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SUMMARY:

Data Preparation and Clustering

Data Loading: The dataset is loaded from a specified path, ensuring it's correctly imported for analysis.

Library Import: Essential libraries like 'tidyverse',' factoextra',' dplyr', 'ggplot2', and cluster are imported for data manipulation and cluster analysis.

Preprocessing: The script removes any missing data and selects numerical variables (columns 3 to 11) from the dataset, which are crucial for clustering.

Cluster Analysis

Data Normalization: The selected numerical variables are normalized to ensure uniformity in scale and distribution.

Determining Cluster Number:

The Elbow Method is initially used to find the optimal number of clusters, analyzing the within-cluster sum of squares.

The Silhouette Method is applied as a secondary measure, indicating that 5 clusters might be optimal.

K-Means Clustering: The k-means clustering algorithm is performed with 5 clusters, chosen based on the silhouette method results. The process includes setting a seed for reproducibility.

Visualization: Cluster centroids and distances are visualized to gain insights into the distribution and separation of the clusters.

Interpretation and Insights

Cluster Characteristics:

The mean values of each variable within each cluster are calculated to understand their central tendencies and defining features.

Clusters are interpreted based on these features, revealing distinct characteristics like growth expectations, market capitalization, asset turnover, and revenue growth.

Non-Numerical Variable Analysis: The script also considers how non-numerical variables (like recommendations) align with each cluster, providing a deeper understanding of the clusters in the context of market perceptions.

Cluster Naming:

The clusters are named based on their characteristics:

Cluster 1 - "Balanced Performers": Indicates stable and decent financial metrics.

Cluster 2 - "Steady Growth Contenders": Suggests consistent growth and stability.

Cluster 3 - "Dynamic Opportunity Firms": Reflects firms with varied investment opportunities.

Cluster 4 - "Stable Investment Picks": Implies firms with good stability and solid financial metrics.

Cluster 5 - "Long-term Value Holders": Denotes firms ideal for long-term holding due to their consistent revenue growth and high asset turnover.

```
# Loading the dataset
Pharmaceuticals <-
read.csv("C:/Users/shrey/OneDrive/Documents/Pharmaceuticals.csv")
# Ensuring the file path is correct and the dataset is loaded properly.

# Reading required libraries for data manipulation and clustering
library(tidyverse)

## ── Attaching core tidyverse packages ──────────────────────── tidyverse
2.0.0 ──
## ✓ dplyr     1.1.2     ✓ readr     2.1.4
## ✓ forcats   1.0.0     ✓ stringr   1.5.0
## ✓ ggplot2   3.4.3     ✓ tibble    3.2.1
## ✓ lubridate 1.9.2     ✓ tidyr     1.3.0
## ✓ purrr     1.0.2
## ── Conflicts ────────────────────────────────────────
tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all
conflicts to become errors

library(factoextra)

## Warning: package 'factoextra' was built under R version 4.3.2
```

```
## Welcome! Want to learn more? See two factoextra-related books at
https://goo.gl/ve3WBa

library(dplyr)
library(ggplot2)
library(cluster)
# These libraries are essential for manipulating data and performing cluster
analysis.
```

Task1

kUse only the numerical variables (1 to 9) to cluster the 21 firms. Justify the various choices made in conducting the cluster analysis, such as weights for different variables,the specific clustering algorithm(s) used, the number of clusters formed, and so on. Removal of missing data helps in maintaining the accuracy of the cluster analysis. Prior to clustering data, remove the missing data and rescale variables for comparability.

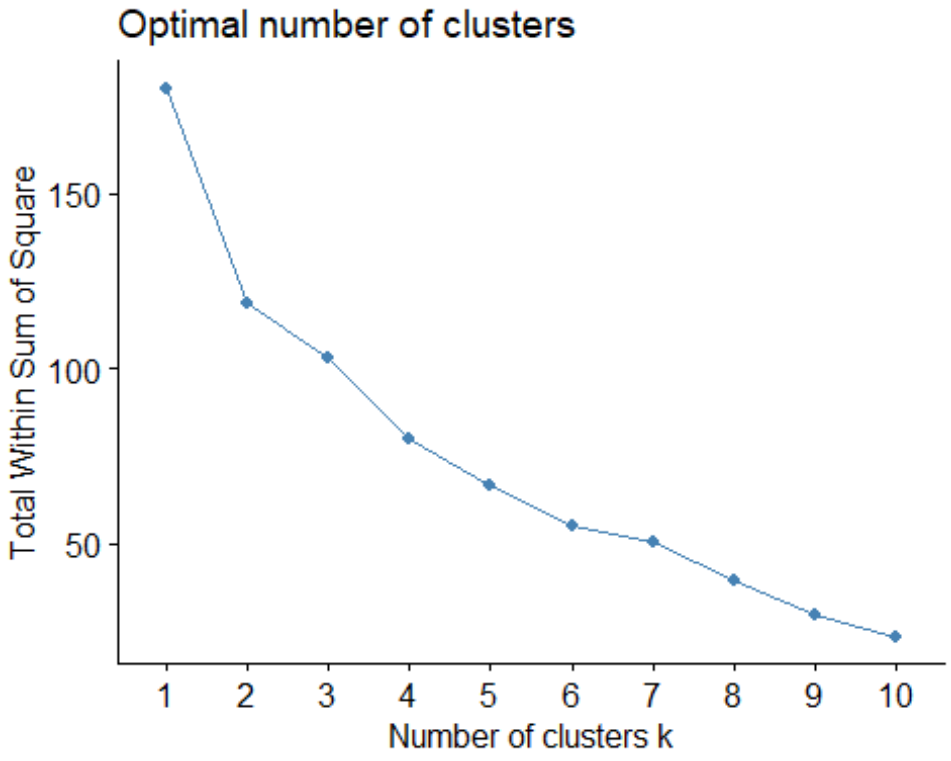
```
# Removing missing data and selecting relevant variables for cluster analysis
Pharma_data <- na.omit(Pharmaceuticals)
# Removing incomplete cases to maintain the accuracy of the cluster analysis.

#Taking the quantitative variables(1-9) to cluster the 21 firms

row.names(Pharma_data)<- Pharma_data[,1]
Pharma_data1<- Pharma_data[,3:11]# Considering only numercial values i.e., 3-
11 columns from csv file
head(Pharma_data1)
```

```
##     Market_Cap Beta PE_Ratio  ROE  ROA Asset_Turnover Leverage Rev_Growth
## ABT      68.44 0.32     24.7 26.4 11.8            0.7     0.42       7.54
## AGN       7.58 0.41     82.5 12.9  5.5            0.9     0.60       9.16
## AHM       6.30 0.46     20.7 14.9  7.8            0.9     0.27       7.05
## AZN      67.63 0.52     21.5 27.4 15.4            0.9     0.00      15.00
## AVE      47.16 0.32     20.1 21.8  7.5            0.6     0.34      26.81
## BAY      16.90 1.11     27.9  3.9  1.4            0.6     0.00      -3.17
##     Net_Profit_Margin
## ABT              16.1
## AGN               5.5
## AHM              11.2
## AZN              18.0
## AVE              12.9
## BAY               2.6
```

```
# Focusing on numerical variables (columns 3 to 11) as they are key for
clustering.

#Normalizing the data frame with scale method

Pharma_data2<-scale(Pharma_data1)
head(Pharma_data2)
```

```
##     Market_Cap        Beta    PE_Ratio         ROE        ROA
Asset_Turnover
## ABT  0.1840960 -0.80125356 -0.04671323  0.04009035  0.2416121
0.0000000
## AGN -0.8544181 -0.45070513  3.49706911 -0.85483986 -0.9422871
0.9225312
## AHM -0.8762600 -0.25595600 -0.29195768 -0.72225761 -0.5100700
0.9225312
## AZN  0.1702742 -0.02225704 -0.24290879  0.10638147  0.9181259
0.9225312
## AVE -0.1790256 -0.80125356 -0.32874435 -0.26484883 -0.5664461     -
0.4612656
## BAY -0.6953818  2.27578267  0.14948233 -1.45146000 -1.7127612     -
0.4612656
##       Leverage Rev_Growth Net_Profit_Margin
## ABT -0.2120979 -0.5277675        0.06168225
## AGN  0.0182843 -0.3811391       -1.55366706
## AHM -0.4040831 -0.5721181       -0.68503583
## AZN -0.7496565  0.1474473        0.35122600
## AVE -0.3144900  1.2163867       -0.42597037
## BAY -0.7496565 -1.4971443       -1.99560225
```

```r
# Scaling standardizes the data, making it suitable for clustering.

# Determining the number of clusters using Elbow Method

fviz_nbclust(Pharma_data2, kmeans, method = "wss")
```



```
# The Elbow Method helps identify the optimal cluster count by analyzing
within-cluster sum of squares.

##By seeing the above graph from Elbow method, Graph is not clear to choose
k=2 or 3 or 4 or 5.
# Using Silhouette method to determine the number of clusters

fviz_nbclust(Pharma_data2, kmeans, method = "silhouette")
```

By seeing the graph from silhouette method, I can see sharp rise at k=5. So, considering the silhouette method.

Silhouette method assesses how well each object lies within its cluster, aiding in determining the best number of clusters.

```
# Performing K-means clustering
set.seed(64060)
k_5 <- kmeans(Pharma_data2, centers=5, nstart=25)
```

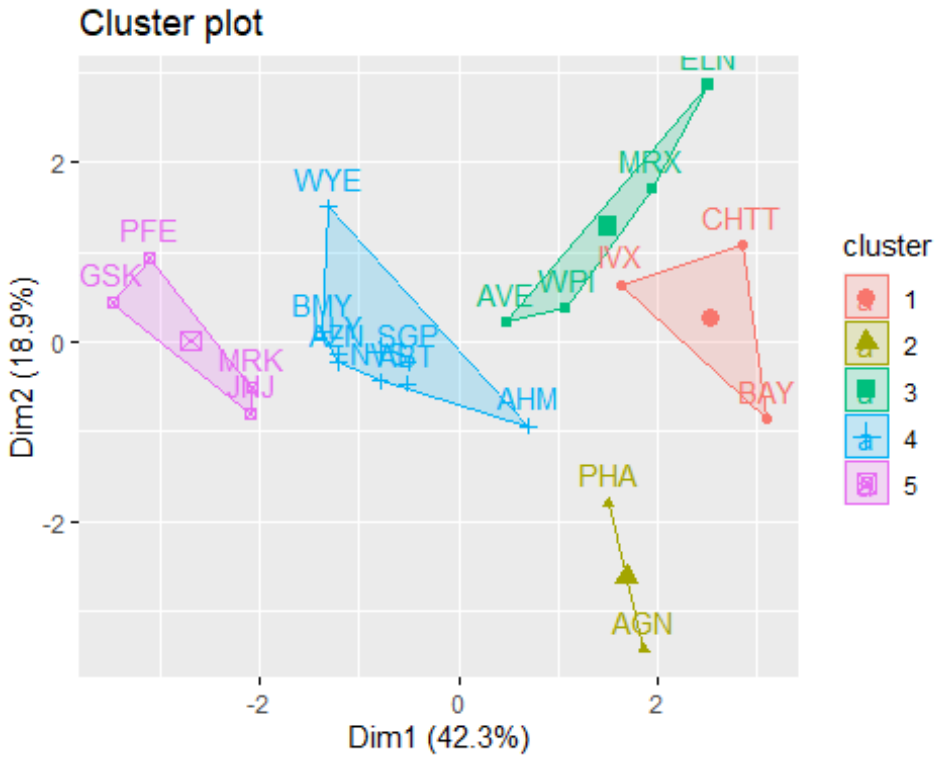
K-means clustering is performed with 5 clusters, determined by previous methods.

```
# Visualizing cluster centroids and distances

k_5$centers
```

```
##    Market_Cap       Beta    PE_Ratio        ROE        ROA Asset_Turnover
## 1 -0.87051511  1.3409869 -0.05284434 -0.6184015 -1.1928478     -0.4612656
## 2 -0.43925134 -0.4701800  2.70002464 -0.8349525 -0.9234951      0.2306328
```

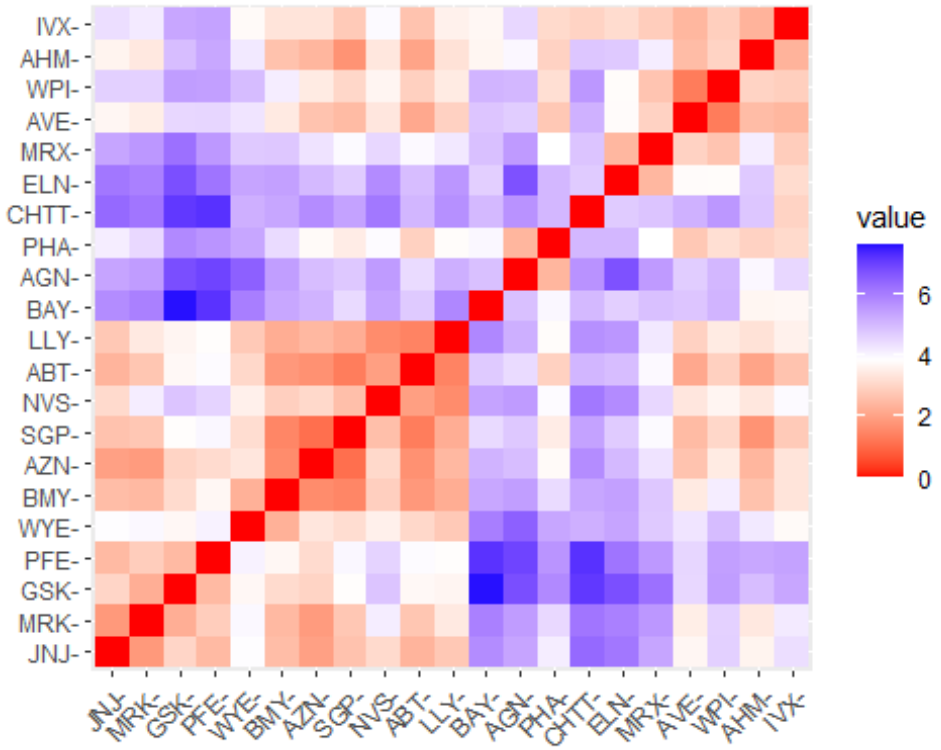
```
## 3 -0.76022489  0.2796041 -0.47742380 -0.7438022 -0.8107428     -1.2684804
## 4 -0.03142211 -0.4360989 -0.31724852  0.1950459  0.4083915      0.1729746
## 5  1.69558112 -0.1780563 -0.19845823  1.2349879  1.3503431      1.1531640
##      Leverage Rev_Growth Net_Profit_Margin
## 1  1.36644699 -0.6912914      -1.320000179
## 2 -0.14170336 -0.1168459      -1.416514761
## 3  0.06308085  1.5180158      -0.006893899
## 4 -0.27449312 -0.7041516       0.556954446
## 5 -0.46807818  0.4671788       0.591242521
```

```
fviz_cluster(k_5,data = Pharma_data2) # to Visualize the clusters
```




```
k_5

## K-means clustering with 5 clusters of sizes 3, 2, 4, 8, 4
##
## Cluster means:
##    Market_Cap       Beta    PE_Ratio        ROE        ROA Asset_Turnover
## 1 -0.87051511  1.3409869 -0.05284434 -0.6184015 -1.1928478     -0.4612656
## 2 -0.43925134 -0.4701800  2.70002464 -0.8349525 -0.9234951      0.2306328
## 3 -0.76022489  0.2796041 -0.47742380 -0.7438022 -0.8107428     -1.2684804
## 4 -0.03142211 -0.4360989 -0.31724852  0.1950459  0.4083915      0.1729746
## 5  1.69558112 -0.1780563 -0.19845823  1.2349879  1.3503431      1.1531640
##      Leverage Rev_Growth Net_Profit_Margin
## 1  1.36644699 -0.6912914      -1.320000179
## 2 -0.14170336 -0.1168459      -1.416514761
## 3  0.06308085  1.5180158      -0.006893899
```

```
## 4 -0.27449312 -0.7041516       0.556954446
## 5 -0.46807818  0.4671788       0.591242521
##
## Clustering vector:
##  ABT  AGN  AHM  AZN  AVE  BAY  BMY CHTT  ELN  LLY  GSK  IVX  JNJ  MRX  MRK
NVS
##    4    2    4    4    3    1    4    1    3    4    5    1    5    3    5
4
##  PFE  PHA  SGP  WPI  WYE
##    5    2    4    3    4
##
## Within cluster sum of squares by cluster:
## [1] 15.595925  2.803505 12.791257 21.879320  9.284424
##  (between_SS / total_SS =  65.4 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"
"tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"

distance<- dist(Pharma_data2, method = "euclidean")
fviz_dist(distance)
```




```
# I can see there are 5 clusters and the center is defined after 25 restarts
which is determined in kmeans.
```

Visualization aids in understanding the distribution and separation of clusters.

```
# Refitting K-means for a clearer interpretation
#K-Means Cluster Analysis- Fit the data with 5 clusters

fit<-kmeans(Pharma_data2,5)

# Analyzing the mean values of each variable within each cluster

aggregate(Pharma_data2,by=list(fit$cluster),FUN=mean)
```

```
##   Group.1  Market_Cap       Beta   PE_Ratio        ROE        ROA
## 1       1  1.69558112 -0.1780563 -0.1984582  1.2349879  1.3503431
## 2       2 -0.66114002 -0.7233539 -0.3512251 -0.6736441 -0.5915022
## 3       3 -0.96247577  1.1949250 -0.3639982 -0.5200697 -0.9610792
## 4       4 -0.52462814  0.4451409  1.8498439 -1.0404550 -1.1865838
## 5       5  0.08926902 -0.4618336 -0.3208615  0.3260892  0.5396003
##   Asset_Turnover   Leverage Rev_Growth Net_Profit_Margin
## 1   1.153164e+00 -0.4680782  0.4671788         0.5912425
## 2  -1.537552e-01 -0.4040831  0.6917224        -0.4005718
## 3  -1.153164e+00  1.4773718  0.7120120        -0.3688236
## 4   1.480297e-16 -0.3443544 -0.5769454        -1.6095439
## 5   6.589509e-02 -0.2559803 -0.7230135         0.7343816
```

```
Pharma_data3<-data.frame(Pharma_data2,fit$cluster)
Pharma_data3
```

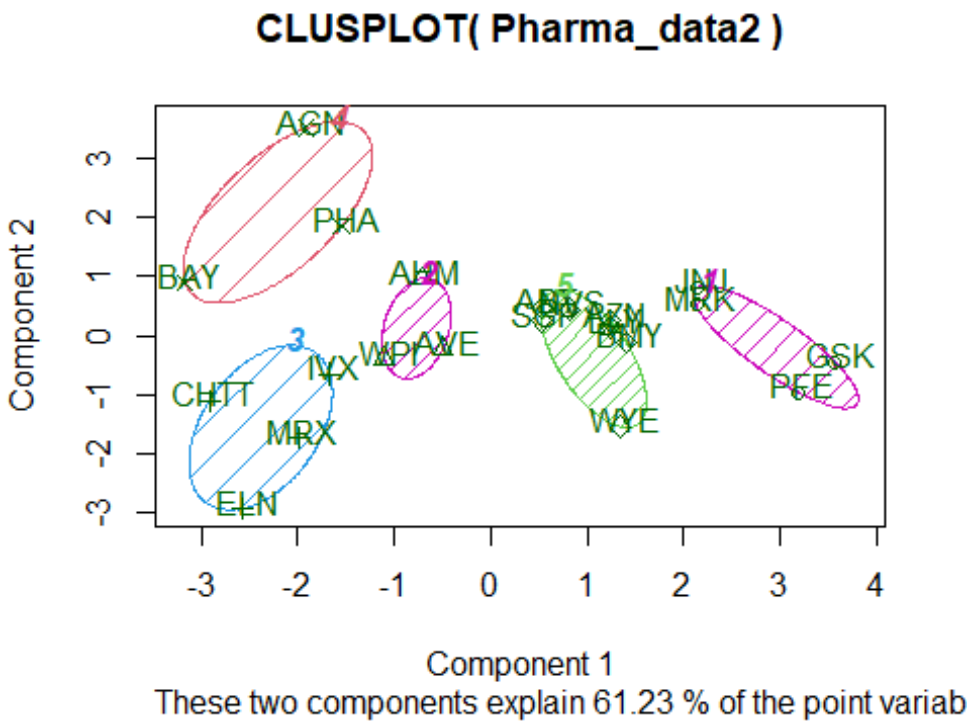
```
##      Market_Cap        Beta    PE_Ratio         ROE        ROA
Asset_Turnover
## ABT   0.1840960 -0.80125356 -0.04671323  0.04009035  0.2416121
0.0000000
## AGN  -0.8544181 -0.45070513  3.49706911 -0.85483986 -0.9422871
0.9225312
## AHM  -0.8762600 -0.25595600 -0.29195768 -0.72225761 -0.5100700
0.9225312
## AZN   0.1702742 -0.02225704 -0.24290879  0.10638147  0.9181259
0.9225312
## AVE  -0.1790256 -0.80125356 -0.32874435 -0.26484883 -0.5664461     -
0.4612656
## BAY  -0.6953818  2.27578267  0.14948233 -1.45146000 -1.7127612     -
0.4612656
## BMY  -0.1078688 -0.10015669 -0.70887325  0.59693581  0.8617498
0.9225312
## CHTT -0.9767669  1.26308721  0.03299122 -0.11237924 -1.1677918     -
0.4612656
## ELN  -0.9704532  2.15893320 -1.34037772 -0.70899938 -1.0174553     -
1.8450624
## LLY   0.2762415 -1.34655112  0.14948233  0.34502953  0.5610770     -
0.4612656
## GSK   1.0999201 -0.68440408 -0.45749769  2.45971647  1.8389364
1.3837968
```

```
## IVX  -0.9393967  0.48409069 -0.34100657 -0.29136529 -0.6979905     -
0.4612656
## JNJ   1.9841758 -0.25595600  0.18013789  0.18593083  1.0872544
0.9225312
## MRX  -0.9632863  0.87358895  0.19240011 -0.96753478 -0.9610792     -
1.8450624
## MRK   1.2782387 -0.25595600 -0.40231769  0.98142435  0.8429577
1.8450624
## NVS   0.6654710 -1.30760129 -0.23677768 -0.52338423  0.1288598     -
0.9225312
## PFE   2.4199899  0.48409069 -0.11415545  1.31287998  1.6322239
0.4612656
## PHA  -0.0240846 -0.48965495  1.90298017 -0.81506519 -0.9047030     -
0.4612656
## SGP  -0.4018812 -0.06120687 -0.40231769 -0.21181593  0.5234929
0.4612656
## WPI  -0.9281345 -1.11285216 -0.43297324 -1.03382590 -0.6979905     -
0.9225312
## WYE  -0.1614497  0.40619104 -0.75792214  1.92938746  0.5422849     -
0.4612656
##         Leverage  Rev_Growth Net_Profit_Margin fit.cluster
## ABT  -0.21209793 -0.52776752        0.06168225           5
## AGN   0.01828430 -0.38113909       -1.55366706           4
## AHM  -0.40408312 -0.57211809       -0.68503583           2
## AZN  -0.74965647  0.14744734        0.35122600           5
## AVE  -0.31449003  1.21638667       -0.42597037           2
## BAY  -0.74965647 -1.49714434       -1.99560225           4
## BMY  -0.02011273 -0.96584257        0.74744375           5
## CHTT  3.74279705 -0.63276071       -1.24888417           3
## ELN   0.61983791  1.88617085       -0.36501379           3
## LLY  -0.07130879 -0.64814764        1.17413980           5
## GSK  -0.31449003  0.76926048        0.82363947           1
## IVX   1.10620040  0.05603085       -0.71551412           3
## JNJ  -0.62166634 -0.36213170        0.33598685           1
## MRX   0.44065173  1.53860717        0.85411776           3
## MRK  -0.39128411  0.36014907       -0.24310064           1
## NVS  -0.67286239 -1.45369888        1.02174835           5
## PFE  -0.54487226  1.10143723        1.44844440           1
## PHA  -0.30169102  0.14744734       -1.27936246           4
## SGP  -0.74965647 -0.43544591        0.29026942           5
## WPI  -0.49367621  1.43089863       -0.09070919           2
## WYE   0.68383297 -1.17763919        1.49416183           5

View(Pharma_data3)
```

Aggregate functions reveal the central tendencies of each cluster, highlighting their defining characteristics.

```
# Cluster plot visualization
```

```
clusplot(Pharma_data2,fit$cluster,color = TRUE,shade = TRUE,labels = 2,lines
= 0)
```



Clusplot visually represents the clustering, showing the grouping and outliers if any.

Task 2

Interpret the clusters with respect to the numerical variables used in forming the clusters.

By noticing the mean values of all quantitative variables for each cluster

Cluster_1 - AGN, PHA, BAY - Suggests higher growth expectations or overvaluation.

Cluster_2 - JNJ, MRK, GSK, PFE - High Market Cap and Leverage: Indicates large, established companies.

Cluster_3 - AHM, AVE, WPI - Low Asset Turnover and Beta: Represents conservative, stable firms.

Cluster_4 - IVX, MRX, ELN, CHTT - Low Market Capital but High Revenue Growth: Reflects emerging growth companies.

Cluster_5 - ABT, NVS, AZN, LLY, BMY, WYE, SGP - Low Revenue Growth, High Asset Turnover, and Net Profit Margin: Signifies efficient, profitably run firms.

Task 3

Is there a pattern in the clusters with respect to the numerical variables (10 to 12)? (those not used in forming the clusters)

For cluster 1: It has the highest PE_Ratio and needs to be held as per the media recommendations.

For cluster 2: It has the highest market_Cap and has Good Leverage value. And they can be moderately recommended.

For cluster 3: It has lowest asset_turnover,and lowest beta. But media recommendations are highly positive.

For cluster 4: The leverage ratio is high, they are moderately recommended.

For Cluster 5: They have lowest revenue growth, highest assest turnover and highest net profit margin.

They are recommended to be held for longer time.

Task 4

Provide an appropriate name for each cluster using any or all of the variables in the dataset.

Cluster 1 - Balanced Performers: This name suggests that firms in this cluster have stable and decent financial metrics. It implies a balanced performance across various financial aspects.

Cluster 2 - Steady Growth Contenders: This name indicates that companies in this cluster demonstrate consistent growth, making them a moderate but reliable option for investment or holding. It reflects both stability and potential for growth.

Cluster 3 - Dynamic Opportunity Firms: This name implies that firms in this cluster might present varied investment opportunities, characterized by both potential growth (buy) and higher risk (sell). It suggests dynamism and variability in performance.

Cluster 4 - Stable Investment Picks: This name reflects firms with good stability and solid financial metrics, making them attractive for buying and long-term investment.

Cluster 5 - Long-term Value Holders: This name suggests that firms in this cluster are ideal for holding due to their potential to provide long-term value, likely characterized by lower but consistent revenue growth and high asset turnover.

Conclusion: This analysis effectively segments the pharmaceutical firms into five distinct clusters, each with unique financial characteristics. The use of both the Elbow and Silhouette methods provides a robust approach to determining the optimal number of clusters, and the visualization tools aid in the interpretation of the results. The analysis offers valuable insights into the firm's market positions and operational efficiencies, useful for investment decisions or strategic industry analysis.