Ford Ka Clustering Analysis

FRE518: Survey Design and Data Analysis

1 Getting started

1a. Create a folder called FRE518 Assignment 1 in your computer (you can name it whatever you like). Then create two subfolders called `Data` and `Code`, respectively.

Open up RStudio and start a new R Project. This project should be associated with this assignment's folder (File -> New Project -> Existing Directory -> FRE518 Assignment 1 folder). You will submit this zip folder in Canvas as part of your assignment.

Start a new `RMarkdown` file (File -> New file -> R Markdown) and save this file in the `Code` folder.

1b. Load the `{pacman}` package. Now use the `p_load()` function to load the following packages: `here`, `dplyr`, `tiydverse`, `readxl`, `janitor`, `modelsummary`, `gtsummary`, `cluster`, `factoextra`, and `kableExtra`.

```
pacman::p_load(dplyr, tidyverse, ggplot2, here, readxl, janitor, modelsummary,
               kableExtra, cluster, factoextra, gtsummary)
```

1c. Download the dataset from Canvas. Save it in the `Data` subfolder of your FRE518 Assignment 1 folder.

1d. Read the the demographic and psychographic sheets into R using the `read_excel()` function. *Hint: You can use the arguments `sheet = sheet_name` and `skip = #_of_rows_to_skip` to load these files without having to make any changes to the Excel file uploaded on Canvas. Then merge these two dataframes by `respondent_id` using the `left_join` function.*

You will notice that some of the variable names are more than one word, and some are capitalized. While this is okay, it might just be more time consuming to call these variables later on. So you can use the `clean_names()` function from the `{janitor}` package to "clean" the variable names.

```
# Read in the data
dg <- read_excel(here("data", "Ford Ka (Student).xls"),
                 sheet = "Demographic Data",
                 skip = 6) %>%
  clean_names()

psyc <- read_excel(here("data", "Ford Ka (Student).xls"),
                   sheet = "Psychographic Data",
                   skip = 6) %>%
  clean_names()

# Merge the two files together
ford <- left_join(dg, psyc, by = c("respondent_number"))
```

1e. All variables are stored as numeric (*you can check with the `glimpse()` function*), which is in the format that we need to do the clustering analysis. It may be helpful to label the demographic variables based on their definition. One way to do this in R is to convert the variables to factors because R stores these variables as numeric but can display text when printed.

Use the `recode_factor()` to convert the following variables to factors: `preference_group`, `gender`, `x1st_time_purchase`, `age_category`, `children_category`, `income_category`.

```
# manually factor variables
ford$preference_group <- recode_factor(factor(ford$preference_group),
                                       `1` = "Ka Chooser (top 3)",
                                       `2` = "Ka Non-Chooser (bottom 3)",
                                       `3` = "Middle (middle 4)")

ford$gender <- recode_factor(factor(ford$gender),
                             `1` = "Male",
                             `2` = "Female")

ford$marital_status <- recode_factor(factor(ford$marital_status),
                                     `1` = "Married",
                                     `2` = "Living Together",
                                     `3` = "Single")

ford$x1st_time_purchase <- recode_factor(factor(ford$x1st_time_purchase),
                                         `1` = "Yes",
                                         `2` = "No")

ford$age_category <- recode_factor(factor(ford$age_category),
                                   `1` = "<25",
                                   `2` = "25-29",
                                   `3` = "30-34",
                                   `4` = "35-39",
                                   `5` = "40-44",
                                   `6` = ">44")

ford$children_category <- recode_factor(factor(ford$children_category),
                                        `0` = "0 child",
                                        `1` = "1 child",
                                        `2` = ">1 child")

ford$income_category <- recode_factor(factor(ford$income_category),
                                      `1` = "<100K",
                                      `2` = "100K-150K",
                                      `3` = "150K-200K",
                                      `4` = "200K-250K",
                                      `5` = "250K-300K",
                                      `6`= ">300K")
```

2 Crosstabs Analysis

Run a cross-tab analysis to check whether different demographic variables separate "Ka Choosers" from "Ka Non-Choosers". You can use either the `datasummary_crosstab()` or `tbl_cross()` functions or another function of your choice. Make sure that you show the row percentages.

```r
# using {datasummary} package
ct_gender <- datasummary_crosstab(preference_group ~ gender,
                     statistic = 1 ~ Percent("row"),
                     data = ford,
                     title = 'Crosstab of Preference Group and Gender',
                     output = 'kableExtra',
                     fmt = 0)

ct_marital <- datasummary_crosstab(preference_group ~ marital_status,
                                  statistic = 1 ~ Percent("row"),
                                  data = ford,
                                  title = 'Crosstab of Preference Group and Marital Status',
                                  fmt = 0)

ct_firstcar <- datasummary_crosstab(preference_group ~ x1st_time_purchase,
                                   statistic = 1 ~ Percent("row"),
                                   title = 'Crosstab of Preference Group and First Car Purhcase',
                                   data = ford,
                                   fmt = 0)

ct_kids <- datasummary_crosstab(preference_group ~ children_category,
                                statistic = 1 ~ Percent("row"),
                                title = 'Crosstab of Preference Group and Number of Kids',
                                data = ford,
                                fmt = 0)

ct_income <- datasummary_crosstab(preference_group ~ income_category,
                                statistic = 1 ~ Percent("row"),
                                title = 'Crosstab of Preference Group and Income Category',
                                data = ford,
                                fmt = 0)

ct_age <- datasummary_crosstab(preference_group ~ age_category,
                               statistic = 1 ~ Percent("row"),
                               title = 'Crosstab of Preference Group and Age Category',
                               data = ford,
                               fmt = 0)
```

Results are the same as the answer sheet

Choosers skewed 54% female, non-choosers 50%

```
ct_gender %>% kable_styling(latex_options = c("striped", "hold_position"))
```

Table 1: Crosstab of Preference Group and Gender

preference_group		Male	Female
Ka Chooser (top 3)	% row	47	53
Ka Non-Chooser (bottom 3)	% row	50	50
Middle (middle 4)	% row	65	35
All	% row	52	48

Choosers skewed 57% married, non-choosers 47% married

```
ct_marital %>% kable_styling(latex_options = c("striped", "hold_position"))
```

Table 2: Crosstab of Preference Group and Marital Status

preference_group		Married	Living Together	Single
Ka Chooser (top 3)	% row	57	12	31
Ka Non-Chooser (bottom 3)	% row	47	8	44
Middle (middle 4)	% row	44	13	44
All	% row	51	11	38

Choosers and non-choosers both 89% not first car purchase

```
ct_firstcar %>% kable_styling(latex_options = c("striped", "hold_position"))
```

Table 3: Crosstab of Preference Group and First Car Purhcase

preference_group		Yes	No
Ka Chooser (top 3)	% row	11	89
Ka Non-Chooser (bottom 3)	% row	11	89
Middle (middle 4)	% row	26	74
All	% row	15	85

Choosers skewed 54% no kids, non-choosers 62% no kids

```
ct_kids %>% kable_styling(latex_options = c("striped", "hold_position"))
```

Choosers skewed 24% 250-300K income, non-choosers 17% 250-300K income

```
ct_income %>% kable_styling(latex_options = c("striped", "hold_position"))
```

Choosers skewed 31% in the 40-44 age group, non-choosers 21%

Table 4: Crosstab of Preference Group and Number of Kids

preference_group		0 child	1 child	>1 child
Ka Chooser (top 3)	% row	53	25	22
Ka Non-Chooser (bottom 3)	% row	62	17	21
Middle (middle 4)	% row	66	11	23
All	% row	59	19	22

Table 5: Crosstab of Preference Group and Income Category

preference_group		<100K	100K-150K	150K-200K	200K-250K	250K-300K	>300K
Ka Chooser (top 3)	% row	9	16	16	16	24	18
Ka Non-Chooser (bottom 3)	% row	7	21	22	22	17	11
Middle (middle 4)	% row	11	19	19	18	18	15
All	% row	9	18	18	18	20	15

```
ct_age %>% kable_styling(latex_options = c("striped", "hold_position"))
```

Table 6: Crosstab of Preference Group and Age Category

preference_group		<25	25-29	30-34	35-39	40-44	>44
Ka Chooser (top 3)	% row	9	16	20	9	31	16
Ka Non-Chooser (bottom 3)	% row	4	18	17	15	21	25
Middle (middle 4)	% row	18	19	19	15	19	10
All	% row	10	17	19	12	25	17

3 Clustering Analysis

3a. Create a new dataframe called `ford_psyc` that contains only the `ford` and `q1:q62` variables only.

3b. Use the `kmeans()` function to run the clustering analysis.

3c. Make sure you use the `set.seed(insert_random_number)` function to ensure I can replicate your answers.

```
ford_psyc <- select(ford, q1:q62)

set.seed(2022)
k3 <- kmeans(ford_psyc, centers = 3, nstart = 25)
set.seed(2022)
k4 <- kmeans(ford_psyc, centers = 4, nstart = 25)
set.seed(2022)
k5 <- kmeans(ford_psyc, centers = 5, nstart = 25)
```

The results of the clustering are presented in the Appendix.

- The three clusters have the following sizes: **107, 65, 78**
- The four clusters have the following sizes: **32, 65, 78, 75** These results replicate the numbers in the file Ford Ka 4-Cluster Results - no variables missing.
- The five clusters have the following sizes: **32, 37, 38, 65, 78** I don't get the same small cluster as noted by the students

4 Further Analysis - Using the output from the 4 cluster analysis

4a. Using the `cbind()` function, join the `ford` dataframe and the `cluster` variable from your `k4` object.

```
ford_cluster <- cbind(ford, k4["cluster"])
```

4b. Run a cross-tab analysis on the 4 segments to identify choice preferences and demographic characteristics of each segment.

\textcolor{blue}{The sample results below show the analysis for Cluster 1 (their cluster 3) with size 32 or 13% of the sample.

- **Gender:** I also get an even 50/50 split for this whole cluster, but not an even split if we look at Ka Chooser only.
- **Income:** I'm getting that they are high (>300K) income and between 100-150K, not <100K
- **Age:** I also get majority <44 years old, but as noted above, this number is for the whole cluster and not just Ka Chooser

```
c1_gender <- datasummary_crosstab(preference_group ~ gender,
                     statistic = 1 ~ Percent("row"),
                     data = ford_cluster %>% filter(cluster == 1),
                     title = 'Crosstab of Preference Group and Gender (Cluster 1)')

c1_income <- datasummary_crosstab(preference_group ~ income_category,
                     statistic = 1 ~ Percent("row"),
                     data = ford_cluster %>% filter(cluster == 1),
```

```r
                    title = ' Crosstab of Preference Group and Income (Cluster 1)')

c1_age <- datasummary_crosstab(preference_group ~ age_category,
                    statistic = 1 ~ Percent("row"),
                    data = ford_cluster %>% filter(cluster == 1),
                    title = ' Crosstab of Preference Group and Age (Cluster 1)')

c1_gender %>% kable_styling(latex_options = c("striped", "hold_position"))
```

Table 7: Crosstab of Preference Group and Gender (Cluster 1)

preference_group		Male	Female
Ka Chooser (top 3)	% row	55.6	44.4
Ka Non-Chooser (bottom 3)	% row	25.0	75.0
Middle (middle 4)	% row	50.0	50.0
All	% row	50.0	50.0

```r
c1_income %>% kable_styling(latex_options = c("striped", "hold_position"))
```

Table 8: Crosstab of Preference Group and Income (Cluster 1)

preference_group		<100K	100K-150K	150K-200K	200K-250K	250K-300K	>300K
Ka Chooser (top 3)	% row	22.2	27.8	0.0	16.7	16.7	16.7
Ka Non-Chooser (bottom 3)	% row	0.0	0.0	50.0	0.0	25.0	25.0
Middle (middle 4)	% row	10.0	20.0	10.0	20.0	10.0	30.0
All	% row	15.6	21.9	9.4	15.6	15.6	21.9

```r
c1_age %>% kable_styling(latex_options = c("striped", "hold_position"))
```

Table 9: Crosstab of Preference Group and Age (Cluster 1)

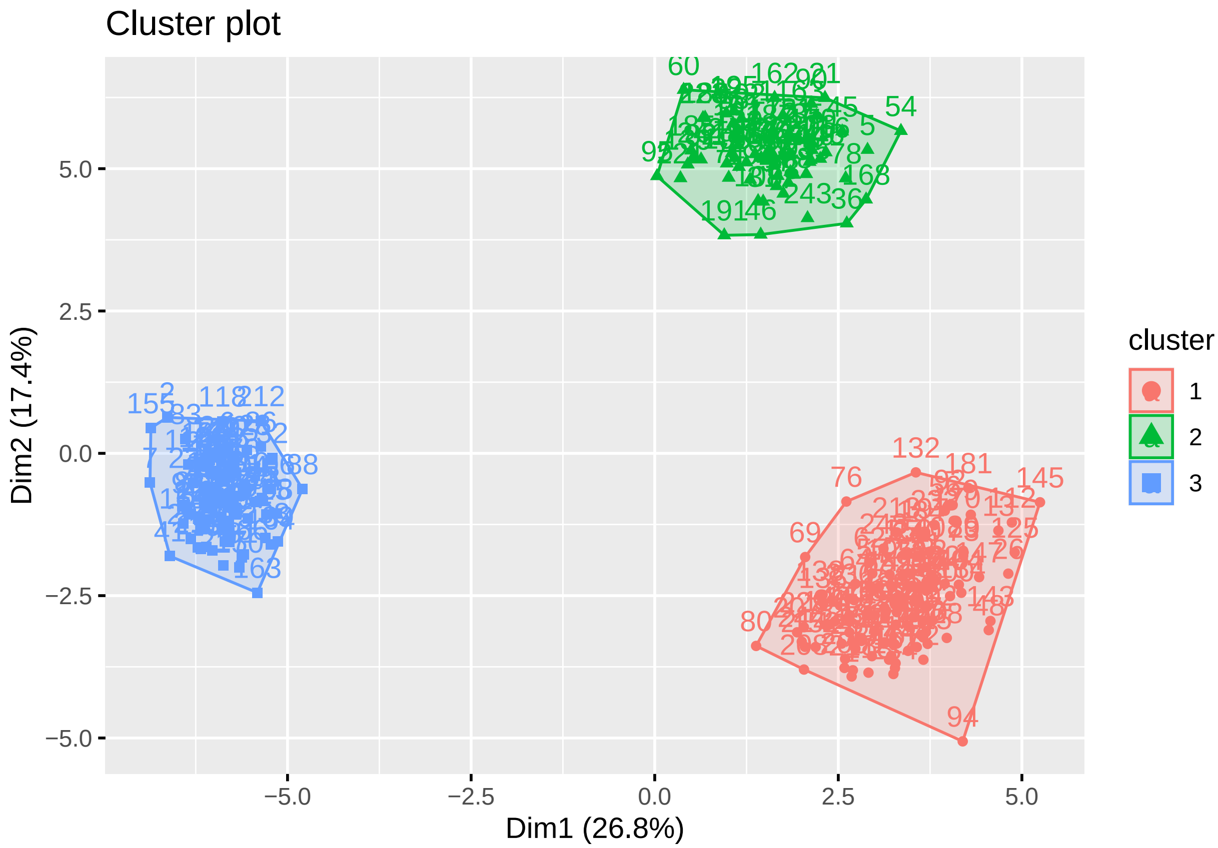
preference_group		<25	25-29	30-34	35-39	40-44	>44
Ka Chooser (top 3)	% row	5.6	16.7	16.7	5.6	38.9	16.7
Ka Non-Chooser (bottom 3)	% row	25.0	50.0	25.0	0.0	0.0	0.0
Middle (middle 4)	% row	20.0	20.0	0.0	30.0	30.0	0.0
All	% row	12.5	21.9	12.5	12.5	31.2	9.4

5 Appendix

```r
# 3 cluster analysis
k3$centers
```

```
##         q1       q2       q3       q4       q5       q6       q7       q8
## 1 4.728972 2.448598 3.943925 3.308411 2.411215 4.018692 3.822430 3.915888
## 2 4.015385 3.769231 5.938462 6.015385 6.015385 3.969231 3.800000 4.107692
## 3 6.512821 6.512821 3.884615 4.025641 4.012821 3.974359 4.025641 3.756410
##         q9      q10      q11      q12      q13      q14      q15      q16
## 1 3.859813 3.878505 3.971963 4.084112 3.934579 6.130841 6.224299 5.308411
## 2 3.769231 3.815385 3.876923 4.138462 4.169231 3.984615 4.169231 3.923077
## 3 4.076923 4.051282 4.089744 4.000000 3.910256 1.512821 3.923077 3.910256
##        q17      q18      q19      q20      q21      q22      q23      q24
## 1 6.205607 5.336449 5.485981 5.383178 6.121495 6.186916 2.542056 2.345794
## 2 2.000000 4.015385 4.215385 4.061538 4.200000 4.107692 3.876923 3.692308
## 3 4.064103 3.858974 3.987179 1.512821 3.846154 4.089744 6.487179 1.320513
##        q25      q26      q27      q28      q29      q30      q31      q32
## 1 1.934579 1.822430 2.691589 1.897196 2.700935 2.598131 4.672897 4.112150
## 2 4.169231 3.800000 4.169231 4.030769 4.107692 3.892308 6.030769 6.046154
## 3 3.961538 3.987179 3.923077 4.038462 3.923077 3.910256 1.564103 4.076923
##        q33      q34      q35      q36      q37      q38      q39      q40
## 1 4.018692 4.018692 4.028037 3.925234 4.813084 4.140187 3.971963 3.841121
## 2 5.969231 5.938462 6.076923 5.969231 6.092308 6.046154 1.861538 2.046154
## 3 4.141026 3.948718 4.102564 3.910256 3.820513 4.076923 4.038462 3.820513
##        q41      q42      q43      q44      q45      q46      q47      q48
## 1 3.205607 3.252336 3.981308 3.990654 4.009346 4.046729 3.803738 4.037383
## 2 1.969231 2.030769 1.892308 2.000000 3.923077 3.800000 4.184615 3.846154
## 3 6.500000 3.935897 3.833333 6.512821 6.435897 6.512821 6.576923 6.564103
##        q49      q50      q51      q52      q53      q54      q55      q56
## 1 4.056075 4.102804 4.158879 4.803738 4.906542 4.009346 4.000000 3.943925
## 2 3.923077 3.969231 4.000000 3.953846 3.984615 3.800000 3.861538 3.953846
## 3 6.474359 6.487179 1.564103 1.435897 1.538462 1.461538 1.346154 1.384615
##        q57      q58      q59      q60      q61      q62
## 1 4.822430 4.785047 4.785047 3.420561 3.102804 3.196262
## 2 3.861538 4.092308 3.830769 3.907692 3.892308 3.969231
## 3 4.000000 4.076923 4.089744 4.141026 4.294872 4.076923
```

```r
fviz_cluster(k3, data = ford_psyc)
```

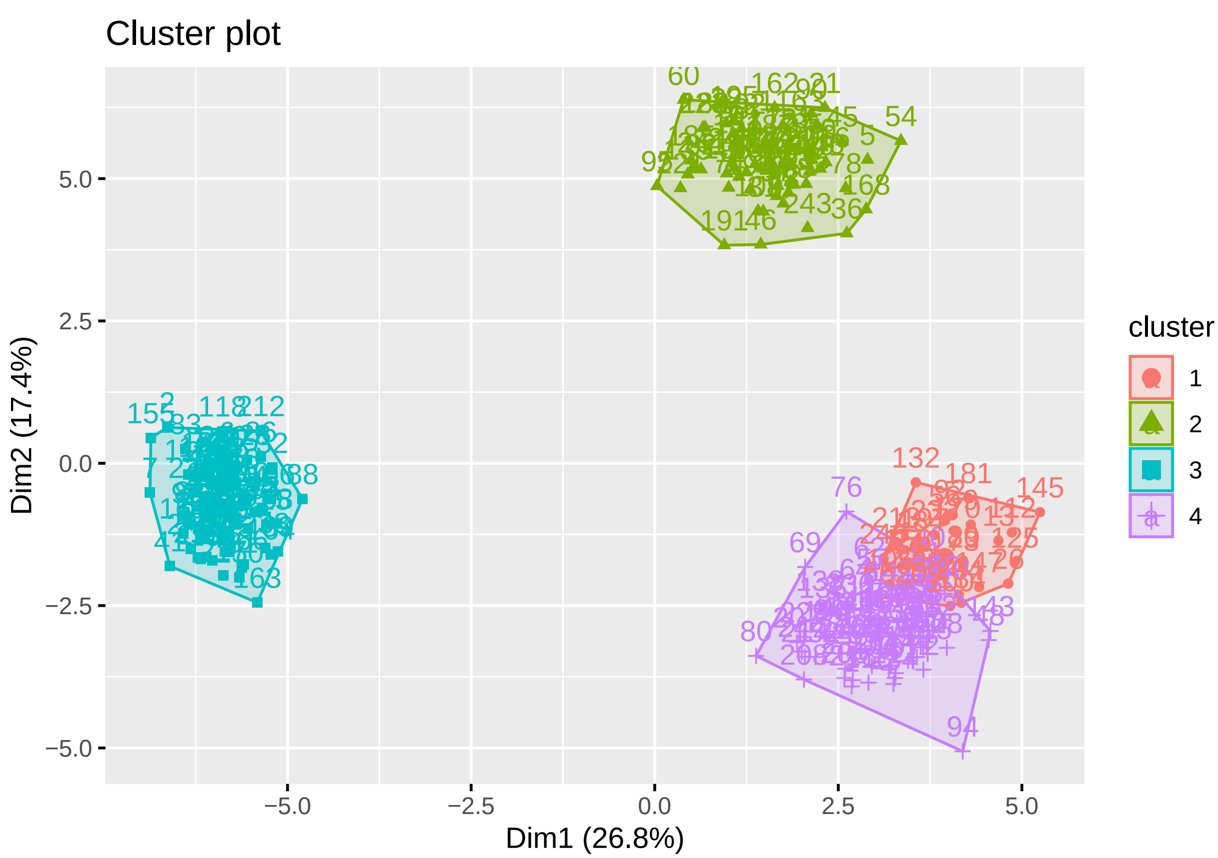



```
# 4 cluster analysis
k4$centers
```

```
##         q1       q2       q3       q4       q5       q6       q7       q8
## 1 6.500000 3.562500 3.781250 1.500000 3.937500 4.218750 3.562500 3.843750
## 2 4.015385 3.769231 5.938462 6.015385 6.015385 3.969231 3.800000 4.107692
## 3 6.512821 6.512821 3.884615 4.025641 4.012821 3.974359 4.025641 3.756410
## 4 3.973333 1.973333 4.013333 4.080000 1.760000 3.933333 3.933333 3.946667
##         q9      q10      q11      q12      q13      q14      q15      q16
## 1 3.718750 3.750000 4.000000 3.875000 3.843750 6.468750 6.562500 3.843750
## 2 3.769231 3.815385 3.876923 4.138462 4.169231 3.984615 4.169231 3.923077
## 3 4.076923 4.051282 4.089744 4.000000 3.910256 1.512821 3.923077 3.910256
## 4 3.920000 3.933333 3.960000 4.173333 3.973333 5.986667 6.080000 5.933333
##        q17      q18      q19      q20      q21      q22      q23      q24
## 1 6.468750 3.843750 4.281250 4.218750 6.437500 6.562500 3.968750 3.625000
## 2 2.000000 4.015385 4.215385 4.061538 4.200000 4.107692 3.876923 3.692308
## 3 4.064103 3.858974 3.987179 1.512821 3.846154 4.089744 6.487179 1.320513
## 4 6.093333 5.973333 6.000000 5.880000 5.986667 6.026667 1.933333 1.800000
##        q25      q26      q27      q28      q29      q30      q31      q32
## 1 1.625000 1.468750 4.187500 1.656250 4.062500 4.125000 6.562500 3.937500
## 2 4.169231 3.800000 4.169231 4.030769 4.107692 3.892308 6.030769 6.046154
## 3 3.961538 3.987179 3.923077 4.038462 3.923077 3.910256 1.564103 4.076923
## 4 2.066667 1.973333 2.053333 2.000000 2.120000 1.946667 3.866667 4.186667
##        q33      q34      q35      q36      q37      q38      q39      q40
## 1 4.062500 4.000000 4.218750 3.875000 6.656250 4.312500 4.093750 3.750000
## 2 5.969231 5.938462 6.076923 5.969231 6.092308 6.046154 1.861538 2.046154
```

```
## 3 4.141026 3.948718 4.102564 3.910256 3.820513 4.076923 4.038462 3.820513
## 4 4.000000 4.026667 3.946667 3.946667 4.026667 4.066667 3.920000 3.880000
##        q41      q42      q43      q44      q45      q46      q47      q48
## 1 1.437500 1.468750 4.187500 4.375000 4.062500 4.406250 3.718750 4.000000
## 2 1.969231 2.030769 1.892308 2.000000 3.923077 3.800000 4.184615 3.846154
## 3 6.500000 3.935897 3.833333 6.512821 6.435897 6.512821 6.576923 6.564103
## 4 3.960000 4.013333 3.893333 3.826667 3.986667 3.893333 3.840000 4.053333
##        q49      q50      q51      q52      q53      q54      q55      q56
## 1 4.093750 4.187500 4.343750 6.375000 6.468750 3.843750 3.656250 4.125000
## 2 3.923077 3.969231 4.000000 3.953846 3.984615 3.800000 3.861538 3.953846
## 3 6.474359 6.487179 1.564103 1.435897 1.538462 1.461538 1.346154 1.384615
## 4 4.040000 4.066667 4.080000 4.133333 4.240000 4.080000 4.146667 3.866667
##        q57      q58      q59      q60      q61      q62
## 1 6.468750 6.562500 6.406250 1.500000 1.406250 1.593750
## 2 3.861538 4.092308 3.830769 3.907692 3.892308 3.969231
## 3 4.000000 4.076923 4.089744 4.141026 4.294872 4.076923
## 4 4.120000 4.026667 4.093333 4.240000 3.826667 3.880000
```

```
fviz_cluster(k4, data = ford_psyc)
```

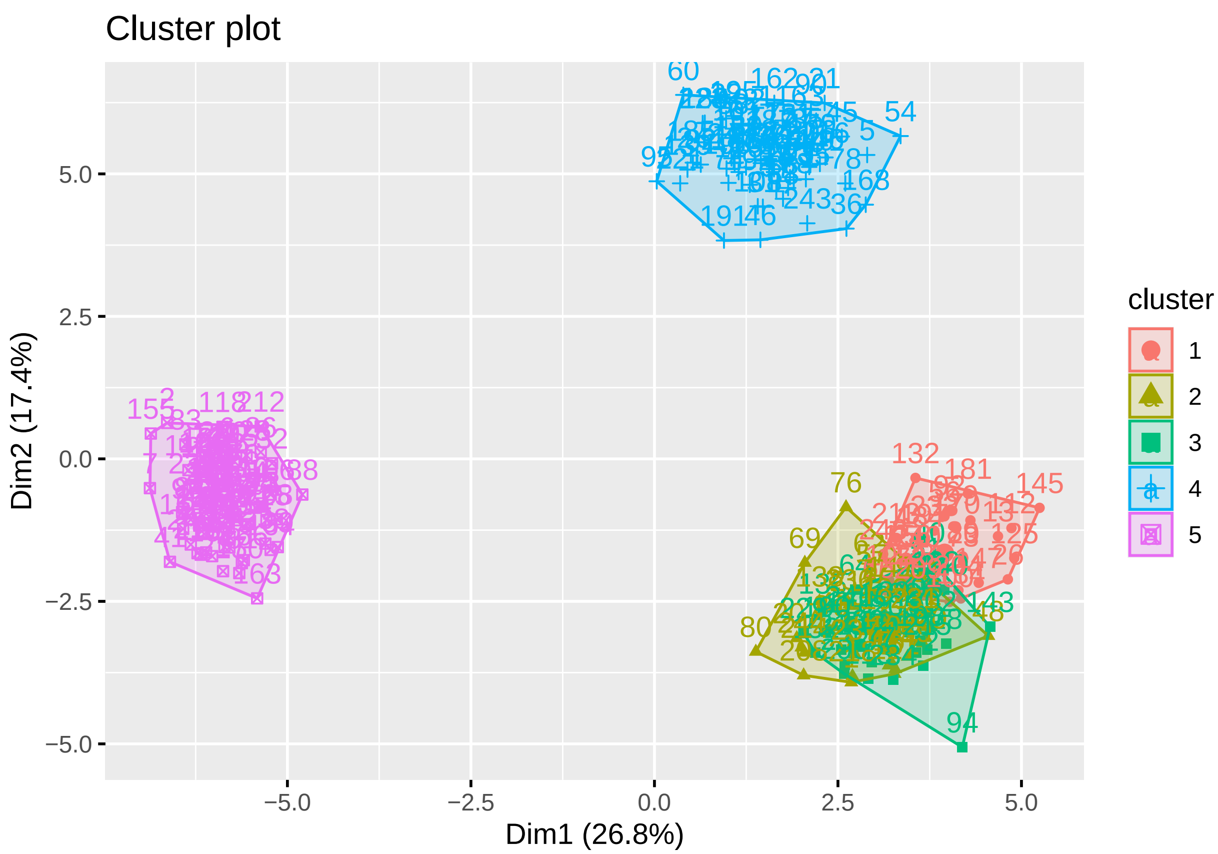



```
# 5 cluster analysis
k5$centers
```

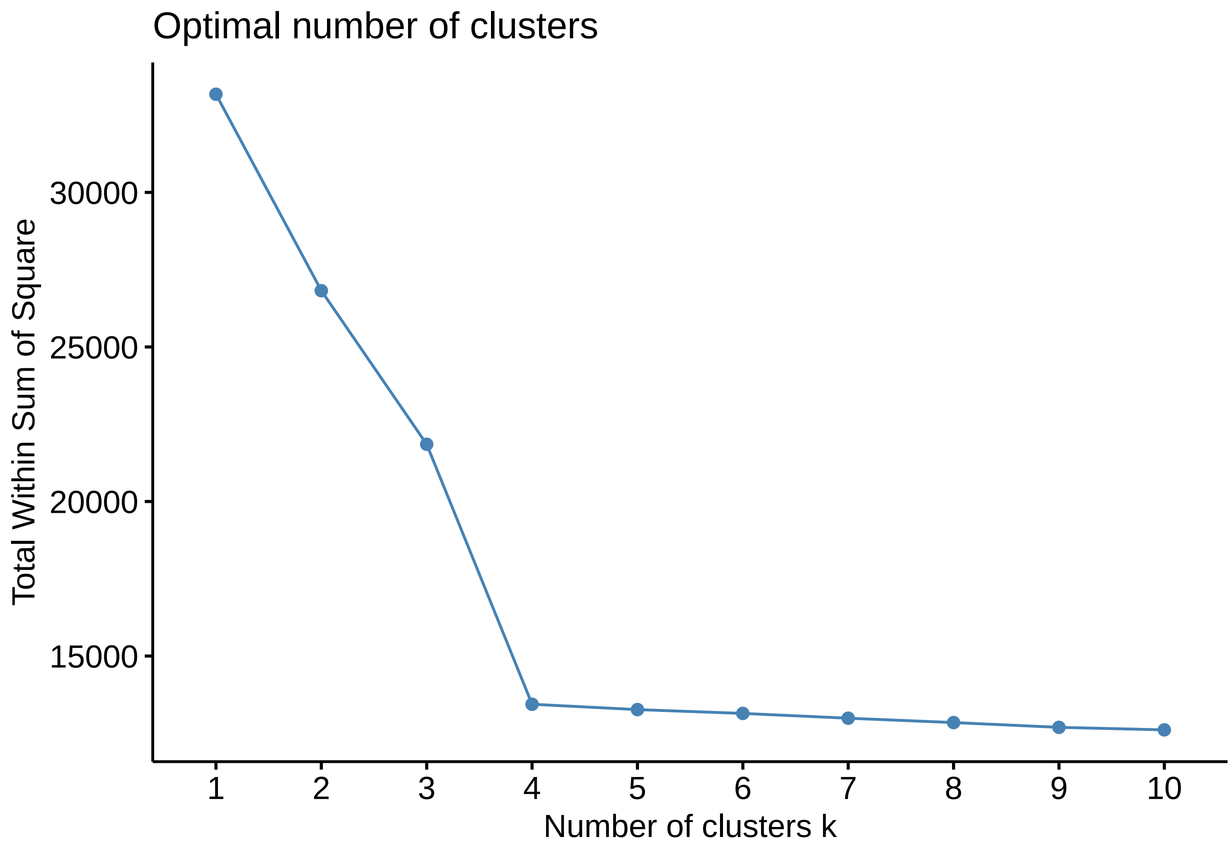
```
##        q1       q2       q3       q4       q5       q6       q7       q8
## 1 6.500000 3.562500 3.781250 1.500000 3.937500 4.218750 3.562500 3.843750
```

```
## 2 4.216216 1.972973 4.162162 3.918919 1.783784 3.864865 4.081081 3.513514
## 3 3.736842 1.973684 3.868421 4.236842 1.736842 4.000000 3.789474 4.368421
## 4 4.015385 3.769231 5.938462 6.015385 6.015385 3.969231 3.800000 4.107692
## 5 6.512821 6.512821 3.884615 4.025641 4.012821 3.974359 4.025641 3.756410
##         q9      q10      q11      q12      q13      q14      q15      q16
## 1 3.718750 3.750000 4.000000 3.875000 3.843750 6.468750 6.562500 3.843750
## 2 3.405405 4.351351 3.918919 4.675676 4.567568 6.027027 6.054054 5.945946
## 3 4.421053 3.526316 4.000000 3.684211 3.394737 5.947368 6.105263 5.921053
## 4 3.769231 3.815385 3.876923 4.138462 4.169231 3.984615 4.169231 3.923077
## 5 4.076923 4.051282 4.089744 4.000000 3.910256 1.512821 3.923077 3.910256
##        q17      q18      q19      q20      q21      q22      q23      q24
## 1 6.468750 3.843750 4.281250 4.218750 6.437500 6.562500 3.968750 3.625000
## 2 5.891892 5.864865 5.810811 5.918919 5.918919 5.891892 1.918919 1.837838
## 3 6.289474 6.078947 6.184211 5.842105 6.052632 6.157895 1.947368 1.763158
## 4 2.000000 4.015385 4.215385 4.061538 4.200000 4.107692 3.876923 3.692308
## 5 4.064103 3.858974 3.987179 1.512821 3.846154 4.089744 6.487179 1.320513
##        q25      q26      q27      q28      q29      q30      q31      q32
## 1 1.625000 1.468750 4.187500 1.656250 4.062500 4.125000 6.562500 3.937500
## 2 2.162162 1.972973 2.135135 2.000000 2.189189 1.864865 3.864865 4.297297
## 3 1.973684 1.973684 1.973684 2.000000 2.052632 2.026316 3.868421 4.078947
## 4 4.169231 3.800000 4.169231 4.030769 4.107692 3.892308 6.030769 6.046154
## 5 3.961538 3.987179 3.923077 4.038462 3.923077 3.910256 1.564103 4.076923
##        q33      q34      q35      q36      q37      q38      q39      q40
## 1 4.062500 4.000000 4.218750 3.875000 6.656250 4.312500 4.093750 3.750000
## 2 4.216216 3.837838 3.648649 4.027027 4.162162 4.027027 4.189189 4.027027
## 3 3.789474 4.210526 4.236842 3.868421 3.894737 4.105263 3.657895 3.736842
## 4 5.969231 5.938462 6.076923 5.969231 6.092308 6.046154 1.861538 2.046154
## 5 4.141026 3.948718 4.102564 3.910256 3.820513 4.076923 4.038462 3.820513
##        q41      q42      q43      q44      q45      q46      q47      q48
## 1 1.437500 1.468750 4.187500 4.375000 4.062500 4.406250 3.718750 4.000000
## 2 4.270270 4.135135 3.837838 3.810811 3.918919 3.972973 3.675676 3.756757
## 3 3.657895 3.894737 3.947368 3.842105 4.052632 3.815789 4.000000 4.342105
## 4 1.969231 2.030769 1.892308 2.000000 3.923077 3.800000 4.184615 3.846154
## 5 6.500000 3.935897 3.833333 6.512821 6.435897 6.512821 6.576923 6.564103
##        q49      q50      q51      q52      q53      q54      q55      q56
## 1 4.093750 4.187500 4.343750 6.375000 6.468750 3.843750 3.656250 4.125000
## 2 4.081081 3.972973 3.972973 3.891892 4.054054 4.027027 4.000000 3.837838
## 3 4.000000 4.157895 4.184211 4.368421 4.421053 4.131579 4.289474 3.894737
## 4 3.923077 3.969231 4.000000 3.953846 3.984615 3.800000 3.861538 3.953846
## 5 6.474359 6.487179 1.564103 1.435897 1.538462 1.461538 1.346154 1.384615
##        q57      q58      q59      q60      q61      q62
## 1 6.468750 6.562500 6.406250 1.500000 1.406250 1.593750
## 2 4.189189 4.270270 3.783784 4.324324 4.270270 3.540541
## 3 4.052632 3.789474 4.394737 4.157895 3.394737 4.210526
## 4 3.861538 4.092308 3.830769 3.907692 3.892308 3.969231
## 5 4.000000 4.076923 4.089744 4.141026 4.294872 4.076923
```

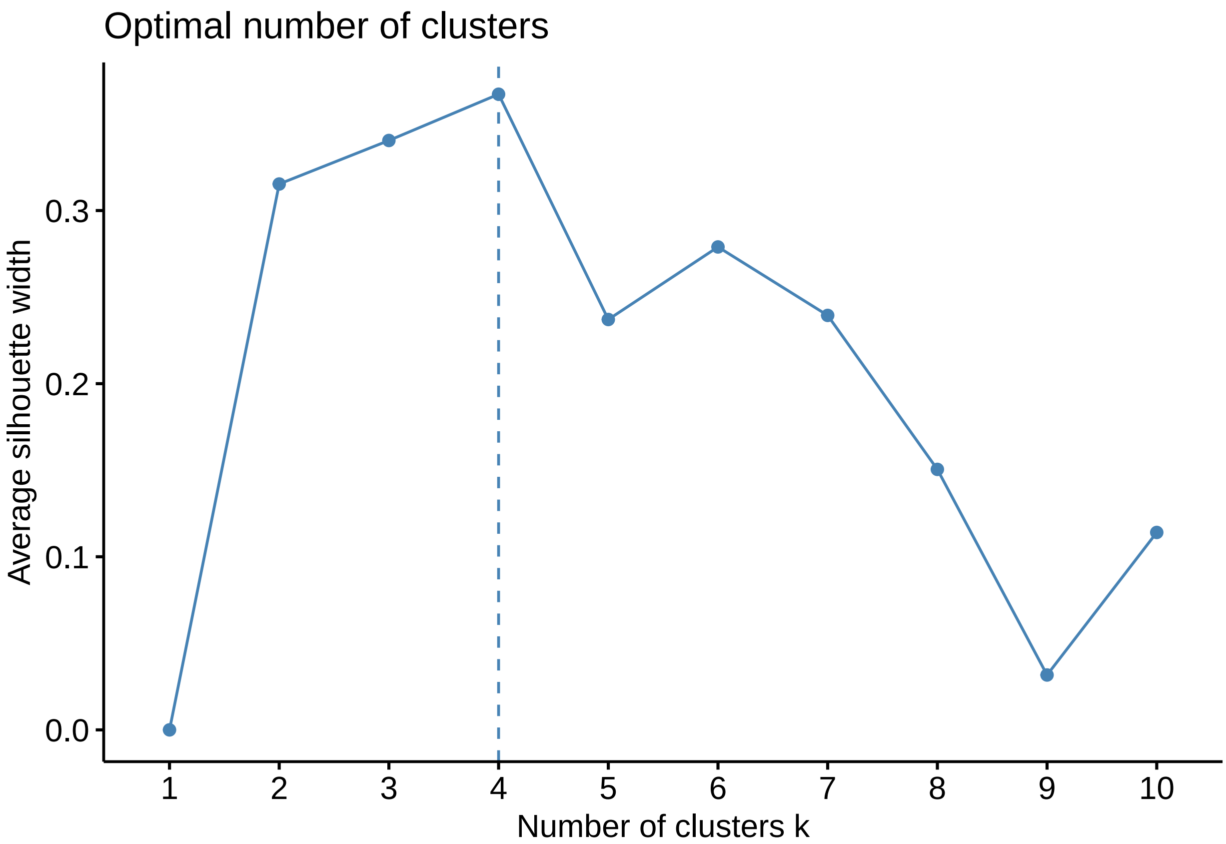
```
fviz_cluster(k5, data = ford_psyc)
```




```r
# optimal clusters - elbow method
fviz_nbclust(ford_psyc, kmeans, method = "wss")
```




```
# optimal clusters - silhouette method
fviz_nbclust(ford_psyc, kmeans, method = "silhouette")
```



Optimal number of clusters
Average silhouette width
0.0
0.1
0.2
0.3
1
2
3
4
5
6
7
8
9
10
Number of clusters k