Case Study Report

Module Code: BEMM463J

Module Name: Marketing Analytics

Candidate Number: 211433

Word Count: 2000 word

1. **How many distinct and meaningful segments are present in the market ? Please determine the number of distinct segments are present in the market as represented in the current respondent sample.**

Answer 1:

In order to create meaningful segments from the available data, first we need to understand and manage the customer dynamics. With a foundational assumption in Marketing Analytics that 'All customers differ', it is relatively difficult to divide customers into segments by merely looking at the available data and variable values.

To deal with customer heterogeneity, we can divide customers into homogeneous segments/clusters, where they share similar needs/desires and could fall into matching demographics, based on the survey response data from the available sample.

To decide on the number of clusters, we have used combination of Elbow Curve method and Cluster dendrograms with help of Analytical tool RStudio(code of both are methods are added in the Appendix) and obtained following Clustering Analysis results.

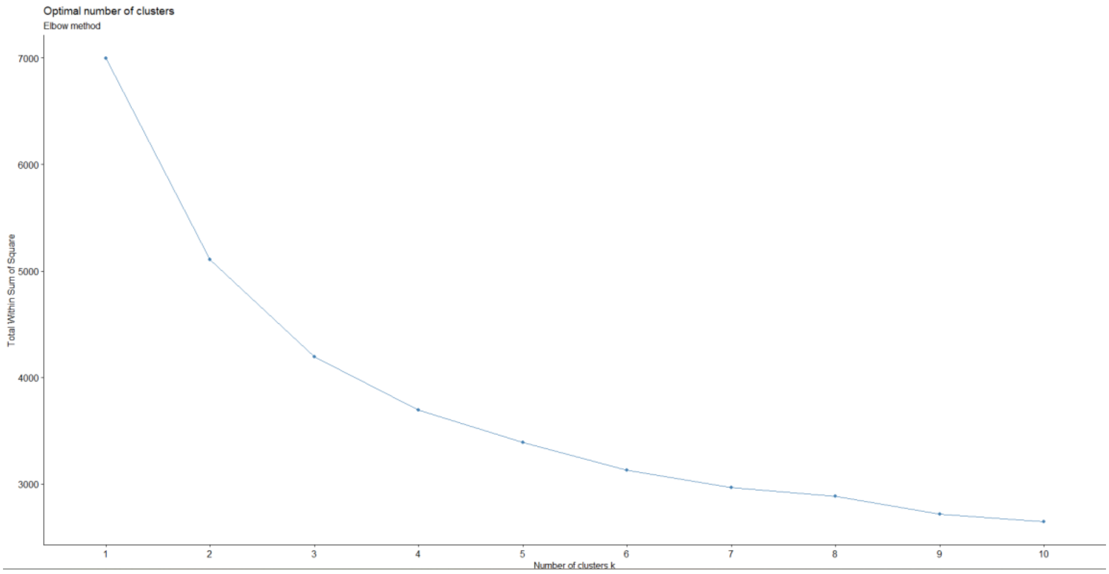

Figure 1 : Elbow Curve using K-mean Clustering Analysis

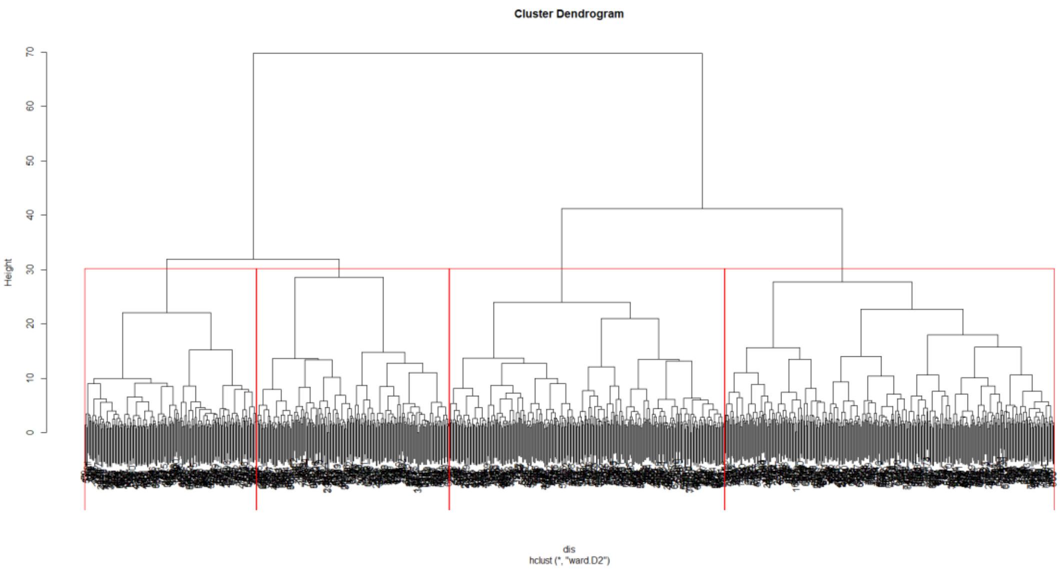

Figure 2: Cluster Dendrogram

From Figure 1 of Elbow curve, we can see that the curve is relatively less declining and becomes almost flat after number 4 on X-axis, hence we used number of clusters as 4(k=4) in the R code of dendrograms to get the output presented in Figure 2 of Cluster Dendrogram. Based on both of these outputs, we can see that loss of information is significantly less when we choose number of clusters as 4, which gives us optimal solution by diving sample data into homogenous segments for further analysis.

R code also provided the exact percentage proportion of customers for each segment, given in following table:

Segment number	1	2	3	4
Segment Size	28.40%	34%	17.70%	19.90%

2. **How would you describe each segment ?Please provide a detailed description of each identified segment using variable in the dataset(e.g., with mean values) Based on the segment characteristics, create a name for each segment that captures the essence of what makes it unique.**

Answer 2 :

By Calculating mean values of each variable from dataset, customers are divided into four segments, which are presented in the following tables:

		Light users	Tech Enthus	Fitness Fanatics	Techy Divas
	Segment Size	**28.40%**	**34%**	**17.70%**	**19.90%**
	Clusters	1	2	3	4
Feature Preferences	Constant communication	3.82	5.13	5.58	4.39
	Timely information	3.32	5.01	4.53	4.23
	Task management	3.24	4.27	5.62	4.14
	Device sturdiness	2.44	4.39	4.55	4.27
	Well-being	3.28	3.71	6.31	5.32
	Athlete	3.26	2.73	4.85	5.54
	Style	3.63	3.71	5.99	4.76
	Amazon Account	0.27	0.59	0.95	0.59
Demographics	Female or Male	0.56	0.45	0.55	0.78
	Type of Degree	1.10	1.40	1.69	1.23
	Income	2.64	3.47	3.89	3.38
	Age	38.55	39.38	31.50	28.15

Table 1: Segment sizes and mean value of all the variables for each segment

Based on their unique characteristics, each cluster are labelled which distinguishes them from one another and highlights their speciality through their names. The table provides insightful information about feature preferences of users from each segment, whereas demographics acts as descriptors and provides knowledge about types of users.

Let us discuss more about insights obtained from these clusters:

Segment 1 : Light users

Occupying 28.4% of population from survey dataset, we call users from this groups as light users, since these users only use basic features of a technology and are not likely to explore more features unless they are forced or influenced by others. 56% of users from this group are female having average age around 38. Highest level of education in the group is 'Undergraduate Degree' denoted by mean value 1.10. Income range of this group is just below £70K, having mean value of 2.6. Mean value of variable Amazon account is 0.27 indicating that, users from this group does not indulge much in online shopping.

From mean value of 3.8 for 'Constant communication' for this cluster , the customers are expecting only necessary communications from their family, friends, along with work emails and message from other relatives. Low value of 'Timely information' 3.32, indicates less inclination towards getting daily updates of news, weather forecasts etc. The group also has low mean value for 'Task Management' having only 3.2 indicates users are not using to-do , event reminder features for managing their daily activities. Having only 2.4 mean value for 'Device sturdiness' is indicator that the users are not overly concerned about safety and long-lasting usage of the device.

Wellness feature preference has a mean score of 3.2, indicating that users in this group are not interested in configuring their devices to receive real-time updates and check daily health reports. The average score of 'Athlete,' which is 3.26, indicates that people in this group will be uninterested in incorporating a sporty routine into their daily lives.

Segment 2 : Tech Enthus

This clusters comprises of highest number of users among other clusters, contributing 34% of users from whole survey population. Users from this group are very enthusiastic about using technology and its enhanced features during their day-to-day activities, hence this group is named as 'Tech Enthus'. 55% of population from this group is male, having average score of income 3.4 and average age around 39 years, which highest compared to other clusters. This indicates users from this group are mostly men in their 40s, who have income above $80K. Amazon Prime account value is also good being 0.59, which indicates the users from this group could be using online shopping frequently.

The combination of a high mean value for 'Contact Communication' of 5.5 and a high mean value for 'Timely Information' of 5.01 indicates that users place a high value on their social life and daily communications with family, friends, colleagues, and would also like to stay updated on their surroundings such as weather, latest news, and event reminders. Users also want the item to be durable, as evidenced by the 4.3 mean score for 'Device sturdiness.' Along with this, task management is a popular tool for users in these clusters who want to manage their everyday activities.

The lowest mean value in this group is contributed to feature preference 'Athlete' having average score of only 2.7, whereas 'Wellness' parameter has relatively higher value of 3.7, which is convincing since men from their 40s would like to a close tap on their health for every moment. Professionals from this group are also concerned about their style status, to look apart from the crowd by owning a stylish watch which serves multiple purposes.

Segment 3: Fitness Fanatics

Contributing 17.7% portion of the entire population from the survey, users from this group are highly focused on fitness measurement features offered on a smartwatch, hence this group is named as Fitness Fanatics. 55% of users from this group having average age value around 31 are female candidates, and rest are male. This group represents highest mean value of 1.69 for education parameter as well as highest

'Income' value of 3.89 compared other three clusters. This indicates the user base from this group are young professionals between 25-34 age group. Another noticeably highest mean value is for 'Amazon Prime' account, which is 0.95, which is convincing since most of the young professionals tend to spend more on online shopping and would like to receive premium services.

Being young professionals, features like 'Constant Communication', 'Timely information' and 'Task Management' have combined high values compared to other clusters. This group is also like to give high priority to features which provides 'Wellness'(mean value 6.3) reports, 'Athlete' (mean value 4.8) level fitness measurement reports along with sturdiness for carrying a stylish watch in their day-to-day life.

Segment 4: Techy Divas

This group comprises 19.9% of users from the dataset population. 78% of users from this group are female, who likes to using technology for focusing on a healthy and organized daily life, hence 'Techy Divas' seems like the right kind of name for this group. Most of females from this group are young undergraduates with mean value of age 28, which is youngest group of people compared other clusters. Around 59% of users also opted for 'Amazon Prime' services, which indicates suggests they are frequent online shoppers.

Young females from this group gives highest priority to features like 'Wellness'(mean value 5.3) , 'Athlete' (mean value 5.5) and 'Style'(mean value 4.7), but they would also like to get advantages of features like 'Contact Communication' , 'Task Management' to have an organized day-to-day life and staying updated with feature of 'Time information'

3. **Which segment should be targeted by Intel? How should Intel Position themselves to compete strongly in the targeted segment(s)? Please provide a detailed discussion of each identified segment, based on the attractiveness of the segment for Intel and the strengths of competitor offerings (e.g., Samsung, Apple, etc.). Explain the factors that used to rate the attractiveness of each segment and Intel's competitive strength.**

Answer:

Targeting identified segments:

To be able to systematically target the required segments Intel can follow GE Matrix Analysis and identify which segments will provide best results by analysing survey outcomes carefully.

By considering two parameters for targeting namely: Market attractiveness and Competitive strength, we have calculated total weightage(using MS-Excel application) for each segment for mentioned factors leveraging available survey data.

Following table illustrates calculations of total weightages of both mentioned parameters for all four segments:

		Market Attractiveness (score out of 7) Mean value of features for each respective segment			
Market Attractiveness Factors	**Weightages(%)**	**Light Users**	**Tech Enthus**	**Fitness Fanatics**	**Techy Divas**
Constant Communication	26.84%	3.82	5.13	5.58	4.39
Weighted Average		1.025288	1.376892	1.497672	1.178276
Timely information	24.55%	3.32	5.01	4.53	4.23
Weighted Average		0.81506	1.229955	1.112115	1.038465
Task Management	23.98%	3.24	4.27	5.62	4.14
Weighted Average		0.776952	1.023946	1.347676	0.992772
Style	24.60%	3.63	3.71	5.99	4.76
Weighted Average		0.89298	0.91266	1.47354	1.17096
Total weightage	100%	3.51028	4.543453	5.431003	4.380473

Table 3: Total weightage of market Attractiveness factors for all four segments

Market attractiveness factors:

By performing an external market research on 'Basis Peak' smartwatch, it was found that four market demanded features were missing or lacking in the finished product (Duffy, 2016) which was launched in 2015. Since the dataset provides survey data about some of these missing features, four(1. Constant Communication, 2. Timely information, 3. Task Management, 4. Style) of them were selected for calculating weightage of market attractiveness for all the identified segments.

Figures from table provides us with clear understanding of which segments scores highest to further leverage them for either targeting or omitting any segment(s).

		Competitive Strengths (score out of 7,excpet for Income) Mean value of features for each respective segment			
Competitive Strength Factors	**Weightages(%)**	**Light Users**	**Tech Enthus**	**Fitness Fanatics**	**Techy Divas**
Athlete	24.90%	3.26	2.73	4.85	5.54
Weighted Average		0.81174	0.67977	1.20765	1.37946
Device Sturdiness	25.07%	2.44	4.39	4.55	4.27
Weighted Average		0.611708	1.100573	1.140685	1.070489
Wellness	28.51%	3.28	3.71	6.31	5.32
Weighted Average		0.935128	1.057721	1.798981	1.516732
Income	21.49%	2.64	3.47	3.89	3.38
Weighted Average		0.567336	0.745703	0.835961	0.726362
Total weightage	100%	2.925912	3.583767	4.983277	4.693043

Table 4: Total weightage of competitive strength factors for all four segments

Competitive Strength factors:

Based on case description, we know that 'Basis Peak' smartwatch got its reputation for providing some of the best features like : Heart rate sensors, Activity tracker, Sleep pattern monitor, and waterproof(up to 50 meters) etc. Adding to this, it was affordable compared to its existing competitors' smartwatches. Assuming that Basis Peak has solve the battery overheating issue, some of the variables from survey data can be matched with already implemented features of 'Basis Peak' to get statistical figures for assessing Intel's competitive strength in the smartwatch market.

To further simplify the targeting process of identified segments, we have created a visualisation using Tableau application. In this graph, the size of bubbles represents the size of each segment(in percentage) and their graphical position based on the total weightage of two parameters 'Market Attractiveness'(on Y-axis) and 'Competitive Strength'(on X-axis)

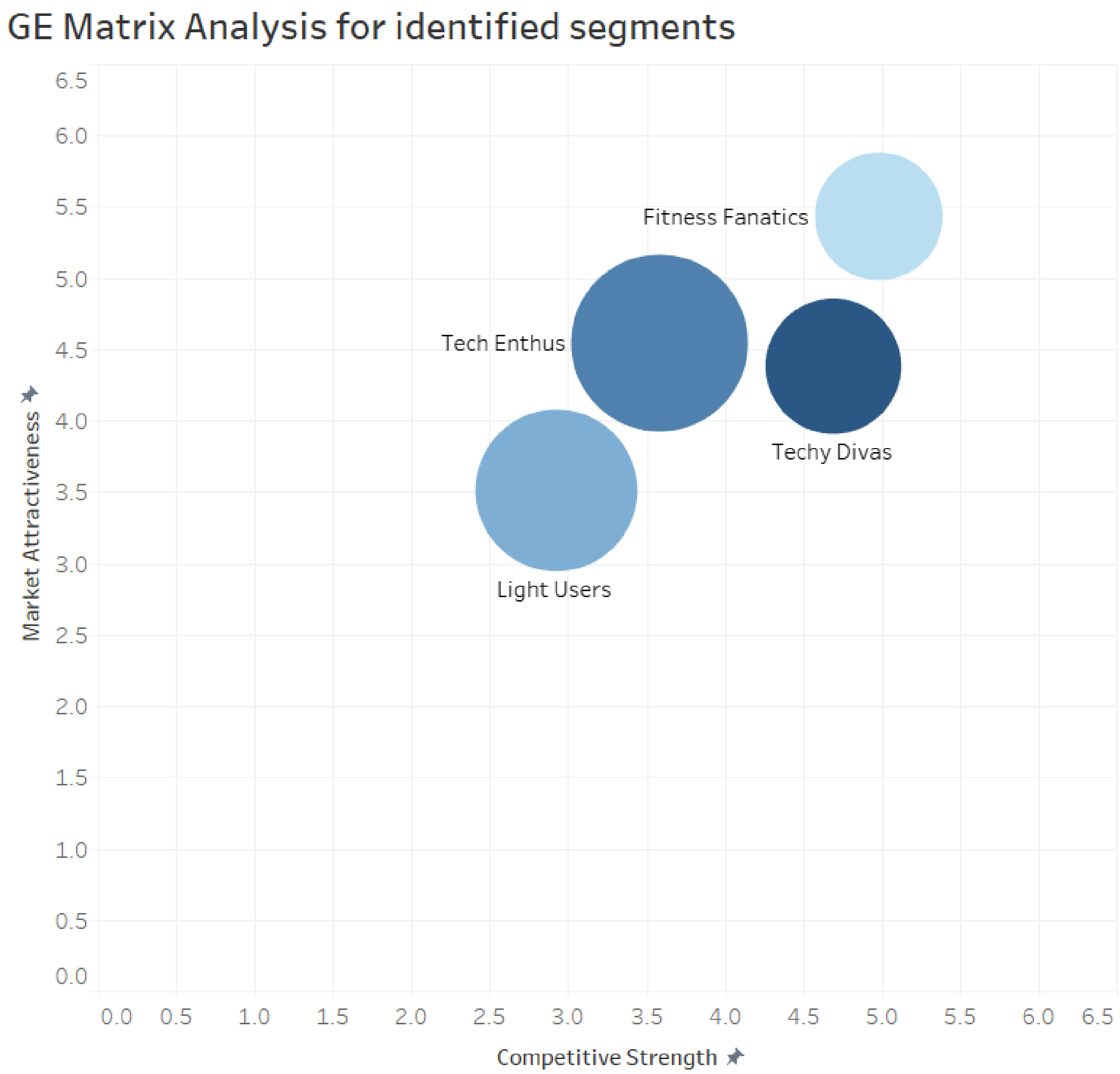

Figure 3: GE Matrix Analysis for identified segments from the survey data.

From above figure it is evident that, Intel need to target following three market segments in the given order:

1. Fitness Fanatics
2. Tech Enthus
3. Techy Divas

Favourable positioning strategy for Intel:

After the overheating issue caused due to battery of 'Basis Peak' first model, for Intel to resell revised version of same product and regain its position in the market, requires a solid marketing strategy implementation. Considering Intel will be competing with not only range of smartwatches offered by numerous brands, but also with well-established brands like Samsung and Apple, who already has a loyal userbase and a large market reach. To be able to compete with, Intel requires a partner which will enhance not only its reach by also help retain their lost customers and earn new customers through minimum marketing expenditure. According to my analysis, Google is the best fit in this situation. Reason being the production integration features offered by the Google. Having an Android OS synergy with its existing features, the Intel's smartwatch could establish a favourable position in the market among other competitors. Integration with Google, will provide access to all the Playstore applications, including GooglePay, and many other Google services. Where Apple's lowest price watch costs around £323 and Samsung' watch costs around £210, 'Basis Peak' which was sold at £199 has a lower price advantage when trying to target userbase from lower income groups. Along with this Google's brand name would be advantageous when running promotional campaigns for entering back in market to create a sustainable position for the product.

Appendix:

R Code for Elbow Curve, Segmentation and Dendrogram:

```r
#install necessary packages
install.packages("readxl")
install.packages("tidyverse")
install.packages("gt")
install.packages("cluster")
install.packages("factoextra")

#load packages
library(readxl)
library(tidyverse)
library(gt)
library(cluster)
library(factoextra)
#importing data from Excel
imported <- read_excel("C:/Users/anand/Dropbox/PC/Desktop/Marketing Analytics/Assignment 1, Case study Report/SmartWatch Data File.xlsx")
#explore data set
names(imported)
summary(imported)
#save data set without id variable
df <- imported
names(df)
##Segmentation step
#standardize values
dfz <- scale(df)
## Ward Hierarchical Clustering
# calculate distance matrix with euclidian distance
dis <- dist(dfz, method = "euclidean")
#clustering algorithm
fit <- hclust(dis, method="ward.D2")
# display dendrogram
plot(fit)
# cut dendrogram into 4 clusters
cluster <- cutree(fit, k=4)
#explore clusters
cluster
table(cluster)
# draw dendogram with red borders around the 4 clusters
rect.hclust(fit, k=4, border="red")
#add cluster to original data set
df_final <- cbind(df, cluster)
names(df_final)
```

```r
View(df_final)
##Description step
#calculate segment size in percentages
proportions <- table(df_final$cluster)/length(df_final$cluster)
percentages <- proportions*100
percentages
#Explore mean values of variables in clusters
segments <- df_final %>%
  group_by(cluster) %>%
  summarise_at(vars(ConstCom, TimelyInf, TaskMgm,  DeviceSt,  Wellness, Athlete,  Style,AmznP,  Female, Degree, Income ,Age),
               list(M = mean))
segments
#Create simple table with mean values
segments %>%
  gt() %>%
  tab_header(
    title = md("Mean Values for Clusters"))


#Elbow Curve Code

data <- imported[1:11]

data_scale <- scale(data)

data <- dist(data_scale)

fviz_nbclust(data_scale,kmeans,method ="wss") +
  labs(subtitle = "Elbow method")
```

```
R 4.1.2 · ~/
> #importing data from Excel
> imported <- read_excel("C:/Users/anand/Dropbox/PC/Desktop/Marketing Analytics/Assignment 1, Case study Report/SmartWatch Data File.xlsx")
New names:
* `` -> ...13
* `` -> ...14
* `` -> ...15
* `` -> ...18
* `` -> ...19
* ...
> #explore data set
> names(imported)
 [1] "ConstCom"      "TimelyInf"      "TaskMgm"       "DeviceSt"      "Wellness"
 [6] "Athlete"       "Style"          "AmznP"         "Female"        "Degree"
[11] "Income"        "Age"            "...13"         "...14"         "...15"
[16] "Total Sum"     "Weightages(%)"  "...18"         "...19"         "...20"
> summary(imported)
    ConstCom       TimelyInf        TaskMgm         DeviceSt        Wellness         Athlete
 Min.   :1.00   Min.   :1.00   Min.   :1.00   Min.   :1.00   Min.   :1.000   Min.   :1.000
 1st Qu.:4.00   1st Qu.:3.00   1st Qu.:3.00   1st Qu.:3.00   1st Qu.:3.000   1st Qu.:3.000
 Median :5.00   Median :4.00   Median :4.00   Median :4.00   Median :5.000   Median :4.000
 Mean   :4.69   Mean   :4.29   Mean   :4.19   Mean   :3.84   Mean   :4.367   Mean   :3.814
 3rd Qu.:6.00   3rd Qu.:5.00   3rd Qu.:5.00   3rd Qu.:5.00   3rd Qu.:6.000   3rd Qu.:5.000
 Max.   :7.00   Max.   :7.00   Max.   :7.00   Max.   :7.00   Max.   :7.000   Max.   :7.000
     Style           AmznP            Female           Degree          Income            Age
 Min.   :1.000   Min.   :0.000   Min.   :0.000   Min.   :1.000   Min.   :1.000   Min.   :24.00
 1st Qu.:3.000   1st Qu.:0.000   1st Qu.:0.000   1st Qu.:1.000   1st Qu.:3.000   1st Qu.:31.00
 Median :4.000   Median :1.000   Median :1.000   Median :1.000   Median :3.000   Median :36.00
 Mean   :4.299   Mean   :0.564   Mean   :0.566   Mean   :1.332   Mean   :3.292   Mean   :35.52
 3rd Qu.:5.000   3rd Qu.:1.000   3rd Qu.:1.000   3rd Qu.:2.000   3rd Qu.:4.000   3rd Qu.:40.00
 Max.   :7.000   Max.   :1.000   Max.   :1.000   Max.   :2.000   Max.   :5.000   Max.   :47.00
   ...13          ...14            ...15              Total Sum           Weightages(%)
 Mode:logical   Mode:logical   Length:1000        Length:1000        Length:1000
 NA's:1000      NA's:1000      Class :character   Class :character   Class :character
                               Mode  :character   Mode  :character   Mode  :character


    ...18              ...19              ...20
 Length:1000        Length:1000        Length:1000
 Class :character   Class :character   Class :character
 Mode  :character   Mode  :character   Mode  :character
```

```
R 4.1.2 · ~/
 [1] "ConstCom"      "TimelyInf"      "TaskMgm"       "DeviceSt"      "Wellness"
 [6] "Athlete"       "Style"          "AmznP"         "Female"        "Degree"
[11] "Income"        "Age"            "...13"         "...14"         "...15"
[16] "Total Sum"     "Weightages(%)"  "...18"         "...19"         "...20"
> ##Segmentation step
> #standardize values
> dfz <- scale(df)
Error in colMeans(x, na.rm = TRUE) : 'x' must be numeric
> ## Ward Hierarchical Clustering
> # calculate distance matrix with euclidian distance
> dis <- dist(dfz, method = "euclidean")
> #clustering algorithm
> fit <- hclust(dis, method="ward.D2")
> # display dendrogram
> plot(fit)
> # cut dendrogram into 4 clusters
> cluster <- cutree(fit, k=4)
> #explore clusters
> cluster
   [1] 1 2 2 2 2 1 2 2 2 3 3 3 2 2 4 2 2 1 3 1 3 1 1 2 1 4 2 2 2 4 1 3 3 4 1 2 2 4 2 2 2 1 3 2 3 1
  [47] 1 2 1 1 2 3 4 2 1 4 3 3 3 1 4 2 2 1 1 3 4 2 1 2 1 1 3 2 2 4 4 2 2 4 4 4 1 3 1 2 2 1 1 4 3 1
  [93] 1 2 2 2 1 2 1 2 2 4 4 1 4 1 3 4 4 2 4 2 3 1 3 4 2 4 1 1 4 3 2 4 3 1 2 4 4 1 3 4 4 3 1 4 4 2
 [139] 2 2 4 3 3 1 3 4 1 1 2 3 1 2 3 1 4 3 1 2 1 2 2 2 3 3 1 1 2 3 1 1 1 1 3 2 2 1 3 1 1 1 3 4 4 1
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 [231] 2 1 2 2 1 2 3 4 4 2 4 3 2 4 2 2 3 4 1 1 1 2 2 2 4 4 2 2 2 2 2 2 4 1 1 2 3 1 3 4 2 3 1 1 2 2
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 [323] 4 2 2 4 4 1 4 2 2 2 2 2 1 2 4 4 3 4 4 1 3 1 1 1 2 2 4 4 4 1 1 1 4 2 2 3 2 4 2 2 2 1 3 4 1 1
 [369] 1 1 3 1 1 1 1 1 4 1 4 4 1 1 1 1 2 4 3 3 4 4 4 3 2 4 2 3 2 1 4 2 3 3 2 4 4 3 1 3 1 4 4 1 3 3
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 [461] 4 1 1 1 1 3 3 1 2 1 1 1 3 1 3 4 2 2 2 2 1 2 3 1 2 2 3 2 3 2 2 4 1 3 1 2 1 2 3 4 2 2 1 2 2 4
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 [553] 2 1 3 1 3 2 1 1 1 2 1 2 1 2 1 2 1 1 3 2 4 4 3 1 3 1 2 2 2 4 1 1 2 1 1 2 1 2 2 3 2 4 1 2 1 4
 [599] 1 2 1 2 1 3 1 2 3 3 2 2 2 4 1 4 2 2 2 1 3 1 1 3 4 1 1 3 1 1 4 2 2 1 1 2 3 2 1 2 1 2 3 2 3 2
 [645] 3 1 1 2 3 4 1 4 3 4 1 1 2 3 1 3 1 1 4 1 4 2 3 3 2 2 4 2 2 4 1 2 1 2 2 1 4 1 2 1 2 2 2 4 2 3
 [691] 2 1 1 4 2 4 2 2 2 4 2 4 3 2 3 2 1 2 1 2 2 2 2 2 1 2 4 2 2 3 3 1 4 4 3 1 4 4 2 1 2 1 2 2 2 4
 [737] 4 2 1 1 2 1 2 1 2 4 3 1 2 3 1 2 3 4 2 3 2 1 4 2 4 1 1 1 2 1 3 4 4 1 4 1 4 3 1 1 1 4 3 2 3 2
 [783] 3 3 2 1 2 4 4 2 4 2 3 2 1 2 2 3 3 1 2 1 4 2 4 2 2 1 3 2 1 2 1 4 1 2 3 3 2 3 1 2 3 1 2 1 1 2
 [829] 4 3 2 2 4 4 2 2 3 2 2 2 2 2 4 3 4 4 1 2 2 3 2 1 4 1 3 1 2 1 2 3 1 2 4 1 1 3 2 2 4 4 4 4 4 4
 [875] 4 3 1 2 1 1 3 2 2 2 3 2 3 1 2 2 4 2 2 3 3 1 3 1 3 4 2 3 3 3 4 3 4 4 4 2 4 4 3 4 3 4 2 4 2 1
 [921] 2 3 2 2 1 2 2 2 4 1 2 3 2 1 1 1 2 3 4 2 2 2 1 2 3 4 2 2 1 2 4 2 4 4 1 2 4 2 2 2 2 1 2 3 2 1
 [967] 3 1 4 2 2 2 2 3 3 1 3 2 1 3 2 3 2 1 4 3 1 4 4 4 4 1 3 4 2 3 2 2 1 3
```

```
R 4.1.2 · ~/
cluster
  1   2   3   4
284 340 177 199
> # draw dendogram with red borders around the 4 clusters
> rect.hclust(fit, k=4, border="red")
> #add cluster to original data set
> df_final <- cbind(df, cluster)
> names(df_final)
 [1] "ConstCom"      "TimelyInf"     "TaskMgm"       "DeviceSt"      "Wellness"
 [6] "Athlete"       "Style"         "AmznP"         "Female"        "Degree"
[11] "Income"        "Age"           "...13"         "...14"         "...15"
[16] "Total Sum"     "Weightages(%)" "...18"         "...19"         "...20"
[21] "cluster"
> View(df_final)
> ##Description step
> #calculate segment size in percentages
> proportions <- table(df_final$cluster)/length(df_final$cluster)
> percentages <- proportions*100
> percentages

   1    2    3    4
28.4 34.0 17.7 19.9
> #Explore mean values of variables in clusters
> segments <- df_final %>%
+   group_by(cluster) %>%
+   summarise_at(vars(ConstCom, TimelyInf, TaskMgm,  DeviceSt,  Wellness, Athlete,  Style,AmznP,  Female, Degree, Income ,Age),
+                list(M = mean))
> segments
# A tibble: 4 x 13
  cluster ConstCom_M TimelyInf_M TaskMgm_M DeviceSt_M Wellness_M Athlete_M Style_M AmznP_M Female_M
    <int>      <dbl>       <dbl>     <dbl>      <dbl>      <dbl>     <dbl>   <dbl>   <dbl>    <dbl>
1       1       3.82        3.32      3.24       2.44       3.28      3.26    3.63   0.271    0.556
2       2       5.13        5.01      4.27       4.39       3.71      2.73    3.71   0.591    0.453
3       3       5.58        4.53      5.62       4.55       6.31      4.85    5.99   0.949    0.554
4       4       4.39        4.23      4.14       4.27       5.32      5.54    4.76   0.593    0.784
# ... with 3 more variables: Degree_M <dbl>, Income_M <dbl>, Age_M <dbl>
```

MS-Excel calculation tables for market attractiveness and competitive strength

	Total Sum	**Weightages(%)**
Constant Comm	4690	26.84755853
Timely info	4290	24.55778808
Task Mgm	4190	23.98534547
Style	4299	24.60930792
Total	17469	100

	Total Sum	**Weightage(%)**
Athlete	3814	24.90694181
DeviceSt	3840	25.07673219
Wellness	4367	28.51825247
Income	3292	21.49807353
Total	15313	10000%

		Competetive Strengths (score out of 7,excpet for Income) Mean value of scores for each respective segment			
Competetive Strength Factors	Weightages(%)	Segment 1	Segment 2	Segment 3	Segment 4
Athlete	24.90694181	3.26	2.73	4.85	5.54
Weighted Average		0.81174	0.67977	1.20765	1.37946
DeviceSt	25.07673219	2.44	4.39	4.55	4.27
Weighted Average		0.611708	1.100573	1.140685	1.070489
Wellness	28.51825247	3.28	3.71	6.31	5.32
Weighted Average		0.935128	1.057721	1.798981	1.516732
Income	21.49807353	2.64	3.47	3.89	3.38
Weighted Average		0.567336	0.745703	0.835961	0.726362
Total weightage		2.925912	3.583767	4.983277	4.693043

		Market Attractiveness (score out of 7) Mean value of scores for each respective segment			
Market Attractiveness Factors	Weightages(%)	Segment 1	Segment 2	Segment 3	Segment 4
Constant Comm	26.84755853	3.82	5.13	5.58	4.39
Weighted Average		1.025288	1.376892	1.497672	1.178276
Timely information	24.55778808	3.32	5.01	4.53	4.23
Weighted Average		0.81506	1.229955	1.112115	1.038465
Task Management	23.98534547	3.24	4.27	5.62	4.14
Weighted Average		0.776952	1.023946	1.347676	0.992772
Style	24.60930792	3.63	3.71	5.99	4.76
Weighted Average		0.89298	0.91266	1.47354	1.17096
Total weightage		3.51028	4.543453	5.431003	4.380473

Segments	X corrdinate	Y Coordinate	Size of the Segment	Segment Labels
Segment 1	2.925912	3.51028	28.4	Light Users
Segment 2	3.583767	4.543453	34	Tech Enthus
Segment 3	4.983277	5.431003	17.7	Fitness Fanatics
Segment 4	4.693043	4.380473	19.9	Techy Divas

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