In [53]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
```

In [2]:
```
df = pd.read_csv(r'C:\Users\yousuf\source\DataAnalysisProjects\Mall_CustomerSegmentation\Mall_Customers.csv')
df.head()
```

Out[2]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
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 [3]:
```
# Summary statistics of df
df.describe()
```

Out[3]:

	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000	200.000000
mean	100.500000	38.850000	60.560000	50.200000
std	57.879185	13.969007	26.264721	25.823522
min	1.000000	18.000000	15.000000	1.000000
25%	50.750000	28.750000	41.500000	34.750000
50%	100.500000	36.000000	61.500000	50.000000
75%	150.250000	49.000000	78.000000	73.000000
max	200.000000	70.000000	137.000000	99.000000

In [4]:
```
# Checking for any missing values
df.isnull().sum()
```

Out[4]:
```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

Description:

The dataset contains 200 rows & 5 columns: 'CustomerID', 'Gender', 'Age', 'Annual Income (k$)', 'Spending Score (1-100)'. Absolutely no missing values present.

Univariate Analysis

Let's examine single variable individually and look at the distribution of 'Age', 'Annual Income (k$)', 'Spending Score (1-100)'

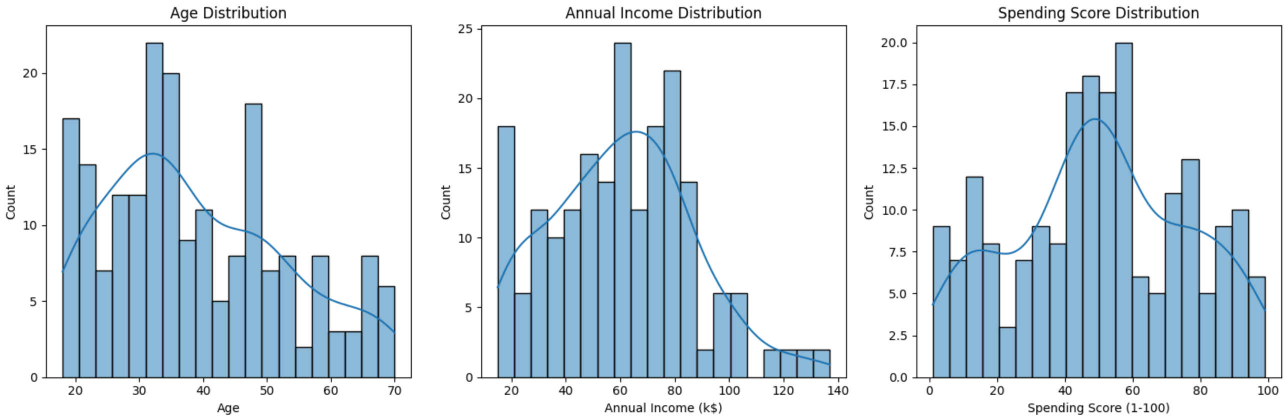
In [5]:
```
plt.figure(figsize=(15, 5))

# Age Distribution
plt.subplot(1, 3, 1)
sns.histplot(df['Age'], kde=True, bins=20)
plt.title('Age Distribution')

# Annual Income Distribution
plt.subplot(1, 3, 2)
sns.histplot(df['Annual Income (k$)'], kde=True, bins=20)
plt.title('Annual Income Distribution')

# Spending Score Distribution
plt.subplot(1, 3, 3)
sns.histplot(df['Spending Score (1-100)'], kde=True, bins=20)
plt.title('Spending Score Distribution')
```

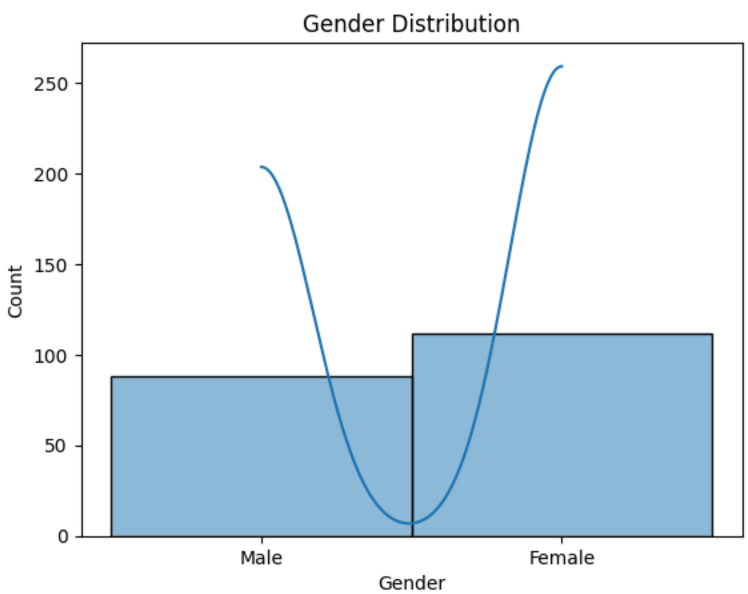
```python
plt.tight_layout()
plt.show()
```



In [6]:

```python
# Let's look into the gender distribution analysis
#plt.figure(figsize=(6, 4))
sns.histplot(df['Gender'], kde=True)
plt.title('Gender Distribution')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()


#Gender contribution Percentage Wise
df['Gender'].value_counts(normalize=True)
```

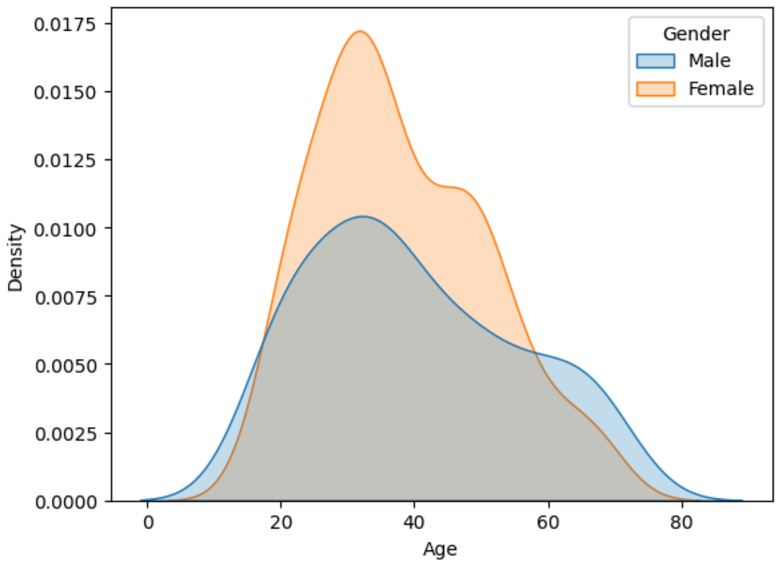


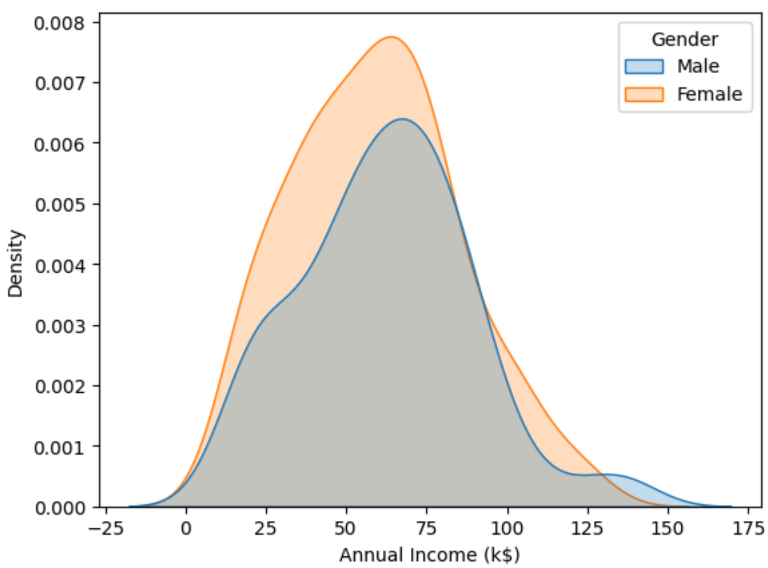
Out[6]:

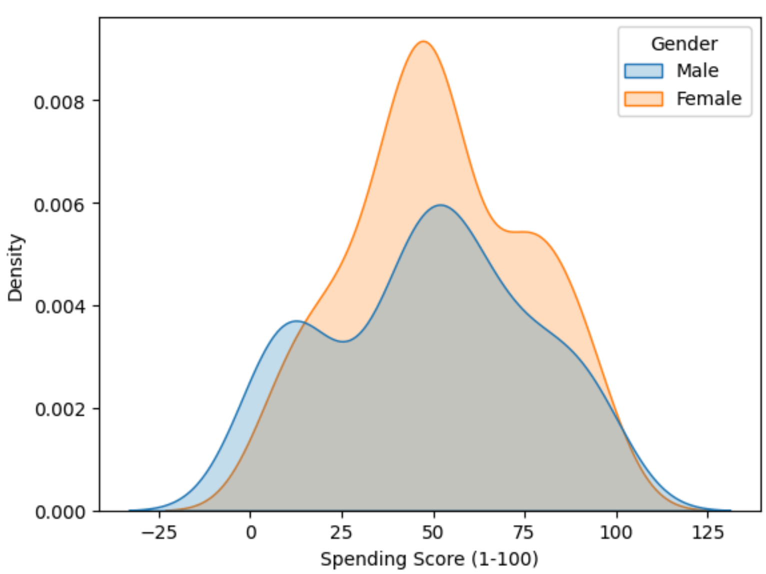
```
Gender
Female    0.56
Male      0.44
Name: proportion, dtype: float64
```

In [7]:

```python
# Univariate analysis based on Gender
columns = ['Age', 'Annual Income (k$)', 'Spending Score (1-100)']
for cols in columns:
    plt.figure()
    sns.kdeplot(data=df, x=cols, fill=True, hue='Gender')
    plt.show()
```







Description:

The above figures show the distribution of Age, Annual Income, and Spending Score:

Age: The distribution appears to be right-skewed, with most customers between 30-50 years old.

Annual Income: The distribution is roughly normal, with most incomes between 40-80k.

Spending Score: This distribution appears to be bimodal, suggesting two distinct groups of customers with different spending habit

NOTE: By all these analysis, we understand that more female are contributing into the mall customer datas.

Bivariate Analysis

In this bivariate analysis, let's examine the relation between two variables individually and look at the distribution of ['Age & Annual Income (k $)'], and['Annual Income(k$) & Spending Score (1-100)'] and ['Age & Spending Score (1-100)']

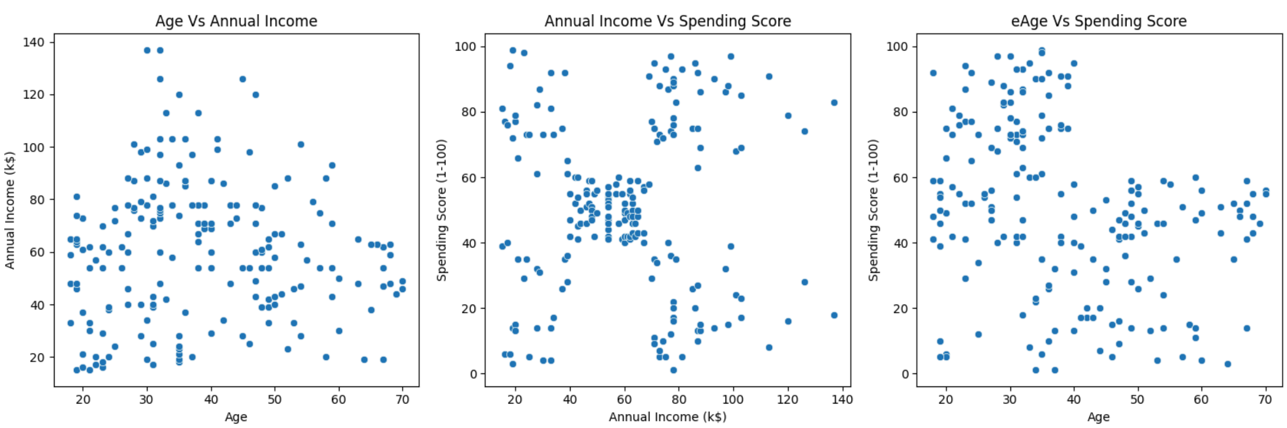
In [8]:
```python
plt.figure(figsize=(15, 5))

# Age Distribution
plt.subplot(1, 3, 1)
sns.scatterplot(data=df, x='Age', y='Annual Income (k$)')
plt.title('Age Vs Annual Income')

# Annual Income Distribution
plt.subplot(1, 3, 2)
sns.scatterplot(data=df, x='Annual Income (k$)', y='Spending Score (1-100)')
plt.title('Annual Income Vs Spending Score')

# Spending Score Distribution
plt.subplot(1, 3, 3)
sns.scatterplot(data=df, x='Age', y='Spending Score (1-100)')
plt.title('eAge Vs Spending Score')

plt.tight_layout()
plt.show()
```



Description:

The above figures show the relationships between pairs of variables, such as:

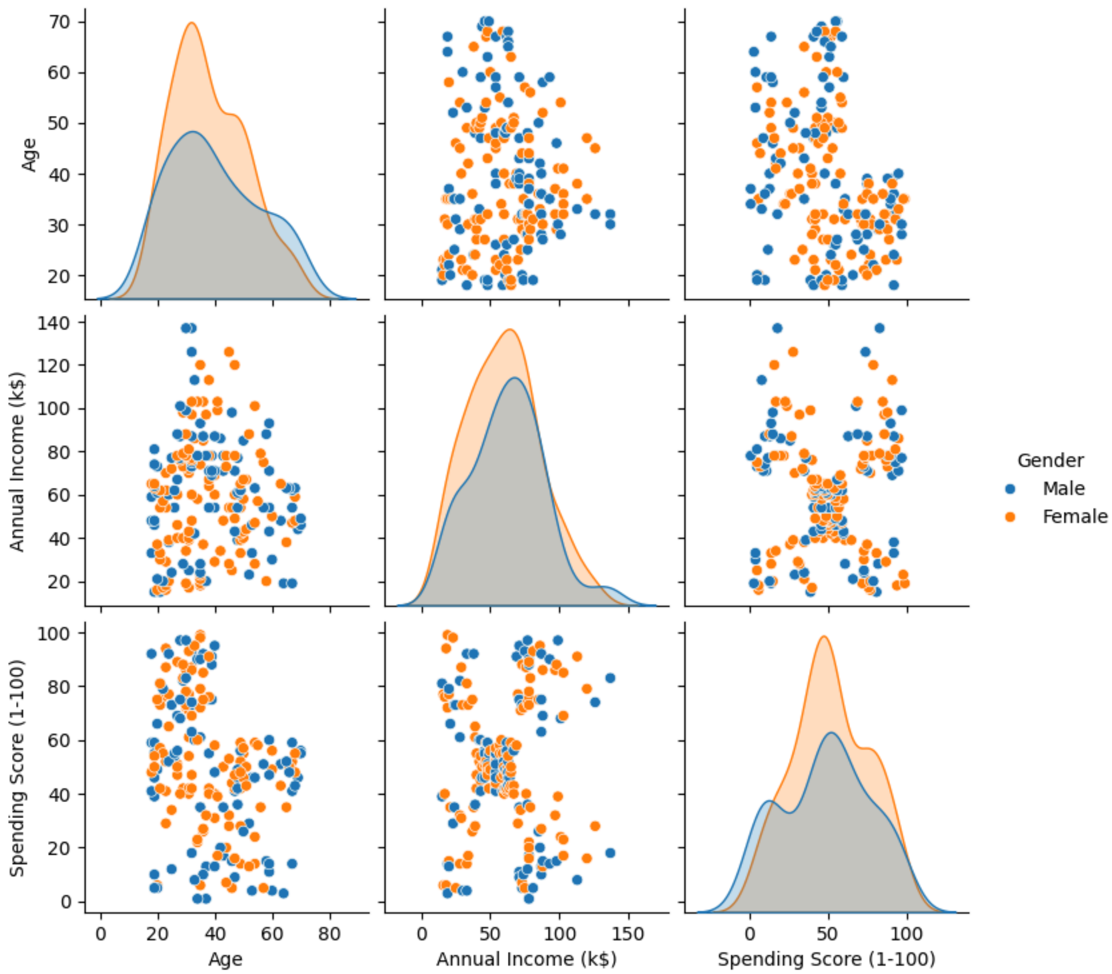
Age vs Annual Income: There's no clear linear relationship, but we can see that higher incomes are more common in between 30-60 age range.

Age vs Spending Score: Younger customers (below 40) seem to have a wider range of spending scores.

Annual Income vs Spending Score: There's an interesting pattern here, suggesting potential customer segments.

In [9]:
```python
# Let's analyze multiple variables and their correlation with respect to Gender
sns.pairplot(df.drop(columns=['CustomerID']), hue='Gender')
```

Out[9]:
```
<seaborn.axisgrid.PairGrid at 0x1f0462acd50>
```



This pairplot provides a comprehensive view for the potential clusters forming, especially in the Annual Income vs Spending Score plot. To further investigate this, performing a clustering analysis, such as K-means clustering can be helpful.

In [10]:
```
# Let's now look at the mean values grouping by Gender
df.groupby(['Gender'])[['Age', 'Annual Income (k$)', 'Spending Score (1-100)']].mean().round(3)
```

Out[10]:

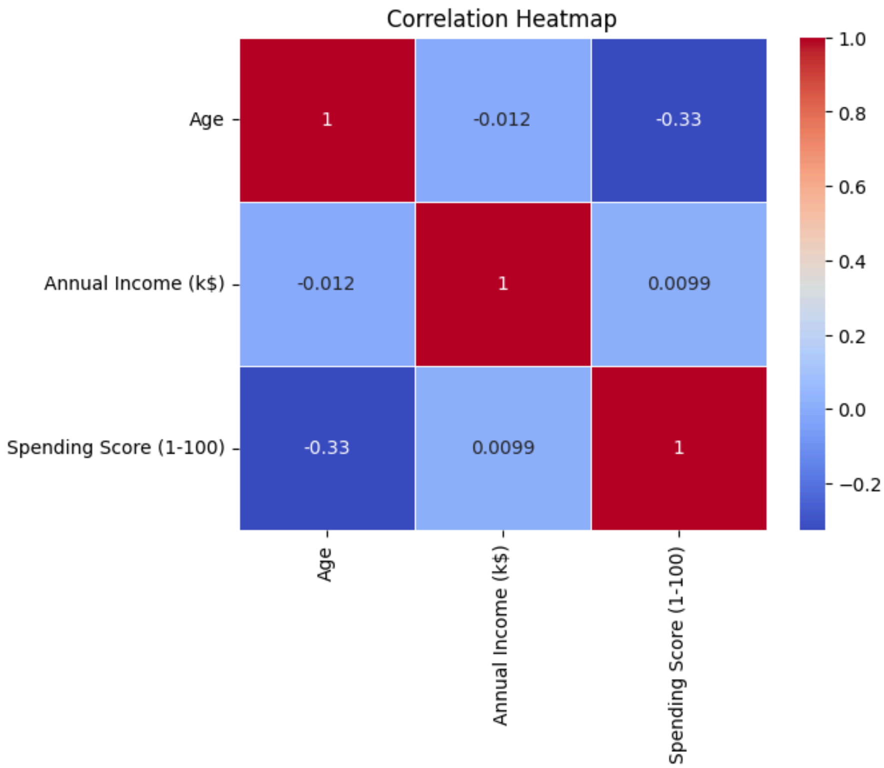
Gender	Age	Annual Income (k$)	Spending Score (1-100)
Female	38.098	59.250	51.527
Male	39.807	62.227	48.511

Multivariate Analysis

In [11]:
```
# Correlation Matrix
print(df.drop(columns=['CustomerID', 'Gender']).corr())
```

```
                             Age  Annual Income (k$)  Spending Score (1-100)
Age                     1.000000           -0.012398               -0.327227
Annual Income (k$)     -0.012398            1.000000                0.009903
Spending Score (1-100) -0.327227            0.009903                1.000000
```

In [12]:
```
# Visualizing correlation matrix
sns.heatmap(df.drop(columns=['CustomerID', 'Gender']).corr(), annot=True, cmap='coolwarm', linewidth=0.5)
plt.title('Correlation Heatmap')
plt.show()
```



Insights from the correlation matrix: 1. Age and Spending Score: There is moderate negative correlation (-0.327) between Age and Spending Score, suggesting that as age increases, the spending score tends to decrease slightly. 2. Age and Annual Income: There is a very weak negative correlation (-0.012) between Age & Income, indicating that there's almost no linear relation between them in dataset. 3. Annual Income & Spending Score: A very weak positive correlation (0.009) between Income & Spending, shows that there's practically no linear relation between them. From above points which provide interesting insights, nevertheless keeping in mind that only linear relationships always might not capture the patterns in data, which makes clustering a good choice to uncover the more complex relations.

KMeans Clustering (Bivariate)

In [13]:

```
# Prepare the data
X = df[['Age', 'Annual Income (k$)', 'Spending Score (1-100)']].values
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Elbow method to find optimal number of clusters
inertias = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    inertias.append(kmeans.inertia_)

# Plot the elbow curve
plt.figure(figsize=(10, 6))
plt.plot(range(1, 11), inertias, marker='o')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal k')
plt.show()
```

```
C:\Users\yousuf\anaconda3\Lib\site-packages\joblib\externals\loky\backend\context.py:110: UserWarning: Could not find the number of ph
ysical cores for the following reason:
[WinError 2] The system cannot find the file specified
Returning the number of logical cores instead. You can silence this warning by setting LOKY_MAX_CPU_COUNT to the number of cores you w
ant to use.
  warnings.warn(
  File "C:\Users\yousuf\anaconda3\Lib\site-packages\joblib\externals\loky\backend\context.py", line 199, in _count_physical_cores
    cpu_info = subprocess.run(
               ^^^^^^^^^^^^^^^
  File "C:\Users\yousuf\anaconda3\Lib\subprocess.py", line 548, in run
    with Popen(*popenargs, **kwargs) as process:
         ^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "C:\Users\yousuf\anaconda3\Lib\subprocess.py", line 1026, in __init__
    self._execute_child(args, executable, preexec_fn, close_fds,
  File "C:\Users\yousuf\anaconda3\Lib\subprocess.py", line 1538, in _execute_child
    hp, ht, pid, tid = _winapi.CreateProcess(executable, args,
                       ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
dows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS
=1.
  warnings.warn(
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
dows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS
=1.
  warnings.warn(
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
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=1.
  warnings.warn(
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
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  warnings.warn(
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
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=1.
  warnings.warn(
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
dows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS
=1.
  warnings.warn(
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
dows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS
=1.
  warnings.warn(
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
dows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS
=1.
  warnings.warn(
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
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=1.
  warnings.warn(
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
dows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS
=1.
  warnings.warn(
```
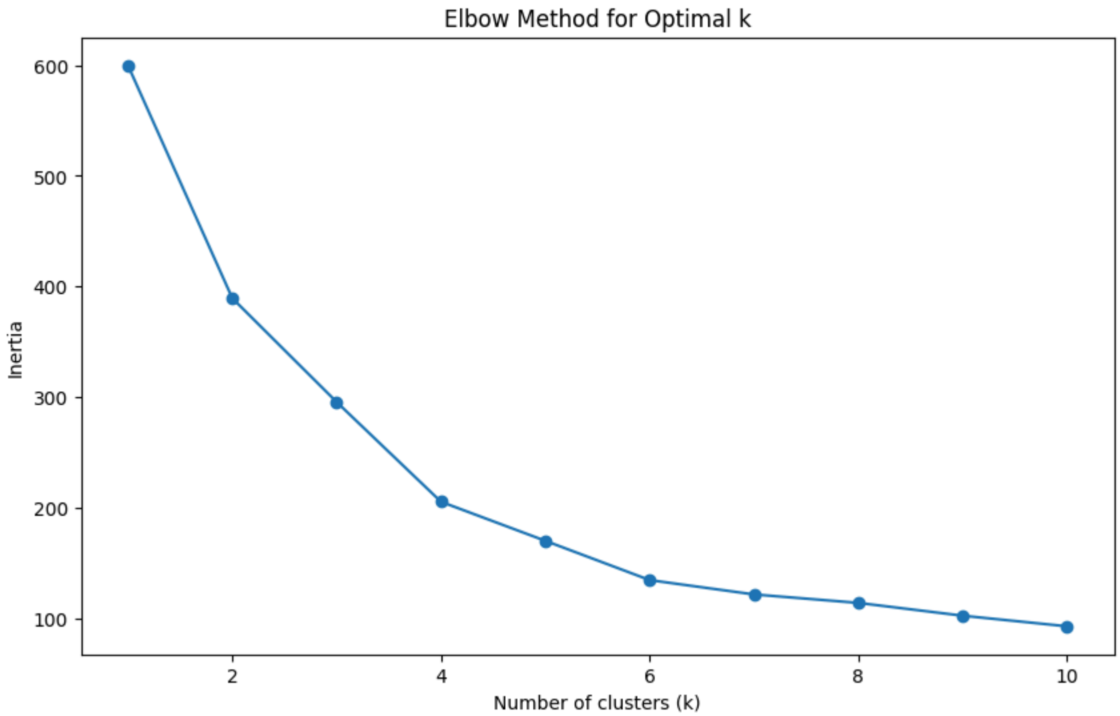



In [ ]:

In [14]:
```
# Setting the clusters to 5 as PCA
clustering = KMeans(n_clusters=5)
clustering.fit(df[['Annual Income (k$)', 'Spending Score (1-100)']])

# Assigning Cluster Labels to new column
df['Income & Spending Clusters'] = clustering.labels_
df.head()
```

```
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
dows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS
=1.
  warnings.warn(
```

Out[14]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)	Income & Spending Clusters
0	1	Male	19	15	39	4
1	2	Male	21	15	81	2
2	3	Female	20	16	6	4
3	4	Female	23	16	77	2
4	5	Female	31	17	40	4

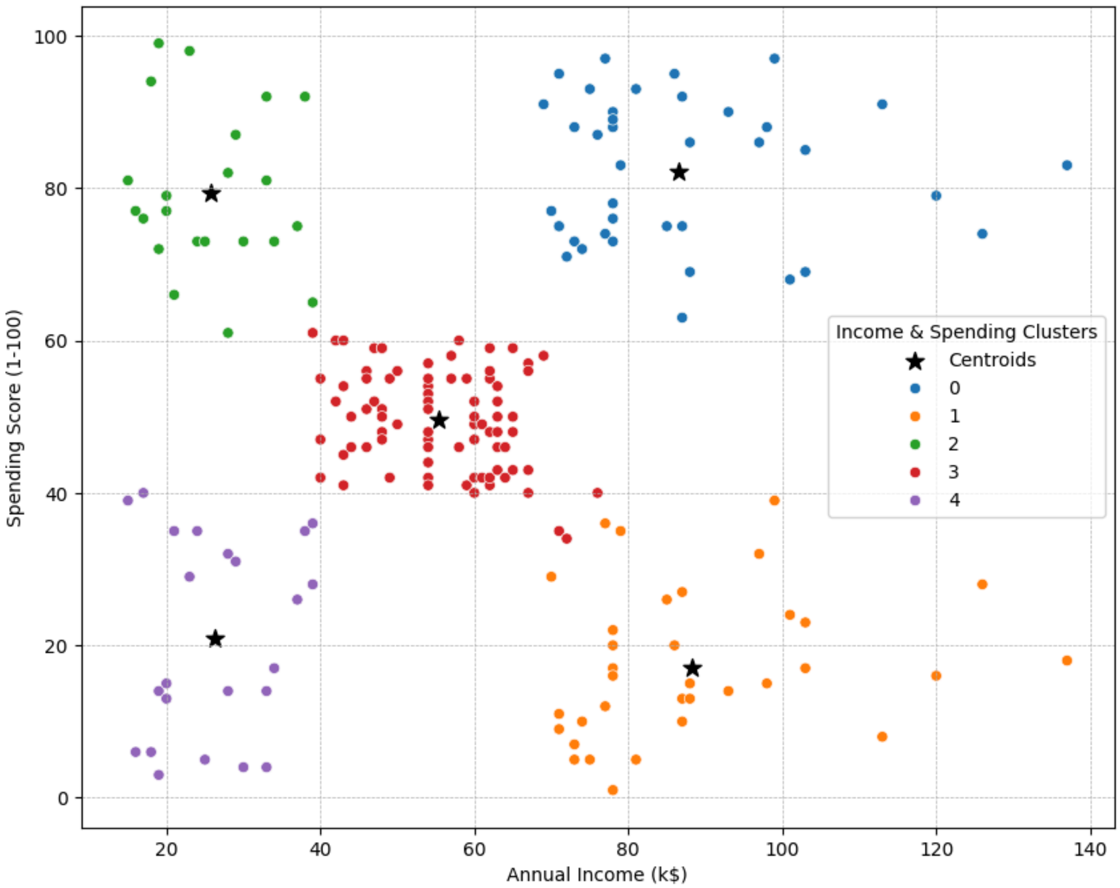
In [15]:
```
# Extract cluster centers
cluster_centers = clustering.cluster_centers_

# Creating dataframe for cluster center points
centers_df = pd.DataFrame(cluster_centers, columns=['Annual Income (k$)', 'Spending Score (1-100)'])
centers_df.columns = ['x', 'y']
centers_df.head()
```

Out[15]:

	x	y
0	86.538462	82.128205
1	88.200000	17.114286
2	25.727273	79.363636
3	55.296296	49.518519
4	26.304348	20.913043

In [20]:
```
plt.figure(figsize=(10,8))
plt.scatter(x=centers_df['x'], y=centers_df['y'], s=100, color='black', marker='*', label='Centroids')
sns.scatterplot(data=df, x='Annual Income (k$)', y='Spending Score (1-100)', hue='Income & Spending Clusters', palette='tab10')
# Adding grid lines
```

```
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.savefig('Clustered_Segmented_Customers_Analysis.png')
```



This scatter plot visualizes the customer segments based on their annual income and spending score. The clustering algorithm has identified five distinct groups:

Low Income, Low Spending (Cluster 0)

Low Income, High Spending (Cluster 4)

Medium Income, Medium Spending (Cluster 1)

High Income, Low Spending (Cluster 3)

High Income, High Spending (Cluster 2)

In [17]:
```
pd.crosstab(df['Income & Spending Clusters'], df['Gender'], normalize='index')
```

Out[17]:

Gender	Female	Male
Income & Spending Clusters		
0	0.538462	0.461538
1	0.457143	0.542857
2	0.590909	0.409091
3	0.592593	0.407407
4	0.608696	0.391304

In [18]:
```
# Grouping the 'Income & Spending Clustering' and calculates the mean values for each cluster
df.groupby('Income & Spending Clusters')[['Age', 'Annual Income (k$)', 'Spending Score (1-100)']].mean().round(2)
```

Out[18]:

Income & Spending Clusters	Age	Annual Income (k$)	Spending Score (1-100)
0	32.69	86.54	82.13
1	41.11	88.20	17.11
2	25.27	25.73	79.36
3	42.72	55.30	49.52
4	45.22	26.30	20.91

Detailed Insights: Clustering of Annual Income and Spending Scores (Bivariate Analysis)

The insights from the clustering analysis grouped by 'Income & Spending Clusters' can provide valuable information for the marketing team. Here is a detailed analysis of each cluster based on the mean values for 'Age', 'Annual Income (k$)', and 'Spending Score (1-100)':

Insights for Each Cluster:

Cluster 0:

Average Age: 45.22 Annual Income (k$): 26.30 Spending Score (1-100): 20.91 Insights:

This cluster represents older customers with high annual income but low spending scores. These customers might be more financially secure but less inclined to spend on discretionary items. Marketing Strategy: Target this group with promotions for premium products, luxury items, or high-quality goods that justify their spending.

Cluster 1:

Average Age: 42.72 Annual Income (k$): 55.30 Spending Score (1-100): 49.52

Insights:

This cluster consists of younger customers with lower annual incomes but high spending scores. These customers are likely to spend a significant portion of their income on shopping. Marketing Strategy: Focus on affordable yet trendy products, discounts, and loyalty programs to retain these high-spending young customers.

Cluster 2:

Average Age: 32.69 Annual Income (k$): 86.54 Spending Score (1-100): 82.13

Insights:

This cluster includes middle-aged customers with moderate annual incomes and spending scores. They represent a balanced spending behavior. Marketing Strategy: Offer value-for-money products, moderate discounts, and quality service to attract and retain this balanced spending group.

Cluster 3:

Average Age: 32.69 Annual Income (k$): 86.54 Spending Score (1-100): 82.13

Insights:

This cluster represents relatively young customers with high annual income and high spending scores. They are the most valuable customers due to their high spending potential. Marketing Strategy: Prioritize this segment with exclusive offers, personalized marketing, premium product launches, and VIP customer experiences to maximize their spending and loyalty.

Cluster 4:

Average Age: 25.27 Annual Income (k$): 25.73 Spending Score (1-100): 79.36

Insights:

This cluster comprises older customers with low annual income and low spending scores. These customers are less likely to spend significantly at the mall. Marketing Strategy: Focus on essential and budget-friendly products, basic promotions, and cost-effective marketing strategies to appeal to this price-sensitive segment.

Overall Insights:

The marketing team can use these insights to tailor their strategies to different customer segments, optimizing their campaigns to increase engagement and sales.

High-income clusters with high spending scores (Cluster 2) should be targeted for premium and exclusive offers.

Younger, high-spending but low-income clusters (Cluster 4) can be attracted with affordable pricing and trendy products.

Balanced spenders and income (Cluster 1) can be targeted with value-for-money offers.

Older, low-income, low-spending clusters (Cluster 0) might need more basic and essential product offerings.

Older, high-income but low-spending clusters (Cluster 3) might appreciate premium quality over quantity.

KMeans Clustering (Multivariate)

In [72]:
```
df.columns
```

Out[72]:
```
Index(['CustomerID', 'Gender', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)', 'Income & Spending Clusters'],
      dtype='object')
```

In [73]:
```
# Let's transform the 'Gender' values into numerical values using one hot encoding
dummied_df = pd.get_dummies(df, columns=['Gender'], dtype=int)
dummied_df.columns
dummied_df.head()
```

Out[73]:

	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)	Income & Spending Clusters	Gender_Female	Gender_Male
0	1	19	15	39	4	0	1
1	2	21	15	81	2	0	1
2	3	20	16	6	4	1	0
3	4	23	16	77	2	1	0
4	5	31	17	40	4	1	0

In [74]:
```
dummied_df = dummied_df.drop(columns=['Gender_Male'])

# Invert the 'gender' column values: 0 -> Female; 1 -> Male
dummied_df = dummied_df.rename(columns={'Gender_Female': 'Gender'})
dummied_df.head()
```

Out[74]:

	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)	Income & Spending Clusters	Gender
0	1	19	15	39	4	0
1	2	21	15	81	2	0
2	3	20	16	6	4	1
3	4	23	16	77	2	1
4	5	31	17	40	4	1

In [75]:
```
dummied_df1 = dummied_df[['Age', 'Annual Income (k$)', 'Spending Score (1-100)']]
dummied_df1
```

Out[75]:

	Age	Annual Income (k$)	Spending Score (1-100)
0	19	15	39
1	21	15	81
2	20	16	6
3	23	16	77
4	31	17	40
...	...	...	...
195	35	120	79
196	45	126	28
197	32	126	74
198	32	137	18
199	30	137	83

200 rows × 3 columns

In [76]:
```
# Now scaling the dataframe
scale = StandardScaler()
scaled_dummied_df = pd.DataFrame(scale.fit_transform(dummied_df1))
scaled_dummied_df.head()
```

Out[76]:

	0	1	2
0	-1.424569	-1.738999	-0.434801
1	-1.281035	-1.738999	1.195704
2	-1.352802	-1.700830	-1.715913
3	-1.137502	-1.700830	1.040418
4	-0.563369	-1.662660	-0.395980

In [77]:

```
# Calculate the inertia for different number of clusters
inertia_values_scaled_dummied_df= []
cluster_range = range(1, 11)
for k in cluster_range:
    kmeans_dummied_df = KMeans(n_clusters=k)
    kmeans_dummied_df.fit(scaled_dummied_df)
    inertia_values_scaled_dummied_df.append(kmeans_dummied_df.inertia_)
print(inertia_values_scaled_dummied_df)
```

```
[600.0, 389.3861889564372, 297.02654463384187, 252.10682456184531, 168.24758017556834, 134.3008171098464, 117.08803464058246, 103.8462
3824277769, 94.18328388567025, 89.91298719440587]
```

```
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
dows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS
=1.
  warnings.warn(
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
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=1.
  warnings.warn(
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
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=1.
  warnings.warn(
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
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=1.
  warnings.warn(
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
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dows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS
=1.
  warnings.warn(
```
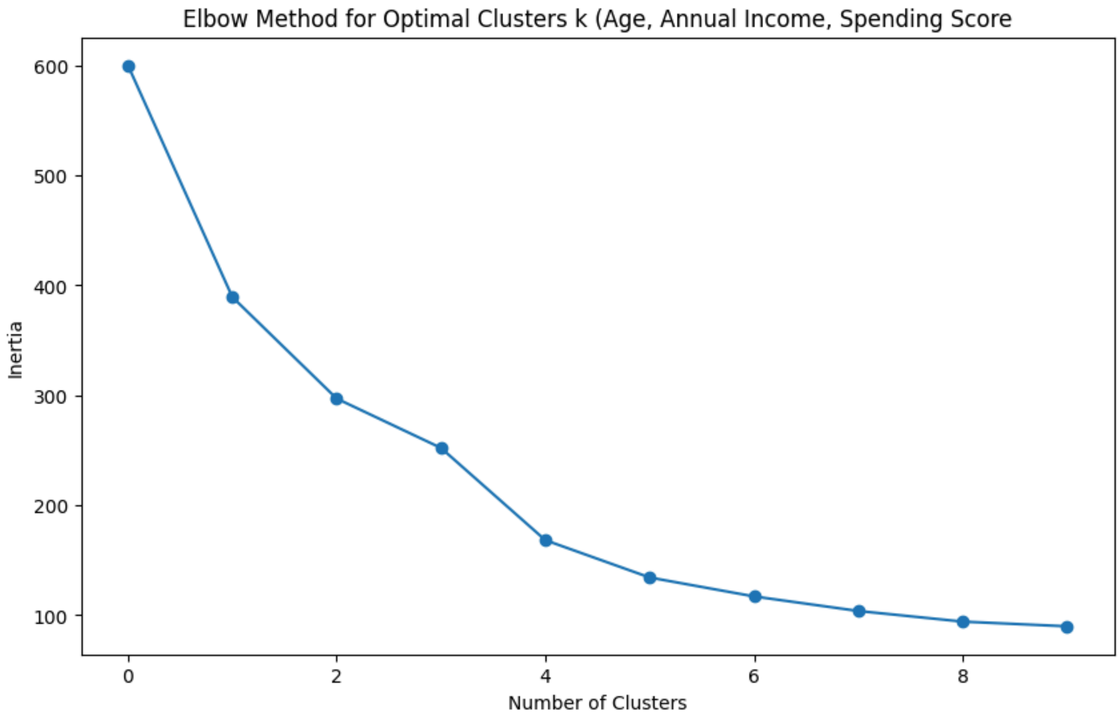

In [78]:

```
# Plot the inertia values
plt.figure(figsize = (10, 6))
plt.plot(inertia_values_scaled_dummied_df, marker='o')
plt.title('Elbow Method for Optimal Clusters k (Age, Annual Income, Spending Score')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.show()
```



In [83]:
```
# Setting the clusters to 5 as PCA
multivariate_clustering = KMeans(n_clusters=5)
multivariate_clustering.fit(dummied_df[['Age', 'Annual Income (k$)', 'Spending Score (1-100)']])

# Assigning Cluster Labels to new column
dummied_df1['Age, Income, & Spending Clusters'] = multivariate_clustering.labels_
dummied_df1.head()
```

```
C:\Users\yousuf\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1426: UserWarning: KMeans is known to have a memory leak on Win
dows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS
=1.
  warnings.warn(
C:\Users\yousuf\AppData\Local\Temp\ipykernel_14192\915840326.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  dummied_df1['Age, Income, & Spending Clusters'] = multivariate_clustering.labels_
```

Out[83]:

	Age	Annual Income (k$)	Spending Score (1-100)	Age, Income, & Spending Clusters
0	19	15	39	0
1	21	15	81	0
2	20	16	6	1
3	23	16	77	0
4	31	17	40	1

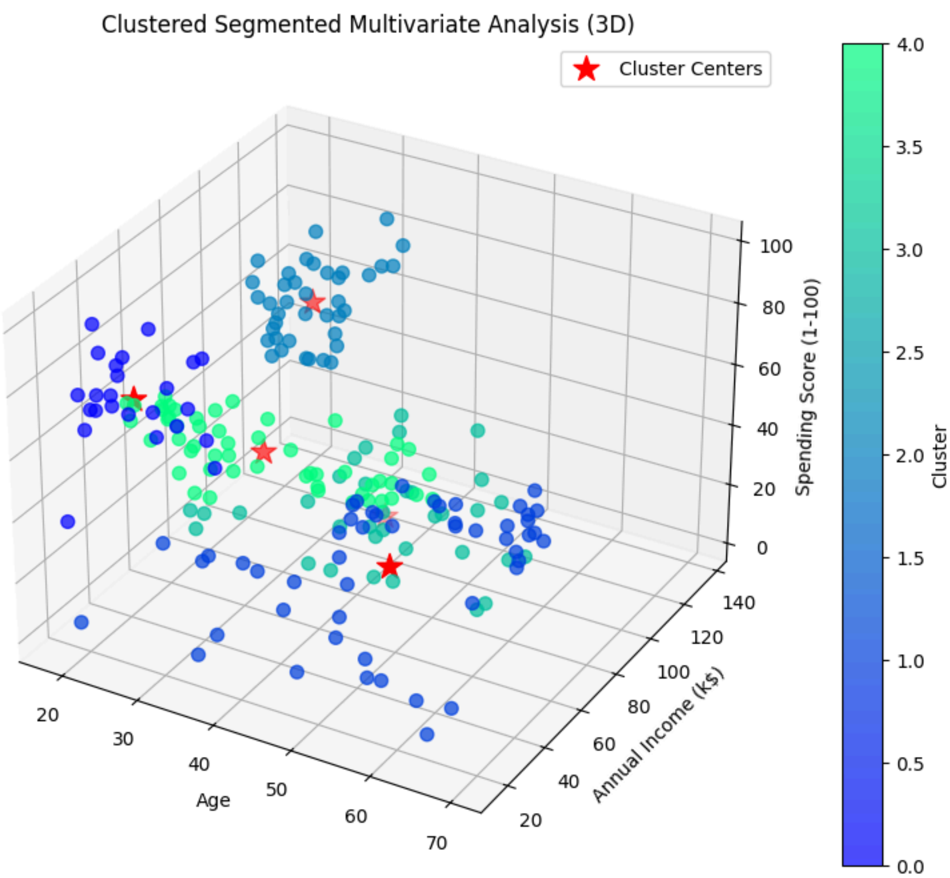
In [84]:
```
# Cluster center points
cluster_centers_dummied_df = multivariate_clustering.cluster_centers_
print(cluster_centers_dummied_df)
```

```
[[25.25       25.83333333 76.91666667]
 [54.06       40.46       36.72      ]
 [32.69230769 86.53846154 82.12820513]
 [41.64705882 88.73529412 16.76470588]
 [33.39622642 58.05660377 48.77358491]]
```

In [85]:
```
# Column names for the features
cluster_center_df = pd.DataFrame(cluster_centers_dummied_df, columns=['Age', 'Annual Income (k$)', 'Spending Score (1-100)'])
print(cluster_center_df)
```

```
         Age  Annual Income (k$)  Spending Score (1-100)
0  25.250000           25.833333               76.916667
1  54.060000           40.460000               36.720000
2  32.692308           86.538462               82.128205
3  41.647059           88.735294               16.764706
4  33.396226           58.056604               48.773585
```

In [86]:
```
from mpl_toolkits.mplot3d import Axes3D

fig = plt.figure(figsize=(12, 8))
ax = fig.add_subplot(111, projection='3d')

# Scatter plot of the data points, colored by cluster
scatter = ax.scatter(dummied_df1['Age'], dummied_df1['Annual Income (k$)'], dummied_df1['Spending Score (1-100)'], c=dummied_df1['Age

# Plot cluster centers
ax.scatter(cluster_centers_dummied_df[:, 0], cluster_centers_dummied_df[:, 1], cluster_centers_dummied_df[:, 2], c='red', marker='*',

ax.set_title('Clustered Segmented Multivariate Analysis (3D)')
ax.set_xlabel('Age')
ax.set_ylabel('Annual Income (k$)')
ax.set_zlabel('Spending Score (1-100)')
ax.legend()
fig.colorbar(scatter, ax=ax, label='Cluster')

# Save the plot
plt.savefig('Clustered_MultivariatePlot_3DView.png')

plt.show()
```



In [91]:
```
crosstab_df = pd.crosstab(dummied_df1['Age, Income, & Spending Clusters'], dummied_df['Gender'], normalize='index')
# Rename the columns
crosstab_df = crosstab_df.rename(columns={0: 'Female', 1: 'Male'})
crosstab_df
```

Out[91]:

Gender	Female	Male
Age, Income, & Spending Clusters		
0	0.416667	0.583333
1	0.440000	0.560000
2	0.461538	0.538462
3	0.558824	0.441176
4	0.358491	0.641509

In [93]:
```
# Grouping the 'Income & Spending Clustering' and calculates the mean values for each cluster
```

```python
dummied_df1.groupby('Age, Income, & Spending Clusters')[['Age', 'Annual Income (k$)', 'Spending Score (1-100)']].mean().round(2)
```

Out[93]:

Age, Income, & Spending Clusters	Age	Annual Income (k$)	Spending Score (1-100)
0	25.25	25.83	76.92
1	54.06	40.46	36.72
2	32.69	86.54	82.13
3	41.65	88.74	16.76
4	33.40	58.06	48.77

In [94]:

```python
dummied_df1.columns
```

Out[94]:

```
Index(['Age', 'Annual Income (k$)', 'Spending Score (1-100)',
       'Age, Income, & Spending Clusters'],
      dtype='object')
```

In [104…

```python
dummied_df['Gender'] = dummied_df['Gender'].replace({0: 'Female', 1: 'Male'})
dummied_df.columns
```

Out[104…

```
Index(['CustomerID', 'Age', 'Annual Income (k$)', 'Spending Score (1-100)',
       'Income & Spending Clusters', 'Gender'],
      dtype='object')
```

In [105…

```python
dummied_df1.columns
```

Out[105…

```
Index(['Age', 'Annual Income (k$)', 'Spending Score (1-100)',
       'Age, Income, & Spending Clusters'],
      dtype='object')
```

In [106…

```python
# Assigning the columns to final df
dummied_df['Age, Income, & Spending Clusters'] = dummied_df1['Age, Income, & Spending Clusters']

# Display the updated DataFrame
print(dummied_df.head())
```

```
   CustomerID  Age  Annual Income (k$)  Spending Score (1-100)  \
0           1   19                  15                      39
1           2   21                  15                      81
2           3   20                  16                       6
3           4   23                  16                      77
4           5   31                  17                      40

   Income & Spending Clusters  Gender  Age, Income, & Spending Clusters
0                           4  Female                                 0
1                           2  Female                                 0
2                           4    Male                                 1
3                           2    Male                                 0
4                           4    Male                                 1
```

In [107…

```python
# Saving thie clustered data file
dummied_df.to_csv('Clustered_Segmented_Data.csv')
```

Based on the output of multivariate clustering, the derived insights are as follows: Cluster 0: Average Age: 25.25 years Average Annual Income: 25.83*kAverageSpendingScore* : 76.92*GenderDistribution* : *Female* : 41.67*Male* : 58.33*Insights* : *Thisclusterhastheyoungestaverageage*. *Theyhavethelowestaverageannualincome*. *They* *indicatingtheyareenthusiasticspendersdespitetheirlowerincome*. *Malesareslightlymoreprevalentinthiscluster*. *Cluster*1 : *AverageAge* : 54.06*yearsAverageAnnualIncome* : 40.46k Average Spending Score: 36.72 Gender Distribution: Female: 44.00% Male: 56.00% Insights: This cluster has the oldest average age. Their average income is moderate. They have a lower spending score, suggesting they are conservative spenders. Males are more prevalent in this cluster. Cluster 2: Average Age: 32.69 years Average Annual Income: 86.54*kAverageSpendingScore* : 82.13*GenderDistribution* : *Female* : 46.15*Male* : 53.85*Insights* : *Thisclusterhasayoungeraverageagecomparedtoothers*. *Theyhavethehighestaverageinco* . *Theyalsohavethehighestspendingscore*, *indicatinghighspendingcapabilityandbehavior*. *Thereisarelativelybalancedgenderdistribution*, *withaslightmalemajority*. *Cluster*3 : *AverageAge* : 41.65*yearsAverageAnnualIncome* : 88.74k Average Spending Score: 16.76 Gender Distribution: Female: 55.88% Male: 44.12% Insights: This cluster has a middle-aged average age. They have a high average income. They have the lowest spending score, indicating they are very conservative spenders. Females are more prevalent in this cluster. Cluster 4: Average Age: 33.40 years Average Annual Income: $58.06k Average Spending Score: 48.77 Gender Distribution: Female: 35.85% Male: 64.15% Insights: This cluster has a slightly older average age than Cluster 2. Their average income is moderate. They have a moderate spending score. Males are more prevalent in this cluster, with the highest male proportion among all clusters. Summary: Young High Spenders (Cluster 0): Younger individuals with low income but high spending tendencies, slightly more males. Older Conservative Spenders (Cluster 1): Older individuals with moderate income and low spending tendencies, slightly more males. Young High Earners and Spenders (Cluster 2): Younger individuals with high income and high spending tendencies, balanced gender distribution. Middle-Aged Conservative High Earners (Cluster 3): Middle-aged individuals with high income and very low spending tendencies, more females. Moderate Earners and Spenders (Cluster 4): Individuals with moderate income and spending tendencies, with a significant male majority.

In [ ]: