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Data Mining II - D212
Task 1: Clustering Techniques
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Part I: Research Question
A1. Research Question

I will use hierarchical clustering within the WGU Medical Dataset to look at the survey responses, Items 1 - 8, to determine if there are distinct groups of patient satisfaction.

A2. Goal of the Data Analysis

I am using hierarchical clustering to help determine distinct groups of patients within the survey data. The goal of this analysis is to determine if there are patient populations that are disproportionately satisfied or dissatisfied with their experience in the hospital system.

Part II: Explain the reasons for your chosen clustering technique from part A1 by doing the following:

B1. Explain how the clustering technique you chose analyzes the selected dataset. Include expected outcomes.

Hierarchical clustering is a technique that builds hierarchies of clusters. How it works is by taking observations to generate clusters that have hierarchical relationships. Eventually all data will be related to each other at the highest level. At lower levels clusters are built by groups of observations that are close to one another, and so on and so forth, until you have numerous small clusters. A great real world example of this is how animals are classified in cladograms. All living things fall under 3 domains or 'clusters', those are Bacteria, Archaea, and Eukaryota. From there other clusters are built based on similarities within groups. Living things that have similar features will be grouped together and form different heirarchies of organization.

The expected outcome of this analysis is to hopefully find distrinct group of patients within the survey data. This can then hopefully be compared to patient re-admissions and used to find trends in patient experience and re-admission rate. This project is just focused on the first part of the analysis.

B2. Summarize one assumption of the clustering technique.

One of the assumptions that we have to take into account with hierachical clustering techniques is that variables that have a larger range can dominate variables that have a smaller range. To get around this we can use 'scaling' to normalize the data when using this clustering technique. However, because I am using the survey data, all data is already normalized as being 1-8 so this step can be skipped in this analysis.

B3. List the packages or libraries you have chosen for Python or R, and justify how each item on the list supports the analysis.

Packages	Usage
Pandas	Importing data and data manipulation
Numpy	Provides array objects for calculations
Seaborn	For visualizations like ...
Matplotlib.pyplot	For visualizations like ...
scipy.cluster.hierarchy	For linkage and clusters functions, as well and dendrogram generation
sklearn.metrics	For silhouette score to determine how close the clusters are

In [45]:
```python
# Data Analytics imports
import pandas as pd
import numpy as np

# Visualization imports
import matplotlib.pyplot as plt
import seaborn as sns

# Clustering imports
from scipy.cluster.hierarchy import linkage, fcluster
from scipy.cluster.hierarchy import dendrogram
from sklearn.metrics import silhouette_score
```

Part III: Data Preparation

C. Perform data preparation for the chosen dataset by doing the following

C1. Describe one data preprocessing goal relevant to the clustering technique from part A1.

After exploring the data and checking for outliers and missing data the only preprocessing that needed to be done was inverting our survey data. According to the data dictionary provided by WGU, the survey data defines 1 as being most important and 8 as being least important. This doesn't make sense from a data standpoint. I want larger numbers to carry more 'weight' so to speak so I will be inverting our data using a .map command, as well as recasting our data to float so as to use in the linkage command. When using this data as an int type the linkage analysis technique does not work.

C2. Identify the initial dataset variables that you will use to perform the analysis for the clustering question from part A1, and label each as continuous or categorical.

In this analysis we are only focusing on the eight survey results column.

Column Name	Data Type
Item1	Categorical/Qualitative
Item2	Categorical/Qualitative
Item3	Categorical/Qualitative
Item4	Categorical/Qualitative
Item5	Categorical/Qualitative
Item6	Categorical/Qualitative
Item7	Categorical/Qualitative
Item8	Categorical/Qualitative

Though these columns contain data that are numerical, it still qualifies as categorical or qualitative data as the numbers are essentially placeholders to determine how important the topic of the question is to the patient. Because these numbers have a specific range it is not continuous and has to be categorical.

C3. Explain each of the steps used to prepare the data for the analysis. Identify the code segment for each step.

Comments on each code segment below are meant to identify the code segment for each step of my data preparation.

In [3]:
```
#Loading the CSV of the default dataset
df = pd.read_csv(r'C:\Users\mmorg\WGU\D212\medical_clean.csv')
```

In [4]:
```
#Viewing Data to evaluate structure and types
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 50 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   CaseOrder           10000 non-null  int64  
 1   Customer_id         10000 non-null  object 
 2   Interaction         10000 non-null  object 
 3   UID                 10000 non-null  object 
 4   City                10000 non-null  object 
 5   State               10000 non-null  object 
 6   County              10000 non-null  object 
 7   Zip                 10000 non-null  int64  
 8   Lat                 10000 non-null  float64
 9   Lng                 10000 non-null  float64
 10  Population          10000 non-null  int64  
 11  Area                10000 non-null  object 
 12  TimeZone            10000 non-null  object 
 13  Job                 10000 non-null  object 
 14  Children            10000 non-null  int64  
 15  Age                 10000 non-null  int64  
 16  Income              10000 non-null  float64
 17  Marital             10000 non-null  object 
 18  Gender              10000 non-null  object 
 19  ReAdmis             10000 non-null  object 
 20  VitD_levels         10000 non-null  float64
 21  Doc_visits          10000 non-null  int64  
 22  Full_meals_eaten    10000 non-null  int64  
 23  vitD_supp           10000 non-null  int64  
 24  Soft_drink          10000 non-null  object 
 25  Initial_admin       10000 non-null  object 
 26  HighBlood           10000 non-null  object 
 27  Stroke              10000 non-null  object 
 28  Complication_risk   10000 non-null  object 
 29  Overweight          10000 non-null  object 
 30  Arthritis           10000 non-null  object 
 31  Diabetes            10000 non-null  object 
 32  Hyperlipidemia      10000 non-null  object 
 33  BackPain            10000 non-null  object 
 34  Anxiety             10000 non-null  object 
 35  Allergic_rhinitis   10000 non-null  object 
 36  Reflux_esophagitis  10000 non-null  object 
 37  Asthma              10000 non-null  object 
```

```
 38  Services            10000 non-null  object 
 39  Initial_days        10000 non-null  float64
 40  TotalCharge         10000 non-null  float64
 41  Additional_charges  10000 non-null  float64
 42  Item1               10000 non-null  int64  
 43  Item2               10000 non-null  int64  
 44  Item3               10000 non-null  int64  
 45  Item4               10000 non-null  int64  
 46  Item5               10000 non-null  int64  
 47  Item6               10000 non-null  int64  
 48  Item7               10000 non-null  int64  
 49  Item8               10000 non-null  int64  
dtypes: float64(7), int64(16), object(27)
memory usage: 3.8+ MB
```

In [5]:
```
#Detect null values
print(df.isnull().sum())
```

```
CaseOrder             0
Customer_id           0
Interaction           0
UID                   0
City                  0
State                 0
County                0
Zip                   0
Lat                   0
Lng                   0
Population            0
Area                  0
TimeZone              0
Job                   0
Children              0
Age                   0
Income                0
Marital               0
Gender                0
ReAdmis               0
VitD_levels           0
Doc_visits            0
Full_meals_eaten      0
vitD_supp             0
Soft_drink            0
Initial_admin         0
HighBlood             0
Stroke                0
Complication_risk     0
Overweight            0
Arthritis             0
Diabetes              0
Hyperlipidemia        0
BackPain              0
Anxiety               0
Allergic_rhinitis     0
Reflux_esophagitis    0
Asthma                0
Services              0
Initial_days          0
TotalCharge           0
Additional_charges    0
Item1                 0
```

```
Item2          0
Item3          0
Item4          0
Item5          0
Item6          0
Item7          0
Item8          0
dtype: int64
```

In [6]:
```
# Look at what type of data is in each column and the name of the columns
df.head()
```

Out[6]:

	CaseOrder	Customer_id	Interaction	UID	City	State	County	Zip	Lat	Lng
0	1	C412403	8cd49b13-f45a-4b47-a2bd-173ffa932c2f	3a83ddb66e2ae73798bdf1d705dc0932	Eva	AL	Morgan	35621	34.34960	-86.72508
1	2	Z919181	d2450b70-0337-4406-bdbb-bc1037f1734c	176354c5eef714957d486009feabf195	Marianna	FL	Jackson	32446	30.84513	-85.22907
2	3	F995323	a2057123-abf5-4a2c-abad-8ffe33512562	e19a0fa00aeda885b8a436757e889bc9	Sioux Falls	SD	Minnehaha	57110	43.54321	-96.63772
3	4	A879973	1dec528d-eb34-4079-adce-0d7a40e82205	cd17d7b6d152cb6f23957346d11c3f07	New Richland	MN	Waseca	56072	43.89744	-93.51479
4	5	C544523	5885f56b-d6da-43a3-8760-83583af94266	d2f0425877b10ed6bb381f3e2579424a	West Point	VA	King William	23181	37.59894	-76.88958

5 rows × 50 columns

In [7]:
```
# See how many rows and columns are present
df.shape
```

Out[7]: (10000, 50)

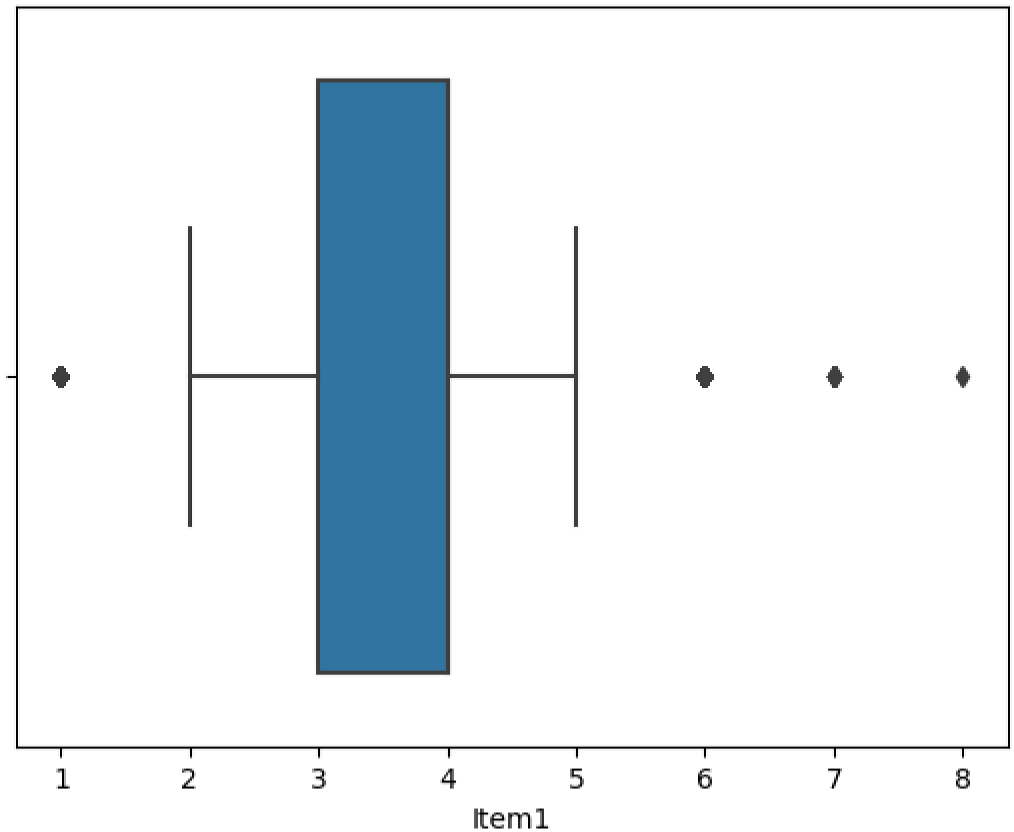
In [8]:
```
# Change dataframe to only include variables used for analysis
df=df[['Item1', 'Item2', 'Item3', 'Item4', 'Item5', 'Item6', 'Item7', 'Item8']]
```

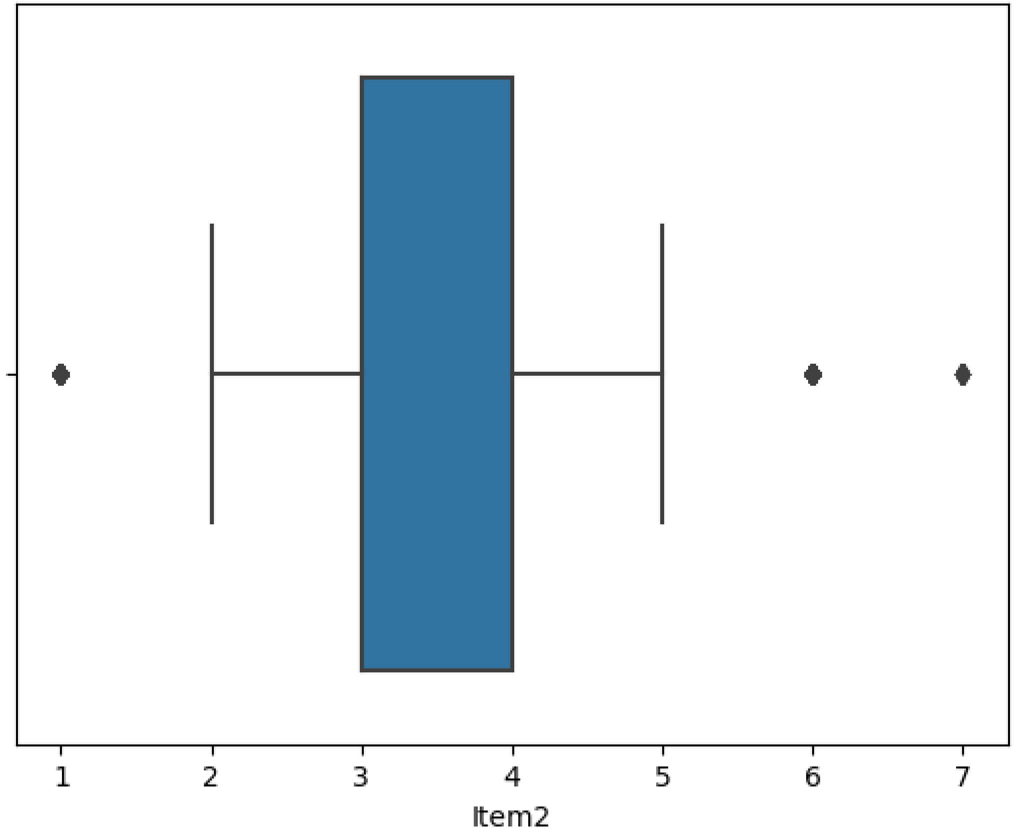
In [9]:
```
# Pull .head again to make sure the new dataframe is correct
df.head()
```

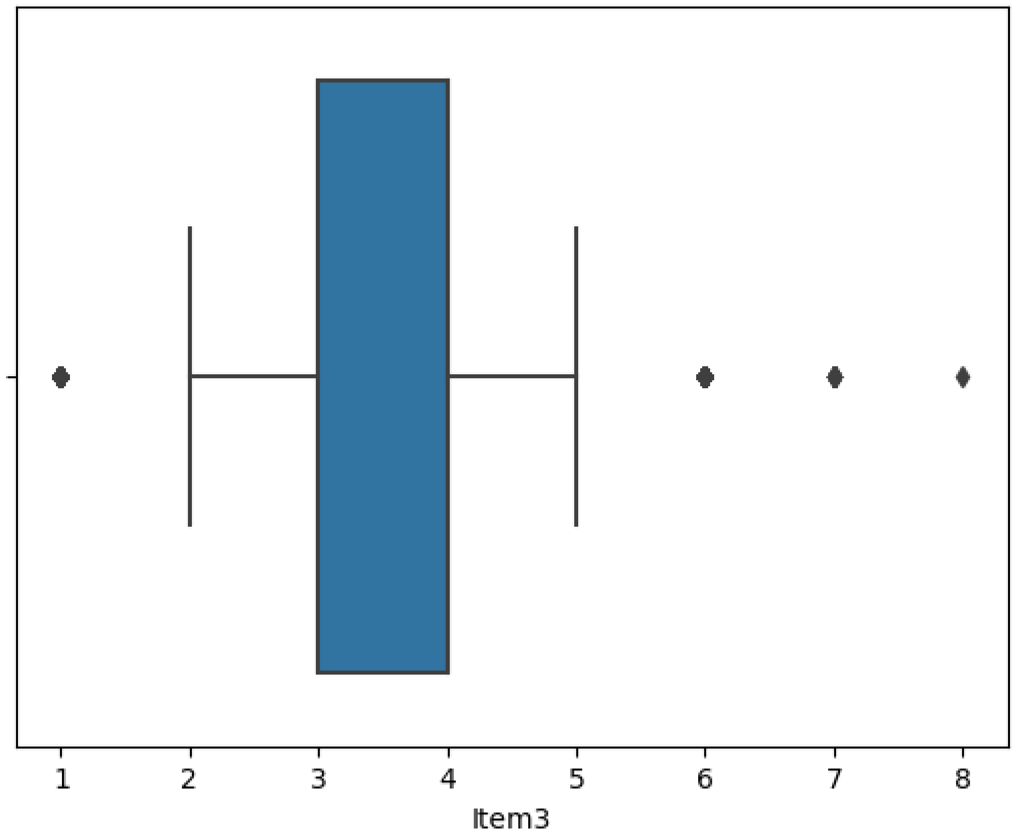
Out[9]:

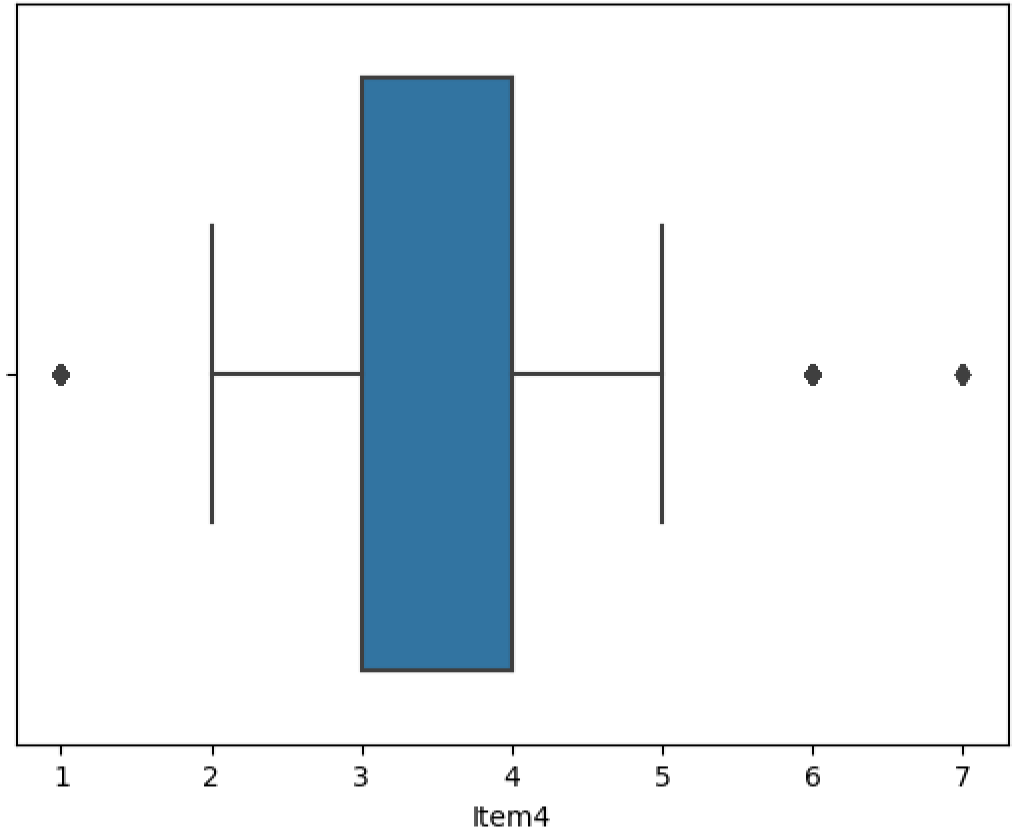
	Item1	Item2	Item3	Item4	Item5	Item6	Item7	Item8
0	3	3	2	2	4	3	3	4
1	3	4	3	4	4	4	3	3
2	2	4	4	4	3	4	3	3
3	3	5	5	3	4	5	5	5
4	2	1	3	3	5	3	4	3

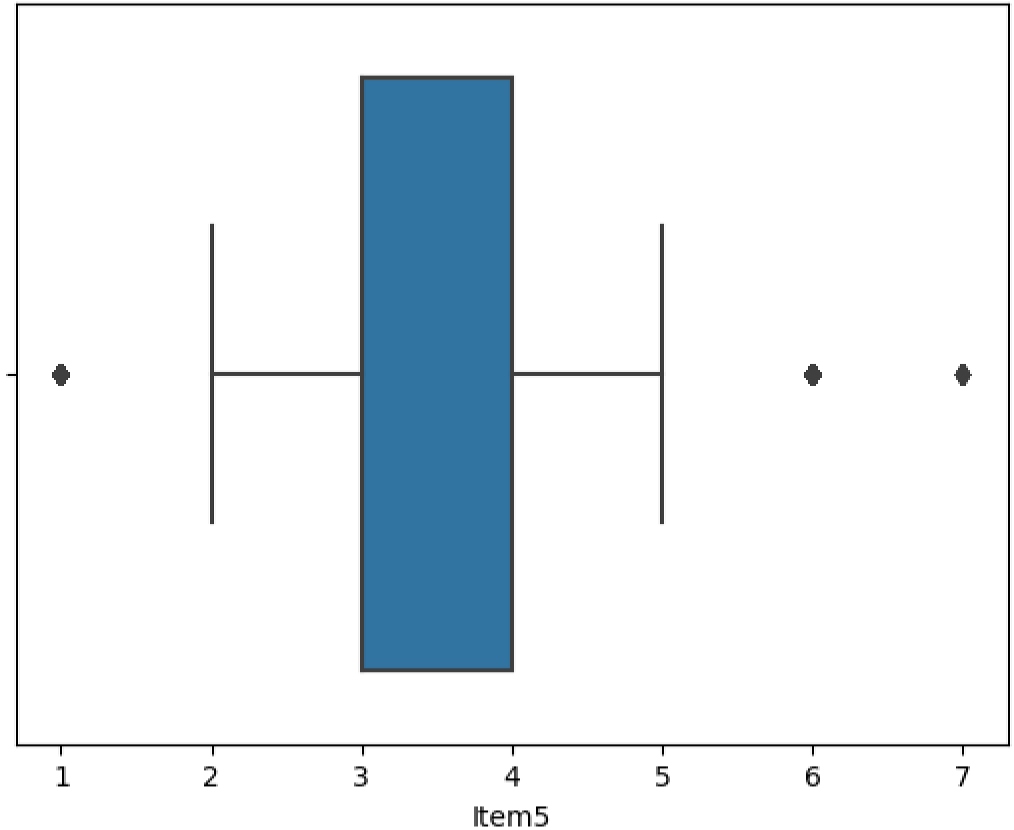
In [10]:
```
#Detection of outliers for quantitative values
boxplot=sns.boxplot(x='Item1',data=df)
plt.show()
boxplot=sns.boxplot(x='Item2',data=df)
plt.show()
boxplot=sns.boxplot(x='Item3',data=df)
plt.show()
boxplot=sns.boxplot(x='Item4',data=df)
plt.show()
boxplot=sns.boxplot(x='Item5',data=df)
plt.show()
boxplot=sns.boxplot(x='Item6',data=df)
plt.show()
boxplot=sns.boxplot(x='Item7',data=df)
plt.show()
boxplot=sns.boxplot(x='Item8',data=df)
plt.show()
```

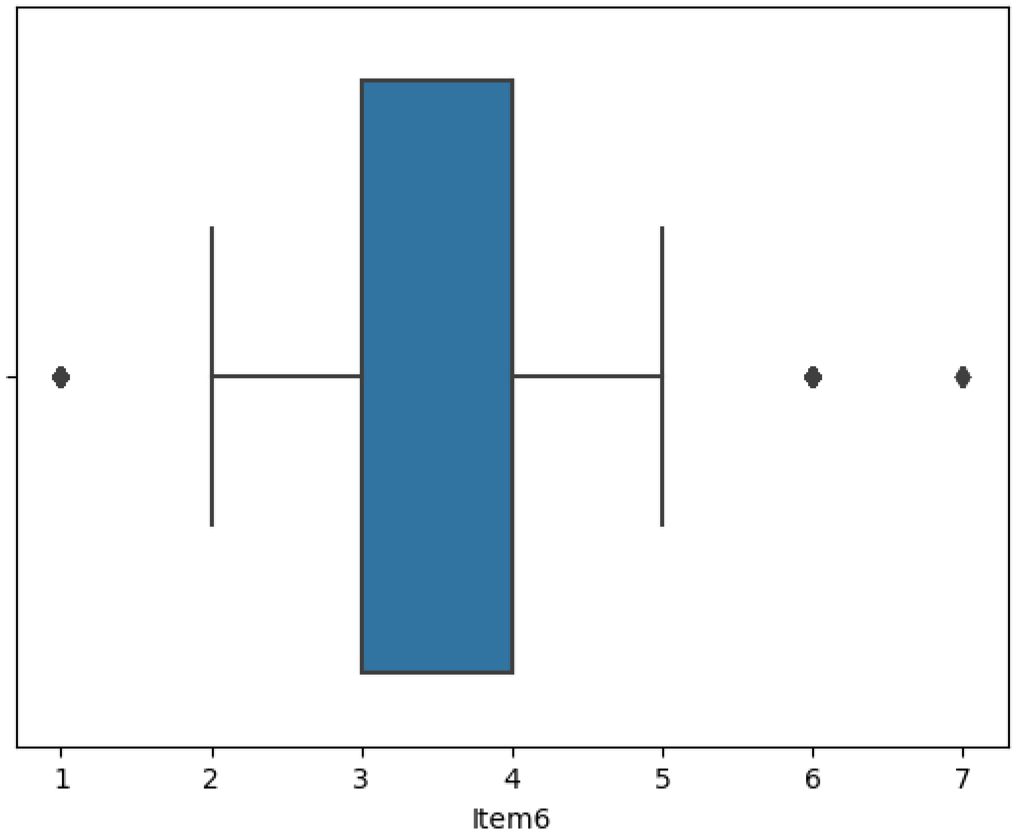

1
2
3
4
5
6
7
8
Item1

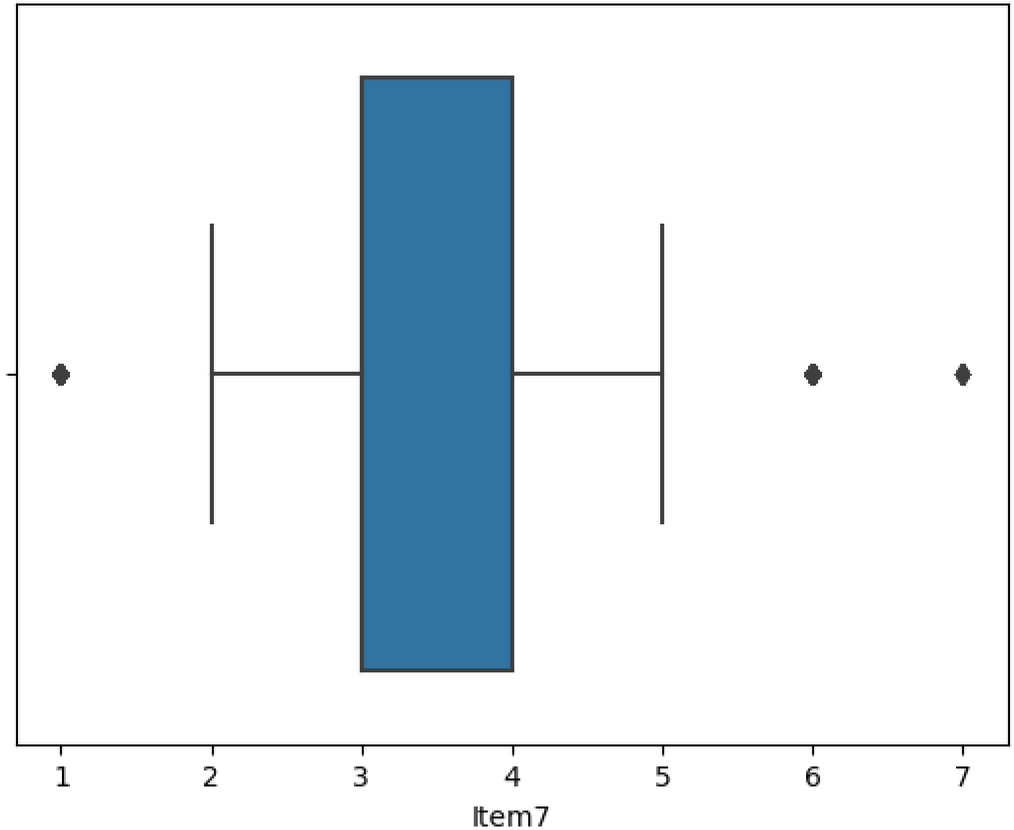

1
2
3
4
5
6
7
Item2

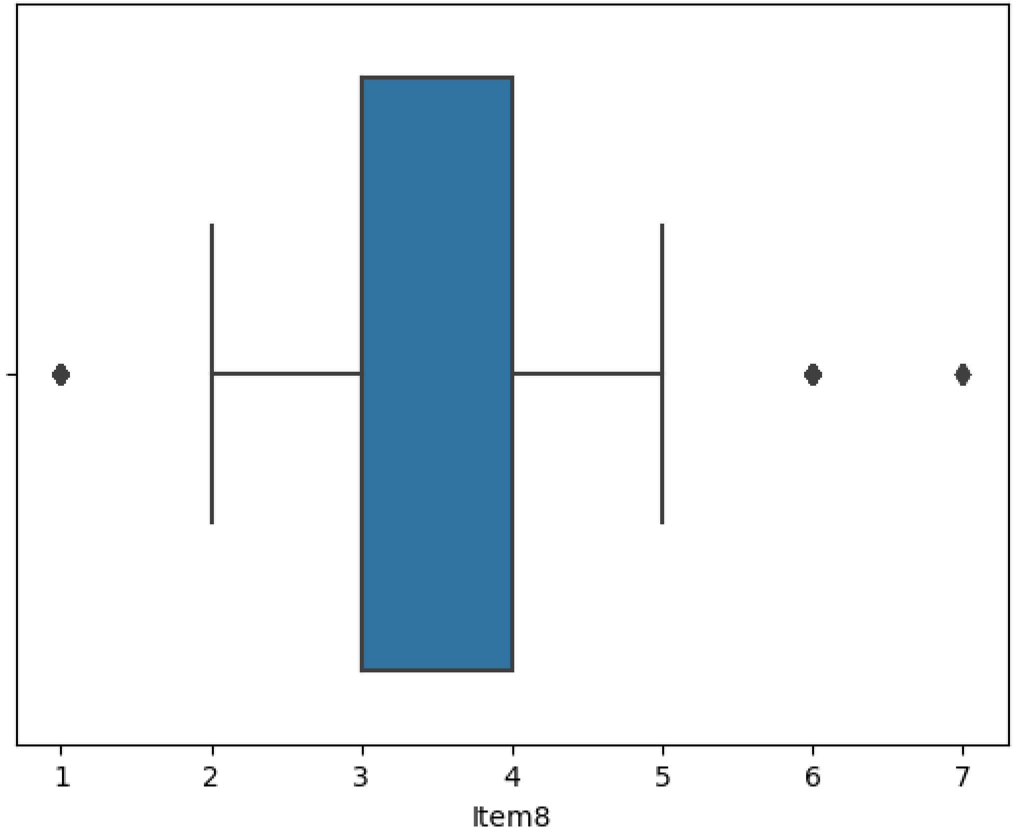

1
2
3
4
5
6
7
8
Item3


1
2
3
4
5
6
7
Item4


1
2
3
4
5
6
7
Item5


1
2
3
4
5
6
7
Item6


1
2
3
4
5
6
7
Item7


1
2
3
4
5
6
7
Item8

In [11]:
```
# Counting occurences of each unique value to make sure my inversion works correctly
print('Item1 Unique Value Counts:\n', df['Item1'].value_counts())
print('Item2 Unique Value Counts:\n', df['Item2'].value_counts())
print('Item3 Unique Value Counts:\n', df['Item3'].value_counts())
print('Item4 Unique Value Counts:\n', df['Item4'].value_counts())
print('Item5 Unique Value Counts:\n', df['Item5'].value_counts())
print('Item6 Unique Value Counts:\n', df['Item6'].value_counts())
print('Item7 Unique Value Counts:\n', df['Item7'].value_counts())
print('Item8 Unique Value Counts:\n', df['Item8'].value_counts())
```

```
Item1 Unique Value Counts:
 4    3455
3    3404
5    1377
2    1315
6     225
1     213
7      10
8       1
Name: Item1, dtype: int64
Item2 Unique Value Counts:
 3    3439
4    3351
5    1421
2    1360
1     213
6     204
7      12
Name: Item2, dtype: int64
Item3 Unique Value Counts:
 4    3464
3    3379
5    1358
2    1356
6     220
1     211
7      11
8       1
Name: Item3, dtype: int64
Item4 Unique Value Counts:
 3    3422
4    3394
5    1388
2    1346
6     231
1     207
7      12
Name: Item4, dtype: int64
Item5 Unique Value Counts:
 4    3446
3    3423
2    1380
5    1308
```

```
6     219
1     211
7      13
Name: Item5, dtype: int64
Item6 Unique Value Counts:
 4    3464
3    3371
5    1403
2    1319
6     220
1     213
7      10
Name: Item6, dtype: int64
Item7 Unique Value Counts:
 4    3487
3    3456
2    1345
5    1274
1     215
6     212
7      11
Name: Item7, dtype: int64
Item8 Unique Value Counts:
 3    3401
4    3337
5    1429
2    1391
6     221
1     209
7      12
Name: Item8, dtype: int64
```

In [12]:
```
# Invert survey data using map() function
inversion_table = {8: 1, 7: 2, 6: 3, 5: 4, 4: 5, 3: 6, 2: 7, 1: 8}
# Invert columns and change data type to float, as kmeans failed when running as int64
df["Item1"] = df["Item1"].map(inversion_table)
df["Item1"] = df["Item1"].astype('float64')
df["Item2"] = df["Item2"].map(inversion_table)
df["Item2"] = df["Item2"].astype('float64')
df["Item3"] = df["Item3"].map(inversion_table)
df["Item3"] = df["Item3"].astype('float64')
df["Item4"] = df["Item4"].map(inversion_table)
df["Item4"] = df["Item4"].astype('float64')
df["Item5"] = df["Item5"].map(inversion_table)
df["Item5"] = df["Item5"].astype('float64')
df["Item6"] = df["Item6"].map(inversion_table)
df["Item6"] = df["Item6"].astype('float64')
df["Item7"] = df["Item7"].map(inversion_table)
df["Item7"] = df["Item7"].astype('float64')
df["Item8"] = df["Item8"].map(inversion_table)
df["Item8"] = df["Item8"].astype('float64')
```

In [13]:
```
# Comparing this to previous use of .value_counts to make sure inversion worked correctly
print('Item1 Unique Value Counts:\n', df['Item1'].value_counts())
print('Item2 Unique Value Counts:\n', df['Item2'].value_counts())
print('Item3 Unique Value Counts:\n', df['Item3'].value_counts())
print('Item4 Unique Value Counts:\n', df['Item4'].value_counts())
print('Item5 Unique Value Counts:\n', df['Item5'].value_counts())
print('Item6 Unique Value Counts:\n', df['Item6'].value_counts())
print('Item7 Unique Value Counts:\n', df['Item7'].value_counts())
print('Item8 Unique Value Counts:\n', df['Item8'].value_counts())
```

```
Item1 Unique Value Counts:
 5.0    3455
6.0    3404
4.0    1377
7.0    1315
3.0     225
8.0     213
2.0      10
1.0       1
Name: Item1, dtype: int64
Item2 Unique Value Counts:
 6.0    3439
5.0    3351
4.0    1421
7.0    1360
8.0     213
3.0     204
2.0      12
Name: Item2, dtype: int64
Item3 Unique Value Counts:
 5.0    3464
6.0    3379
4.0    1358
7.0    1356
3.0     220
8.0     211
2.0      11
1.0       1
Name: Item3, dtype: int64
Item4 Unique Value Counts:
 6.0    3422
5.0    3394
4.0    1388
7.0    1346
3.0     231
8.0     207
2.0      12
Name: Item4, dtype: int64
Item5 Unique Value Counts:
 5.0    3446
6.0    3423
7.0    1380
4.0    1308
```

```
3.0     219
8.0     211
2.0      13
Name: Item5, dtype: int64
Item6 Unique Value Counts:
 5.0    3464
6.0    3371
4.0    1403
7.0    1319
3.0     220
8.0     213
2.0      10
Name: Item6, dtype: int64
Item7 Unique Value Counts:
 5.0    3487
6.0    3456
7.0    1345
4.0    1274
8.0     215
3.0     212
2.0      11
Name: Item7, dtype: int64
Item8 Unique Value Counts:
 6.0    3401
5.0    3337
4.0    1429
7.0    1391
3.0     221
8.0     209
2.0      12
Name: Item8, dtype: int64
```

In [14]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 8 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Item1   10000 non-null  float64
 1   Item2   10000 non-null  float64
 2   Item3   10000 non-null  float64
 3   Item4   10000 non-null  float64
 4   Item5   10000 non-null  float64
 5   Item6   10000 non-null  float64
 6   Item7   10000 non-null  float64
 7   Item8   10000 non-null  float64
dtypes: float64(8)
memory usage: 625.1 KB
```

In [15]:
```
# Calculate means of each item response to see how data varies
df_means = df.agg(['mean']).round(2)

print(df_means)
```

```
      Item1  Item2  Item3  Item4  Item5  Item6  Item7  Item8
mean   5.48   5.49   5.49   5.48    5.5   5.48   5.51   5.49
```

In [16]:
```
# Calculate standard deviation of each item response to see how data varies
df_std = df.agg(['std']).round(2)

print(df_std)
```

```
     Item1  Item2  Item3  Item4  Item5  Item6  Item7  Item8
std   1.03   1.03   1.03   1.04   1.03   1.03   1.02   1.04
```

In [17]:
```
# Calculate max of each item response to confirm lack of outliers and full use of survey responses
df_max = df.agg(['max']).round(2)

print(df_max)
```

```
     Item1  Item2  Item3  Item4  Item5  Item6  Item7  Item8
max    8.0    8.0    8.0    8.0    8.0    8.0    8.0    8.0
```

In [18]:
```
# Calculate min of each item response to confirms lack of outliers and full use of survey responses
df_min = df.agg(['min']).round(2)

print(df_min)
```

```
     Item1  Item2  Item3  Item4  Item5  Item6  Item7  Item8
min    1.0    2.0    1.0    2.0    2.0    2.0    2.0    2.0
```

In [19]:
```
#C4. Cleaned Dataset:
# Provide a copy of the cleaned Data Set
df.to_csv(r'C:\Users\mmorg\WGU\D212\d212_task1_clean.csv')
```

Part IV: Analysis

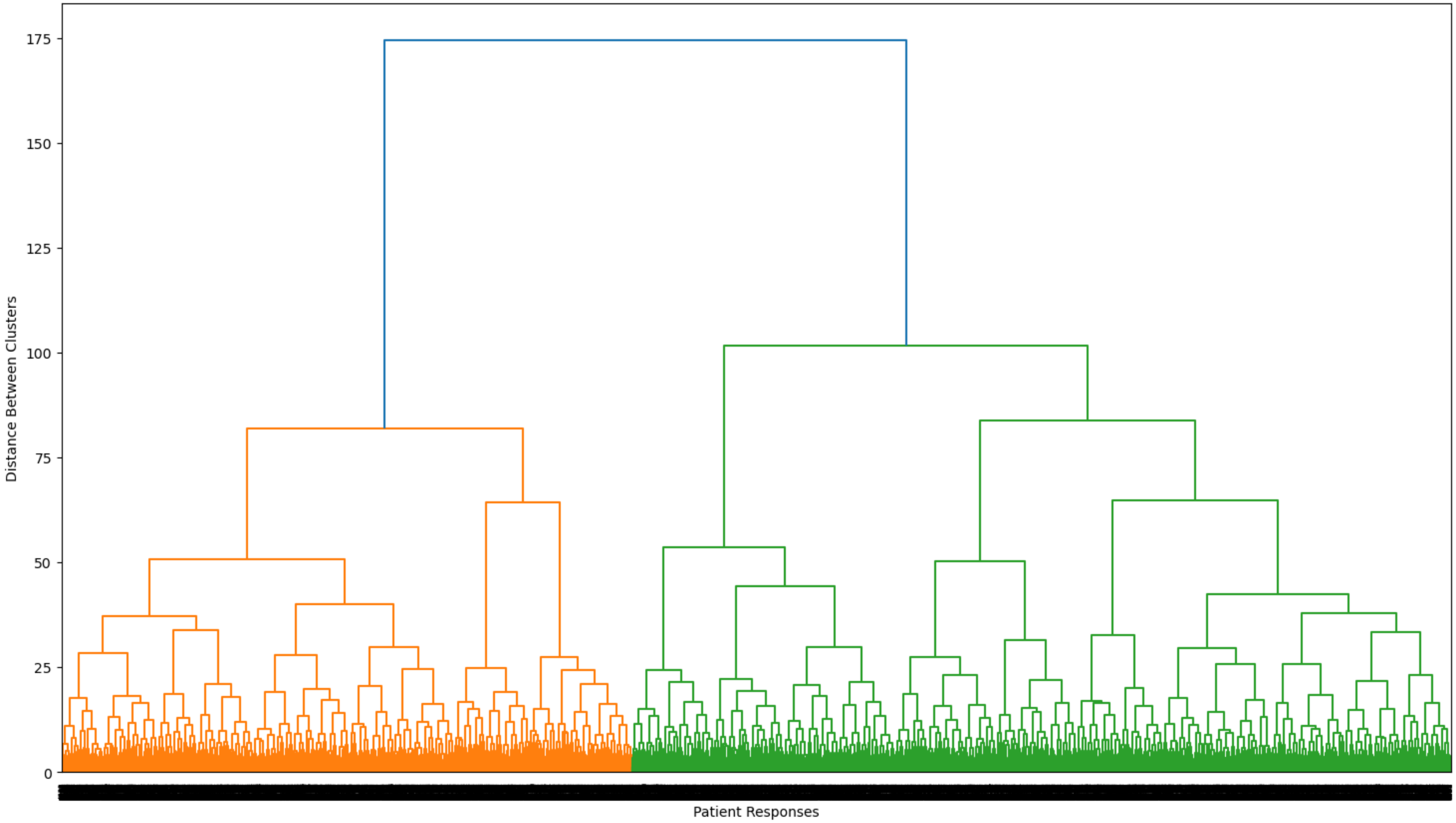
D. Perform the data analysis and report on the results by doing the following:

D1. Describe the analysis technique you used to appropriately analyze the data. Include screenshots of the intermediate calculations you performed.

As stated previously I decided to use hierarchical clustering for this analysis. Through the course materials I learned about the three methods that can be used for hierarchical clustering and those are; single, complete, and ward. When trying to use the single method my kernel crashed, and the complete method produced clusters that were not distinct enough to do any further analysis on.

Using the ward method however I was able to define 2 distinct groups among the patient survey observations. These groups can be seen as orange and green in the dendrogram below.

In [20]:
```
# Use linkage() to run hierarchical clustering using the ward method
distance_matrix = linkage(df[["Item1", "Item2", "Item3",
                              "Item4", "Item5", "Item6",
                              "Item7", "Item8"]],
                          method = 'ward',
                          metric = 'euclidean')
# Plot Dendrogram
plt.figure(figsize = [18,10])
dendrogram_ward = dendrogram(distance_matrix)
plt.xlabel("Patient Responses")
plt.ylabel("Distance Between Clusters");
plt.show()
```



In this dendrogram the x axis shows the results of all 10,000 patient responses to the survey, and the y axis shows the distance between the clusters. There are many clusters within this dataset but it's obvious that after using the ward method we have 2 distinct groups with a clear difference between each other based on the dendrogram.

From these two groups we will now use fcluster to label our 2 clusters and create a new column in the dataframe titled cluster_labels.

In [21]:
```
# Label Clusters
df['cluster_labels'] = fcluster(distance_matrix, 2, criterion='maxclust')
```

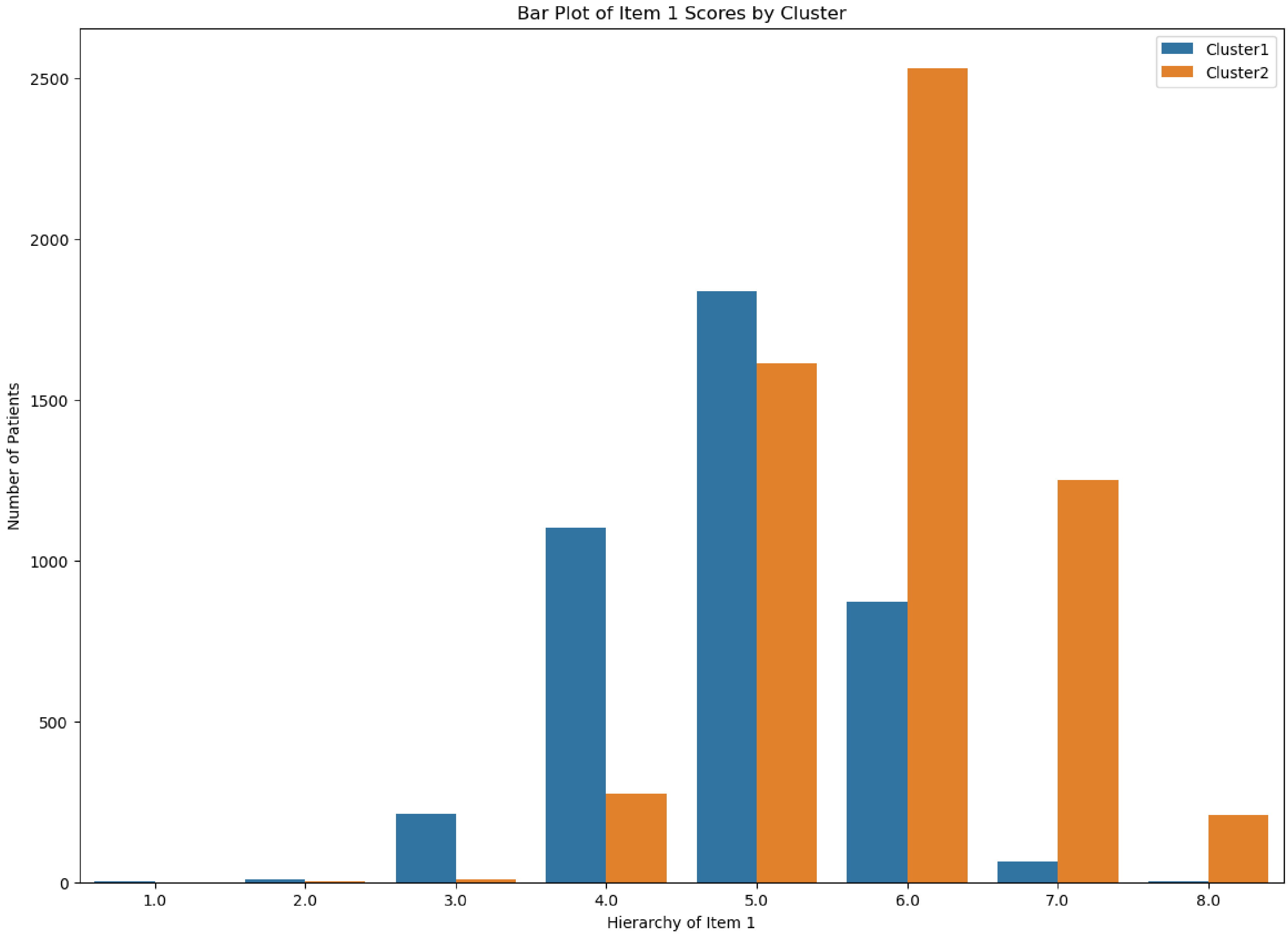
In [22]:
```
# Counting the population of each cluster
df['cluster_labels'].value_counts()
```

Out[22]:
```
2    5895
1    4105
Name: cluster_labels, dtype: int64
```

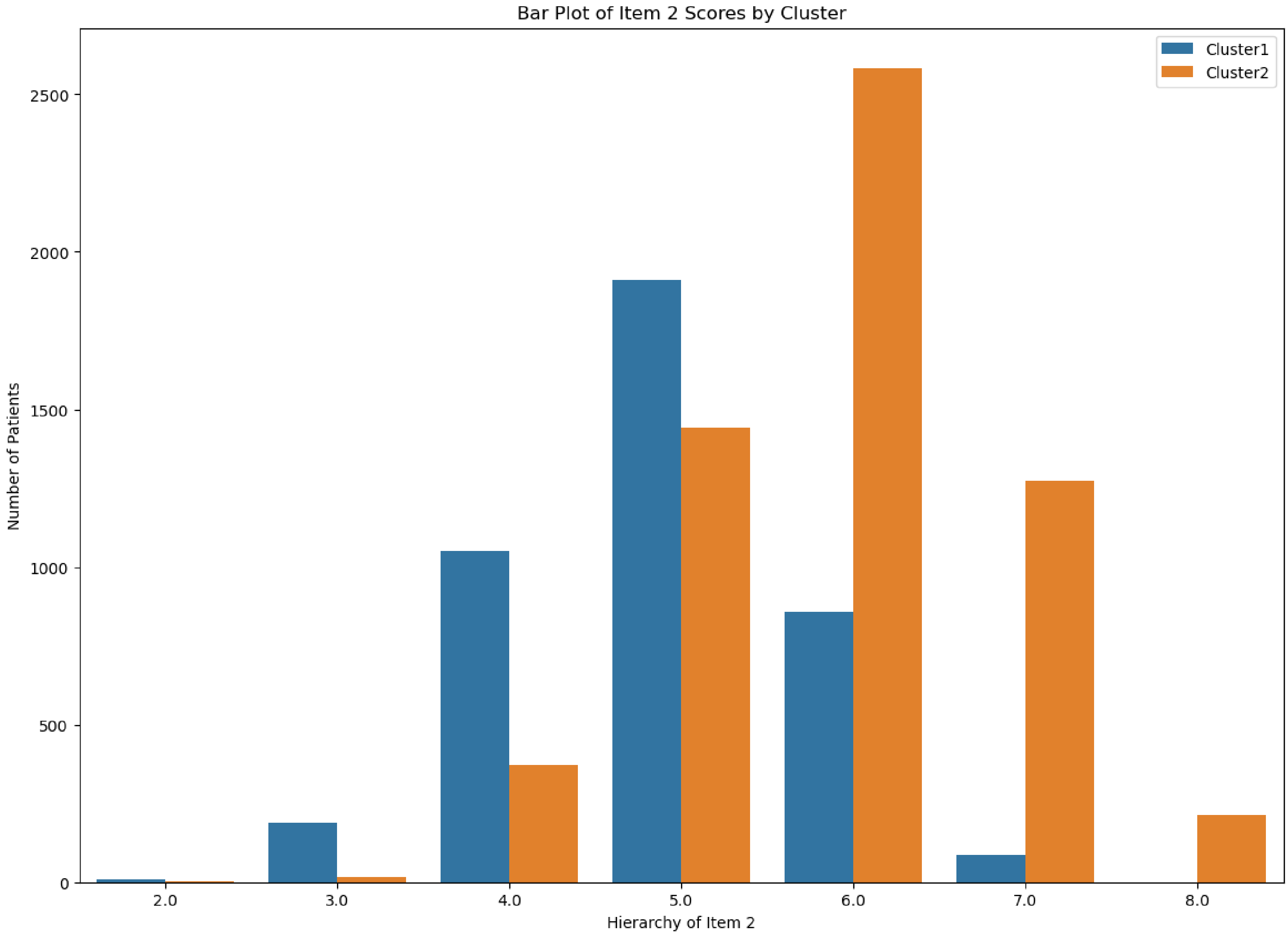
Now that we have divided our observations into two clusters we can look at the survey results of each question and compare the clusters to each other.

In [23]:
```
# Size adjustment to make visualization more clear
plt.figure(figsize = [14,10])

# Item 1 Visulizations
plt.title('Bar Plot of Item 1 Scores by Cluster')
sns.countplot(data = df, x="Item1", hue="cluster_labels")
plt.legend(["Cluster1", "Cluster2"])
plt.xlabel("Hierarchy of Item 1")
plt.ylabel("Number of Patients")
```

Out[23]:
```
Text(0, 0.5, 'Number of Patients')
```

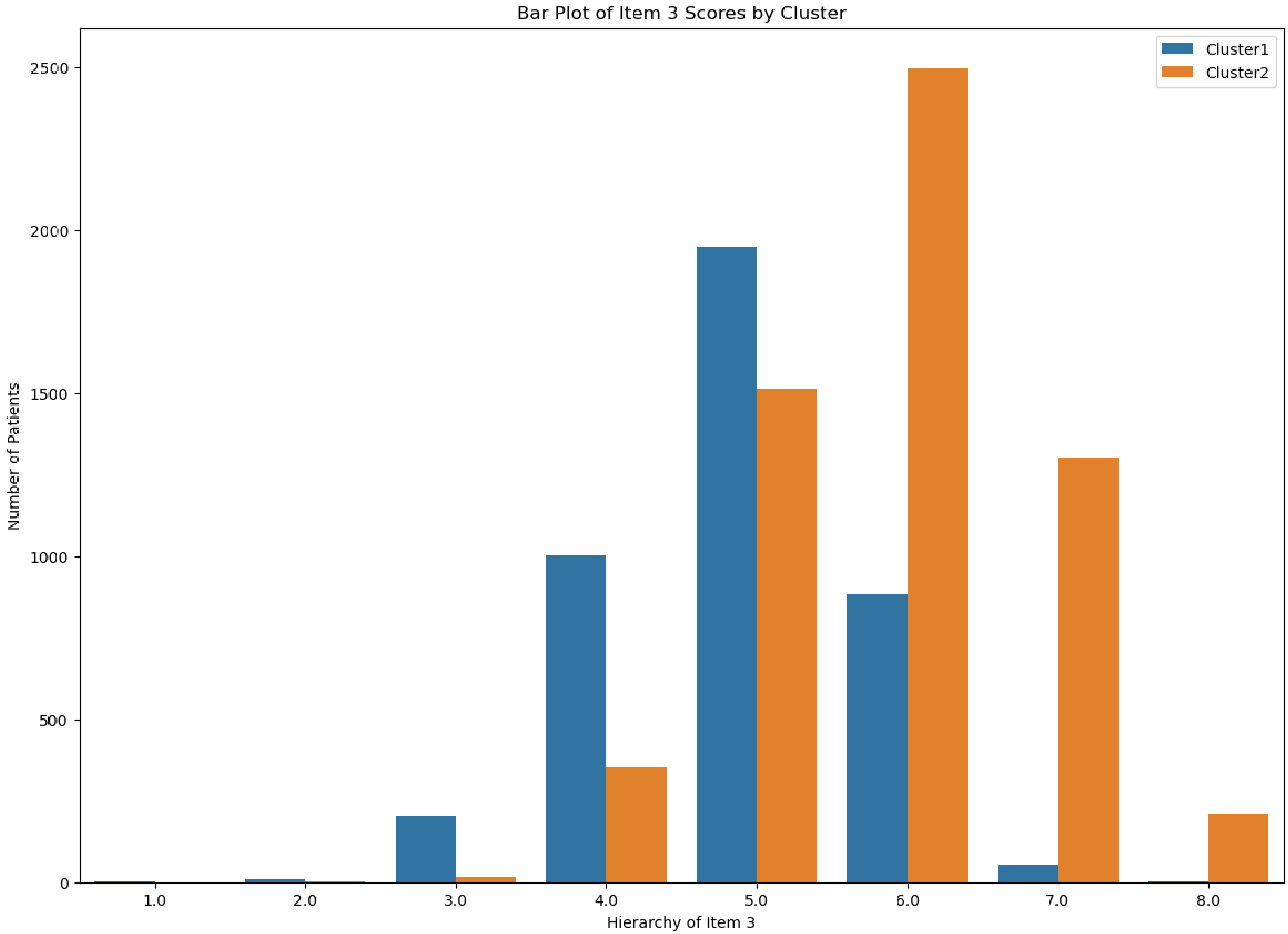

Bar Plot of Item 1 Scores by Cluster
Cluster1
Cluster2
Number of Patients
0
500
1000
1500
2000
2500
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
Hierarchy of Item 1

In [24]:
```
# Size adjustment to make visualization more clear
plt.figure(figsize = [14,10])

# Item 2 Visualization
plt.title("Bar Plot of Item 2 Scores by Cluster")
sns.countplot(data = df, x="Item2", hue="cluster_labels")
plt.legend(["Cluster1", "Cluster2"])
plt.xlabel("Hierarchy of Item 2")
plt.ylabel("Number of Patients");
```

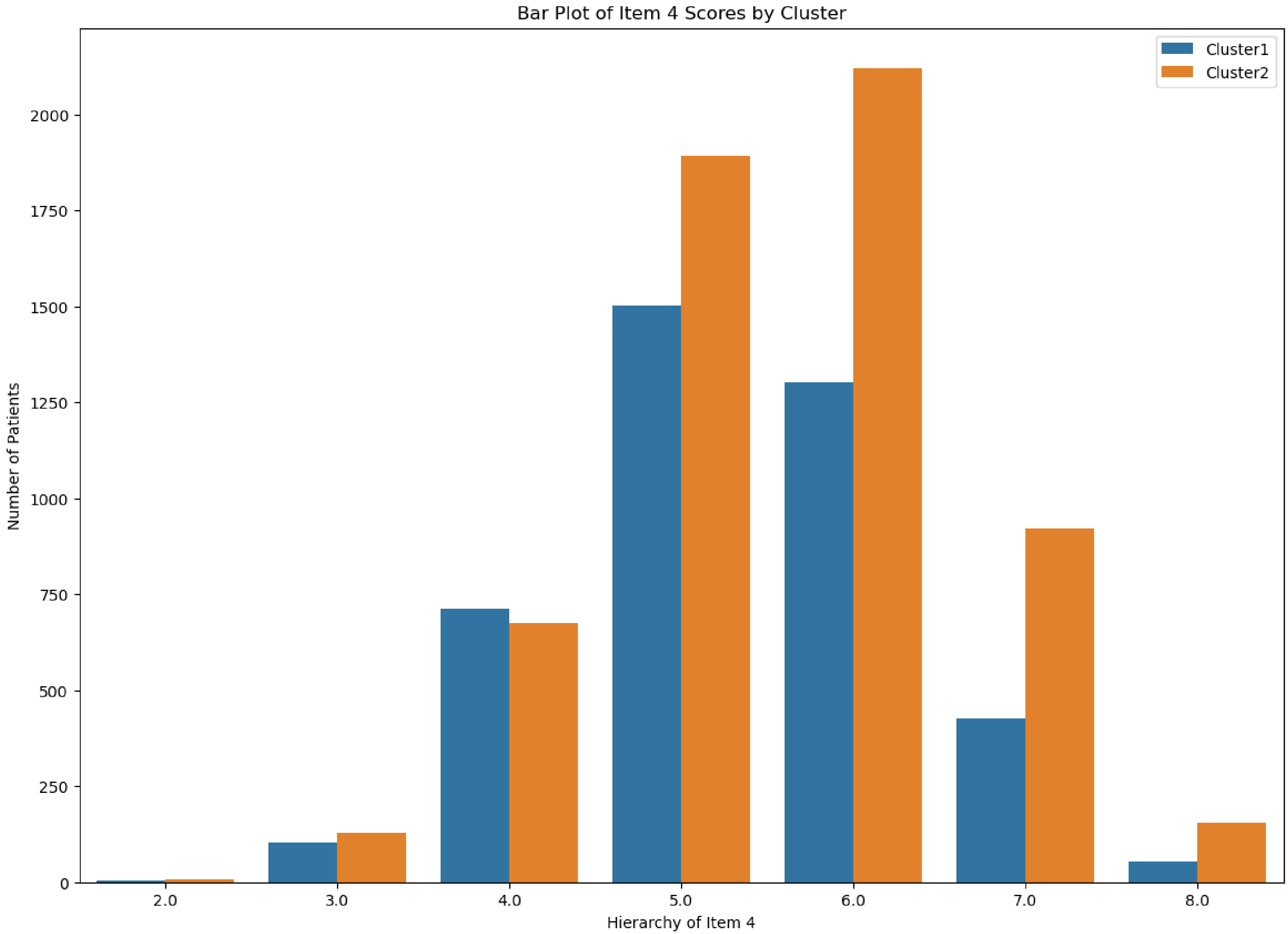


Bar Plot of Item 2 Scores by Cluster
Cluster1
Cluster2
Number of Patients
0
500
1000
1500
2000
2500
2.0
3.0
4.0
5.0
6.0
7.0
8.0
Hierarchy of Item 2

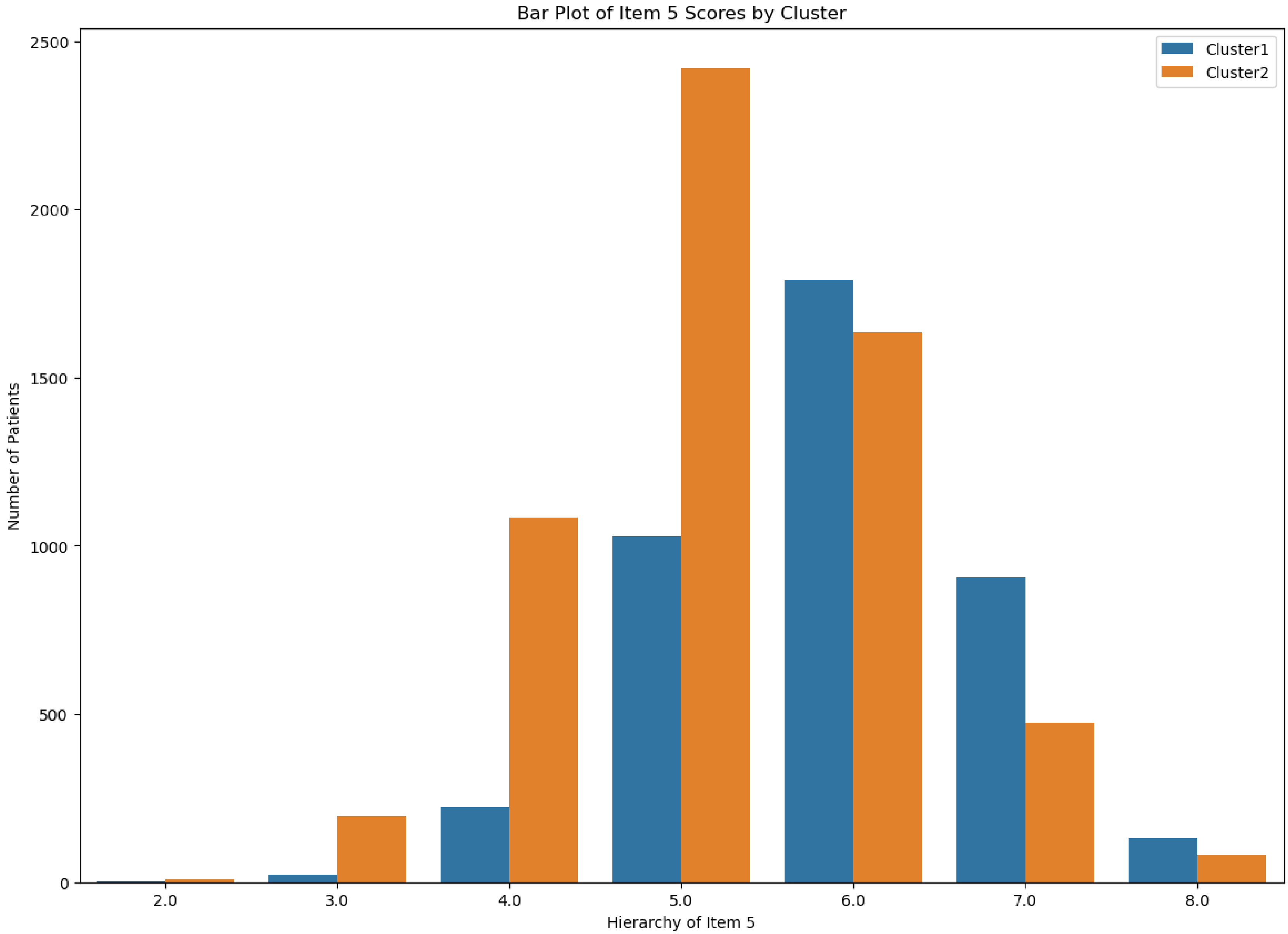
In [25]:
```
# Size adjustment to make visualization more clear
plt.figure(figsize = [14,10])

# Item 3 Visualization
plt.title('Bar Plot of Item 3 Scores by Cluster')
sns.countplot(data = df, x="Item3", hue="cluster_labels")
plt.legend(["Cluster1", "Cluster2"])
plt.xlabel("Hierarchy of Item 3")
plt.ylabel("Number of Patients");
```


Bar Plot of Item 3 Scores by Cluster
Cluster1
Cluster2
Number of Patients
0
500
1000
1500
2000
2500
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
Hierarchy of Item 3

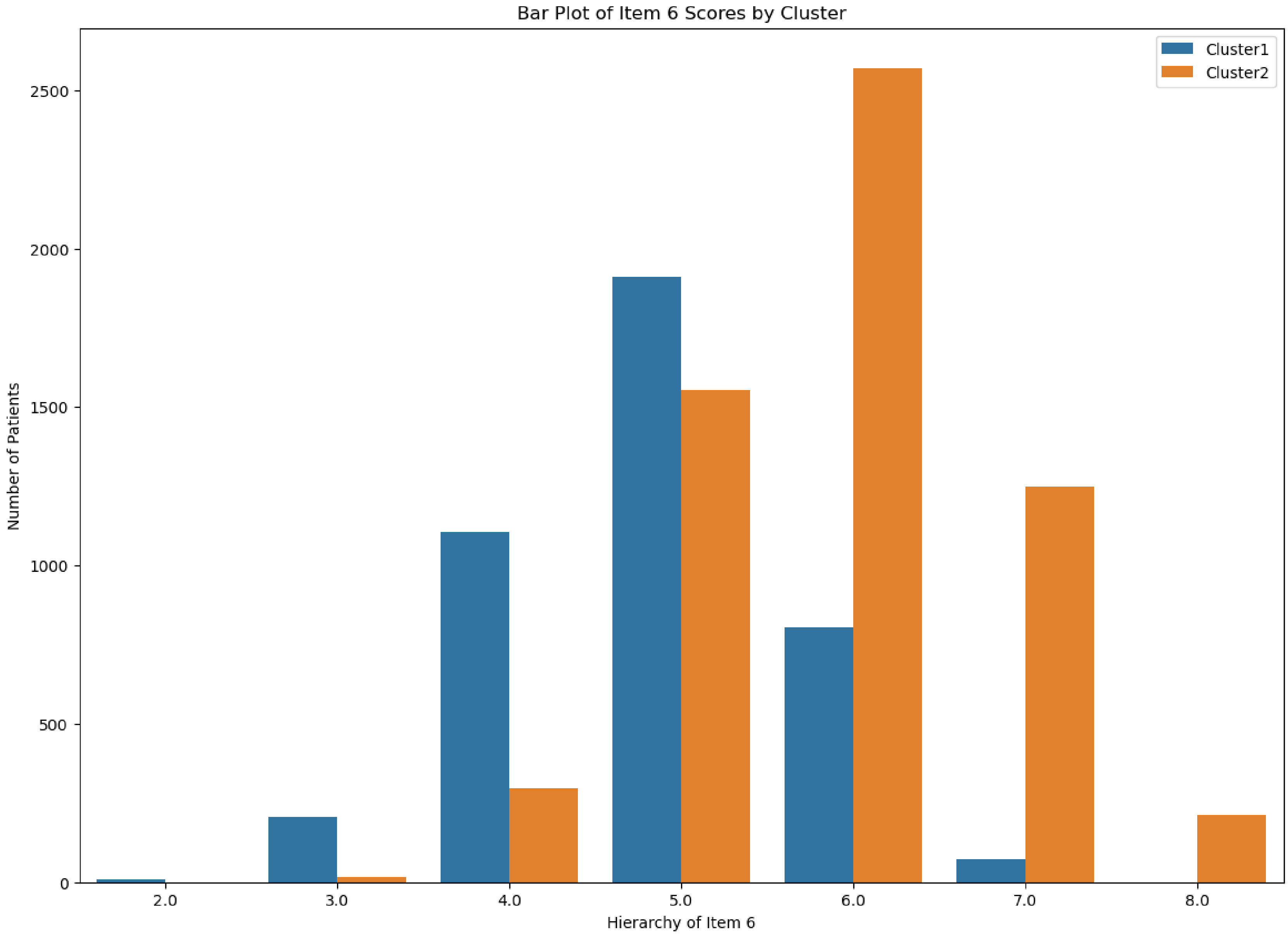
In [26]:
```
# Size adjustment to make visualization more clear
plt.figure(figsize = [14,10])

# Item 4 Visualization
plt.title("Bar Plot of Item 4 Scores by Cluster")
sns.countplot(data = df, x="Item4", hue="cluster_labels")
plt.legend(["Cluster1", "Cluster2"])
plt.xlabel("Hierarchy of Item 4")
plt.ylabel("Number of Patients");
```


Bar Plot of Item 4 Scores by Cluster
Cluster1
Cluster2
Number of Patients
0
250
500
750
1000
1250
1500
1750
2000
2.0
3.0
4.0
5.0
6.0
7.0
8.0
Hierarchy of Item 4

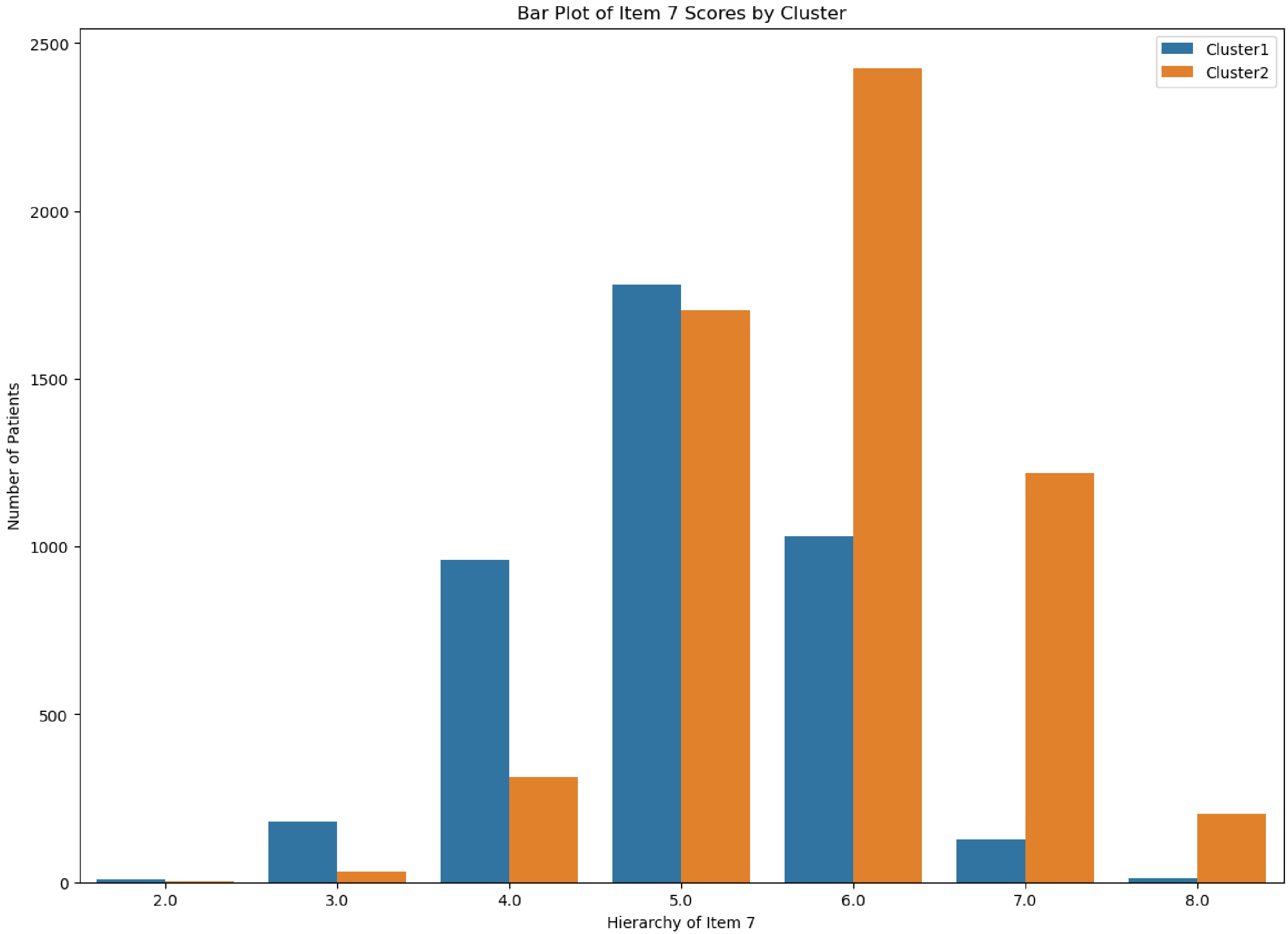
In [27]:
```
# Size adjustment to make visualization more clear
plt.figure(figsize = [14,10])

# Item 5 Visualization
plt.title('Bar Plot of Item 5 Scores by Cluster')
sns.countplot(data = df, x="Item5", hue="cluster_labels")
plt.legend(["Cluster1", "Cluster2"])
plt.xlabel("Hierarchy of Item 5")
plt.ylabel("Number of Patients");
```


Bar Plot of Item 5 Scores by Cluster
Cluster1
Cluster2
Number of Patients
0
500
1000
1500
2000
2500
2.0
3.0
4.0
5.0
6.0
7.0
8.0
Hierarchy of Item 5

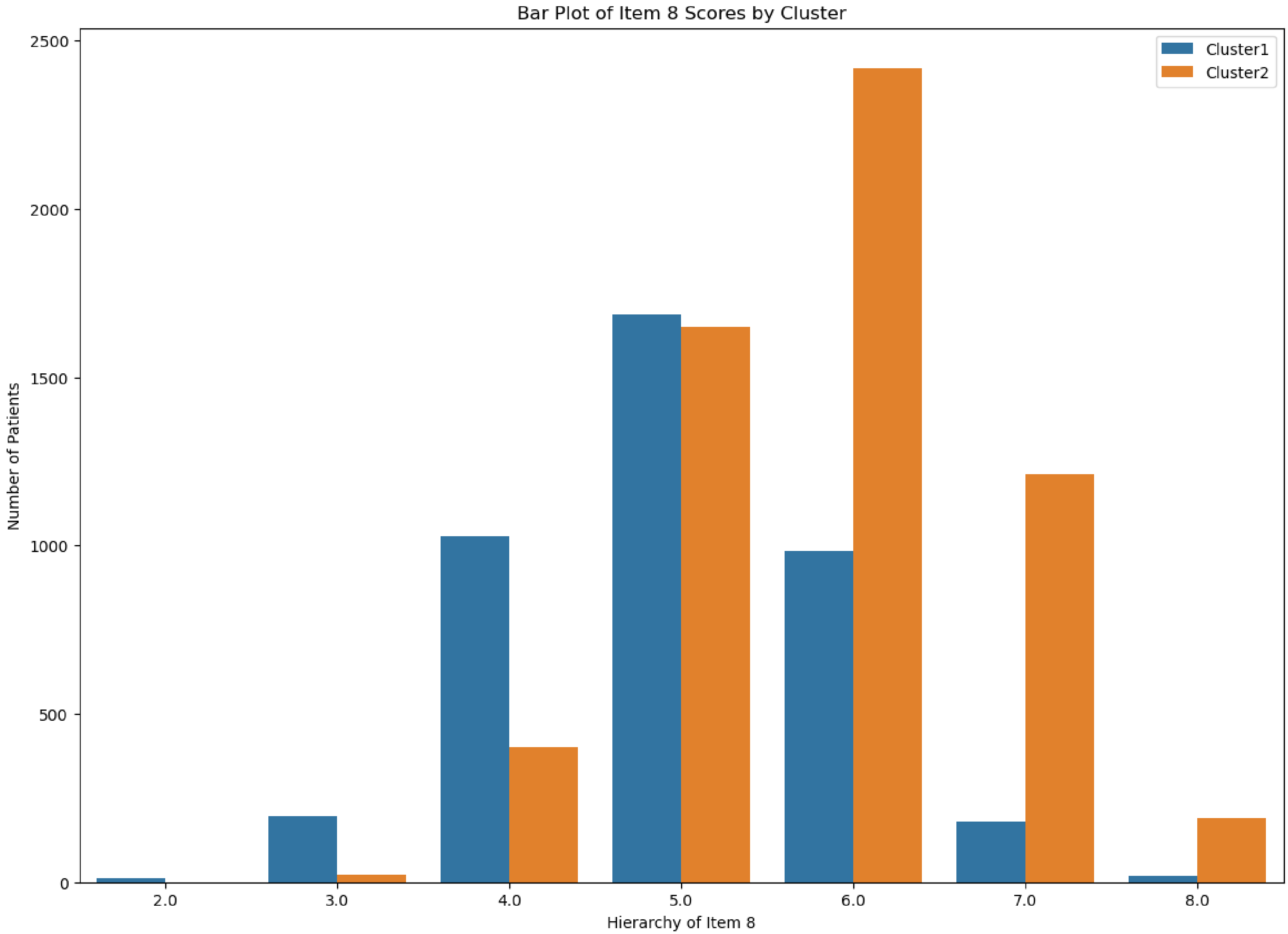
In [28]:
```
# Size adjustment to make visualization more clear
plt.figure(figsize = [14,10])

# Item 6 Visualization
plt.title("Bar Plot of Item 6 Scores by Cluster")
sns.countplot(data = df, x="Item6", hue="cluster_labels")
plt.legend(["Cluster1", "Cluster2"])
plt.xlabel("Hierarchy of Item 6")
plt.ylabel("Number of Patients");
```


Bar Plot of Item 6 Scores by Cluster
Cluster1
Cluster2
Number of Patients
0
500
1000
1500
2000
2500
2.0
3.0
4.0
5.0
6.0
7.0
8.0
Hierarchy of Item 6

In [29]:
```
# Size adjustment to make visualization more clear
plt.figure(figsize = [14,10])

# Item 7 Visualization
plt.title('Bar Plot of Item 7 Scores by Cluster')
sns.countplot(data = df, x="Item7", hue="cluster_labels")
plt.legend(["Cluster1", "Cluster2"])
plt.xlabel("Hierarchy of Item 7")
plt.ylabel("Number of Patients");
```


Bar Plot of Item 7 Scores by Cluster
Cluster1
Cluster2
Number of Patients
Hierarchy of Item 7
0
500
1000
1500
2000
2500
2.0
3.0
4.0
5.0
6.0
7.0
8.0

In [30]:
```
# Size adjustment to make visualization more clear
plt.figure(figsize = [14,10])

# Item 8 Visualization
plt.title("Bar Plot of Item 8 Scores by Cluster")
sns.countplot(data = df, x="Item8", hue="cluster_labels")
plt.legend(["Cluster1", "Cluster2"])
plt.xlabel("Hierarchy of Item 8")
plt.ylabel("Number of Patients");
```


Bar Plot of Item 8 Scores by Cluster
Cluster1
Cluster2
Number of Patients
2500
2000
1500
1000
500
0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
Hierarchy of Item 8

In [31]:
```
# Looking at mean scores of each survey response for each cluster
df_grouped = df.groupby('cluster_labels')

df_grouped_means = df_grouped.agg(['mean']).round(2)

print(df_grouped_means)
```

```
               Item1 Item2 Item3 Item4 Item5 Item6 Item7 Item8
                mean  mean  mean  mean  mean  mean  mean  mean
cluster_labels
1               4.87  4.90  4.89  5.34  5.90  4.85  4.99  4.99
2               5.91  5.91  5.91  5.59  5.22  5.91  5.86  5.84
```

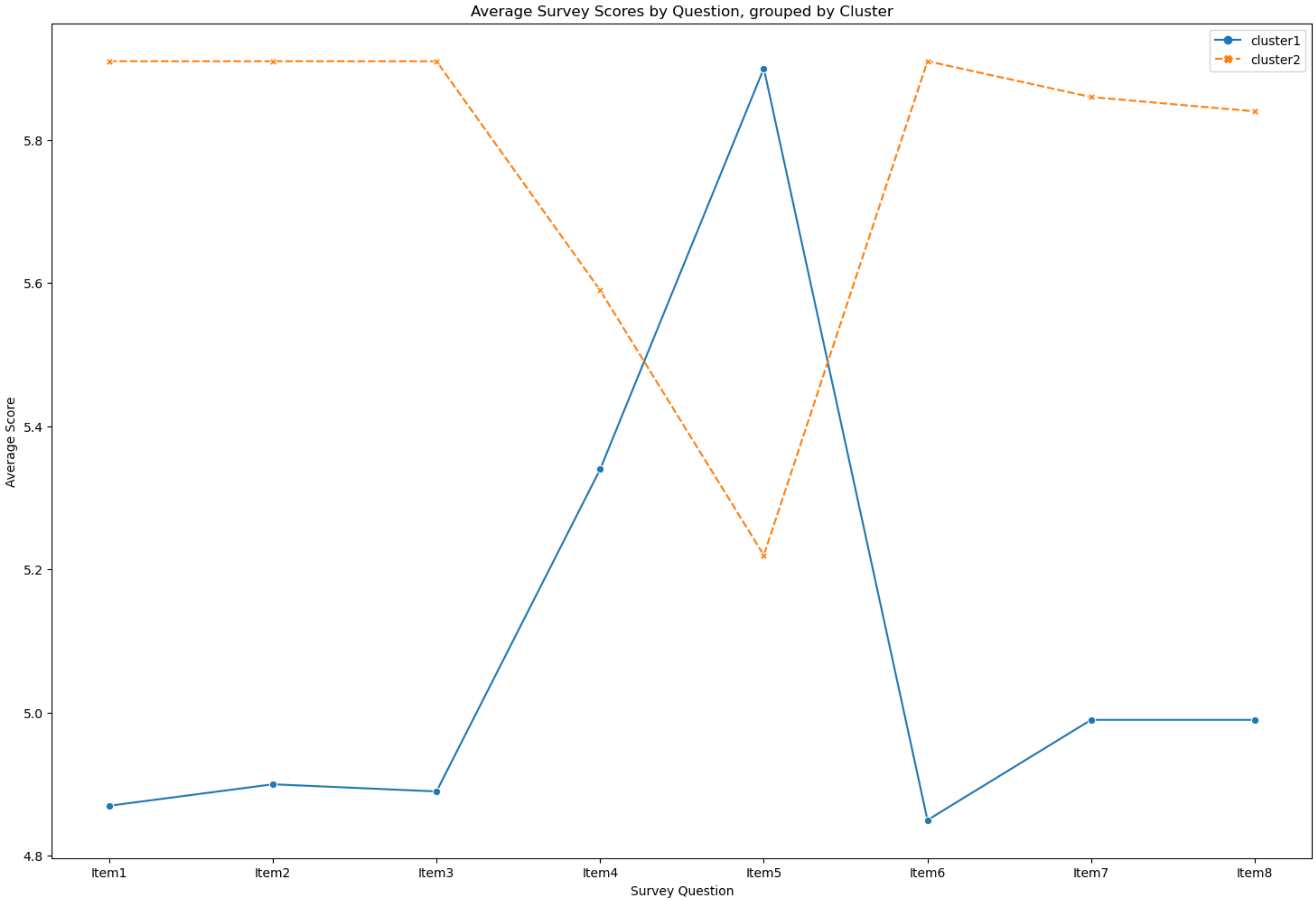
In [40]:
```
# Creat new array to more easily create a visualization
df_plot_dict = {'cluster1' : [4.87, 4.90, 4.89, 5.34, 5.90, 4.85, 4.99, 4.99],
           'cluster2' : [5.91, 5.91, 5.91, 5.59, 5.22, 5.91, 5.86, 5.84]}
df_plot = pd.DataFrame(data = df_plot_dict, index=['Item1', 'Item2',
                                                   'Item3', 'Item4',
                                                   'Item5', 'Item6',
                                                   'Item7', 'Item8'])

df_plot
```

Out[40]:

	cluster1	cluster2
Item1	4.87	5.91
Item2	4.90	5.91
Item3	4.89	5.91
Item4	5.34	5.59
Item5	5.90	5.22
Item6	4.85	5.91
Item7	4.99	5.86
Item8	4.99	5.84

In [41]:
```
# Visualization of mean scores for each survey item from each cluster
plt.figure(figsize = [18,12])
sns.lineplot(data=df_plot, markers=True)
plt.title("Average Survey Scores by Question, grouped by Cluster")
plt.xlabel("Survey Question")
plt.ylabel("Average Score")
```

Out[41]:
```
Text(0, 0.5, 'Average Score')
```



D2. Provide the code used to perform the clustering analysis technique from part 2.

Code included above

Part V: Data Summary and Implications

E. Summarize your data analysis by doing the following:

E1. Explain the accuracy of your clustering technique.

I don't think it's possible to generate a true accuracy score for this type of analysis, however the webinar provided by Dr. Kamara did mention running a silhouette score. After researching silhouette scores I found that it allows us to determine if we have distinct or overlappiong clusters. Score closer to 1 show clusters that are far away, scores closer to 0 show clusters that are overlapping, and scores in the negatives indicate that an incorrect cluster has been assigned. (sklearn.metrics.silhouette_score, 2023)

In [46]:
```
# Define X and y variables
X = df[["Item1", "Item2", "Item3",
        "Item4", "Item5", "Item6",
        "Item7", "Item8"]]

y = df['cluster_labels']

# Generate the silhouette score and print
silhouette_score = silhouette_score(X, y, metric='euclidean')
print(f"Silhouette score is: {round(silhouette_score, 3)}")
```

```
Silhouette score is: 0.148
```

My silhouette score is 0.148. This is very close to zero showing that my two clusters have some degree of overlap. This makes sense when looking at the calculated means and standard deviation from each item and each cluster. The means were very close together and the standard deviations were all close to 1 showing that there isn't a distinct difference between the two clusters.

E2. Discuss the results and implications of your clustering analysis.

When looking at these numbers and the silhouette score together we can see that the data provided by the survey results is all very middle of the road so to speak.

Let's look at the numbers and visualization again.

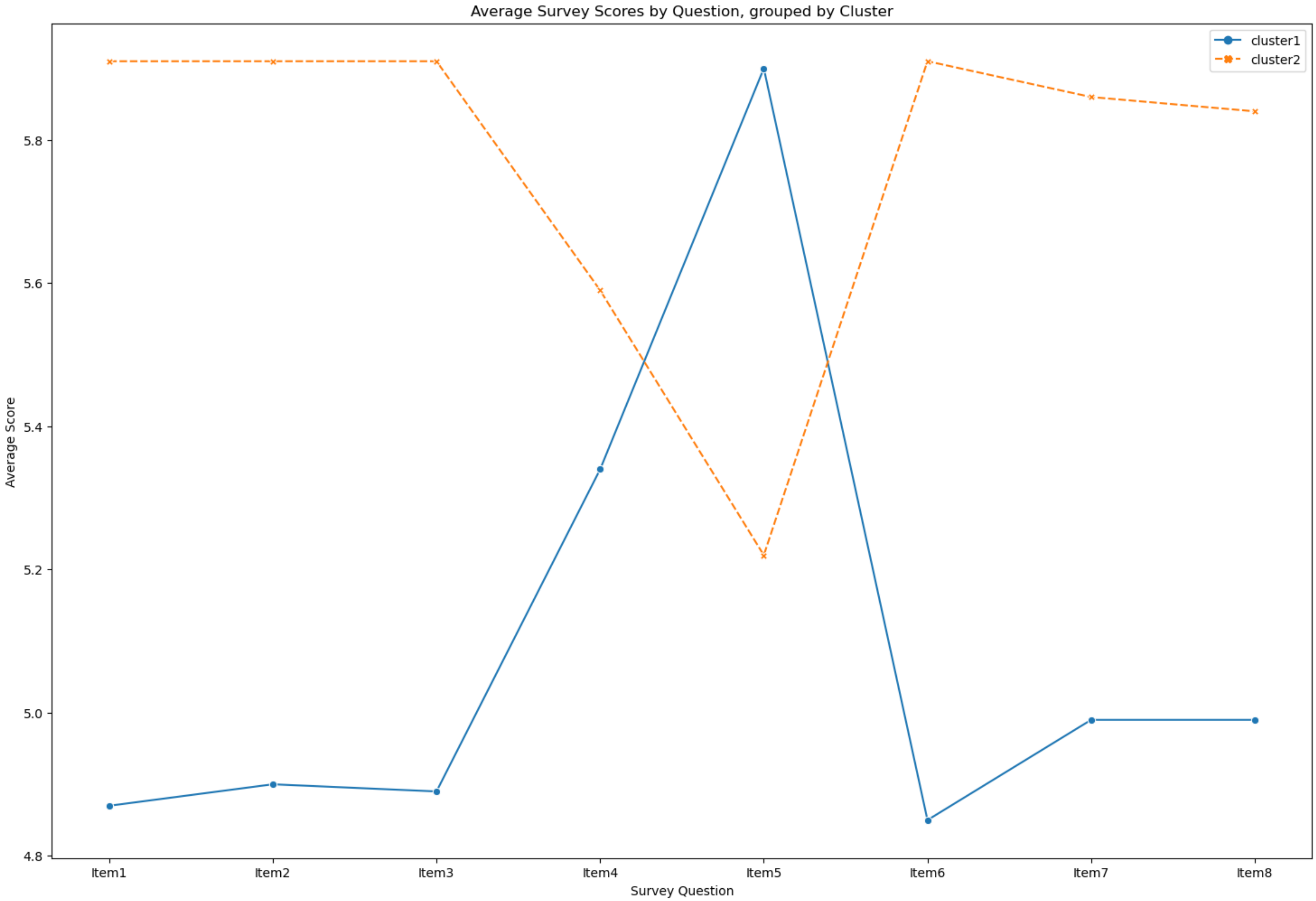
In [43]:
```
df_plot
```

Out[43]:

	cluster1	cluster2
Item1	4.87	5.91
Item2	4.90	5.91
Item3	4.89	5.91
Item4	5.34	5.59
Item5	5.90	5.22
Item6	4.85	5.91
Item7	4.99	5.86
Item8	4.99	5.84

In [44]:
```
# Visualization of mean scores for each survey item from each cluster
plt.figure(figsize = [18,12])
sns.lineplot(data=df_plot, markers=True)
plt.title("Average Survey Scores by Question, grouped by Cluster")
plt.xlabel("Survey Question")
plt.ylabel("Average Score")
```

Out[44]:
```
Text(0, 0.5, 'Average Score')
```



When looking at this again, with the knowlege of the silhouette score, we can clearly see that patients don't really think anything is not important, but also largely don't think anything is very important. The means of responses for all questions in both clusters range anywhere from about 4.90 to 5.90. Showing that largely the patients, regardless of cluster, believe all of these qualities are somewhat important.

E3. Discuss one limitation of your data analysis.

One limitation in my data analysis is cluster determination. I chose to divide the data into two clusters based on the dendrogram and was shown through my silhouette score that there is definite overlap in the clusters. This shows that I probably could have drilled down deeper and chosen 3 or more clusters to hopefully differentiate my groups more.

E4. Recommend a course of action for the real-world organizational situation from part A1 based on your results and implications discussed in part E2.

Going back to E2, the two clusters aren't very distinct. I am not sure this is a problem necessarily with the analysis but more so the survey itself. Patients are presented with a number of options, 1-8, to determine how important they are. In their survey 1 means most important whereas 8 means least important. I inverted those numbers for this analysis so that bigger numbers related to more importance as that's a more intuitive way to look at it.

My recommendation based on this deals with how we handle patient surveys in the future. I think a ranked survey would help to better determine patient priorities. What I mean is that the patients should be offered all 8 items and have to rank them in order of importance. This would require the patients to determine what is most and least important to them in order and hopefully provide us data on what patients find most important so that resources can be focused on those areas.

In this current survey data we can't draw any meaningful conclusions in regards to what patients find most important. With the current analysis patients feel everything is kind of important, but not really. In this case we fall into the trap of if everything is important then nothing is important. Forcing survey participants to actually rank all 8 items in order could help us glean meaningful survey results and more effectively determine what requires more resources.

F. Panopto Recording

https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=4719bf00-0f05-4359-9b06-b01f014a95a7 (https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=4719bf00-0f05-4359-9b06-b01f014a95a7)

G. Record the web sources used to acquire data or segments of third-party code to support the analysis. Ensure the web sources are reliable.

https://realpython.com/python-map-function/ (https://realpython.com/python-map-function/) and https://www.geeksforgeeks.org/python-map-function/ (https://www.geeksforgeeks.org/python-map-function/) was used for the map functions to perform survey data inversion

https://stackoverflow.com/questions/60006995/round-while-groupping-by-in-pandas-with-agg-function#:~:text=Round(2)%20will%20round%20it,(3)%20and%20so%20on (https://stackoverflow.com/questions/60006995/round-while-groupping-by-in-pandas-with-agg-function#:~:text=Round(2)%20will%20round%20it,(3)%20and%20so%20on) was used for performing the aggregate mean, std, max, and min calculations [https://scikit-learn.org/stable/modules/generated/sklearn.metrics.silhouette_score.html (https://scikit-learn.org/stable/modules/generated/sklearn.metrics.silhouette_score.html)](https://scikit-learn.org/stable/modules/generated/sklearn.metrics.silhouette_score.html) was used for silhouette score

H. Acknowledge sources, using in-text citations and references, for content that is quoted, paraphrased, or summarized.

"Sklearn.Metrics.Silhouette_score." Scikit-learn.Org, 1 Mar. 2023, scikit-