Clustering & Customer Segmentation

The objective of this project is to analyze customer behavioral data and segment them into distinct groups using clustering techniques. By applying machine learning algorithms like K-Means, Hierarchical Clustering, and RFM Analysis.

There is a record of 1000 customers.

In [36]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.cluster import KMeans, AgglomerativeClustering
from sklearn.metrics import silhouette_score
from scipy.cluster.hierarchy import dendrogram, linkage, fcluster

import warnings
warnings.filterwarnings('ignore')
```

In [37]:
```
cust_data = pd.read_csv('/content/customer_segmentation_data.csv')
cust_data.head(10)
```

Out[37]:

	id	age	gender	income	spending_score	membership_years	purchase_frequency	preferred_ca
0	1	38	Female	99342	90	3	24	Gr
1	2	21	Female	78852	60	2	42	
2	3	60	Female	126573	30	2	28	C
3	4	40	Other	47099	74	9	5	Home &
4	5	65	Female	140621	21	3	25	Elec
5	6	31	Other	57305	24	3	30	Home &
6	7	19	Other	54319	68	5	43	C
7	8	43	Male	108115	94	9	27	Gr
8	9	53	Male	34424	29	6	7	
9	10	55	Female	45839	55	7	2	Elec

In [38]:
```
cust_data.shape
```

Out[38]:
```
(1000, 9)
```

There are 1000 records and 9 columns in dataset.

In [39]:
```
cust_data.info()
```

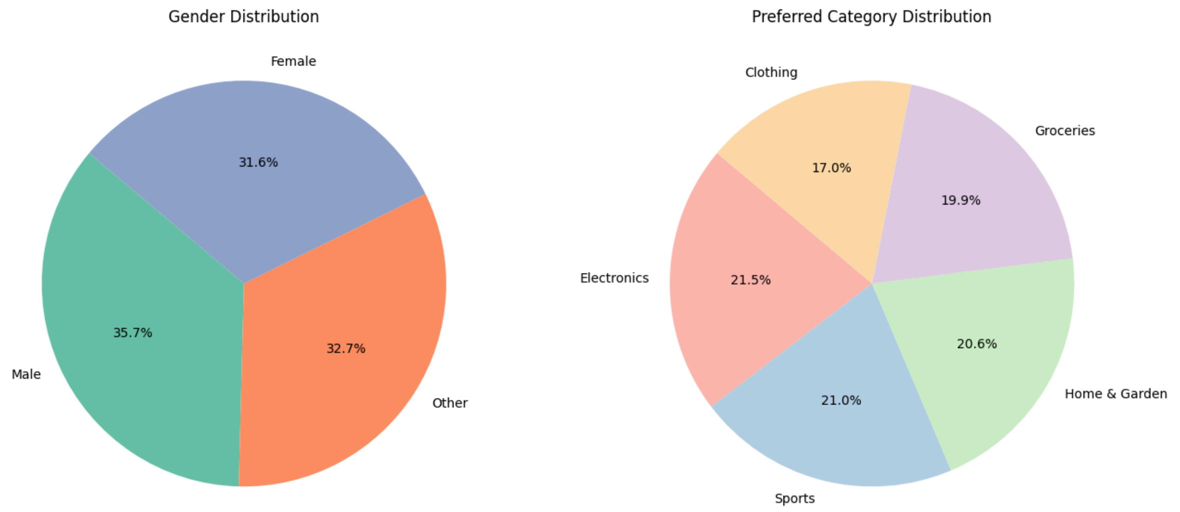
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   id                    1000 non-null   int64  
 1   age                   1000 non-null   int64  
 2   gender                1000 non-null   object 
 3   income                1000 non-null   int64  
 4   spending_score        1000 non-null   int64  
 5   membership_years      1000 non-null   int64  
 6   purchase_frequency    1000 non-null   int64  
 7   preferred_category    1000 non-null   object 
 8   last_purchase_amount  1000 non-null   float64
dtypes: float64(1), int64(6), object(2)
memory usage: 70.4+ KB
```

There are no null values in the data.

Exploratory Data Analysis

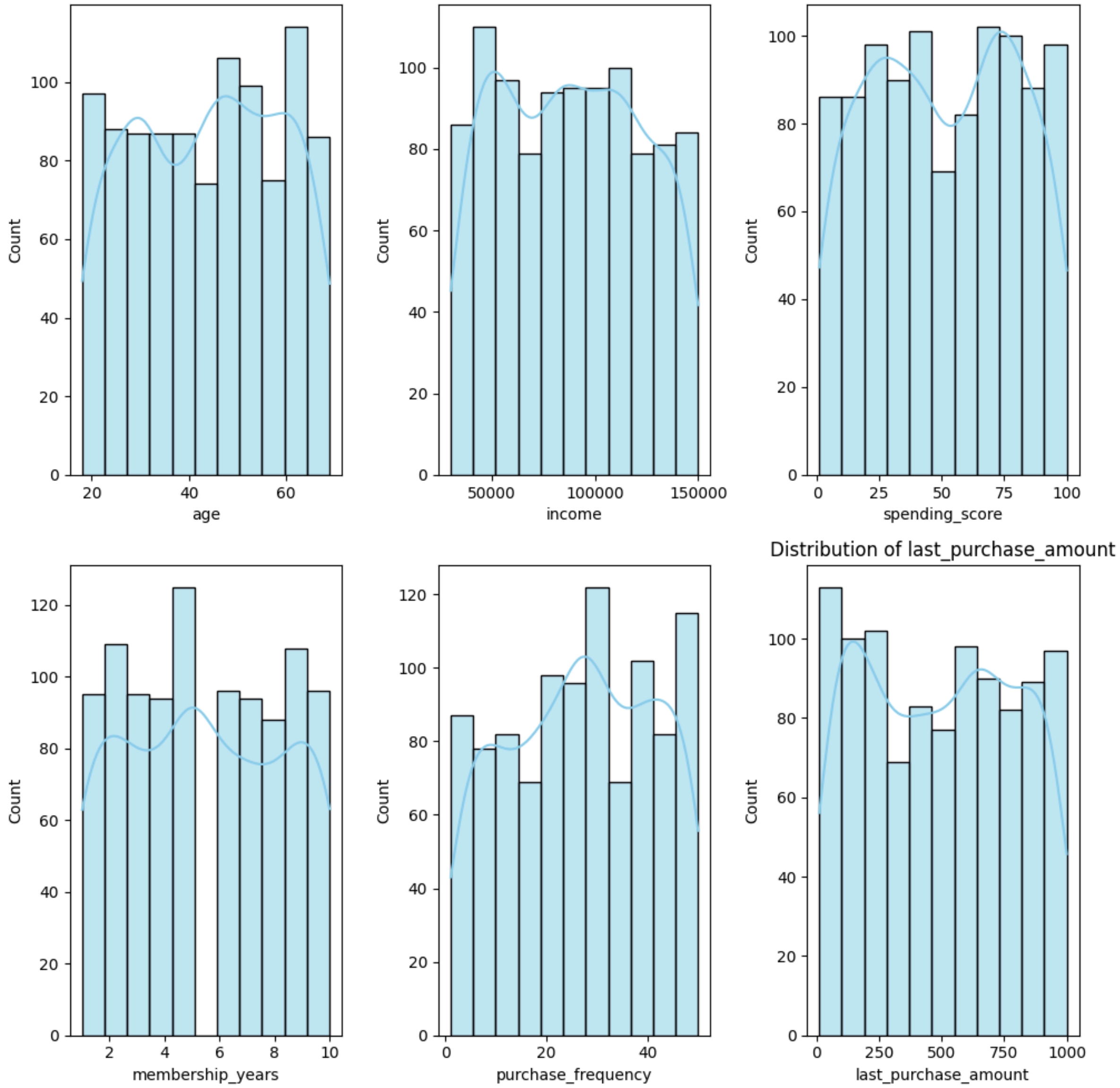
Univariate Analysis

In [40]:
```
#Pie Chart
fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# Gender
gender_counts = cust_data['gender'].value_counts()
axes[0].pie(gender_counts, labels=gender_counts.index, autopct='%1.1f%%', startangl
axes[0].set_title('Gender Distribution')

# Preferred Category
category_counts = cust_data['preferred_category'].value_counts()
axes[1].pie(category_counts, labels=category_counts.index, autopct='%1.1f%%', start
axes[1].set_title('Preferred Category Distribution')

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



- The above pie chart for gender shows almost same distribution for each gender.
- Similar with the preferred category have approx same distribution among each category.

In [41]:
```
# Histogram
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(10, 10))
axes = axes.flatten()

numeric_cols = ['age', 'income', 'spending_score', 'membership_years', 'purchase_fr

for i, col in enumerate(numeric_cols):
    sns.histplot(cust_data[col], kde=True, ax=axes[i], color='skyblue')
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Count')

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



The above graph interprets:

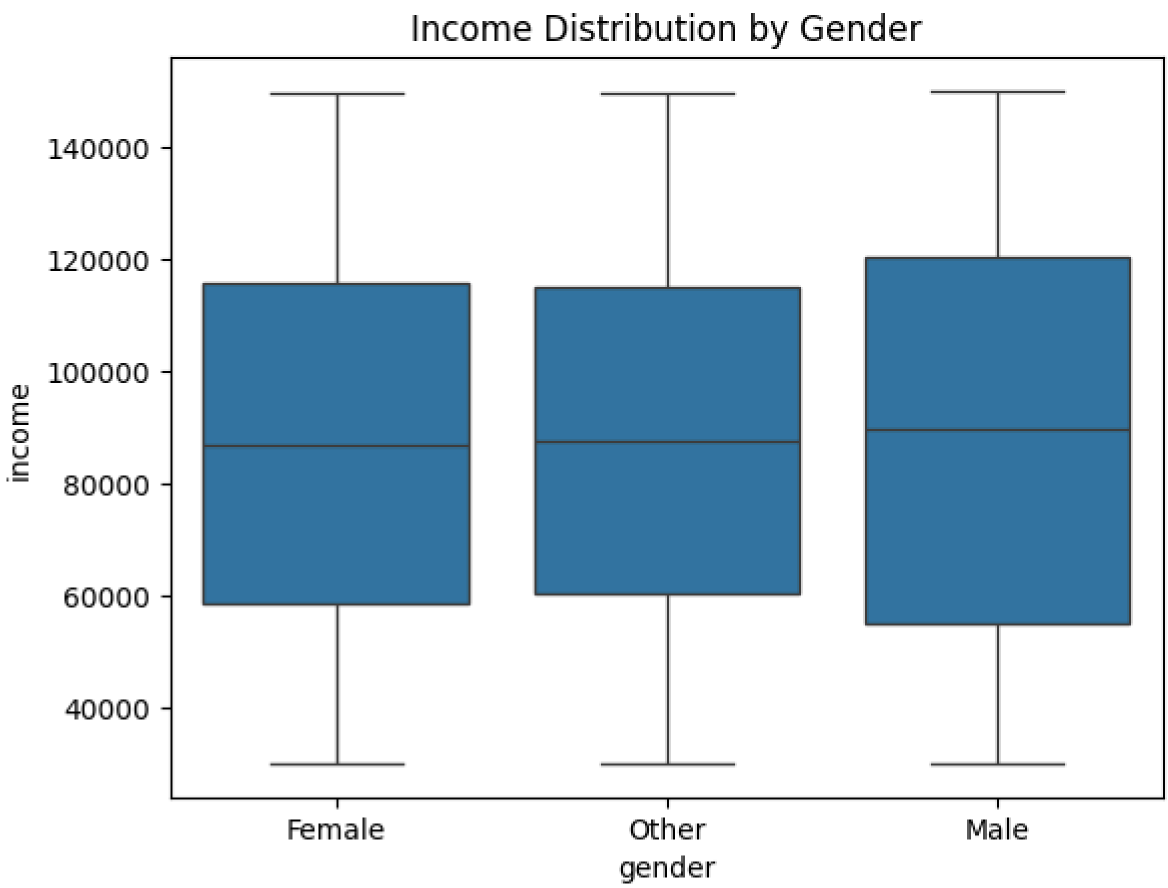
- Age is uniformly distributed across the range of 20 to 65. Slight peaks around 30–35 and 60–65, suggesting small clusters of younger and older shoppers.
- Income ranges from 30,000 to 150,000. Peaks around 50,000–60,000 and 100,000–120,000 suggest two income segments — possibly mid-income and upper-income groups.
- Spending Score is uniform distribution between 0 and 100. A moderate peak near 75–80, indicating many customers have high spending tendencies.

- Membership Years show most customers have between 2 and 7 years of membership. Slight peaks at 3, 6, and 9 years.
- Purchase Frequency broadly distributed across the range 0 to 50 purchases. Peaks at around 10–15, 25, and 35–40, showing different engagement levels among customers.
- Last Purchase Amount are spread from ₹0 to ₹1000. Peaks around ₹200–300, ₹450–500, and ₹850–950, suggesting three tiers of spending behavior: low, mid, and premium.

Bivariate Analysis

In [42]:
```
# Income vs Gender
sns.boxplot(data=cust_data, x='gender', y='income')
plt.title('Income Distribution by Gender')
```

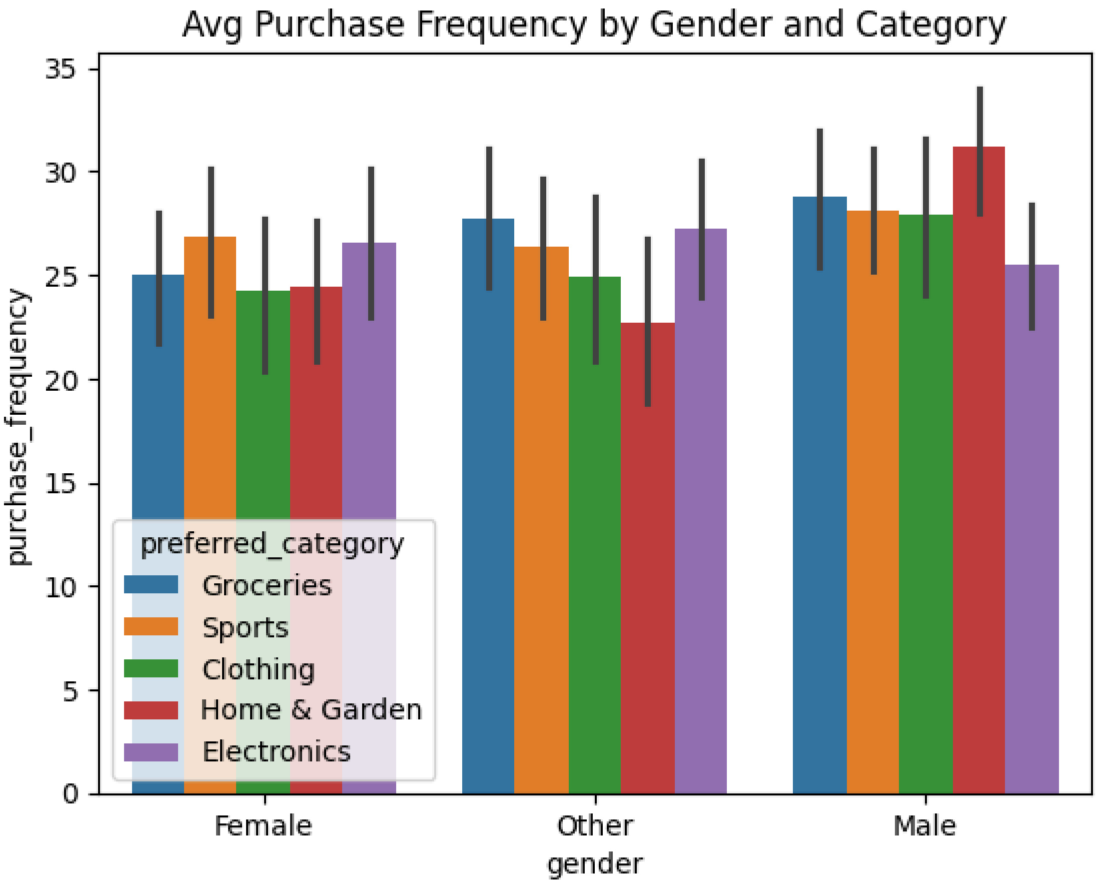
Out[42]: Text(0.5, 1.0, 'Income Distribution by Gender')



The above graph shows male have higher income as compared to female and others.

In [43]:
```
# Avg purchase frequency by gender & category
sns.barplot(data=cust_data, x='gender', y='purchase_frequency', hue='preferred_cate
plt.title('Avg Purchase Frequency by Gender and Category')
```

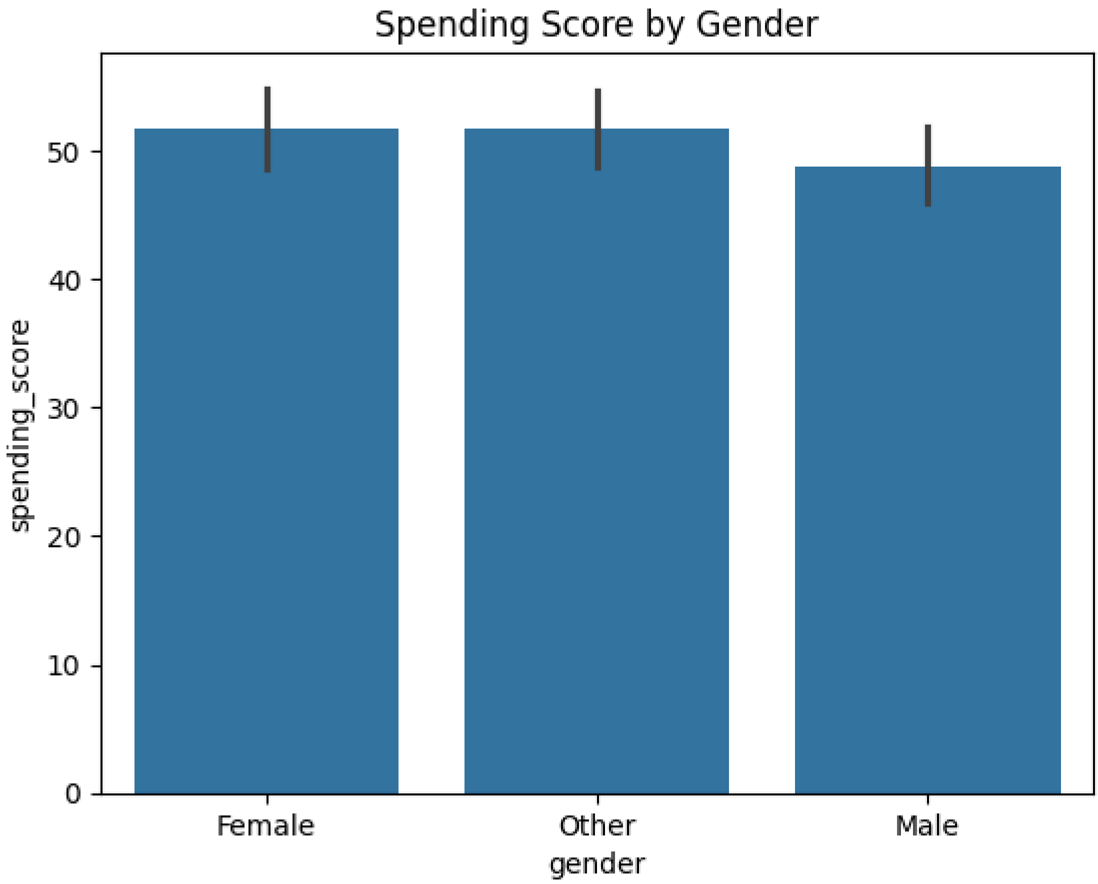
Out[43]: Text(0.5, 1.0, 'Avg Purchase Frequency by Gender and Category')



The above graph shows that females purchase electronics and sports mostly. Males have the highest purchase frequency in the Home and Garden and Groceries categories. Others have frequent purchases in electronics and groceries.

In [44]:
```
# Spending score by gender
sns.barplot(data=cust_data, x='gender', y='spending_score')
plt.title('Spending Score by Gender')
```

Out[44]:
```
Text(0.5, 1.0, 'Spending Score by Gender')
```

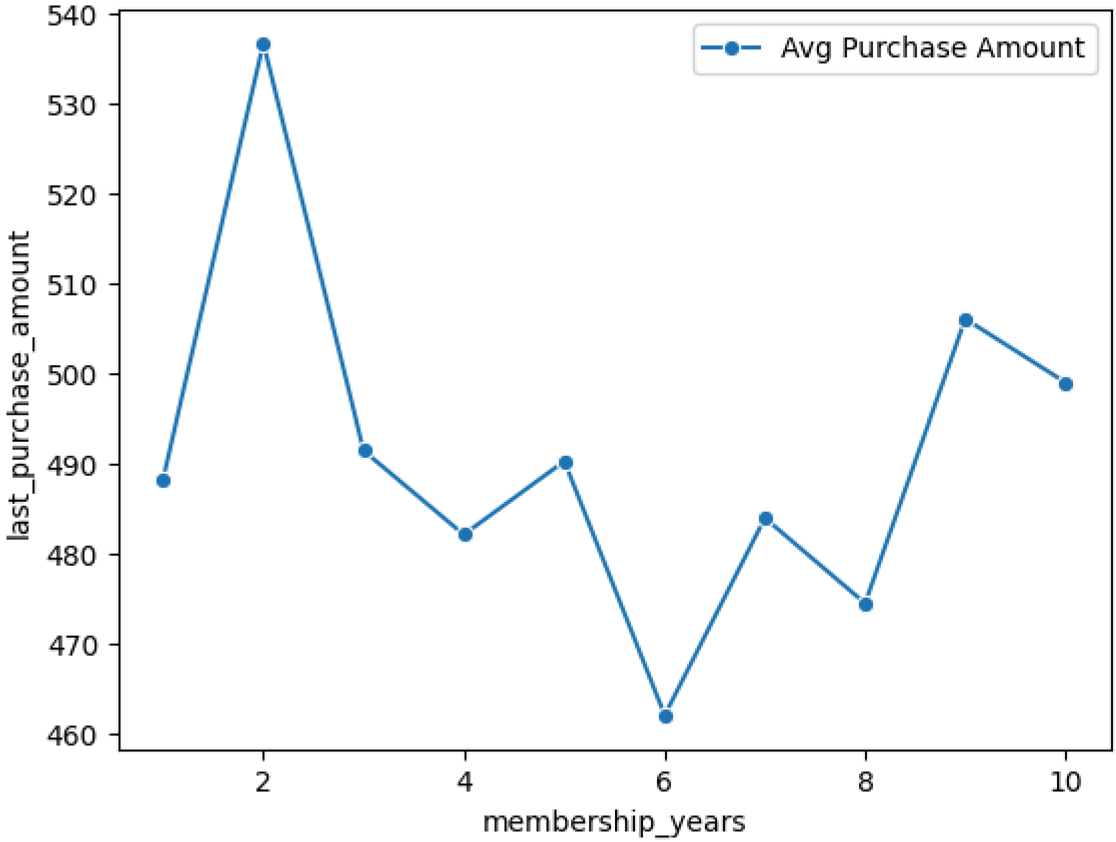


The above graph shows that females and others have the highest spending score compared to males.

In [45]:
```
# Group last purchase amount and purchase frequency by Membership years
avg_purchase = cust_data.groupby('membership_years')[['last_purchase_amount', 'purc
```

In [46]:
```
# Last purchase amount by Membership years
sns.lineplot(data=avg_purchase, x='membership_years', y='last_purchase_amount', lab
```

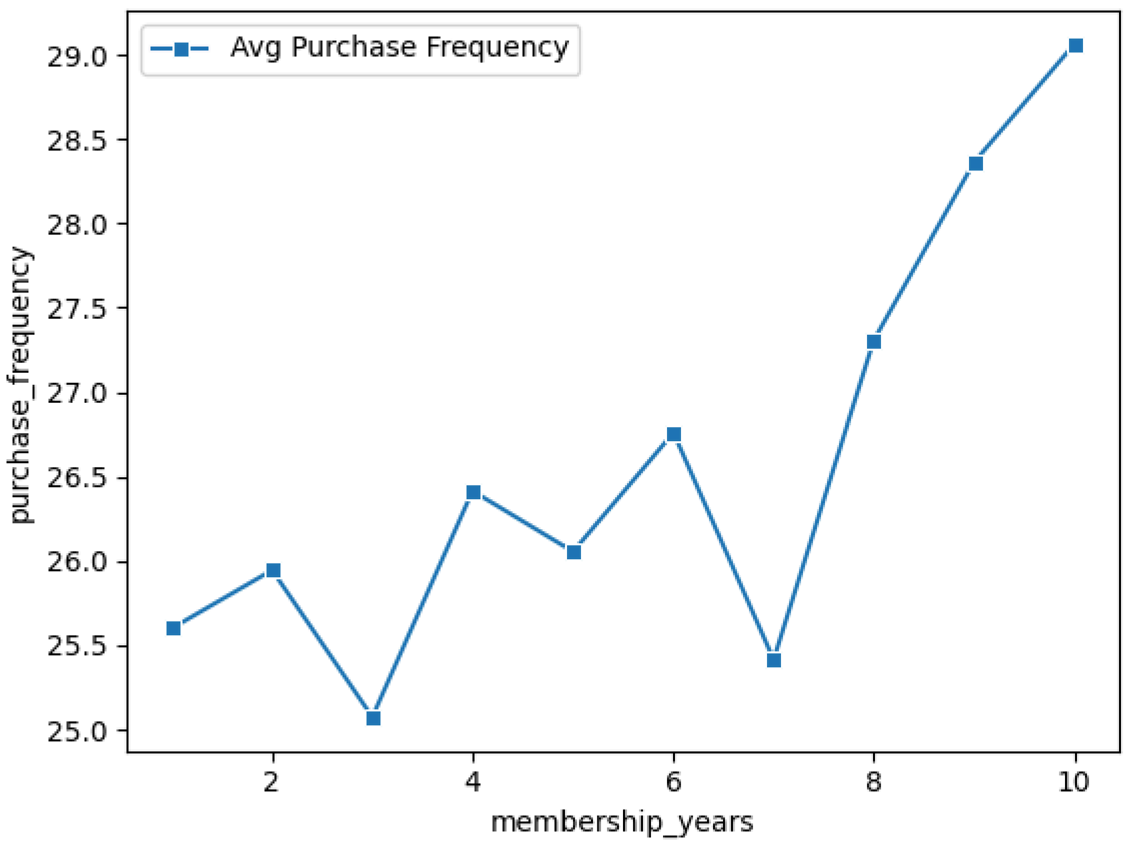
Out[46]:
```
<Axes: xlabel='membership_years', ylabel='last_purchase_amount'>
```



As we can see in the above graph, the purchase amount is higher in the 2 years of membership and lower in the 6 years.

In [47]:
```
# Purchase frequency by Membership years
sns.lineplot(data=avg_purchase, x='membership_years', y='purchase_frequency', label
```

Out[47]:
```
<Axes: xlabel='membership_years', ylabel='purchase_frequency'>
```



The above graph shows that purchase frequency increases as the membership year rises.

In [48]:
```
cust_data.drop('id', axis=1, inplace=True)
```

Encoding categorical columns

In [49]:
```
cust_encoded = cust_data.copy()
le_gender = LabelEncoder()
le_category = LabelEncoder()
cust_encoded['gender'] = le_gender.fit_transform(cust_encoded['gender'])
cust_encoded['preferred_category'] = le_category.fit_transform(cust_encoded['prefer
```

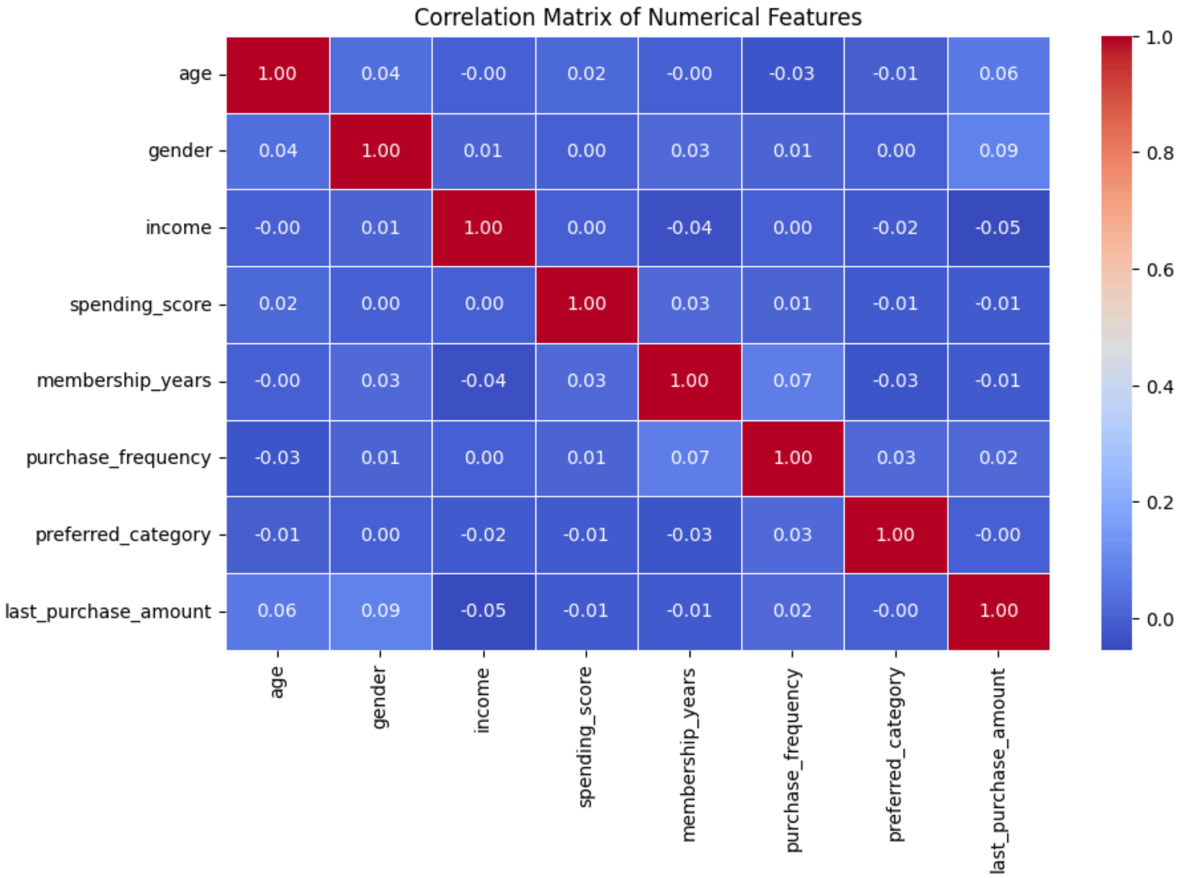
In [50]:
```
cust_encoded.head(5)
```

Out[50]:

	age	gender	income	spending_score	membership_years	purchase_frequency	preferred_catego
0	38	0	99342	90	3	24	
1	21	0	78852	60	2	42	
2	60	0	126573	30	2	28	
3	40	2	47099	74	9	5	
4	65	0	140621	21	3	25	

Correlation Matrix

In [51]:
```
correlation_matrix = cust_encoded.corr()

# Plot correlation heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=
plt.title('Correlation Matrix of Numerical Features')
plt.show()
```



The above correlation matrix show no strong correlations between any pair, indicating low multicollinearity.

Standardization

In [52]:
```
scaler = StandardScaler()
cust_scaled = scaler.fit_transform(cust_encoded)
```

In [53]:
```
cust_scaled
```

Out[53]:
```
array([[-0.38464377, -1.2609171 ,  0.31686767, ..., -0.18234781,
        -0.0510282 , -1.28154045],
       [-1.51536211, -1.2609171 , -0.28201608, ...,  1.08200524,
         1.38638595, -1.52376266],
       [ 1.07863878, -1.2609171 ,  1.11277804, ...,  0.09861954,
        -1.48844236, -0.23000511],
       ...,
       [-1.38233643, -0.01371918,  0.71890017, ...,  1.08200524,
         1.38638595, -1.41158265],
       [-1.44884927, -1.2609171 ,  0.73637858, ...,  1.22248891,
        -0.76973528,  0.04334062],
       [-0.51766946, -1.2609171 ,  0.05609457, ...,  0.30934505,
        -0.0510282 ,  0.59848958]])
```

K-Means Clustering

Elbow method

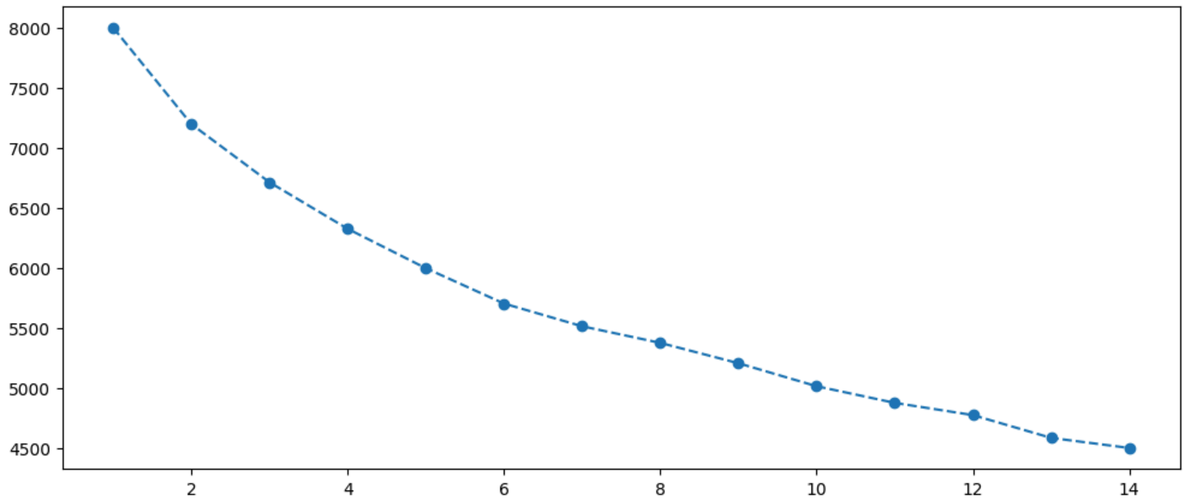
To check optimal number of clusters.

In [54]:
```
wcss = []
for i in range(1, 15):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42, max_iter=200)
    kmeans.fit(cust_scaled)
    wcss.append(kmeans.inertia_)

wcss
```

Out[54]:
```
[8000.000000000004,
 7195.881393056811,
 6711.609182912002,
 6324.081879026728,
 5995.9601407859645,
 5701.156034872316,
 5511.997742493196,
 5373.615471625279,
 5204.068567413817,
 5012.481794292014,
 4873.76827703794,
 4772.029090237208,
 4582.1949221178875,
 4498.027682434519]
```

In [55]:
```
# plotting the elbow graph
plt.figure(figsize=(12,5))
plt.plot(range(1, 15), wcss, marker='o', linestyle='--')
```

Out[55]:
```
[<matplotlib.lines.Line2D at 0x79e083d36090>]
```



The above elbow graph shows that the optimal number of clusters is usually at the "elbow point" — the value of k where the rate of WCSS reduction sharply decreases. In this graph, the elbow occurs at k = 4.

Silhoutte Score

In [56]:
```
for cluster in range(2, 15):
 kmeans = KMeans(n_clusters=cluster,init='k-means++',max_iter = 200, n_init=10)
 kmeans.fit_predict(cust_scaled)

 score = silhouette_score(cust_scaled, kmeans.labels_, metric='euclidean')
 print(f'for cluster: {cluster} --> Silhouette Score: %.3f' % score)
```

```
for cluster: 2 --> Silhouette Score: 0.099
for cluster: 3 --> Silhouette Score: 0.090
for cluster: 4 --> Silhouette Score: 0.092
for cluster: 5 --> Silhouette Score: 0.094
for cluster: 6 --> Silhouette Score: 0.097
for cluster: 7 --> Silhouette Score: 0.100
for cluster: 8 --> Silhouette Score: 0.101
for cluster: 9 --> Silhouette Score: 0.101
for cluster: 10 --> Silhouette Score: 0.102
for cluster: 11 --> Silhouette Score: 0.105
for cluster: 12 --> Silhouette Score: 0.105
for cluster: 13 --> Silhouette Score: 0.107
for cluster: 14 --> Silhouette Score: 0.107
```

The silhouette scores are all low (< 0.2), which indicates that clusters are not well-separated.

The elbow method (k = 4)

Train the K-Means with 4 clusters

In [57]:
```
kmeans = KMeans(n_clusters=4, init='k-means++', random_state=42, max_iter=200)
```

In [58]:
```
y = kmeans.fit_predict(cust_scaled)
y
```

Out[58]:
```
array([0, 0, 2, 1, 2, 1, 1, 3, 1, 0, 1, 1, 0, 1, 2, 3, 2, 0, 3, 2, 0, 3,
       2, 1, 0, 3, 1, 0, 0, 2, 1, 0, 3, 2, 1, 0, 2, 1, 0, 3, 2, 2, 0, 1,
       1, 2, 2, 0, 2, 2, 3, 0, 3, 0, 0, 1, 1, 0, 0, 0, 0, 3, 0, 0, 2, 2,
       0, 3, 2, 1, 0, 1, 0, 0, 3, 3, 1, 1, 2, 1, 3, 2, 0, 3, 2, 1, 1, 0,
       1, 1, 2, 1, 1, 3, 1, 3, 1, 1, 2, 0, 0, 0, 3, 2, 1, 3, 1, 1, 3, 0,
       2, 1, 1, 0, 2, 3, 2, 1, 3, 0, 0, 0, 1, 0, 1, 0, 1, 3, 1, 3, 1, 3,
       3, 0, 3, 3, 3, 2, 0, 0, 3, 0, 1, 0, 3, 1, 3, 0, 2, 3, 2, 0, 1, 1,
       2, 0, 0, 1, 1, 1, 2, 2, 0, 1, 2, 0, 1, 3, 0, 1, 2, 2, 3, 1, 0, 2,
       2, 2, 3, 2, 0, 3, 0, 3, 0, 3, 3, 2, 2, 1, 2, 3, 0, 1, 1, 3, 0, 3,
       0, 3, 3, 1, 2, 3, 3, 2, 1, 0, 2, 1, 0, 2, 3, 2, 2, 3, 0, 3, 1, 3,
       3, 1, 3, 0, 0, 0, 3, 1, 1, 0, 3, 3, 0, 0, 0, 1, 1, 2, 3, 3, 0, 2,
       2, 0, 2, 3, 1, 1, 3, 0, 3, 2, 2, 3, 3, 1, 2, 2, 0, 0, 3, 1, 1, 0,
       3, 1, 3, 2, 3, 0, 1, 0, 1, 2, 2, 0, 1, 1, 2, 0, 1, 1, 3, 2, 2, 2,
       2, 2, 3, 0, 0, 1, 1, 2, 3, 2, 2, 2, 1, 2, 0, 2, 0, 3, 1, 1, 2, 0,
       0, 3, 2, 3, 1, 2, 0, 0, 2, 1, 1, 0, 0, 2, 1, 3, 2, 1, 1, 3, 2, 0,
       3, 1, 2, 1, 2, 1, 2, 3, 3, 1, 1, 0, 0, 2, 3, 0, 0, 3, 1, 3, 2, 0,
       3, 1, 1, 3, 2, 2, 2, 1, 3, 3, 2, 2, 2, 3, 0, 3, 1, 0, 0, 0, 2, 1,
       0, 0, 2, 0, 0, 2, 3, 2, 2, 2, 1, 1, 3, 0, 2, 0, 2, 0, 3, 0, 3, 1,
       1, 1, 0, 2, 2, 3, 2, 0, 0, 3, 2, 3, 0, 0, 0, 1, 0, 2, 1, 1, 1, 3,
       1, 1, 0, 1, 3, 2, 2, 3, 0, 1, 0, 2, 2, 3, 3, 1, 0, 2, 1, 0, 2, 3,
       3, 0, 3, 1, 0, 1, 1, 0, 0, 1, 2, 3, 0, 2, 3, 1, 2, 1, 2, 2, 2, 0,
       1, 3, 0, 2, 2, 1, 3, 3, 1, 1, 0, 2, 3, 2, 2, 2, 3, 0, 3, 2, 0, 0,
       1, 2, 3, 3, 0, 3, 0, 3, 2, 2, 2, 0, 3, 0, 0, 1, 2, 0, 3, 3, 3, 2,
       3, 1, 2, 2, 3, 3, 0, 0, 3, 2, 2, 0, 0, 1, 2, 0, 0, 3, 0, 2, 2, 2,
       2, 2, 1, 3, 2, 2, 1, 0, 0, 1, 0, 1, 0, 2, 1, 2, 0, 1, 1, 0, 1, 0,
       0, 0, 1, 0, 1, 0, 1, 0, 3, 2, 2, 3, 2, 2, 1, 0, 3, 0, 0, 3, 0, 3,
       3, 1, 1, 2, 0, 1, 0, 2, 3, 3, 0, 3, 0, 2, 2, 1, 1, 2, 2, 0, 3, 3,
       1, 1, 3, 1, 1, 3, 3, 2, 0, 0, 3, 0, 3, 1, 1, 0, 0, 0, 1, 2, 2, 1,
       1, 2, 1, 1, 2, 3, 0, 1, 1, 3, 0, 2, 1, 2, 3, 0, 3, 3, 0, 0, 1, 0,
       1, 1, 2, 3, 3, 2, 2, 3, 2, 0, 2, 1, 0, 3, 3, 2, 1, 3, 0, 2, 3, 0,
       0, 1, 0, 1, 3, 1, 3, 0, 3, 1, 1, 3, 0, 1, 0, 0, 3, 1, 3, 3, 3, 2,
       3, 1, 3, 2, 1, 0, 1, 3, 1, 1, 2, 1, 0, 1, 0, 1, 1, 1, 3, 0, 0, 0,
       1, 0, 2, 3, 3, 0, 1, 3, 0, 2, 1, 3, 3, 2, 3, 1, 3, 2, 0, 2, 3, 3,
       3, 1, 1, 3, 0, 1, 1, 1, 3, 3, 2, 3, 2, 2, 0, 1, 2, 3, 3, 1, 0, 0,
       0, 1, 1, 2, 2, 1, 1, 3, 2, 0, 2, 3, 2, 3, 2, 2, 2, 2, 1, 2, 0, 1,
       1, 0, 0, 1, 0, 2, 1, 0, 1, 1, 2, 3, 1, 1, 3, 0, 1, 0, 0, 2, 0, 3,
       2, 2, 0, 1, 2, 1, 2, 2, 1, 2, 2, 0, 0, 3, 0, 2, 3, 3, 0, 1, 1, 3,
       0, 3, 2, 2, 1, 1, 1, 0, 1, 0, 0, 3, 1, 0, 3, 2, 0, 1, 3, 3, 0, 1,
       0, 2, 2, 0, 3, 0, 2, 3, 0, 1, 2, 2, 0, 2, 1, 0, 2, 0, 0, 2, 3, 2,
       3, 1, 2, 3, 1, 3, 2, 0, 1, 2, 0, 2, 3, 1, 2, 2, 3, 3, 2, 0, 2, 2,
       2, 1, 2, 0, 3, 3, 2, 2, 2, 1, 3, 1, 0, 1, 2, 2, 3, 2, 2, 1, 3, 0,
       1, 2, 2, 3, 2, 3, 0, 1, 0, 1, 0, 3, 1, 3, 1, 0, 1, 1, 3, 2, 2, 2,
       1, 0, 1, 3, 0, 3, 1, 1, 2, 2, 2, 2, 0, 1, 1, 0, 1, 1, 2, 1, 1, 3,
       3, 2, 2, 2, 3, 0, 3, 2, 1, 1, 1, 0, 0, 1, 0, 3, 3, 2, 1, 3, 0, 0,
       1, 0, 0, 3, 3, 1, 0, 1, 2, 0, 0, 3, 2, 1, 3, 1, 1, 1, 3, 2, 0, 1,
       2, 1, 3, 0, 1, 2, 1, 3, 3, 0], dtype=int32)
```

The clusters have been formed.

Customer Segmentation

In [59]:
```
cust_data['Cust_Segment'] = y
```

In [60]:
```
cust_data.head(10)
```

Out[60]:

	age	gender	income	spending_score	membership_years	purchase_frequency	preferred_catego
0	38	Female	99342	90	3	24	Groceri
1	21	Female	78852	60	2	42	Spo
2	60	Female	126573	30	2	28	Clothi
3	40	Other	47099	74	9	5	Home & Gard
4	65	Female	140621	21	3	25	Electron
5	31	Other	57305	24	3	30	Home & Gard
6	19	Other	54319	68	5	43	Clothi
7	43	Male	108115	94	9	27	Groceri
8	53	Male	34424	29	6	7	Spo
9	55	Female	45839	55	7	2	Electron

Customer Profile

In [61]:
```
customer_profile = cust_data.groupby('Cust_Segment').agg({
    'spending_score': 'mean',
    'age': 'mean',
    'income': 'mean',
    'spending_score': 'mean',
    'membership_years': 'mean',
    'purchase_frequency': 'mean',
    'last_purchase_amount': 'mean'
})
```

In [62]:
```
customer_profile
```

Out[62]:

Cust_Segment	spending_score	age	income	membership_years	purchase_frequency
0	50.755814	39.267442	67717.155039	4.821705	22.236434
1	47.693487	49.038314	60334.417625	6.183908	26.030651
2	50.836000	45.328000	116729.668000	2.876000	25.384000
3	53.822511	41.216450	112987.333333	8.190476	33.415584

In [63]:
```
cust_data['Cust_Segment'].value_counts()
```

Out[63]:

Cust_Segment	count
1	261
0	258
2	250
3	231

dtype: int64

Insights

The 4 clusters were formed by KMeans Clustering:

- Cluster 0 (258 customers) have mid-income, moderate spending score, relatively younger, medium tenure. Balanced customer group.
- Cluster 1 (261 customers) lower income but high last purchase amount, older 50s, with longer membership. Likely loyal & committed customers.
- Cluster 2 (250 customers) high income, customer average age upto 45, shorter tenure but decent frequency, high-potential spenders.
- Cluster 3 (231 customers) higher spending score, highest purchase frequency, older customers, longest tenure. Most engaged and loyal segment.

Hierarchical Clustering

In [64]:

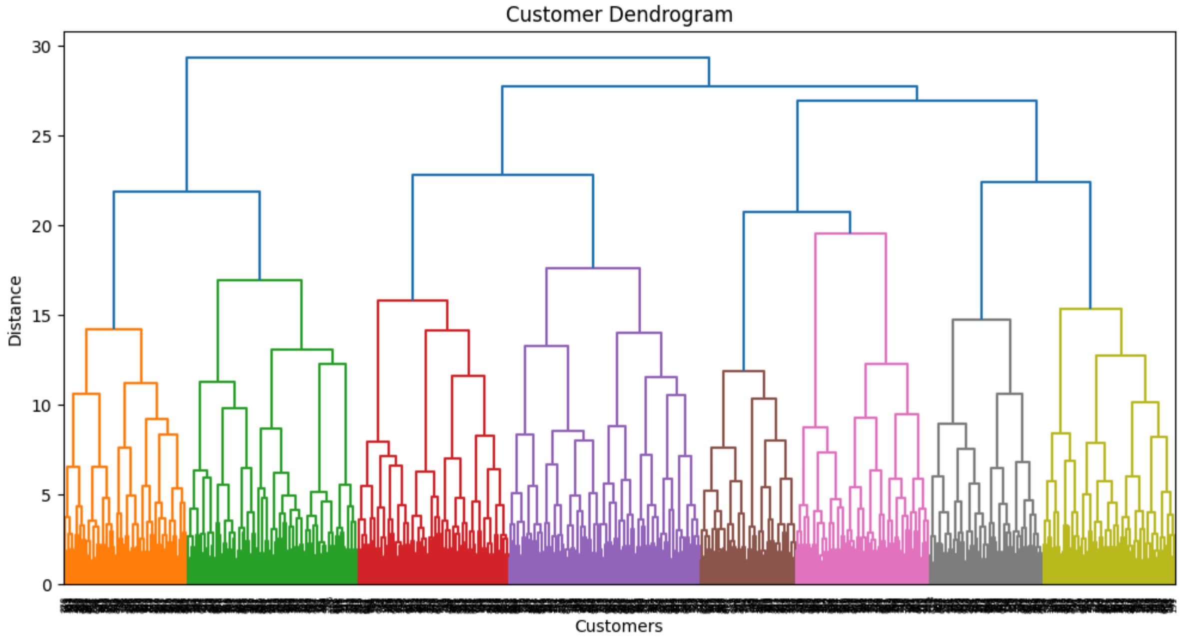
```
for i in range(2, 20):
    hc = AgglomerativeClustering(n_clusters=i, metric = 'euclidean', linkage='compl
    y1 = hc.fit_predict(cust_scaled)

    score = silhouette_score(cust_scaled, y1, metric='euclidean')
    print(f'for cluster: {i} --> Silhouetter Score: %.3f' % score)
```

```
for cluster: 2 --> Silhouetter Score: 0.047
for cluster: 3 --> Silhouetter Score: 0.030
for cluster: 4 --> Silhouetter Score: 0.012
for cluster: 5 --> Silhouetter Score: 0.012
for cluster: 6 --> Silhouetter Score: 0.011
for cluster: 7 --> Silhouetter Score: 0.015
for cluster: 8 --> Silhouetter Score: 0.023
for cluster: 9 --> Silhouetter Score: 0.031
for cluster: 10 --> Silhouetter Score: 0.032
for cluster: 11 --> Silhouetter Score: 0.031
for cluster: 12 --> Silhouetter Score: 0.029
for cluster: 13 --> Silhouetter Score: 0.034
for cluster: 14 --> Silhouetter Score: 0.035
for cluster: 15 --> Silhouetter Score: 0.037
for cluster: 16 --> Silhouetter Score: 0.034
for cluster: 17 --> Silhouetter Score: 0.036
for cluster: 18 --> Silhouetter Score: 0.036
for cluster: 19 --> Silhouetter Score: 0.037
```

The silhouette scores are all low (< 0.2), which indicates that clusters are not well-separated. K=2

In [65]:
```
# Hierarchical Clustering with 2 clusters
hc = AgglomerativeClustering(n_clusters=2, metric = 'euclidean', linkage='complete'
y_hc = hc.fit_predict(cust_scaled)
```

In [66]:
```
linkage_matrix = linkage(cust_scaled, method='ward')
plt.figure(figsize=(12, 6))
dendrogram(linkage_matrix)
plt.title('Customer Dendrogram')
plt.xlabel('Customers')
plt.ylabel('Distance')
plt.show()
```



In [67]:
```
cust_data['Agglo_Segment'] = y_hc
```

In [68]:
```
customer_profile_agglo = cust_data.groupby('Agglo_Segment').agg({
    'spending_score': 'mean',
    'age': 'mean',
    'income': 'mean',
    'spending_score': 'mean',
    'membership_years': 'mean',
    'purchase_frequency': 'mean',
    'last_purchase_amount': 'mean'
})
```

In [69]:
```
customer_profile_agglo
```

Out[69]:

	spending_score	age	income	membership_years	purchase_frequency
Agglo_Segment					
0	55.363806	45.692164	87057.927239	5.845149	29.149254
1	45.280172	41.577586	90167.566810	5.034483	23.646552

In [70]:
```
cust_data['Agglo_Segment'].value_counts()
```

Out[70]:

	count
Agglo_Segment	
0	536
1	464

dtype: int64

Insights

The 2 clusters by hierarchical clustering shows:

- Cluster 0 (536 customers) average age 55, lower spending score, more frequent purchases. .
- Cluster 1 (464 customers) higher spending score, higher last purchase, average age 45.

Key Insights

- Customers with high tenure & frequency are loyal — prioritize with retention offers and rewards.
- Newer high-income customers could become loyal high spenders — nurture with personalization.
- Some customers purchase frequently but spend less — introduce bundled offers or loyalty programs.

Conclusion

This customer segmentation successfully used both K-Means and Hierarchical Clustering to uncover meaningful behavioral segments. The K-Means model, with 4 well-differentiated clusters, offers a detailed foundation for personalized marketing.

Recommendations

- For customer retention, focus on VIP rewards and long-term benefit schemes.
- Target with premium options, limited-time deals.
- Use profiles for personalized emails, product recommendations, and dynamic pricing strategies.

RFM Analysis

Recency, Frequency and Monetary Analysis

- Recency: Customers made a purchase recently. In this data, we can assume 'membership years'.
- Frequency: Customers who often make purchases. In this data, we have 'purchase frequency' from which we can map the frequency.
- Monetary: Customers spend on their purchases. In this data, we can take the 'last purchase amount' multiplied by 'purchase frequency'.

In [71]:
```
cust_data1 = pd.read_csv('/content/customer_segmentation_data.csv')
```

In [72]:
```
cust_data1.describe()
```

Out[72]:

	id	age	income	spending_score	membership_years	purchase_freq
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.00000	1000.0
mean	500.500000	43.783000	88500.800000	50.685000	5.46900	26.5
std	288.819436	15.042213	34230.771122	28.955175	2.85573	14.2
min	1.000000	18.000000	30004.000000	1.000000	1.00000	1.0
25%	250.750000	30.000000	57911.750000	26.000000	3.00000	15.0
50%	500.500000	45.000000	87845.500000	50.000000	5.00000	27.0
75%	750.250000	57.000000	116110.250000	76.000000	8.00000	39.0
max	1000.000000	69.000000	149973.000000	100.000000	10.00000	50.0

In [73]:
```
# Year for recency calculation
Year = 2024

# Recency
cust_data1['Recency'] = Year - cust_data1['membership_years']

# Frequency
cust_data1['Frequency'] = cust_data1['purchase_frequency']

# Monetary
cust_data1['Monetary'] = cust_data1['last_purchase_amount']*cust_data1['purchase_fr

rfm_data = cust_data1[['id','Recency','Frequency','Monetary']]
```

In [74]:
```
rfm_data.head(5)
```

Out[74]:

	id	Recency	Frequency	Monetary
0	1	2021	24	2724.72
1	2	2022	42	1761.06
2	3	2022	28	11882.08
3	4	2015	5	4959.65
4	5	2021	25	8677.00

In [75]:
```
# Quantiles
quantiles = rfm_data.quantile(q=[0.25,0.5,0.75])
```

In [76]:
```
# Score based on quantiles
def R_Score(x, p, d):
    if x <= d[p][0.25]:
        return 1
    elif x <= d[p][0.5]:
        return 2
    elif x <= d[p][0.75]:
        return 3
    else:
        return 4

def F_M_Score(x, p, d):
    if x <= d[p][0.25]:
        return 4
    elif x <= d[p][0.5]:
        return 3
    elif x <= d[p][0.75]:
        return 2
    else:
        return 1

rfm_data['R'] = rfm_data['Recency'].apply(R_Score, args=('Recency', quantiles,))
rfm_data['F'] = rfm_data['Frequency'].apply(F_M_Score, args=('Frequency', quantiles
rfm_data['M'] = rfm_data['Monetary'].apply(F_M_Score, args=('Monetary', quantiles,)
```

In [77]:
```
# RFM Segement
rfm_data['RFM_Segment'] = rfm_data['R'].astype(str)+rfm_data['F'].astype(str)+rfm_d
```

In [78]:
```
# Add the RFM Score
rfm_data['RFM_Segment'] = rfm_data[['R','F','M']].sum(axis=1)
```

In [79]:
```
rfm_data.head(5)
```

Out[79]:

	id	Recency	Frequency	Monetary	R	F	M	RFM_Segment
0	1	2021	24	2724.72	3	3	4	10
1	2	2022	42	1761.06	4	1	4	9
2	3	2022	28	11882.08	4	2	2	8
3	4	2015	5	4959.65	1	4	3	8
4	5	2021	25	8677.00	3	3	3	9

In [80]:
```
rfm_data['RFM_Segment'].unique()
```

Out[80]:
```
array([10,  9,  8,  6,  7, 11,  3,  5, 12,  4])
```

In [81]:
```
# Segmentation
segment_labels = ['Low_Value', 'Mid_Value', 'High_Value']

def assign_segment(x):
    if x < 5:
        return 'High_Value'
    elif x < 9:
        return 'Mid_Value'
    else:
```

```
        return 'Low_Value'

rfm_data['Segment_Label'] = rfm_data['RFM_Segment'].apply(assign_segment)
rfm_data.head(5)
```

Out[81]:

	id	Recency	Frequency	Monetary	R	F	M	RFM_Segment	Segment_Label
0	1	2021	24	2724.72	3	3	4	10	Low_Value
1	2	2022	42	1761.06	4	1	4	9	Low_Value
2	3	2022	28	11882.08	4	2	2	8	Mid_Value
3	4	2015	5	4959.65	1	4	3	8	Mid_Value
4	5	2021	25	8677.00	3	3	3	9	Low_Value

In [82]:
```
rfm_data['Segment_Label'].value_counts()
```

Out[82]:

Segment_Label	count
Mid_Value	546
Low_Value	329
High_Value	125

dtype: int64

In [83]:
```
# To plot the graph of the segment
segment_count = rfm_data['Segment_Label'].value_counts().reset_index()
segment_count.columns = ['RFM Segment', 'Count']
segment_count
```

Out[83]:

	RFM Segment	Count
0	Mid_Value	546
1	Low_Value	329
2	High_Value	125

In [84]:
```
fig = px.bar(segment_count,
             x = 'RFM Segment',
             y = 'Count',
             color = 'RFM Segment',
             title='Customer Segments',
             color_discrete_map={'High_Value':'green', 'Mid_Value':'skyblue', 'Low_
            )
fig.show()
```

- High value i.e. customers who are frequent and recent are less as compared to those of mid and low value.
- From the above graph, we can say that more customers fall in the mid value, i.e., they have a good RFM score but might not be frequent or recent.
- Low value i.e. customers who need attention, are more.

In [85]:
```
# Further creating more segments to analyze in depth
rfm_data['RFM_Customer_Segments'] = ' '

rfm_data.loc[rfm_data['RFM_Segment'] == 3, 'RFM_Customer_Segments'] = 'VIP/Potentia
rfm_data.loc[(rfm_data['RFM_Segment'] >= 4) & (rfm_data['RFM_Segment'] <= 6), 'RFM_
rfm_data.loc[(rfm_data['RFM_Segment'] >= 7) & (rfm_data['RFM_Segment'] <= 8), 'RFM_
rfm_data.loc[(rfm_data['RFM_Segment'] >= 9) & (rfm_data['RFM_Segment'] <= 10), 'RFM
rfm_data.loc[(rfm_data['RFM_Segment'] >= 11) & (rfm_data['RFM_Segment'] <= 12), 'RF
```

In [86]:
```
# To plot the graph
segment_count1 = rfm_data['RFM_Customer_Segments'].value_counts().reset_index()
segment_count1.columns = ['RFM Segment', 'Count']
segment_count1
```

Out[86]:

	RFM Segment	Count
0	Loyal Customers	326
1	Need Attention	293
2	At Risk	232
3	Lost Customers	97
4	VIP/Potential Customers	52

In [87]:
```
fig = px.bar(segment_count1,
             x = 'RFM Segment',
             y = 'Count',
             color = 'RFM Segment',
             title='Customer Segments',
            )
fig.show()
```

In [88]:
```
# To plot a treemap
segment_product_counts = rfm_data.groupby(['Segment_Label','RFM_Customer_Segments']
segment_product_counts = segment_product_counts.sort_values('Count', ascending=Fals
segment_product_counts
```

Out[88]:

	Segment_Label	RFM_Customer_Segments	Count
5	Mid_Value	Need Attention	293
4	Mid_Value	Loyal Customers	253
2	Low_Value	At Risk	232
3	Low_Value	Lost Customers	97
0	High_Value	Loyal Customers	73
1	High_Value	VIP/Potential Customers	52

In [89]:

```
fig = px.treemap(segment_product_counts,
                 path=['Segment_Label','RFM_Customer_Segments'], values='Count',
                 color = 'Segment_Label',
                 color_discrete_map={'High_Value':'green', 'Mid_Value':'skyblue', '
                 title='RFM Customer Segments by Value',
                )
fig.show()
```

Insights

- High Value: Loyal and VIP Customers should be prioritized with retention and loyalty programs
- Mid Value: Need Attention or moderately engaged, ideal for reactivation and nurturing strategies

- Low Value: At Risk and Lost Customers focus on cost-effective recovery or minimal targeting

Conclusions

- The customer base is highly diverse, with significant differences in income, engagement, and recency.
- A large proportion of customers are moderately active but at risk of churn, as indicated by RFM and clustering.
- High-value customers, though fewer in number, contribute disproportionately to spending — essential to retain.
- Clustering helped identify actionable customer segments beyond simple demographics.

Recommendations

- Retention & Loyalty focus on VIPs and loyal customers for loyalty programs, rewards, and personalized offers. Introduce early access, referral bonuses, or tiered benefits to deepen engagement.
- Target “Need Attention” and “At Risk” customers with re-engagement emails, Limited-time discounts, and Feedback surveys to understand disengagement.