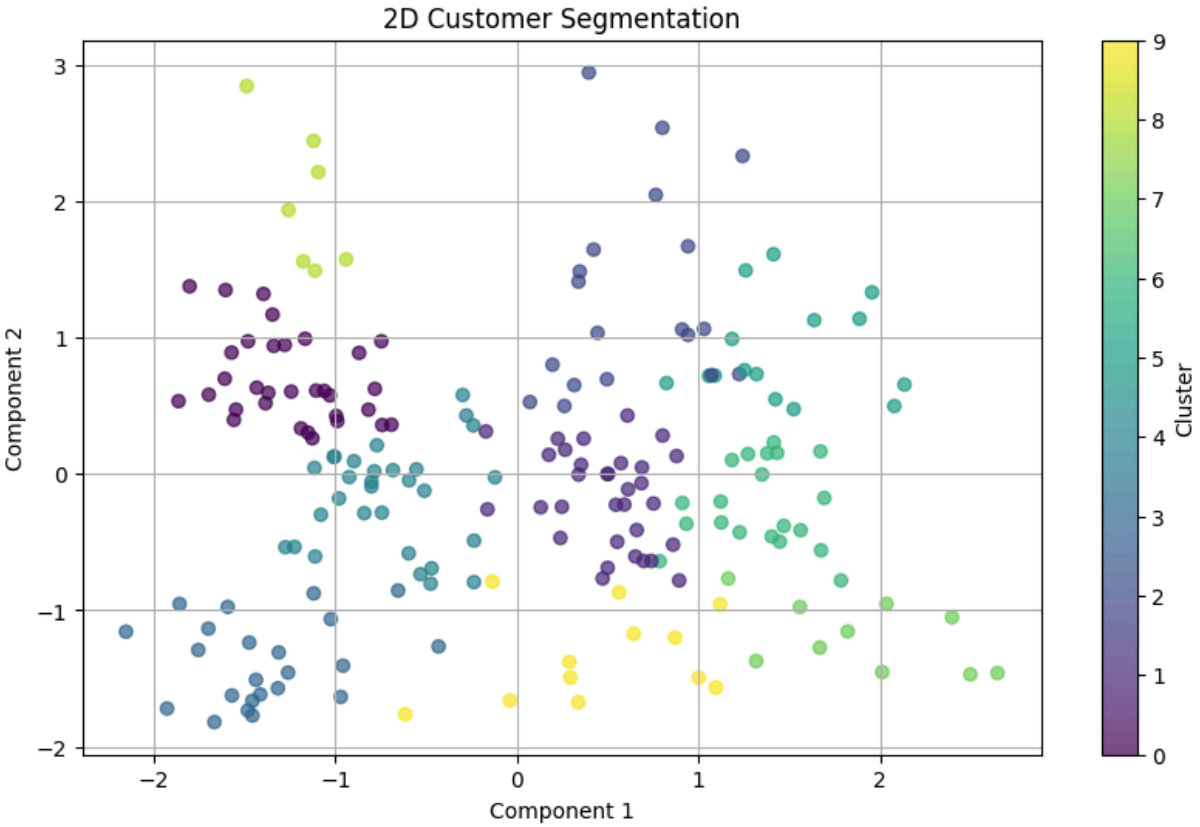
Data Visualization

Create 2D Scatter Plot by using PCA (Principal Component Analysis) or t-SNE to reduce dimensions to two for visualization

In [16]:
```
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
```

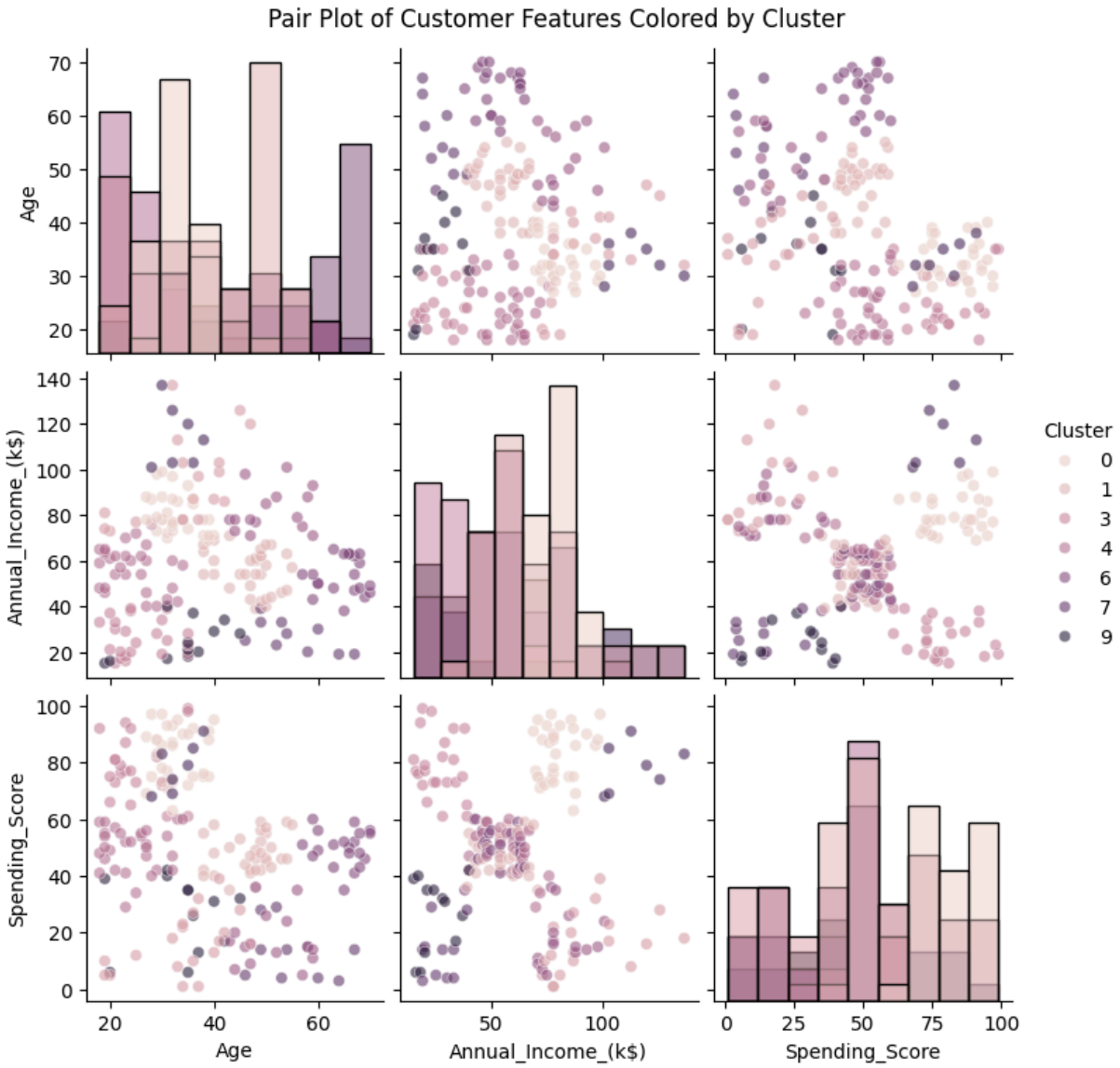
In [17]:
```
# Method 1: PCA (Faster, linear dimensionality reduction)
pca = PCA(n_components=2)
pca_result = pca.fit_transform(scaled_features)

# Method 2: t-SNE (Slower, non-linear, preserves local structure)
# tsne = TSNE(n_components=2, random_state=42, perplexity=30)
# pca_result = tsne.fit_transform(scaled_features)

# Create scatter plot
plt.figure(figsize=(10, 6))
scatter = plt.scatter(pca_result[:, 0], pca_result[:, 1],
                      c=customer_df['Cluster'] if 'Cluster' in customer_df.c
                      cmap='viridis', alpha=0.7)

plt.title('2D Customer Segmentation')
```

```
plt.xlabel('Component 1')
plt.ylabel('Component 2')

# Add colorbar if clusters exist
if 'Cluster' in customer_df.columns:
    plt.colorbar(scatter, label='Cluster')
plt.grid(True)
plt.show()
```



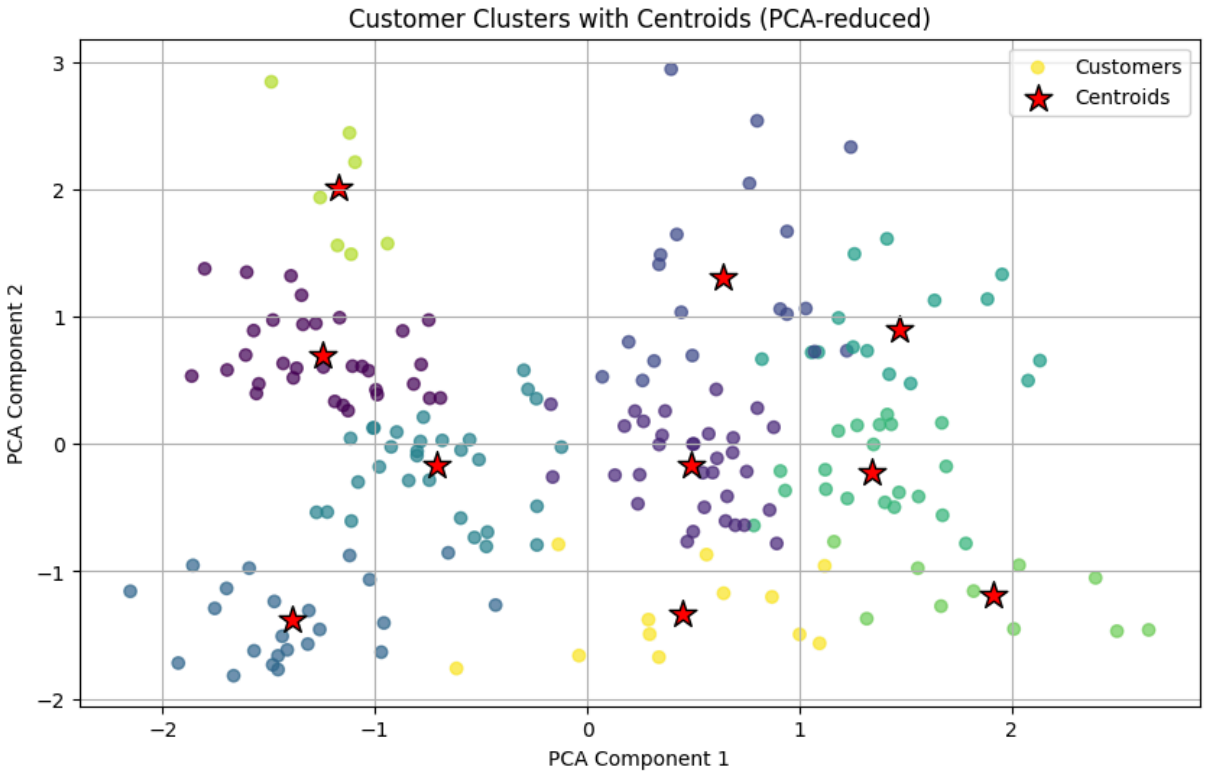
Create Pair Plots to visualize relationships between features within clusters.

In [19]:
```
# Select features for the pair plot
plot_features = ['Age', 'Annual_Income_(k$)', 'Spending_Score', 'Cluster']

# Create pair plot colored by cluster
sb.pairplot(customer_df[plot_features], hue='Cluster', diag_kind='hist', plo
plt.suptitle('Pair Plot of Customer Features Colored by Cluster', y=1.02)
plt.show()
```



Create Centroid Visuals to show the centroid of each cluster for better interpretation.

In [20]:
```
# Get centroids in original feature space and transform to PCA space
centroids = kmeans.cluster_centers_
centroids_pca = pca.transform(centroids)

# Plot the data points
plt.figure(figsize=(10, 6))
plt.scatter(pca_result[:, 0], pca_result[:, 1], c=clusters, cmap='viridis',

# Plot the centroids
plt.scatter(centroids_pca[:, 0], centroids_pca[:, 1], marker='*', s=200, c='

plt.title('Customer Clusters with Centroids (PCA-reduced)')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.legend()
plt.grid(True)
plt.show()
```

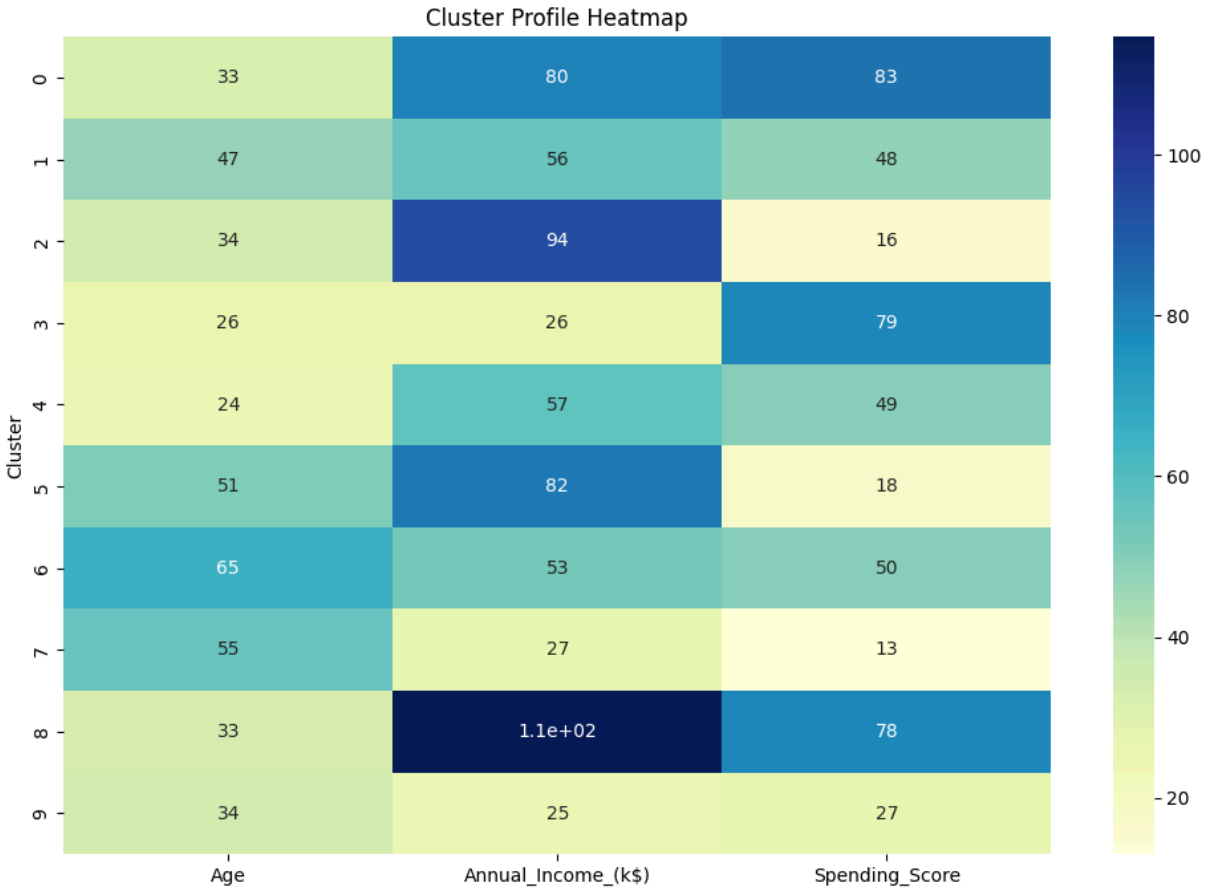


Recommendations

Recommand which groups to target for promotions or premium products.

In [21]:
```
# Analyze cluster characteristics
cluster_profile = customer_df.groupby('Cluster').agg({
    'Age': 'mean',
    'Annual_Income_(k$)': 'mean',
    'Spending_Score': 'mean',
    'CustomerID': 'count'
}).rename(columns={'CustomerID': 'Count'})

# Visualize cluster profiles
plt.figure(figsize=(12, 8))
sb.heatmap(cluster_profile.drop('Count', axis=1), annot=True, cmap='YlGnBu')
plt.title('Cluster Profile Heatmap')
plt.show()

# Generate targeting recommendations
def generate_recommendations(profile):
    recommendations = []

    for cluster_id, row in profile.iterrows():
        age = row['Age']
        income = row['Annual_Income_(k$)']
        spending = row['Spending_Score']
        size = row['Count']

        if income > 80 and spending > 70:
```

```
            rec = f"Cluster {cluster_id}: Target for PREMIUM products (High-
        elif spending > 60:
            rec = f"Cluster {cluster_id}: Ideal for PROMOTIONS (High spendir
        elif income > 70 and age < 40:
            rec = f"Cluster {cluster_id}: Upsell opportunities (Young high-e
        else:
            rec = f"Cluster {cluster_id}: Maintain engagement (Moderate valu

        recommendations.append(rec)

    return recommendations

# Execute and print recommendations
recommendations = generate_recommendations(cluster_profile)
print("\nTargeting Recommendations:")
for rec in recommendations:
    print(f"- {rec}")
```



```
Targeting Recommendations:
- Cluster 0: Target for PREMIUM products (High-income: $80.4k, High spendin
g: 82.9 score)
- Cluster 1: Maintain engagement (Moderate value)
- Cluster 2: Upsell opportunities (Young high-earners: $93.9k)
- Cluster 3: Ideal for PROMOTIONS (High spending: 78.6 score)
- Cluster 4: Maintain engagement (Moderate value)
- Cluster 5: Maintain engagement (Moderate value)
- Cluster 6: Maintain engagement (Moderate value)
- Cluster 7: Maintain engagement (Moderate value)
- Cluster 8: Target for PREMIUM products (High-income: $114.7k, High spendin
g: 78.4 score)
- Cluster 9: Maintain engagement (Moderate value)
```

Identify high-spending customers and propose loyalty programs.

In [22]:

```python
# Define high-spending threshold (top 20% by Spending_Score)
threshold = customer_df['Spending_Score'].quantile(0.8)
high_spenders = customer_df[customer_df['Spending_Score'] >= threshold]

# Print high-spending customers
print("High-Spending Customers:")
print(high_spenders[['CustomerID', 'Genre', 'Age', 'Annual_Income_(k$)', 'Sp

# Propose loyalty programs based on customer characteristics
print("\nProposed Loyalty Programs for High-Spending Customers:")

for idx, customer in high_spenders.iterrows():
    # Premium tier for very high income and spending
    if customer['Annual_Income_(k$)'] > 80 and customer['Spending_Score'] >
        program = (
            f"Customer {customer['CustomerID']}: Premium Loyalty Program (ex
        )
    # Standard rewards for high spending
    elif customer['Spending_Score'] > 80:
        program = (
            f"Customer {customer['CustomerID']}: Rewards Program (points, di
        )
    # Upsell for younger high spenders
    elif customer['Age'] < 40 and customer['Spending_Score'] > 70:
        program = (
            f"Customer {customer['CustomerID']}: Upsell Program (targeted of
        )
    # General loyalty for other high spenders
    else:
        program = (
            f"Customer {customer['CustomerID']}: General Loyalty Program (fr
        )
    print(program)
```

High-Spending Customers:

	CustomerID	Genre	Age	Annual_Income_(k$)	Spending_Score
1	2	Male	21	15	81
3	4	Female	23	16	77
5	6	Female	22	17	76
7	8	Female	23	18	94
11	12	Female	35	19	99
13	14	Female	24	20	77
15	16	Male	22	20	79
19	20	Female	35	23	98
25	26	Male	29	28	82
29	30	Female	23	29	87
33	34	Male	18	33	92
35	36	Female	21	33	81
39	40	Female	20	37	75
41	42	Male	24	38	92
123	124	Male	39	69	91
125	126	Female	31	70	77
127	128	Male	40	71	95
129	130	Male	38	71	75
131	132	Male	39	71	75
135	136	Female	29	73	88
141	142	Male	32	75	93
143	144	Female	32	76	87
145	146	Male	28	77	97
149	150	Male	34	78	90
151	152	Male	39	78	88
153	154	Female	38	78	76
155	156	Female	27	78	89
157	158	Female	30	78	78
161	162	Female	29	79	83
163	164	Female	31	81	93
165	166	Female	36	85	75
167	168	Female	33	86	95
171	172	Male	28	87	75
173	174	Male	36	87	92
175	176	Female	30	88	86
179	180	Male	35	93	90
181	182	Female	32	97	86
183	184	Female	29	98	88
185	186	Male	30	99	97
189	190	Female	36	103	85
193	194	Female	38	113	91
195	196	Female	35	120	79
199	200	Male	30	137	83

Proposed Loyalty Programs for High-Spending Customers:
Customer 2: Rewards Program (points, discounts, birthday offers)
Customer 4: Upsell Program (targeted offers, new product trials)
Customer 6: Upsell Program (targeted offers, new product trials)
Customer 8: Rewards Program (points, discounts, birthday offers)
Customer 12: Rewards Program (points, discounts, birthday offers)
Customer 14: Upsell Program (targeted offers, new product trials)
Customer 16: Upsell Program (targeted offers, new product trials)
Customer 20: Rewards Program (points, discounts, birthday offers)
Customer 26: Rewards Program (points, discounts, birthday offers)

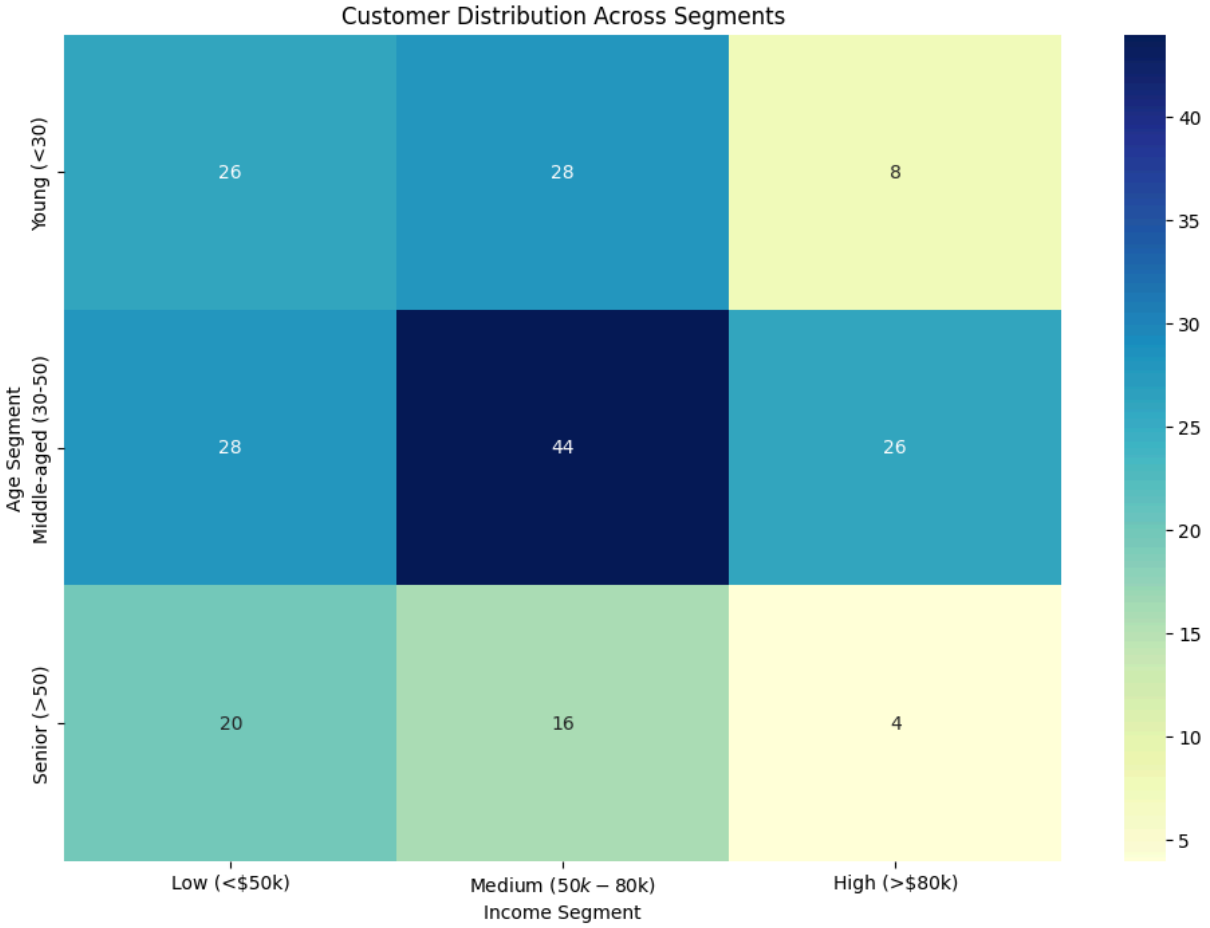
```
Customer 30: Rewards Program (points, discounts, birthday offers)
Customer 34: Rewards Program (points, discounts, birthday offers)
Customer 36: Rewards Program (points, discounts, birthday offers)
Customer 40: Upsell Program (targeted offers, new product trials)
Customer 42: Rewards Program (points, discounts, birthday offers)
Customer 124: Rewards Program (points, discounts, birthday offers)
Customer 126: Upsell Program (targeted offers, new product trials)
Customer 128: Rewards Program (points, discounts, birthday offers)
Customer 130: Upsell Program (targeted offers, new product trials)
Customer 132: Upsell Program (targeted offers, new product trials)
Customer 136: Rewards Program (points, discounts, birthday offers)
Customer 142: Rewards Program (points, discounts, birthday offers)
Customer 144: Rewards Program (points, discounts, birthday offers)
Customer 146: Rewards Program (points, discounts, birthday offers)
Customer 150: Rewards Program (points, discounts, birthday offers)
Customer 152: Rewards Program (points, discounts, birthday offers)
Customer 154: Upsell Program (targeted offers, new product trials)
Customer 156: Rewards Program (points, discounts, birthday offers)
Customer 158: Upsell Program (targeted offers, new product trials)
Customer 162: Rewards Program (points, discounts, birthday offers)
Customer 164: Premium Loyalty Program (exclusive access, priority service, e
arly sales)
Customer 166: Upsell Program (targeted offers, new product trials)
Customer 168: Premium Loyalty Program (exclusive access, priority service, e
arly sales)
Customer 172: Upsell Program (targeted offers, new product trials)
Customer 174: Premium Loyalty Program (exclusive access, priority service, e
arly sales)
Customer 176: Premium Loyalty Program (exclusive access, priority service, e
arly sales)
Customer 180: Premium Loyalty Program (exclusive access, priority service, e
arly sales)
Customer 182: Premium Loyalty Program (exclusive access, priority service, e
arly sales)
Customer 184: Premium Loyalty Program (exclusive access, priority service, e
arly sales)
Customer 186: Premium Loyalty Program (exclusive access, priority service, e
arly sales)
Customer 190: Premium Loyalty Program (exclusive access, priority service, e
arly sales)
Customer 194: Premium Loyalty Program (exclusive access, priority service, e
arly sales)
Customer 196: Upsell Program (targeted offers, new product trials)
Customer 200: Premium Loyalty Program (exclusive access, priority service, e
arly sales)
```

Tailor marketing strategies for different age or income segments.

In [24]:

```python
# Define segmentation boundaries
age_bins = [0, 30, 50, 100]
age_labels = ['Young (<30)', 'Middle-aged (30-50)', 'Senior (>50)']
income_bins = [0, 50, 80, 200]
income_labels = ['Low (<$50k)', 'Medium ($50k-$80k)', 'High (>$80k)']

# Create segments
customer_df['Age Segment'] = pd.cut(customer_df['Age'], bins=age_bins, label
```

```python
customer_df['Income Segment'] = pd.cut(customer_df['Annual_Income_(k$)'], bi

# Analyze segment characteristics
segment_analysis = customer_df.groupby(['Age Segment', 'Income Segment']).ag
    Avg_Spending=('Spending_Score', 'mean'),
    Customer_Count=('CustomerID', 'count')
).reset_index()

# Visualize segment distribution
plt.figure(figsize=(12, 8))
sb.heatmap(
    segment_analysis.pivot_table(index='Age Segment', columns='Income Segmer
    annot=True, cmap='YlGnBu'
)
plt.title('Customer Distribution Across Segments')
plt.show()

# Propose tailored marketing strategies
def propose_strategies(row):
    age = row['Age Segment']
    income = row['Income Segment']
    spending = row['Avg_Spending']
    count = row['Customer_Count']

    if age == 'Young (<30)':
        if income == 'High (>$80k)':
            return "Luxury trend-focused campaigns: Premium tech/experience
        elif income == 'Medium ($50k-$80k)':
            return "Value bundles: Mid-range fashion, subscription models, s
        else:
            return "Entry-level offers: Student discounts, budget-friendly c

    elif age == 'Middle-aged (30-50)':
        if income == 'High (>$80k)':
            return "Premium family packages: High-end home goods, exclusive
        elif income == 'Medium ($50k-$80k)':
            return "Quality-focused promotions: Durable goods, loyalty progr
        else:
            return "Budget solutions: Value packs, discount events, communit

    else:  # Senior (>50)
        if income == 'High (>$80k)':
            return "Luxury leisure: High-end travel, premium health services
        elif income == 'Medium ($50k-$80k)':
            return "Comfort-focused: Quality-of-life products, loyalty benef
        else:
            return "Essential value: Senior discounts, basic necessities, tr

# Generate and display strategies
segment_analysis['Strategy'] = segment_analysis.apply(propose_strategies, ax
print("\nTailored Marketing Strategies:")
print(segment_analysis[['Age Segment', 'Income Segment', 'Customer_Count', '
```



Tailored Marketing Strategies:

	Age Segment	Income Segment	Customer_Count	\
0	Young (<30)	Low (<$50k)	26	
1	Young (<30)	Medium ($50k-$80k)	28	
2	Young (<30)	High (>$80k)	8	
3	Middle-aged (30-50)	Low (<$50k)	28	
4	Middle-aged (30-50)	Medium ($50k-$80k)	44	
5	Middle-aged (30-50)	High (>$80k)	26	
6	Senior (>50)	Low (<$50k)	20	
7	Senior (>50)	Medium ($50k-$80k)	16	
8	Senior (>50)	High (>$80k)	4	

	Strategy
0	Entry-level offers: Student discounts, budget-...
1	Value bundles: Mid-range fashion, subscription...
2	Luxury trend-focused campaigns: Premium tech/e...
3	Budget solutions: Value packs, discount events...
4	Quality-focused promotions: Durable goods, loy...
5	Premium family packages: High-end home goods, ...
6	Essential value: Senior discounts, basic neces...
7	Comfort-focused: Quality-of-life products, loy...
8	Luxury leisure: High-end travel, premium healt...