Watches Case Study

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EXPLORATIVE RESEARCH ON SECONDARY SOURCES

The traditional watch market in the UK has experienced growth in recent years and is projected to reach £1.7 billion by 2022, according to Mintel (English market research firm). The trend has been towards higher-end luxury watches, with Rolex, Omega, and Patek Philippe leading the way. However, mid-range and affordable watches such as Casio, Timex, and Seiko are also gaining popularity among consumers.

A Deloitte study has shown that consumers in the United Kingdom are increasingly considering luxury watches as investments rather than just fashion accessories. Personalised experiences are also becoming more important to buyers, with bespoke or custom-made watches being sought after. The traditional watch market in the UK is highly competitive, with established and emerging brands vying for market share. To remain competitive, traditional watch companies are integrating smart features into their products. Smartwatch manufacturers such as Apple, Samsung, and Fitbit accounted for three of the top five watch brands in the world by volume last year.

Sustainability and ethical sourcing are also important considerations for consumers, with a growing demand for watches made from sustainable and ethical materials. In order to meet these demands, traditional watch companies are also shifting their focus towards sustainability and ethical practices. Overall, the UK's traditional watch market remains a dynamic and competitive industry, with luxury, personalization, and sustainability being key drivers of growth.

Smart Watch Buyer Profile

- AGE >20

- GENDER 63% male

- INCOME > $150k

-EDUCATION College degree or advanced degree

Mechanical Watch Buyer Profile

- AGE >25

- GENDER 60% male

- INCOME > $75k

- EDUCATION College degree or advanced degree

Quartz Watch Buyer Profile
- AGE >20

- GENDER 60% male

- INCOME > $80k

- EDUCATION Varying levels

BACKGROUND

The primary goal of the study is to determine which characteristics and attributes influence traditional watches' perceptions, as well as smart watches' perceptions. To concentrate on the potential market for traditional watches, we need to first establish whether these two types of watches are actually competitors on the same market. Furthermore, we should attempt to highlight similarities and differences in terms of socio-demographic characteristics and lifestyle among consumers of various types of watches.

TRADWATCH

TradWatch has been manufacturing mechanical watches since the beginning of the 20th century, and quartz watches since the 1970s, and has sold them worldwide. With the spreading of smart watches, whose market share has already exceeded that of the other types of watches, TradWatch managers want to investigate if there is still room for "old-style" watches and if there is competition between old-style and smart watches, and/or mechanical and quartz watches.To learn more about the matter, TradWatch executives decide to conduct a market research, focusing specifically on mechanical and quartz watch enthusiasts, with smart watch users constituting the smallest portion of the sample.

SAMPLING DESCRIPTION

The group was gathered from the members of a watch forum. The survey was administered online and collected 237 responses. The forum and the research both refer to the United Kingdom. The questionnaire was composed of 16 questions, mainly divided into a first section about watches, a second section about socio-demographic characteristics, and a question about how respondents came in possession of their watches (to determine

whether inheritance/gift is still an option as a marketing trigger) and another question about willingness to buy, to account for any remaining market share.

DATA CLEANING

We start by importing the dataset.

```
#reading the dataset
Watches <- read.delim("Watches.txt", row.names=1) # row.names=1
argument import the first column (IDs) as row names.
```

Then, we remove the respondent with more than 90 NAs

```
#we create a vector of zeros of length equal to the length of our
dataset
n.na<-rep(0,nrow(Watches))
#for each row we sum the numbers of NAs and record it in the vector
for (i in 1:nrow(Watches)){
n.na[i]<-sum(is.na(Watches[i,])==T)
}
#We remove respondent with 90 or more NAs
watches<-Watches[n.na<=90,]
```

Question 1: Which attributes impact the most on the perceptions of the three products?

To address this question, we created a new dataframe containing only the data useful (Q4: variables V8 to V40) to answer the first research question.

```
#We create a subset of the dataset with only the column we are
interested in
df <-watches[,8:64]
#we select the question to be used as dependent (Y)
per <- df[,1:33]
#replace NA values with the median which is 4 (scale 1 to 7)
scale <-c(1:7)
per[is.na(per)] <- median(scale)
#we select the independent variables
char <- df[,34:57]
```

```
#and we substitute the NA with the median (scale 1 to 7)
char[is.na(char)] <- median(scale)
```

To better understand which attributes impact consumers the most, we divided the dataset based on the type of watch in mechanichal, quartz and smartwatch.

```
#importing dplyr that will be used to select column containing a
specific string
library('dplyr', warn.conflicts = FALSE)

#We divide our perception dataset in three different dataset for each
type of watch we will analyze
per.MW <- per %>% select(contains('_MW'))
per.QW <- per %>% select(contains('_QW'))
per.SW <- per %>% select(contains('_SW'))

char.MW <- char %>% select(contains('_MW'))
char.QW <- char %>% select(contains('_QW'))
char.SW <- char %>% select(contains('_SW'))
```

Since Superfluous has commonly a negative connotation, we constructed a correlation matrix to verify this assumption.

```
#Building the correlations matrix

#mechanical
corr.MW<-round(cor(per.MW),3)
corr.MW

##            classy_MW status_MW soph_MW evergr_MW desire_MW fun_MW
superf_MW
## classy_MW     1.000     0.526   0.501     0.448     0.494  0.221
0.065
## status_MW     0.526     1.000   0.552     0.448     0.540  0.242
0.106
## soph_MW       0.501     0.552   1.000     0.430     0.535  0.283
0.144
## evergr_MW     0.448     0.448   0.430     1.000     0.521  0.221
0.130
## desire_MW     0.494     0.540   0.535     0.521     1.000  0.285
0.110
## fun_MW        0.221     0.242   0.283     0.221     0.285  1.000
```

```
0.039
## superf_MW      0.065       0.106   0.144       0.130       0.110  0.039
1.000
## gratif_MW      0.484       0.486   0.534       0.487       0.671  0.205
0.158
## exc_MW         0.390       0.374   0.421       0.466       0.598  0.233
0.050
## trendy_MW      0.246       0.388   0.375       0.313       0.344  0.444
0.053
## sporty_MW      0.258       0.214   0.243       0.242       0.384  0.334
-0.032
##            gratif_MW exc_MW trendy_MW sporty_MW
## classy_MW      0.484  0.390     0.246     0.258
## status_MW      0.486  0.374     0.388     0.214
## soph_MW        0.534  0.421     0.375     0.243
## evergr_MW      0.487  0.466     0.313     0.242
## desire_MW      0.671  0.598     0.344     0.384
## fun_MW         0.205  0.233     0.444     0.334
## superf_MW      0.158  0.050     0.053    -0.032
## gratif_MW      1.000  0.810     0.350     0.327
## exc_MW         0.810  1.000     0.275     0.303
## trendy_MW      0.350  0.275     1.000     0.439
## sporty_MW      0.327  0.303     0.439     1.000

#quartz watch
corr.QW<-round(cor(per.QW),3)
corr.QW

##            classy_QW status_QW soph_QW evergr_QW desire_QW fun_QW
superf_QW
## classy_QW      1.000       0.547   0.398       0.398       0.515  0.078
-0.074
## status_QW      0.547       1.000   0.422       0.416       0.543  0.247
-0.146
## soph_QW        0.398       0.422   1.000       0.245       0.560  0.315
-0.059
## evergr_QW      0.398       0.416   0.245       1.000       0.425  0.279
-0.066
## desire_QW      0.515       0.543   0.560       0.425       1.000  0.293
-0.212
## fun_QW         0.078       0.247   0.315       0.279       0.293  1.000
-0.002
```

```
## superf_QW    -0.074    -0.146  -0.059    -0.066    -0.212 -0.002
1.000
## gratif_QW     0.344     0.428   0.508     0.410     0.614  0.320
-0.142
## exc_QW        0.366     0.428   0.462     0.382     0.586  0.284
-0.130
## trendy_QW     0.255     0.444   0.365     0.423     0.420  0.383
-0.114
## sporty_QW    -0.010    -0.107   0.111     0.314     0.018  0.407
0.006
##           gratif_QW exc_QW trendy_QW sporty_QW
## classy_QW     0.344  0.366     0.255    -0.010
## status_QW     0.428  0.428     0.444    -0.107
## soph_QW       0.508  0.462     0.365     0.111
## evergr_QW     0.410  0.382     0.423     0.314
## desire_QW     0.614  0.586     0.420     0.018
## fun_QW        0.320  0.284     0.383     0.407
## superf_QW    -0.142 -0.130    -0.114     0.006
## gratif_QW     1.000  0.795     0.454     0.201
## exc_QW        0.795  1.000     0.448     0.082
## trendy_QW     0.454  0.448     1.000     0.165
## sporty_QW     0.201  0.082     0.165     1.000
```

```r
#smart watch
corr.SW<-round(cor(per.SW),3)
corr.SW
```

```
##          classy_SW status_SW soph_SW evergr_SW desire_SW fun_SW
superf_SW
## classy_SW    1.000     0.221   0.296     0.443     0.289  0.090
-0.106
## status_SW    0.221     1.000   0.360     0.167     0.369  0.309
-0.007
## soph_SW      0.296     0.360   1.000     0.206     0.310  0.368
-0.014
## evergr_SW    0.443     0.167   0.206     1.000     0.315  0.109
-0.113
## desire_SW    0.289     0.369   0.310     0.315     1.000  0.503
-0.121
## fun_SW       0.090     0.309   0.368     0.109     0.503  1.000
-0.117
## superf_SW   -0.106    -0.007  -0.014    -0.113    -0.121 -0.117
```

```
1.000
## gratif_SW     0.425       0.341    0.410       0.405       0.596   0.474
-0.166
## exc_SW        0.398       0.313    0.380       0.367       0.578   0.411
-0.092
## trendy_SW     0.014       0.450    0.421       0.032       0.199   0.425
0.074
## sporty_SW     0.025       0.157    0.169       0.091       0.157   0.336
-0.164
##            gratif_SW exc_SW trendy_SW sporty_SW
## classy_SW      0.425  0.398     0.014     0.025
## status_SW      0.341  0.313     0.450     0.157
## soph_SW        0.410  0.380     0.421     0.169
## evergr_SW      0.405  0.367     0.032     0.091
## desire_SW      0.596  0.578     0.199     0.157
## fun_SW         0.474  0.411     0.425     0.336
## superf_SW     -0.166 -0.092     0.074    -0.164
## gratif_SW      1.000  0.792     0.361     0.200
## exc_SW         0.792  1.000     0.261     0.142
## trendy_SW      0.361  0.261     1.000     0.250
## sporty_SW      0.200  0.142     0.250     1.000
```

As can see, "superfluous" negatively correlate with other variables relative only to Quartz Watches and Smartwatches. Consequently, we invert the value of the variable "superfluous" in quartz watches and smartwatches.

In order to visually understand which attributes are the most valued among consumers, we plotted three heatmaps for each category of watches using the answers to question 5 in the questionnaire (Q5: V41-V64). \ The Heatmap is a graphical representation to understand which attributes are the most valued among consumers. Furthermore, the colors of the cells change in response to the respondents' responses, thus the darker the cell, the more frequently it has been responded.
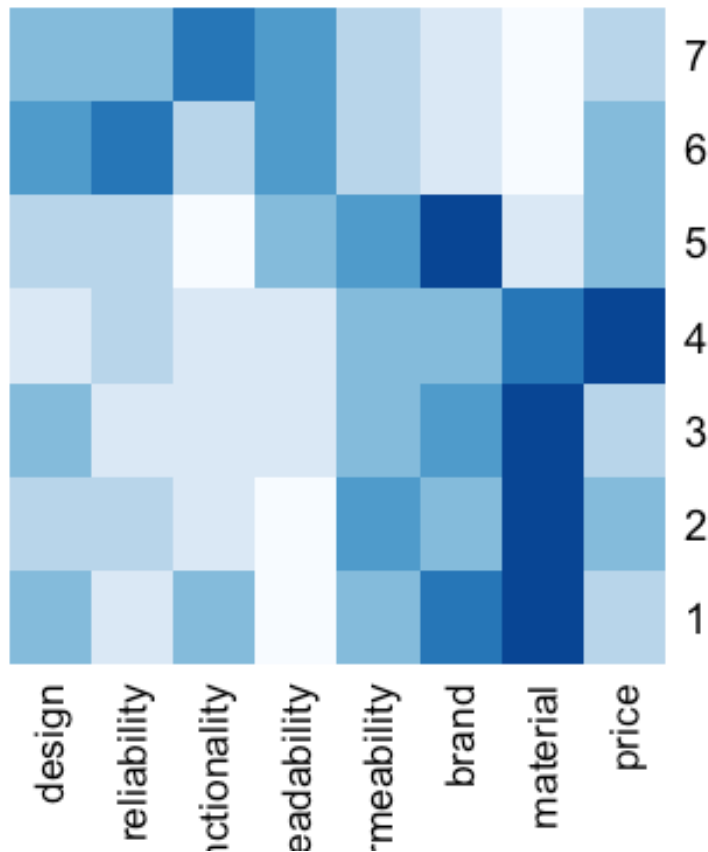
Mechanical Watches
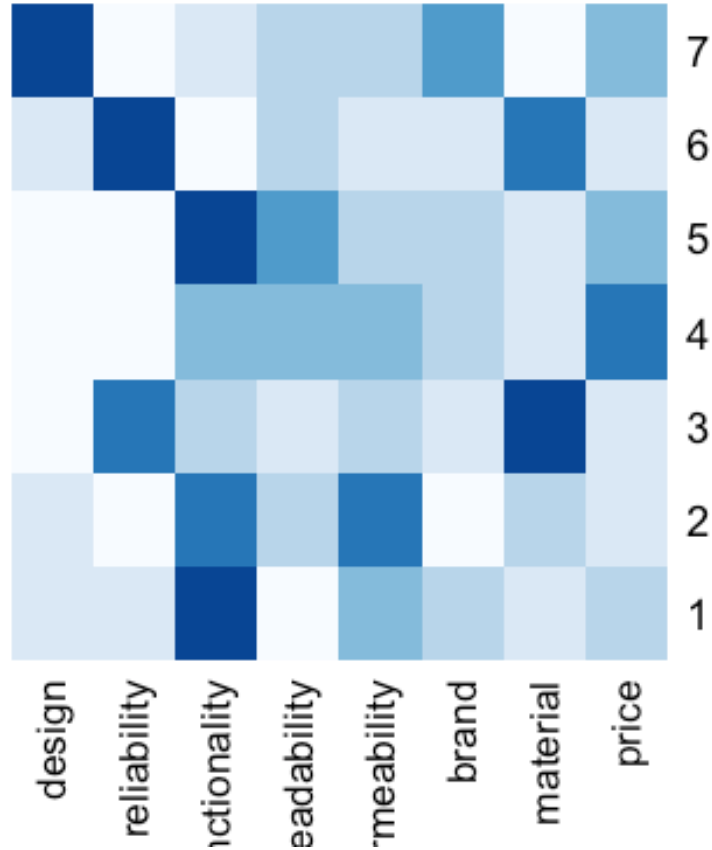
Quartz Watches
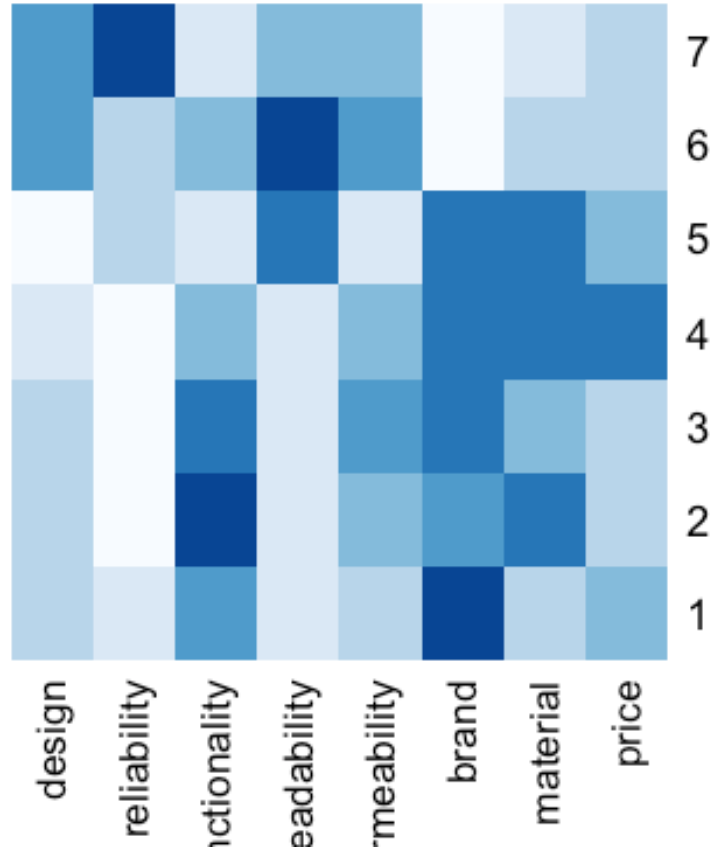
Smart Watches

Given that 1 corresponds to extremely unimportant characteristic and 7 to extremely important characteristic, we can state that:

- For Mechanical Watches: the most valued attributes are design and reliability;

- For Quartz Watches: the most valued attributes are reliability and readability;

- For Smartwatches: the most valued attribute are reliability and functionality.

We may conclude that reliability is the most valued feature among traditional, which includes mechanical and quartz timepieces, and smartwatch customers.

To have a bigger picture on which characteristics impact more consumers' perception, we employ a Multiple Regression model.

We created a variable for each type of watches called "pervar", formed with responses to question 4 (V8-V40), in susch a way that a higher score implies a better perception.

Mechanical Watches

```
#we first build our perception index

#mechanical watches
pervar.MW <- rowSums(per.MW)

# building our multiple regression model
attach(char.MW, warn.conflicts = F)
ff.MW <-pervar.MW ~
imp_design_MW+imp_reliab_MW+imp_funct_MW+imp_read_MW+imp_imperm_MW+imp
_brand_MW+imp_mater_MW+imp_price_MW

summary(lm(ff.MW))

##
## Call:
## lm(formula = ff.MW)
##
## Residuals:
##      Min       1Q  Median       3Q      Max
## -25.000   -5.223   1.135    5.133   27.665
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)    25.67346    4.20585   6.104 6.36e-09 ***
## imp_design_MW   1.90683    0.64120   2.974  0.00335 **
## imp_reliab_MW   0.49800    0.64035   0.778  0.43779
## imp_funct_MW    2.08832    0.40742   5.126 7.71e-07 ***
## imp_read_MW    -0.83267    0.59080  -1.409  0.16047
## imp_imperm_MW   0.49128    0.46641   1.053  0.29363
## imp_brand_MW    2.13655    0.50304   4.247 3.49e-05 ***
## imp_mater_MW    0.09452    0.64172   0.147  0.88307
## imp_price_MW   -0.19537    0.48541  -0.402  0.68782
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.374 on 177 degrees of freedom
## Multiple R-squared:  0.377,  Adjusted R-squared:  0.3488
## F-statistic: 13.39 on 8 and 177 DF,  p-value: 4.542e-15
```

Interpretation of the output for MW:

- Looking at the adjusted R^2, we can affirm that the model explains 35 percent of the variability in the pervar index, and this is significantly different from zero because our p-value is very close to zero (4.542e-15).

- Reliability, readability, impermeability, material and price do not have a significant impact on the pervar index when including the other variables (pvalue larger than 10%).

Although reliability was one of the most valued characteristic among Mechanical watches' buyers, it does not affect consumers' perception.

Considering we found many variables do not have impact on the perception, we decided to remove them.

```
#mechanical watches
attach(char.MW, warn.conflicts = F)
ff.MW <-pervar.MW ~ imp_design_MW+imp_funct_MW+imp_brand_MW

res.MW<-lm(ff.MW)

summary(res.MW)

##
## Call:
## lm(formula = ff.MW)
##
## Residuals:
##      Min      1Q   Median      3Q      Max
## -26.101  -5.904    1.153   4.922   27.666
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)     25.3371     3.4392   7.367 5.87e-12 ***
## imp_design_MW    2.0160     0.5357   3.763 0.000226 ***
## imp_funct_MW     2.1167     0.3975   5.325 2.96e-07 ***
## imp_brand_MW     2.1457     0.4811   4.460 1.43e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.324 on 182 degrees of freedom
## Multiple R-squared:  0.3663, Adjusted R-squared:  0.3558
## F-statistic: 35.06 on 3 and 182 DF,  p-value: < 2.2e-16
```

Interpretation of the output for MW:

- We can see that R-squared is slightly increased improving our model and the p-value is still significantly close to zero.

- Design, functionality and brand have a significant impact on the pervar index. For the design, each point increased on the likert scale (e.g.,from 1 to 2) leads to an increase of 2.01 points on the perception of mechanical watches. For the functionality the increase on the perception is 2.11, while for the brand is 2.15.

Quartz Watches

```
#quartz watches
pervar.QW <- rowSums(per.QW)

# building our multiple regression model
attach(char.QW, warn.conflicts = F)
ff.QW <-pervar.QW ~
imp_design_QW+imp_reliab_QW+imp_funct_QW+imp_read_QW+imp_imperm_QW+imp
_brand_QW+imp_mater_QW+imp_price_QW

summary(lm(ff.QW))

##
## Call:
## lm(formula = ff.QW)
##
## Residuals:
##      Min      1Q  Median      3Q     Max
## -27.608  -6.110   1.845   5.423  22.148
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)    18.44780    3.29127   5.605 7.86e-08 ***
## imp_design_QW   1.78931    0.51223   3.493 0.000603 ***
## imp_reliab_QW  -0.76719    0.61441  -1.249 0.213442
## imp_funct_QW    1.03558    0.42888   2.415 0.016770 *
## imp_read_QW    -0.22663    0.62434  -0.363 0.717042
## imp_imperm_QW  -0.06759    0.50163  -0.135 0.892968
## imp_brand_QW    1.91419    0.50675   3.777 0.000216 ***
## imp_mater_QW    0.97056    0.53388   1.818 0.070767 .
## imp_price_QW    0.39184    0.47238   0.829 0.407940
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.671 on 177 degrees of freedom
## Multiple R-squared:  0.3144, Adjusted R-squared:  0.2834
## F-statistic: 10.15 on 8 and 177 DF,  p-value: 1.286e-11
```

Interpretation of the output for QW:

- Looking at the adjusted R^2, we can affirm that the model explains 28 percent of the variability in the pervar index, and this is significantly different from zero because our p-value is very close to zero (1.286e-11).

- Variables that do not have a significant impact on the pervar index, are the same we mentioned for Mechanical Watches, apart from material that in this case has an impact.

Also here, although reliability and readability were the most valued characteristics among quartz watches' buyers, it does not affect consumers' perception.

We decided to remove variables that do not have impact on the perception also for Quartz watches.

```
attach(char.QW, warn.conflicts = F)
ff.QW <-pervar.QW ~
imp_design_QW+imp_funct_QW+imp_brand_QW+imp_mater_QW
res.QW<-lm(ff.QW)

summary(res.QW)

##
## Call:
## lm(formula = ff.QW)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -26.722  -6.045   1.809   6.278  22.027
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)    16.7576     2.7730   6.043 8.42e-09 ***
## imp_design_QW   1.5297     0.4415   3.464 0.000663 ***
```

```
## imp_funct_QW      0.9339      0.4146    2.253 0.025467 *
## imp_brand_QW      2.0250      0.5000    4.050 7.59e-05 ***
## imp_mater_QW      0.7525      0.5093    1.478 0.141266
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.64 on 181 degrees of freedom
## Multiple R-squared:  0.3033, Adjusted R-squared:  0.2879
## F-statistic:  19.7 on 4 and 181 DF,  p-value: 1.783e-13
```

Interpretation of the output for QW:

- Design, functionality and brand have a significant impact on the pervar index. For the design, each point increased on the likert scale (e.g.,from 1 to 2) leads to an increase of 1.53 points on the perception of mechanical watches. For the functionality the increase on the perception is 0.93, while for the brand is 2.03.

- Since material already had a high level of significance (0.05), now we cannot consider it anymore to have an impact on the perception.

Smartwatches

```
#smart watches
pervar.SW <- rowSums(per.SW)

# building our multiple regression model
attach(char.SW, warn.conflicts = F)
ff.SW <-pervar.SW ~
imp_design_SW+imp_reliab_SW+imp_funct_SW+imp_read_SW+imp_imperm_SW+imp
_brand_SW+imp_mater_SW+imp_price_SW

summary(lm(ff.SW))

##
## Call:
## lm(formula = ff.SW)
##
## Residuals:
##      Min        1Q    Median        3Q       Max
## -22.2893   -7.2712    0.2452    5.7107   24.7551
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)      20.8595       2.9436   7.086 3.14e-11 ***
## imp_design_SW      0.8366       0.4815   1.737 0.084071 .
## imp_reliab_SW     -0.8501       0.7207  -1.180 0.239754
## imp_funct_SW       0.7391       0.6174   1.197 0.232853
## imp_read_SW        0.4812       0.8102   0.594 0.553307
## imp_imperm_SW      0.2904       0.5132   0.566 0.572220
## imp_brand_SW       1.6580       0.4790   3.462 0.000673 ***
## imp_mater_SW       0.7547       0.5121   1.474 0.142340
## imp_price_SW       0.4476       0.5551   0.806 0.421116
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.13 on 177 degrees of freedom
## Multiple R-squared:  0.2434, Adjusted R-squared:  0.2092
## F-statistic: 7.116 on 8 and 177 DF,  p-value: 3.789e-08
```

Intrepretation of the output for SW:

- Looking at the adjusted R^2, we can affirm that the model explains 21 percent of the variability in the pervar index, and this is significantly different from zero because our p-value close to zero (3.789e-08).

- None of the variables have a significant impact on the pervar index besides design and brand.

Also here, although reliability and functionality were the most valued characteristics among Smartwatches watches' buyers, it does not affect consumers' perception.

```
#smart watches
attach(char.SW, warn.conflicts = F)
ff.SW <-pervar.SW ~ imp_design_SW+imp_brand_SW
res.SW<-lm(ff.SW)

summary(res.SW)

##
## Call:
## lm(formula = ff.SW)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -23.7714  -6.8094   0.3114   5.6539  28.0687
```

```
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)    24.7213     2.4203  10.214  < 2e-16 ***
## imp_design_SW   1.3255     0.4188   3.165  0.00182 **
## imp_brand_SW    2.1286     0.4325   4.922  1.9e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.21 on 183 degrees of freedom
## Multiple R-squared:  0.2048, Adjusted R-squared:  0.1961
## F-statistic: 23.56 on 2 and 183 DF,  p-value: 7.847e-10
```

Interpretation of the output for SW:

- Design and brand have a significant impact on the pervar index. For the design, each point increased on the likert scale (e.g.,from 1 to 2) leads to an increase of 1.33 points on the perception of mechanical watches, while for the brand the increase is 2.13.

Diagnostic Check

Right after the interpretation of the model's output, we have to verify the residuals to ensure they are consistent with the model's hypotheses.

Mechanical watches

Residuals vs Fitted

density.default(x = res.MW$residuals)

N = 186   Bandwidth = 2.557
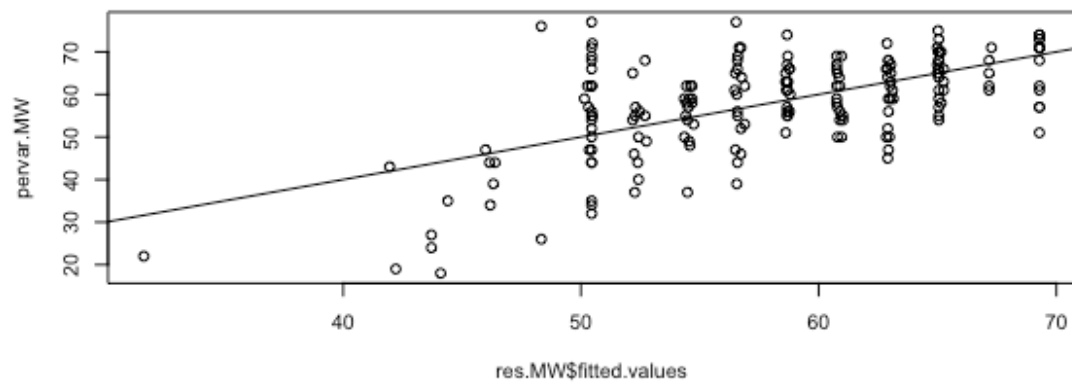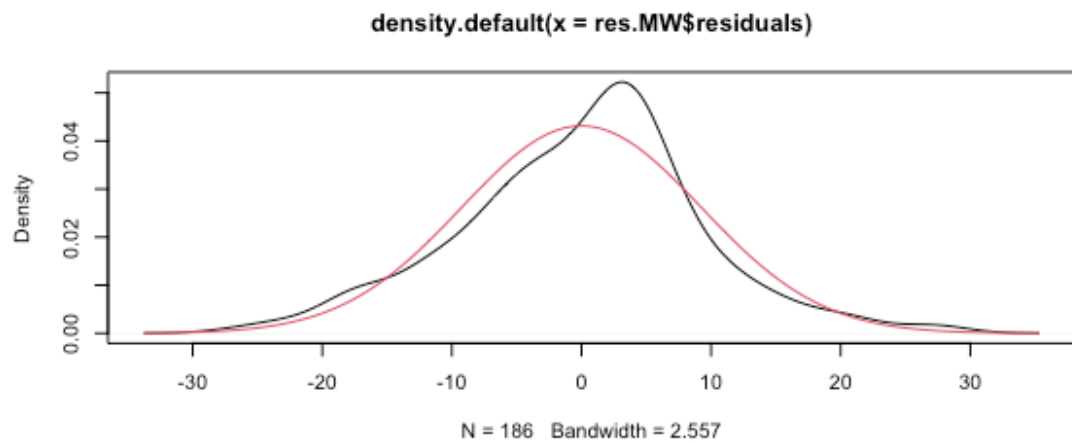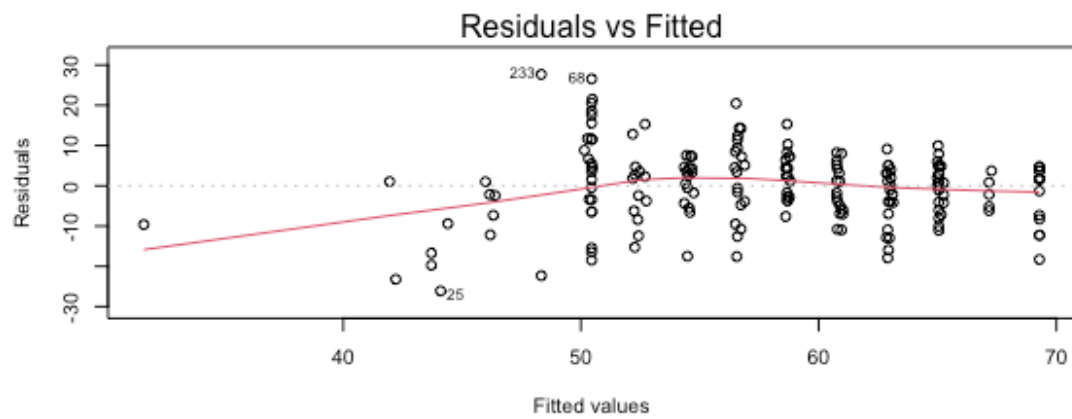
Kolmogorov smirnov test for normality

```
##
##   One-sample Kolmogorov-Smirnov test
##
## data:  (res.MW$residuals - mean(res.MW$residuals))/
sd(res.MW$residuals)
## D = 0.070491, p-value = 0.3137
## alternative hypothesis: two-sided
```

The analysis of residual points out that the residuals have a constant variance, meaning that they are homoscedastic. From the second plot, the distribution seems to be Normally distributed. We confirmed it through the KS test. The fitted and predicted value goes quite well together as most are close to the bisector.
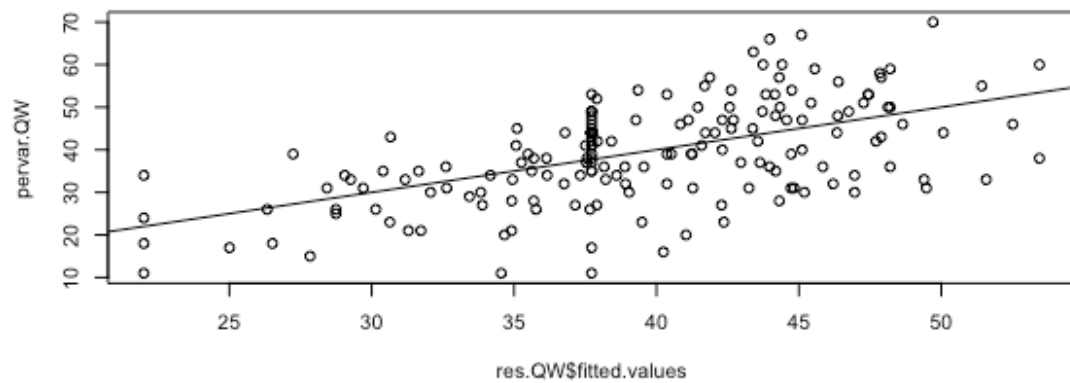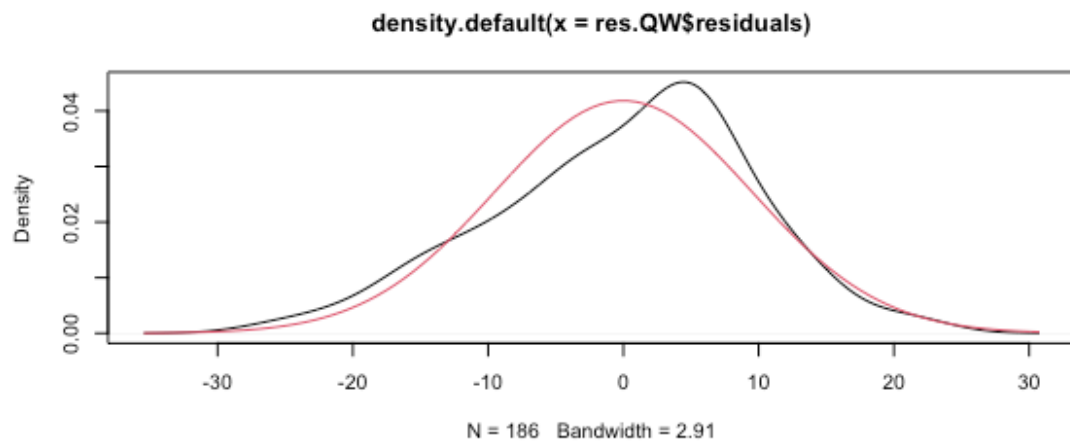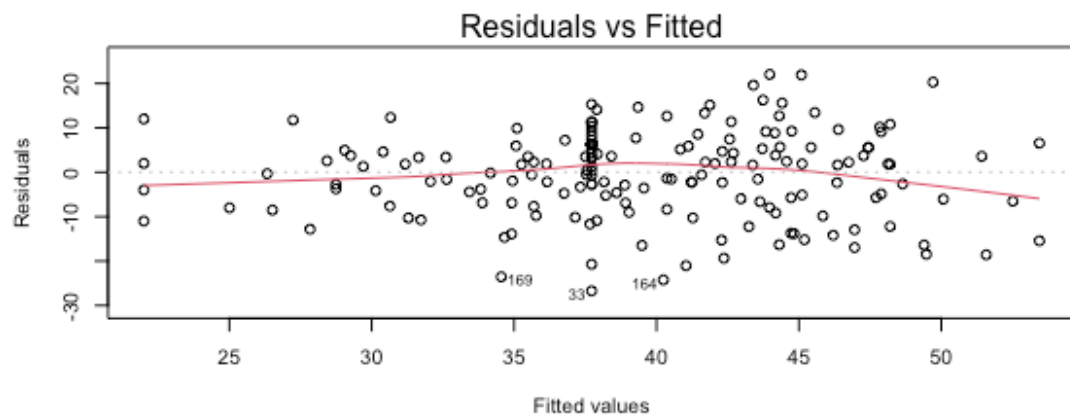
Removing outliers

```r
#mechanical watch
#creating a vector containing the outliers values
outliersMW<-c(25,68,233)

#removing outliers
pervar.MW1<-pervar.MW[-outliersMW]

design <- char.MW$imp_design_MW[-outliersMW]
funct <- char.MW$imp_funct_MW[-outliersMW]
brand <- char.MW$imp_brand_MW[-outliersMW]

#multiple regression model without outliers
ff.MW <-pervar.MW1 ~ design+funct+brand
noout.model.MW<-lm(ff.MW)

#summary(noout.model.MW)

#kolmogorov smirnov test

ks.test((noout.model.MW$residuals-mean(noout.model.MW$residuals))/
sd(noout.model.MW$residuals),"pnorm")

## Warning in ks.test((noout.model.MW$residuals -
## mean(noout.model.MW$residuals))/sd(noout.model.MW$residuals), :
```

```
ties should not
## be present for the Kolmogorov-Smirnov test

##
##   One-sample Kolmogorov-Smirnov test
##
## data:   (noout.model.MW$residuals - mean(noout.model.MW$residuals))/
sd(noout.model.MW$residuals)
## D = 0.0716, p-value = 0.3021
## alternative hypothesis: two-sided
```

Quartz watches

Residuals vs Fitted

density.default(x = res.QW$residuals)

N = 186   Bandwidth = 2.91

Kolmogorov smirnov test for normality

```
## 
##   One-sample Kolmogorov-Smirnov test
## 
## data:  (res.QW$residuals - mean(res.QW$residuals))/
sd(res.QW$residuals)
## D = 0.089052, p-value = 0.1047
## alternative hypothesis: two-sided
```

Also for Quartz watches residuals are homoscedastic, normally distributed and the fitted and predicted value goes well together as most are close to the bisector.

Removing outliers

```
#quartz watch
#creating a vector containing the outliers values
outliersQW<-c(33,164,169)

#removing outliers
pervar.QW1<-pervar.QW[-outliersQW]

design <- char.QW$imp_design_QW[-outliersQW]
funct <- char.QW$imp_funct_QW[-outliersQW]
brand <- char.QW$imp_brand_QW[-outliersQW]
material <- char.QW$imp_mater_QW[-outliersQW]

#multiple regression model without outliers
ff.QW <-pervar.QW1 ~ design+funct+brand+material
noout.model.QW<-lm(ff.QW)

summary(noout.model.QW)

## 
## Call:
## lm(formula = ff.QW)
## 
## Residuals:
##     Min       1Q  Median       3Q      Max 
## -26.708  -6.132   1.651   6.292   21.804 
## 
## Coefficients:
```

```
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  16.9101     2.7716   6.101 6.40e-09 ***
## design        1.5492     0.4403   3.519  0.00055 ***
## funct          0.8096     0.4161   1.946  0.05327 .
## brand          2.1332     0.5010   4.258 3.34e-05 ***
## material       0.7073     0.5129   1.379  0.16963
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.581 on 178 degrees of freedom
## Multiple R-squared:  0.3084, Adjusted R-squared:  0.2929
## F-statistic: 19.85 on 4 and 178 DF,  p-value: 1.585e-13

#kolmogorov smirnov test
ks.test((noout.model.QW$residuals-mean(noout.model.QW$residuals))/
sd(noout.model.QW$residuals),"pnorm")

## Warning in ks.test((noout.model.QW$residuals -
## mean(noout.model.QW$residuals))/sd(noout.model.QW$residuals), :
ties should not
## be present for the Kolmogorov-Smirnov test

##
##   One-sample Kolmogorov-Smirnov test
##
## data:  (noout.model.QW$residuals - mean(noout.model.QW$residuals))/
sd(noout.model.QW$residuals)
## D = 0.084299, p-value = 0.1484
## alternative hypothesis: two-sided
```
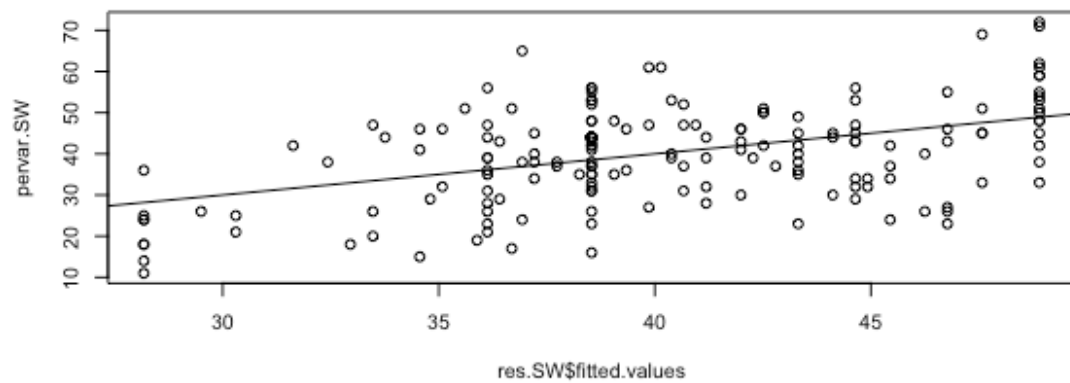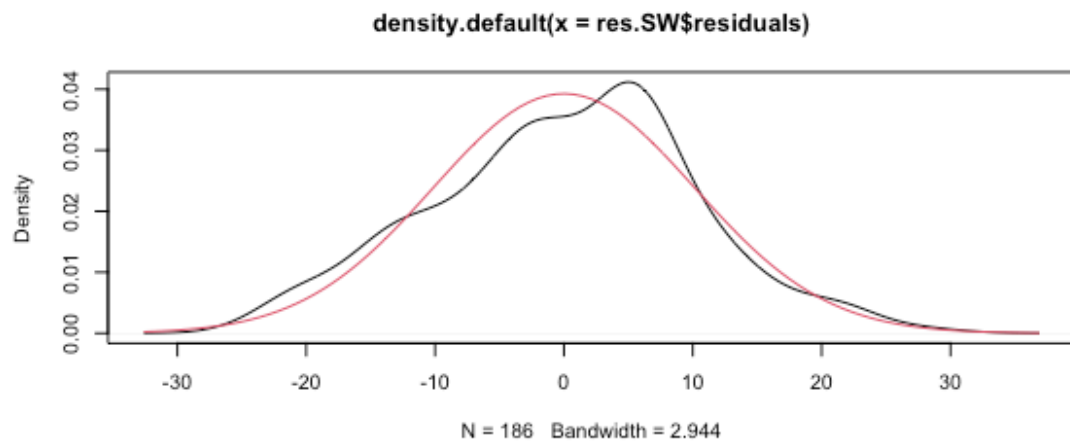
Differently from Mechanical watches, our model slightly improved after removing the outliers. The R-squared and p-value of KS test increased.

Smartwatch

Residuals vs Fitted

density.default(x = res.SW$residuals)

N = 186   Bandwidth = 2.944
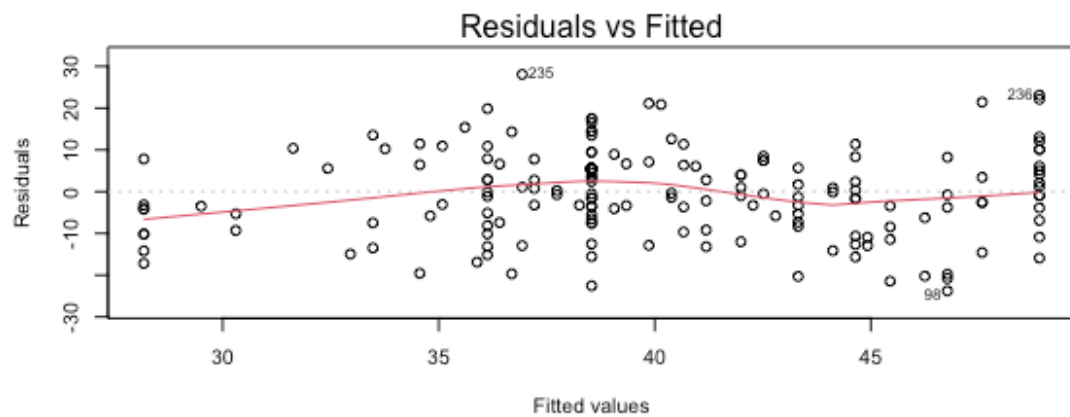
Kolmogorov smirnov test for normality

```
##
##  One-sample Kolmogorov-Smirnov test
##
## data:  (res.SW$residuals - mean(res.SW$residuals))/
sd(res.SW$residuals)
## D = 0.086329, p-value = 0.125
## alternative hypothesis: two-sided
```

Also for Smartwatches residuals are homoscedastic, normally distributed and the fitted and predicted value goes quite well together as most are close to the bisector.

removing outliers

```
#smart watch
#creating a vector containing the outliers values
outliersSW<-c(184,185,21)
#removing outliers
pervar.SW1<-pervar.SW[-outliersSW]

design <- char.SW$imp_design_SW[-outliersSW]
brand <- char.SW$imp_brand_SW[-outliersSW]

#multiple regression model without outliers
ff.SW <-pervar.SW1 ~ design+brand
noout.model.SW<-lm(ff.SW)

#summary(noout.model.SW)

#kolmogorov smirnov test
ks.test((noout.model.SW$residuals-mean(noout.model.SW$residuals))/
sd(noout.model.SW$residuals),"pnorm")

## Warning in ks.test((noout.model.SW$residuals -
## mean(noout.model.SW$residuals))/sd(noout.model.SW$residuals), :
ties should not
## be present for the Kolmogorov-Smirnov test

##
##  One-sample Kolmogorov-Smirnov test
##
```

```
## data:  (noout.model.SW$residuals - mean(noout.model.SW$residuals))/
sd(noout.model.SW$residuals)
## D = 0.089516, p-value = 0.1065
## alternative hypothesis: two-sided
```

By removing outliers, the model didn't significantly changed.

After our diagnostic check resulted in a positive outcome we can use the multiple regression models to draw our conclusions.

Conclusion of the multiple regression

To conclude, we found different characteristics of watches that have an impact on the customers' perception of traditional watches and smartwatches that the company can focus on in order to its products perception. For both categories of watches, design and brand have a positive impact on the perception of customers on watches. More specifically, we found that among traditional watches, functionality and materials also play a crucial role. The company may use this findings to further investigate on which kind of materials and functionality are more preferred by its customer. TradWatch may also improve their designs and branding to increase the perception of its products.

Question 2: Are they all separate or some of them can be somewhat reduced to common factors?

To address this question, we carried out a factor analysis. First of all, we need to evaluate if there is any correlation worth exploring among the variables through the KMO and Bartlett tests.

```
## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = fact.MW)
## Overall MSA =  0.81
## MSA for each item =
## imp_design_MW imp_reliab_MW  imp_funct_MW   imp_read_MW
imp_imperm_MW
##           0.82          0.81          0.80          0.78
0.80
##  imp_brand_MW  imp_mater_MW  imp_price_MW
##           0.80          0.85          0.86

## R was not square, finding R from data
```

```
## $chisq
## [1] 301.1467
##
## $p.value
## [1] 1.452741e-47
##
## $df
## [1] 28

## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = fact.QW)
## Overall MSA =  0.81
## MSA for each item =
## imp_design_QW imp_reliab_QW  imp_funct_QW   imp_read_QW
imp_imperm_QW
##           0.87          0.81          0.75          0.81
0.87
##  imp_brand_QW  imp_mater_QW  imp_price_QW
##           0.68          0.78          0.88

## R was not square, finding R from data

## $chisq
## [1] 364.2797
##
## $p.value
## [1] 3.31608e-60
##
## $df
## [1] 28

## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = fact.SW)
## Overall MSA =  0.85
## MSA for each item =
## imp_design_SW imp_reliab_SW  imp_funct_SW   imp_read_SW
imp_imperm_SW
##           0.92          0.87          0.84          0.82
0.88
##  imp_brand_SW  imp_mater_SW  imp_price_SW
##           0.82          0.78          0.91
```

```
## R was not square, finding R from data

## $chisq
## [1] 604.7079
##
## $p.value
## [1] 1.448051e-109
##
## $df
## [1] 28
```

We can proceed with the factorial analysis, since:

Mechanical Watches

1. the overall MSA of the KMO index is 0.81

2. the Chi-square test for sphericity of the correlation matrix rejects the hypothesis of our matrix being equal to the identity matrix with a pvalue close to zero, 1.452741e-47.

Quartz Watches

1. the overall MSA of the KMO index is 0.81

2. the Chi-square test for sphericity of the correlation matrix rejects the hypothesis of our matrix being equal to the identity matrix with a pvalue close to zero, 3.31608e-60.

Smart Watches

1. the overall MSA of the KMO index is 0.85

2. the Chi-square test for sphericity of the correlation matrix rejects the hypothesis of our matrix being equal to the identity matrix with a pvalue close to zero, 1.448051e-109.

We start with 4 factors which is the maximum allowed for 8 variables by R

Mechanical Watches

```
#performing the factor analysis
#mechanical watch
anfatt.MW<-factanal(fact.MW,4)
anfatt.MW
```
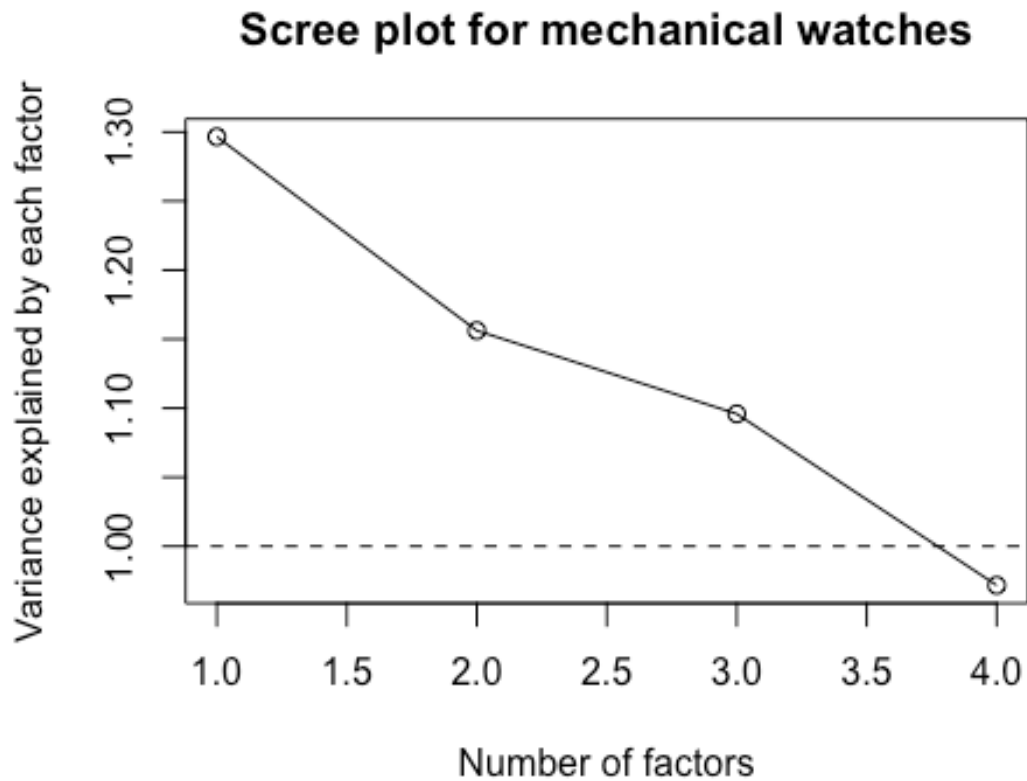
```
## 
## Call:
## factanal(x = fact.MW, factors = 4)
## 
## Uniquenesses:
## imp_design_MW imp_reliab_MW  imp_funct_MW    imp_read_MW
imp_imperm_MW
##          0.499          0.329          0.882          0.005
0.683
##   imp_brand_MW  imp_mater_MW  imp_price_MW
##          0.555          0.521          0.005
## 
## Loadings:
##                Factor1 Factor2 Factor3 Factor4
## imp_design_MW 0.212   0.461   0.472   0.144
## imp_reliab_MW 0.225   0.141   0.772
## imp_funct_MW          0.312           0.121
## imp_read_MW   0.972           0.191
## imp_imperm_MW 0.429   0.249   0.262
## imp_brand_MW  0.110   0.649
## imp_mater_MW  0.221   0.522   0.386
## imp_price_MW  0.104   0.257   0.106   0.952
## 
##                Factor1 Factor2 Factor3 Factor4
## SS loadings      1.297   1.156   1.096   0.972
## Proportion Var   0.162   0.145   0.137   0.121
## Cumulative Var   0.162   0.307   0.444   0.565
## 
## Test of the hypothesis that 4 factors are sufficient.
## The chi square statistic is 1 on 2 degrees of freedom.
## The p-value is 0.606
```

Looking at the loadings , we see that the Factor4 does no explain more variance than each of the original variables (because it is smaller than 1). So, we constructed a Scree Plot to choose the optimal number of factors

```
#mechanical watches
plot(seq(1:4),colSums(anfatt.MW$loadings^2), xlab="Number of factors",
ylab="Variance explained by each factor", main = "Scree plot for
mechanical watches")
```

```
lines(seq(1:4),colSums(anfatt.MW$loadings^2))
abline(h=1,lty=2)
```

Scree plot for mechanical watches

From the scree plot we select 3 factors.

```
#mechanical watch
anfatt.MW<-factanal(fact.MW,3, rotation="varimax",
scores="regression")
anfatt.MW

##
## Call:
## factanal(x = fact.MW, factors = 3, scores = "regression", rotation
= "varimax")
##
## Uniquenesses:
## imp_design_MW imp_reliab_MW   imp_funct_MW    imp_read_MW
```

```
imp_imperm_MW
##        0.498              0.257              0.876              0.005
0.689
##  imp_brand_MW  imp_mater_MW  imp_price_MW
##        0.598              0.524              0.792
##
## Loadings:
##                Factor1 Factor2 Factor3
## imp_design_MW 0.519    0.217    0.431
## imp_reliab_MW 0.168    0.227    0.814
## imp_funct_MW  0.346
## imp_read_MW   0.104    0.976    0.176
## imp_imperm_MW 0.264    0.428    0.241
## imp_brand_MW  0.622    0.100
## imp_mater_MW  0.554    0.219    0.348
## imp_price_MW  0.405    0.168    0.125
##
##                Factor1 Factor2 Factor3
## SS loadings     1.357   1.322   1.083
## Proportion Var  0.170   0.165   0.135
## Cumulative Var  0.170   0.335   0.470
##
## Test of the hypothesis that 3 factors are sufficient.
## The chi square statistic is 2.98 on 7 degrees of freedom.
## The p-value is 0.887
```

As we can see, SS Loadings are all larger than 1, almost 50% of the variance is explained by the three factors and the p-value is larger than 5% (it is 89%). So we can accept the solution and go ahead with naming and interpreting the factors.

Naming and interpretations of factors

Mechanical Watches

- Factor1: **Quality**: design + functionality + brand + material + price

- Factor2: **Adaptability**: readability + impermeability

- Factor3: **reliability**: reliability

#naming the factors

```
#Mechanical
fact.scoresMW<-anfatt.MW$scores
colnames(fact.scoresMW)<-c("Quality","Adaptability", "Reliability")
cor(fact.scoresMW)

##                Quality Adaptability Reliability
## Quality     1.00000000   0.02251651  0.18944396
## Adaptability 0.02251651   1.00000000  0.04999667
## Reliability  0.18944396   0.04999667  1.00000000
```

Quartz Watches

```
#performing the factor analysis
#quartz watch
anfatt.QW<-factanal(fact.QW,4)
anfatt.QW

##
## Call:
## factanal(x = fact.QW, factors = 4)
##
## Uniquenesses:
## imp_design_QW imp_reliab_QW  imp_funct_QW    imp_read_QW
imp_imperm_QW
##         0.005          0.460         0.607          0.313
0.621
##  imp_brand_QW  imp_mater_QW  imp_price_QW
##         0.658          0.005         0.752
##
## Loadings:
##              Factor1 Factor2 Factor3 Factor4
## imp_design_QW 0.395   0.177   0.887   0.141
## imp_reliab_QW 0.657   0.172   0.243   0.141
## imp_funct_QW  0.165                   0.599
## imp_read_QW   0.804   0.137   0.145
## imp_imperm_QW 0.512   0.138           0.304
## imp_brand_QW          0.417   0.145   0.377
## imp_mater_QW  0.271   0.953   0.102
## imp_price_QW  0.403           0.214   0.183
##
##              Factor1 Factor2 Factor3 Factor4
## SS loadings    1.765   1.190   0.955   0.670
```

```
## Proportion Var     0.221     0.149     0.119     0.084
## Cumulative Var      0.221     0.369     0.489     0.572
##
## Test of the hypothesis that 4 factors are sufficient.
## The chi square statistic is 3.22 on 2 degrees of freedom.
## The p-value is 0.2
```

Looking at the loadings , we see that the Factor3 and Factor4 do no explain more variance than each of the original variables (because it is smaller than 1). So, we constructed a Scree Plot to choose the optimal number of factors.

Scree plot for quartz watches
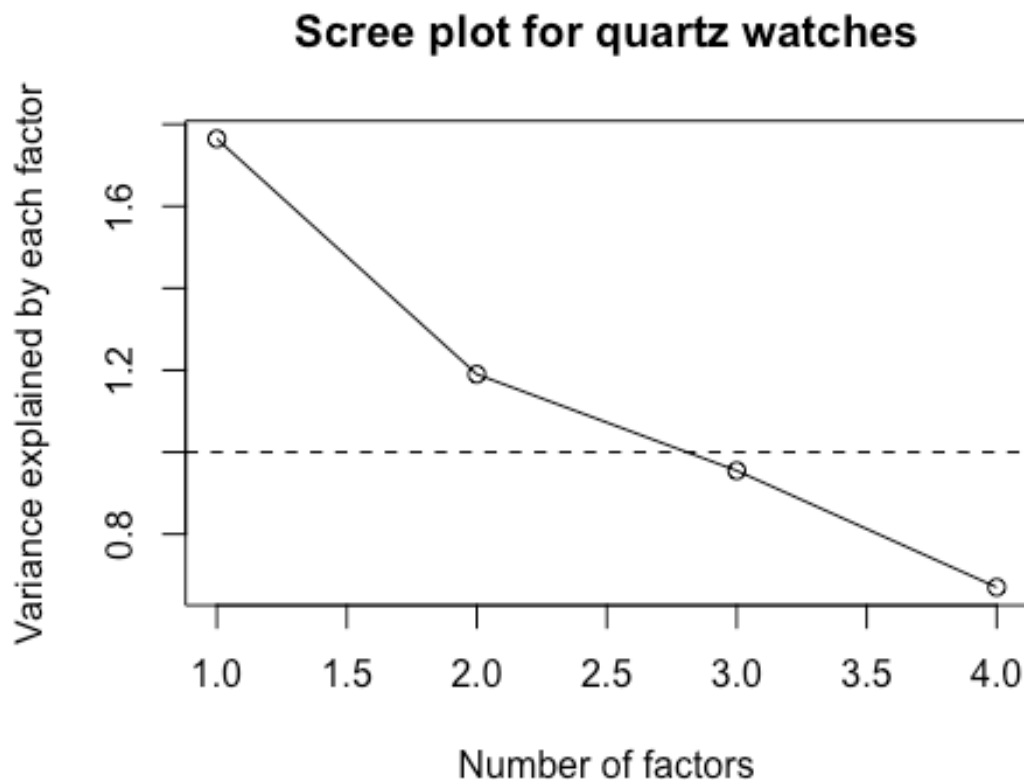
From the scree plot we select 2 factors.

```
#we redo the factor analysis with the correct number of factors

#quartz watch
```

```
anfatt.QW<-factanal(fact.QW,2, rotation="varimax",
scores="regression")
anfatt.QW

##
## Call:
## factanal(x = fact.QW, factors = 2, scores = "regression", rotation
= "varimax")
##
## Uniquenesses:
## imp_design_QW imp_reliab_QW  imp_funct_QW   imp_read_QW
imp_imperm_QW
##         0.549           0.402          0.875          0.422
0.679
##   imp_brand_QW  imp_mater_QW  imp_price_QW
##         0.005          0.652          0.749
##
## Loadings:
##               Factor1 Factor2
## imp_design_QW 0.626   0.244
## imp_reliab_QW 0.762   0.129
## imp_funct_QW  0.242   0.258
## imp_read_QW   0.752   0.110
## imp_imperm_QW 0.539   0.174
## imp_brand_QW          0.995
## imp_mater_QW  0.408   0.426
## imp_price_QW  0.469   0.175
##
##               Factor1 Factor2
## SS loadings     2.280   1.388
## Proportion Var  0.285   0.174
## Cumulative Var  0.285   0.458
##
## Test of the hypothesis that 2 factors are sufficient.
## The chi square statistic is 13.41 on 13 degrees of freedom.
## The p-value is 0.416
```

As we can see, SS Loadings are all larger than 1, round 46% of the variance is explained by the two factors and the p-value is larger than 5% (it is 42%). So we can accept the solution and go ahead with naming and interpreting the factors.

```
#Quartz
fact.scoresQW<-anfatt.QW$scores
colnames(fact.scoresQW)<-c("Performance","Craftsmanship")
cor(fact.scoresQW)

##                  Performance Craftsmanship
## Performance       1.00000000    0.01498377
## Craftsmanship     0.01498377    1.00000000
```

Naming and interpretations of factors

Quartz Watches

-Factor1: **Performance**: design + reliability + readability + impermeability + price

-Factor2: **Craftsmanship**: brand + material

Smartwatches

```
#performing the factor analysis
#smartwatch
anfatt.SW<-factanal(fact.SW,4)
anfatt.SW

##
## Call:
## factanal(x = fact.SW, factors = 4)
##
## Uniquenesses:
## imp_design_SW imp_reliab_SW   imp_funct_SW    imp_read_SW
imp_imperm_SW
##         0.005         0.285          0.296          0.147
0.456
##  imp_brand_SW  imp_mater_SW   imp_price_SW
##         0.569         0.502          0.516
##
## Loadings:
##                Factor1 Factor2 Factor3 Factor4
## imp_design_SW 0.287   0.219   0.916   0.158
## imp_reliab_SW 0.737   0.133   0.185   0.347
## imp_funct_SW  0.784           0.126   0.266
## imp_read_SW   0.848   0.279   0.205   0.119
## imp_imperm_SW 0.272   0.265   0.105   0.623
```

```
## imp_brand_SW  0.184    0.616                0.101
## imp_mater_SW           0.628    0.134    0.290
## imp_price_SW  0.373    0.263    0.129    0.510
##
##                Factor1 Factor2 Factor3 Factor4
## SS loadings      2.207   1.059   0.986   0.972
## Proportion Var   0.276   0.132   0.123   0.121
## Cumulative Var   0.276   0.408   0.532   0.653
##
## Test of the hypothesis that 4 factors are sufficient.
## The chi square statistic is 0.69 on 2 degrees of freedom.
## The p-value is 0.709
```

Looking at the loadings , we see that the Factor3 and Factor4 do no explain more variance than each of the original variables (because it is smaller than 1). So, we constructed a Scree Plot to choose the optimal number of factors.

Scree plot for smart watches
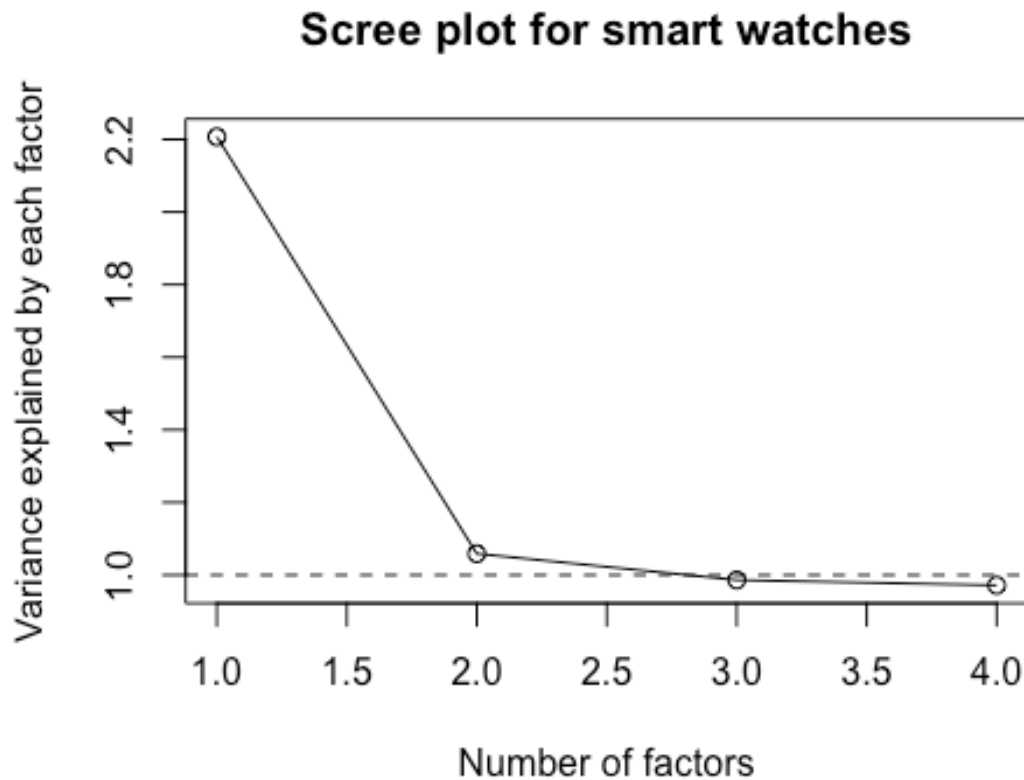
From the scree plot we select 3 factors.

```
#we redo the factor analysis with the correct number of factors

#smartwatch
anfatt.SW<-factanal(fact.SW,3, rotation="varimax",
scores="regression")
anfatt.SW

##
## Call:
## factanal(x = fact.SW, factors = 3, scores = "regression", rotation
= "varimax")
##
## Uniquenesses:
## imp_design_SW imp_reliab_SW   imp_funct_SW    imp_read_SW
imp_imperm_SW
```

```
##          0.651           0.284           0.306           0.125
0.476
##   imp_brand_SW  imp_mater_SW  imp_price_SW
##          0.612           0.465           0.512
##
## Loadings:
##               Factor1 Factor2 Factor3
## imp_design_SW 0.435    0.347   0.197
## imp_reliab_SW 0.742    0.143   0.381
## imp_funct_SW  0.776            0.299
## imp_read_SW   0.879    0.292   0.128
## imp_imperm_SW 0.271    0.288   0.606
## imp_brand_SW  0.197    0.582   0.108
## imp_mater_SW           0.676   0.274
## imp_price_SW  0.371    0.278   0.523
##
##                Factor1 Factor2 Factor3
## SS loadings      2.367   1.184   1.017
## Proportion Var   0.296   0.148   0.127
## Cumulative Var   0.296   0.444   0.571
##
## Test of the hypothesis that 3 factors are sufficient.
## The chi square statistic is 1.81 on 7 degrees of freedom.
## The p-value is 0.97
```

In this case we can accept the solution, as the SS Loadings are all larger than 1, around 57% of the variance is explained by the three factors and the p-value is larger than 5% (it is 97%).

```
#naming the factors

#SmartWatches
fact.scoresSW<-anfatt.SW$scores
colnames(fact.scoresSW)<-c("Usability","Craftsmanship", "Value")
cor(fact.scoresSW)

##                Usability Craftsmanship      Value
## Usability      1.0000000     0.1024170 0.1477973
## Craftsmanship  0.1024170     1.0000000 0.2153809
## Value          0.1477973     0.2153809 1.0000000
```

smartwatches

- Factor1 **Usability**: design + reliability + functionality + readability

- Factor2 **Craftsmanship**: brand + material

- Factor3 **Value** : impermeability + price

Conclusion of the factor analysis

To sum up, we can conclude that the characteristics of the watches can be reduced to common factors. By using these factors, TradWatch can conduct a marketing research in a easier and efficient way. Factors, since they include different characteristics, can be used by the company to develop question that are easy and quicker to answer, in order to achieve an higher rate of response without losing any meaningful informations.

Qustion 5: Can we segment the market according to the underlying factors?

To investigate this issue, we applied the cluster analysis algorithm to the factors we identified and then characterize the clusters based on socio-demographic variables useful in market segmentation.

First of all, we calculated the distance matrix.

```
#computing the distance matrix

#mechanical watches
d.MW<- dist(fact.scoresMW,method="euclidean")
#quartz watches
d.QW<- dist(fact.scoresQW,method="euclidean")
#smart watches
d.SW<- dist(fact.scoresSW,method="euclidean")
```

Then, we agglomerated objects using the Ward Linkage agglomeration method.

```
#mechanical
clu.MW<-hclust(d.MW,method="ward.D")
#quartz
clu.QW<-hclust(d.QW,method="ward.D")
#smartwatch
clu.SW<-hclust(d.SW,method="ward.D")
```
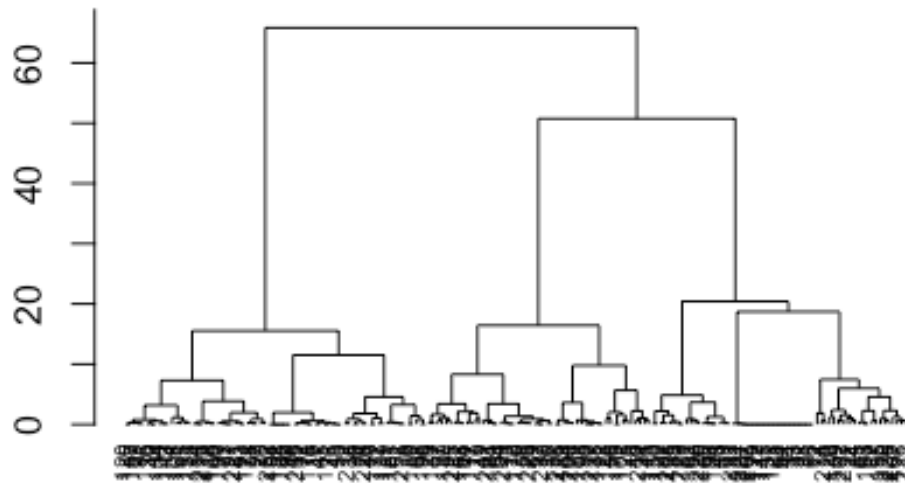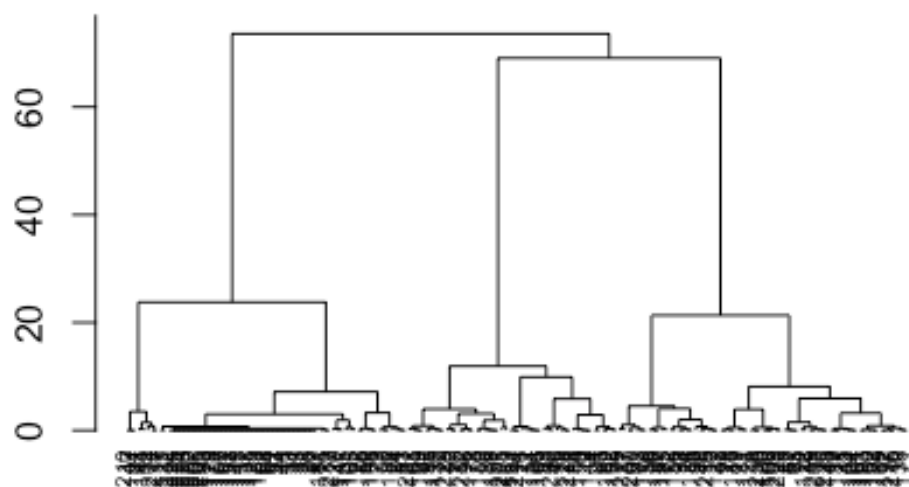
Mechanical

hclust (*, "ward.D")

Quartz

hclust (*, "ward.D")

Smartwatches
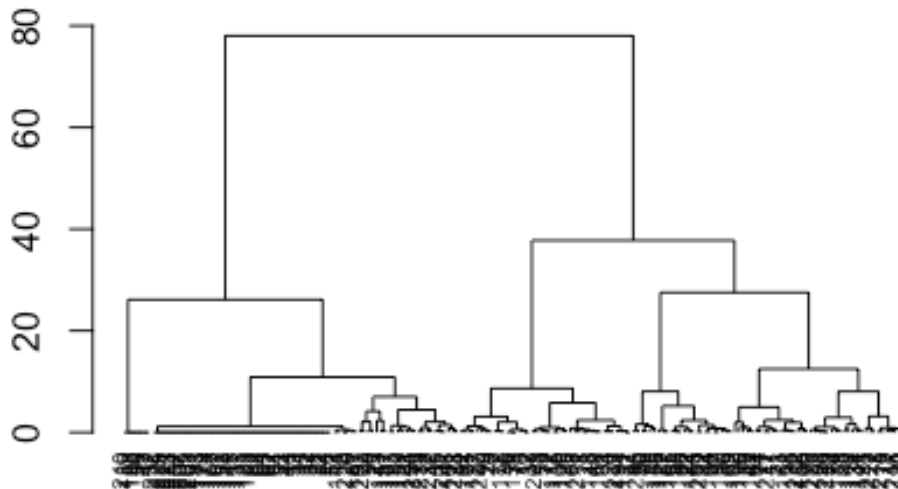
hclust (*, "ward.D")

Mechanical watches Looking at the distance of agglomeration and at the homogeneity of clusters, it seems that a three cluster solution is the more indicated.

Quartz watches The graph shows three large dendrogram branches, indicating that the three groups are well separated.

Smartwatches Based on the agglomeration distance and cluster homogeneity, a five-cluster approach appears to be the most appropriate.

We used the "rect.hclust" function to point out the clusters:

Cluster Dendrogram
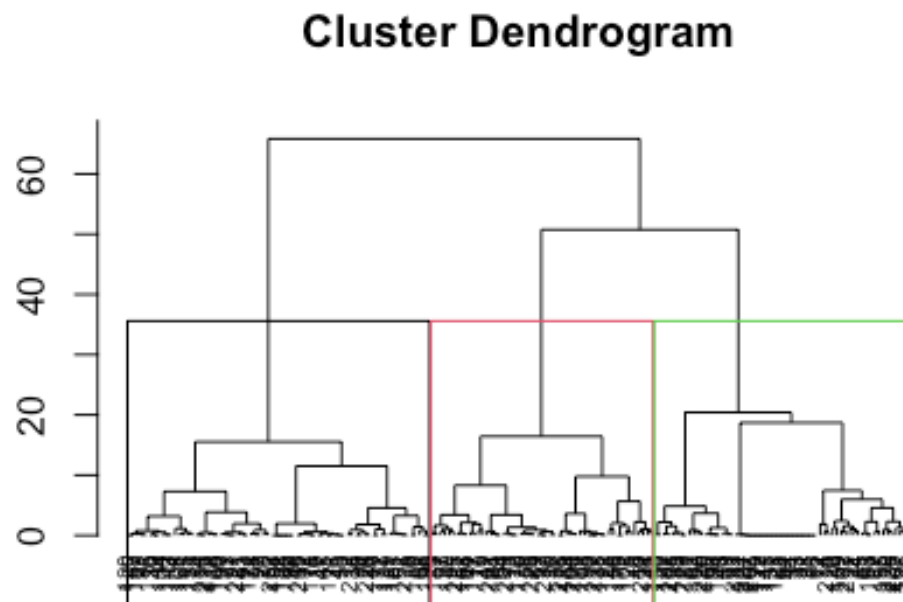
hclust (*, "ward.D")

Cluster Dendrogram
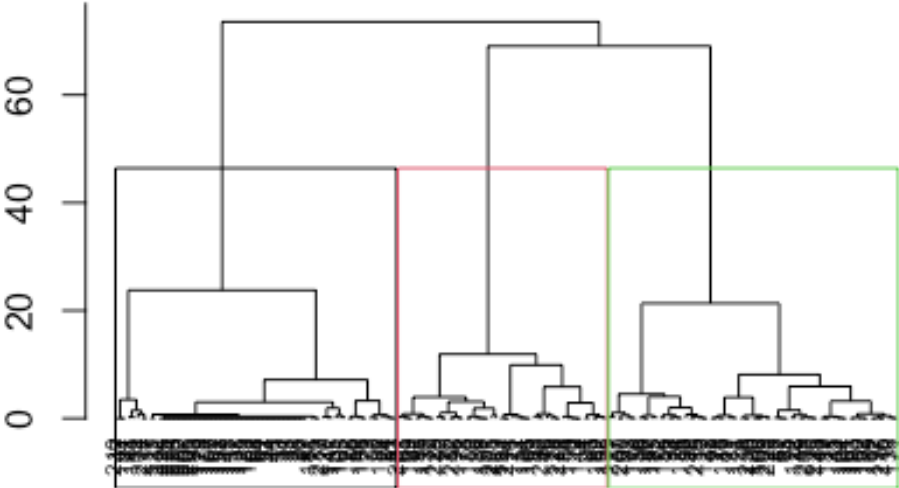
hclust (*, "ward.D")

Cluster Dendrogram
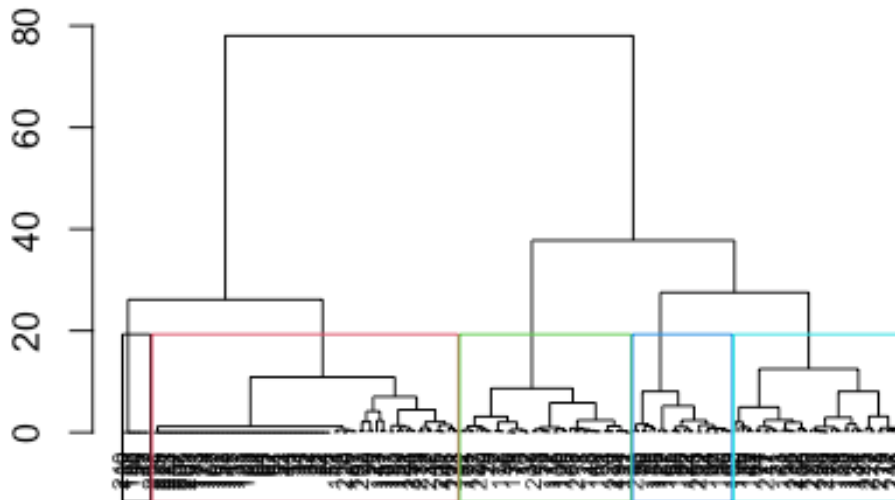
hclust (*, "ward.D")

To validate the number of clusters, we computed the R^2 index, which compares the deviance between clusters to the total deviance.

```r
#importing two functions we will use below
source("pseudo_F.R")
source("nclusters.R")

# computing R-squared index
#mechanical watches
pseudo_F.R(fact.scoresMW, clu.MW, 10)

##      n of clusters loss in R-squared
## [1,]            10        0.03136658
## [2,]             9        0.01999569
## [3,]             8        0.03061895
## [4,]             7        0.01923211
```

```
##  [5,]                 6          0.03793353
##  [6,]                 5          0.05929585
##  [7,]                 4          0.04514011
##  [8,]                 3          0.07314969
##  [9,]                 2          0.22479631
```

```
#quartz watches
pseudo_F.R(fact.scoresQW, clu.QW, 8)
```

```
##      n of clusters loss in R-squared
## [1,]             8       0.008602048
## [2,]             7       0.016052964
## [3,]             6       0.028351583
## [4,]             5       0.028598952
## [5,]             4       0.067238723
## [6,]             3       0.097906108
## [7,]             2       0.355200235
```

```
#smartwatches
pseudo_F.R(fact.scoresSW, clu.SW, 8)
```

```
##      n of clusters loss in R-squared
## [1,]             8       0.026249688
## [2,]             7       0.019548555
## [3,]             6       0.003460617
## [4,]             5       0.046708847
## [5,]             4       0.090625839
## [6,]             3       0.133022124
## [7,]             2       0.158255205
```

Based on the R-squared index we confirmed:

- 3 cluster for Mechanical Watches;

- 3 cluster for Quartz Watches;

- 5 cluster for Smartwatches.

Next, we provided a graphical representation of the clusters in order to identify the position of our respondent towards the factors.

Mechanical Watches
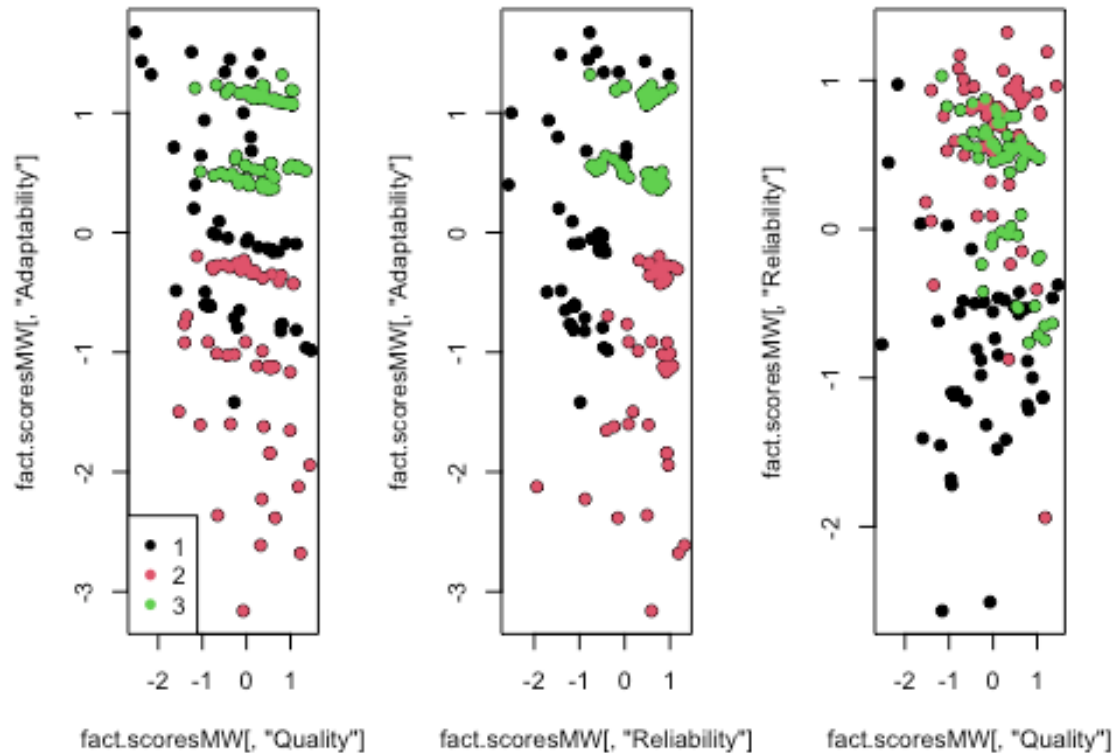
Overall, the clustering algorithm has successfully identified three distinct groups of data points based on their values on the three pairs of variables, and the graphical results provide a useful visual representation of the clustering result.

Analyzing the plots we can state that:

- **Cluster 1** values the most adaptability and quality;

- **Cluster 2** values the most reliability and quality;

- **Cluster 3** values all three factors.

Quartz watches

```
#quartz watches
membQW<-cutree(clu.QW,k=3) #vector assigning each respondent the
membership to a cluster
```

```r
plot(fact.scoresQW[,"Performance"],fact.scoresQW[,"Craftsmanship"])
for (i in 1:3){
points(fact.scoresQW[membQW==i,"Performance"],fact.scoresQW[membQW==i,
"Craftsmanship"],
       col=i,pch=16)
}
legend("bottomleft",legend=c(1,2,3),col=c(1,2,3),pch=16)
```


According to the graph:

- People belonging to **Cluster 1** place a higher value on performance;

- People in **Cluster 2** place a higher value on craftsmanship;

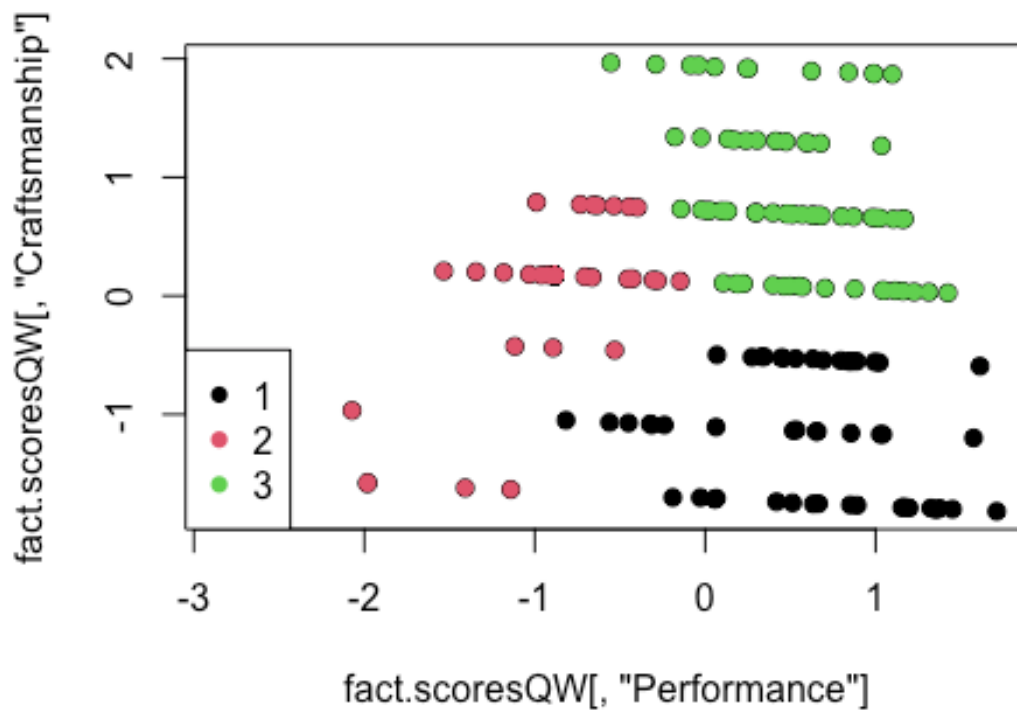- People belonging to **Cluster 3** value both performance and craftsmanship.

Smartwatches

```r
par(mfcol=c(1,3))

#smartwatches
membSW<-cutree(clu.SW,k=5) #vector assigning each respondent the
membership to a cluster
plot(fact.scoresSW[,"Usability"],fact.scoresSW[,"Craftsmanship"])
for (i in 1:5){
points(fact.scoresSW[membSW==i,"Usability"],fact.scoresSW[membSW==i,"C
raftsmanship"],
       col=i,pch=16)
}
legend("bottomleft",legend=c(1,2,3,4,5),col=c(1,2,3,4,5),pch=16)

plot(fact.scoresSW[,"Usability"],fact.scoresSW[,"Value"])
for (i in 1:5){
points(fact.scoresSW[membSW==i,"Usability"],fact.scoresSW[membSW==i,"V
alue"],
       col=i,pch=16)
}

plot(fact.scoresSW[,"Craftsmanship"],fact.scoresSW[,"Value"])
for (i in 1:5){
points(fact.scoresSW[membSW==i,"Craftsmanship"],fact.scoresSW[membSW==
i,"Value"],
       col=i,pch=16)
}
```
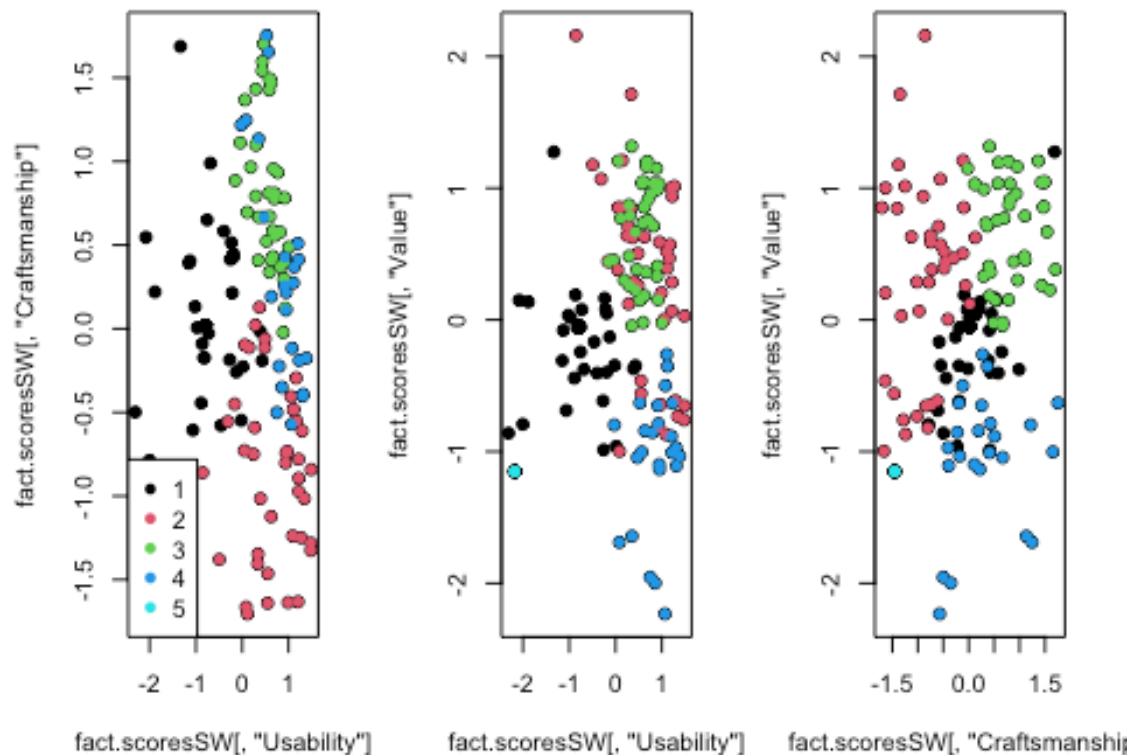
From the plots we can ifer that:

- **Cluster 1** seems to value just craftsmanship;

- **Cluster 2** rates highly usability and value;

- **Cluster 3** rates highly all of the three factors;

- **Cluster 4** rates highly usability and craftsmanship;

- **Cluster 5** doesn't value none of them.

Then, we plot them in a 3D graph to get a more complete picture of the clusters' positions in relation to the clustering factors.

```
#importing the lattice library to plot a 3D plot
library(lattice)
```

```
#mechanical watch
cloud(fact.scoresMW[,3]~fact.scoresMW[,1]+fact.scoresMW[,2],groups=mem
bMW,
      scales=list(arrows=F), screen=list(z=30,x=-60),
xlab="Quality",ylab="Adaptability",
      zlab="Reliability", auto.key=T, pch=16,main="Mechanical Watch")
```
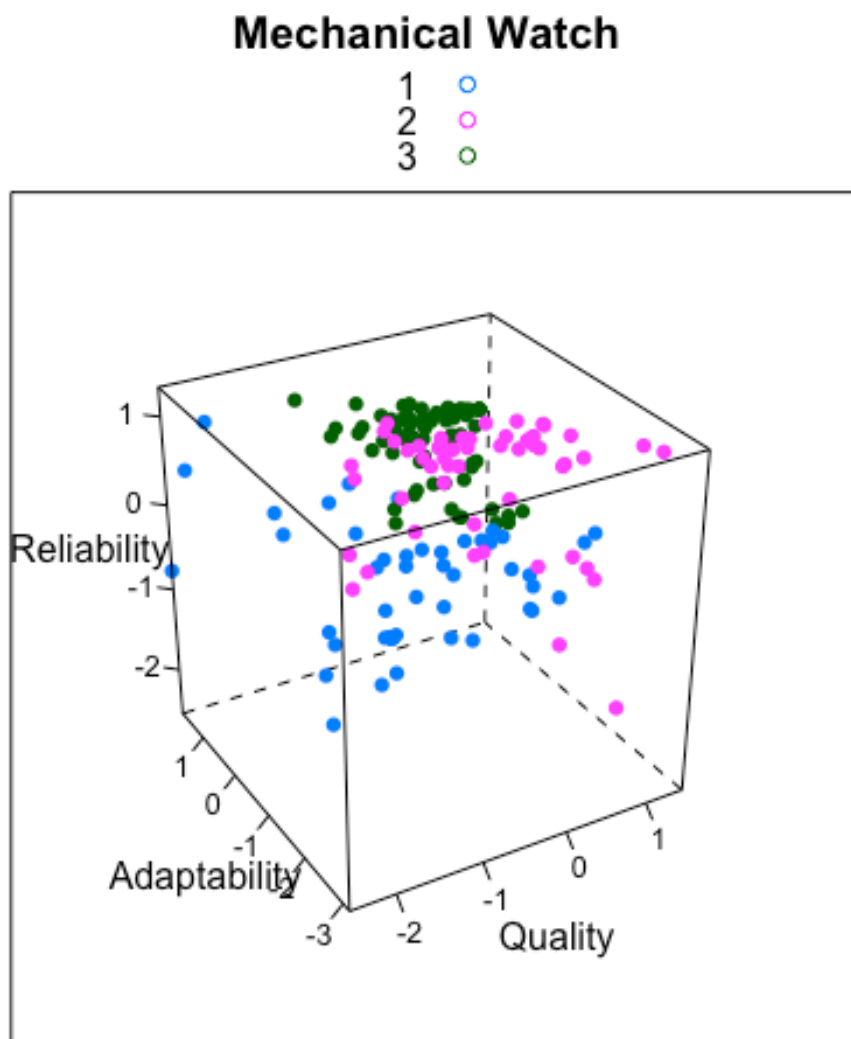


```
#smartwatch
cloud(fact.scoresSW[,3]~fact.scoresSW[,1]+fact.scoresSW[,2],groups=mem
```

```
bSW,
      scales=list(arrows=F), screen=list(z=35,x=-65),
xlab="Usability",ylab="Craftsmanship",
      zlab="Value", auto.key=T, pch=16, main="Smartwatch")
```
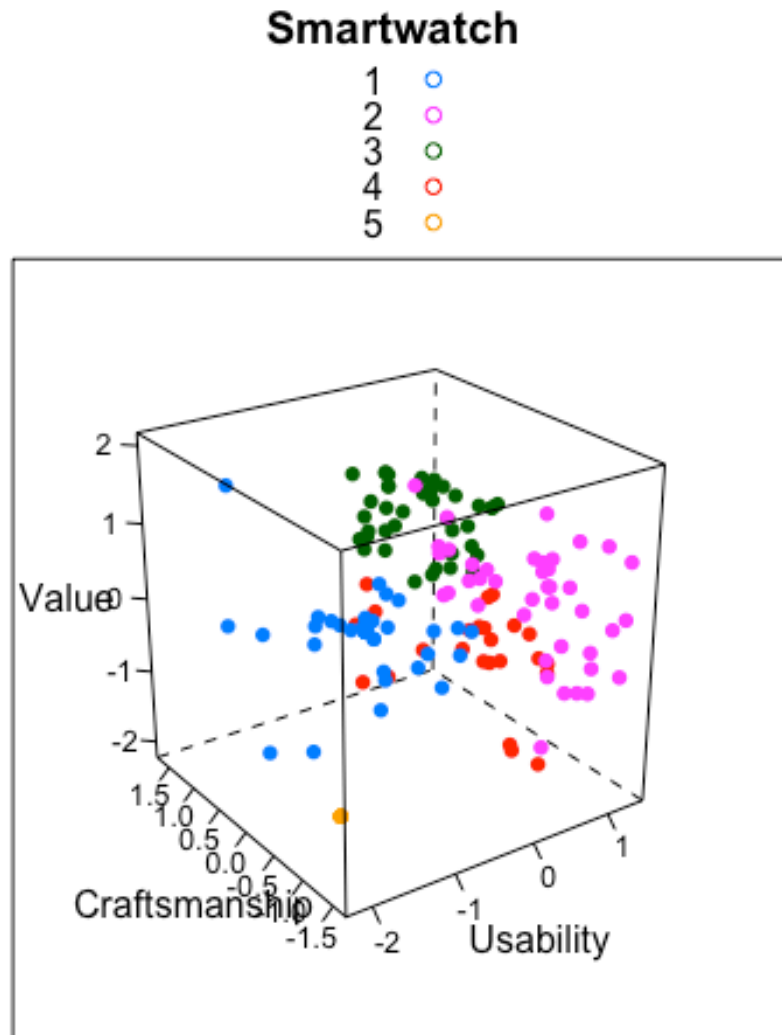

We proceed to the cluster naming and profiling, according to the factors used in defining the clusters.

Cluster naming and profiling

First, we need to build a demographics dataset.

Next, We calculated the centroids of the clusters.

```
##
------------------------------------------------------------------------
--------

## You have loaded plyr after dplyr - this is likely to cause
problems.
## If you need functions from both plyr and dplyr, please load plyr
first, then dplyr:
## library(plyr); library(dplyr)

##
------------------------------------------------------------------------
--------

##      Quality adaptability reliability size
## clu1  -0.439      -0.098      -0.922   61
## clu2   0.041      -1.024       0.597   53
## clu3   0.342       0.837       0.342   72

##      Performance Craftsmanship size
## clu1        0.594        -1.176   50
## clu2       -0.983         0.006   67
## clu3        0.524         0.847   69

##      Usability Craftsmanship  Value size
## clu1   -0.767         0.049 -0.119   73
## clu2    0.666        -0.851  0.328   41
## clu3    0.565         0.828  0.693   41
## clu4    0.865         0.313 -1.046   24
## clu5   -2.173        -1.454 -1.151    7
```

Mechanical Watches

- The first cluster's respondents do not value any of the three factors. We can call them the **indifferent watches buyers**.

- The second cluster does not value the adaptability side when buying a watch, because of the large negative value for the adaptability factor. At the same time they

somewhat value the quality and reliability of mechanical watches. We can call them the **meticulous watches buyers**.We selected this name to signal to the TradWatch the aspect on which these customers should be addressed when designing marketing stategies.

-We can name the third cluster as the **demanding watches buyers**, since they care a lot about the quality, adaptability and reliability when buying a mechanical watch.These customers should be addressed with the best possible product that satisfy their high expectations.

Quartz Watches

- We can name the first cluster as the **performance watches buyers**, since it is composed of consumers that value the performance value, but does not value the craftsmanship side of watches.

- The second cluster's respondents does not value the performance side of watches, but instead the craftsmanship side. This is why we can call them **craftsmanship watches buyers**.

- We can call the third cluster as the **classic watches buyers**, since it is composed of consumers which agree with positive aspects of watches' attributes with respect to all factors.

smartwatches

- The first cluster does not appreciate the usability and value side of watches' attributes, but instead values craftsmanship more. We can call them **connoiseur watches buyers**.

- We can name the second cluster as **pragmatic watches buyers**, since they appreciate more the value and usability of watches' attributes, but these customers don't value the craftsmanship factor.

- We can name the third cluster as **confident watches buyers** , since they positively care about the usability, craftsmanship and value factors of the watches' attributes.

- The fourth cluster does not assign worth on the value side (large negative value), but at the same time they value usability and craftsmanship.We can call them **discerning watches buyers** we need this name to remind the aspect on which these customers should be addressed when designing our policies.

- The fifth cluster does not value any of the factors, which is why we can call them **uninterested consumer**.

Characterization of the clusters

After naming the clusters based on the factors used to construct them, we wanted to show the composition of these clusters using socio-demographic variables. This way the company is able to better profile customers according to their preferred watches attributes.

Conclusion cluster analysis

After conducting the cluster analysis, we can affirm that we can segment the market according to characteristic factors. The cluster analysis that we develop may help TradWatch to create different groups of customers combined by similar preferences on watches' attributes. We were also able to give the company a clearer picture of the composition of these distinct clusters because we used socio-demographic factors to characterize the cluster. It allows the company to develop tailored marketing strategies to target their desired customers.

Qustion 4: Owners of different type of watches are different also in terms of their socio-demographic characteristics?

To answer this question we decided to plot two sets of histograms:

- the first, represent individuals who own only traditional watches (blue histograms);

- the second, represent individuals who own both kinds of watches (red histograms).

We had to compare traditional owners with owners of both types of watches becasue no respondent in our datasets owned only smartwatches.

large_city

Large	Medium	Small
39.5 %	26.3 %	34.2 %

Year_born

Boomers	GenX	GenZ	Millennials
13.2 %	47.4 %	2.6 %	36.8 %

Job

Employee	Other	Self employed	Student	Unemployed
50 %	10.5 %	26.3 %	10.5 %	2.6 %

Gender

female	male
18.4 %	81.6 %

Education

Bachelor Degree	high school	Master degree	middle school	Other
13.2 %	36.8 %	21.1 %	5.3 %	23.7 %

Income

> 75,000	0-15,000	15,000-28,000	28,000-55,000	55,000-75,000
31.6 %	10.5 %	18.4 %	23.7 %	15.8 %
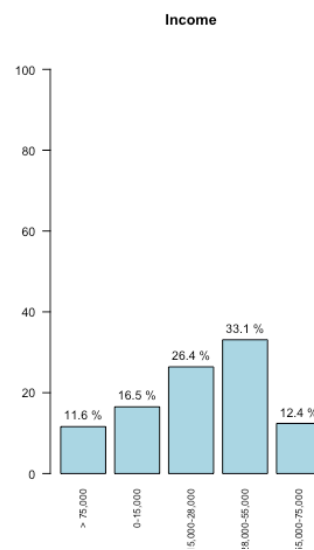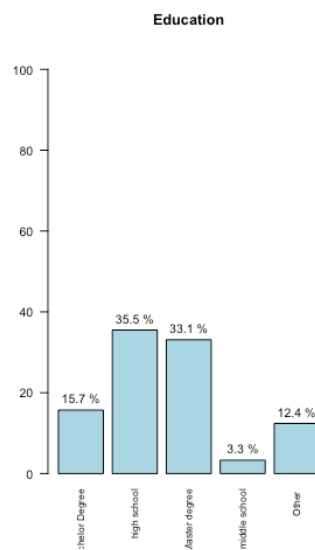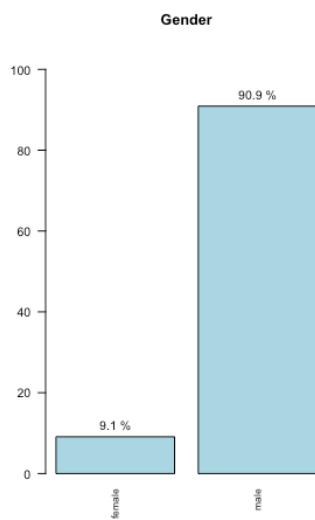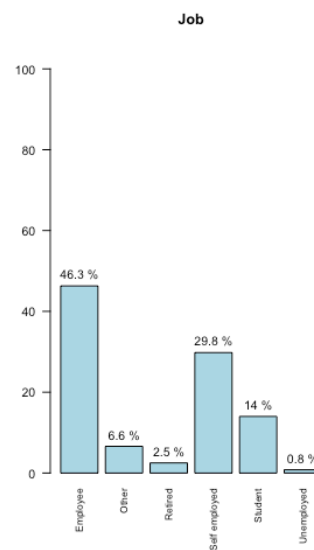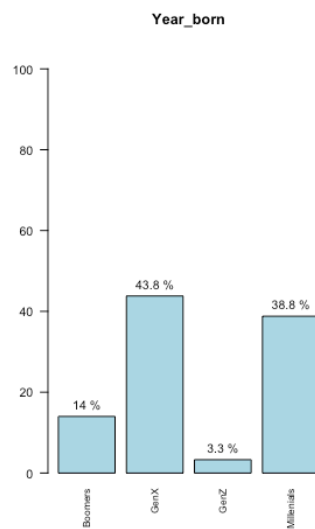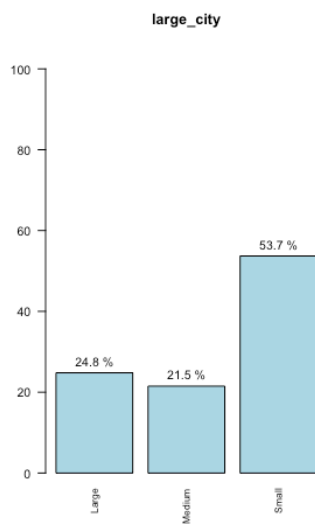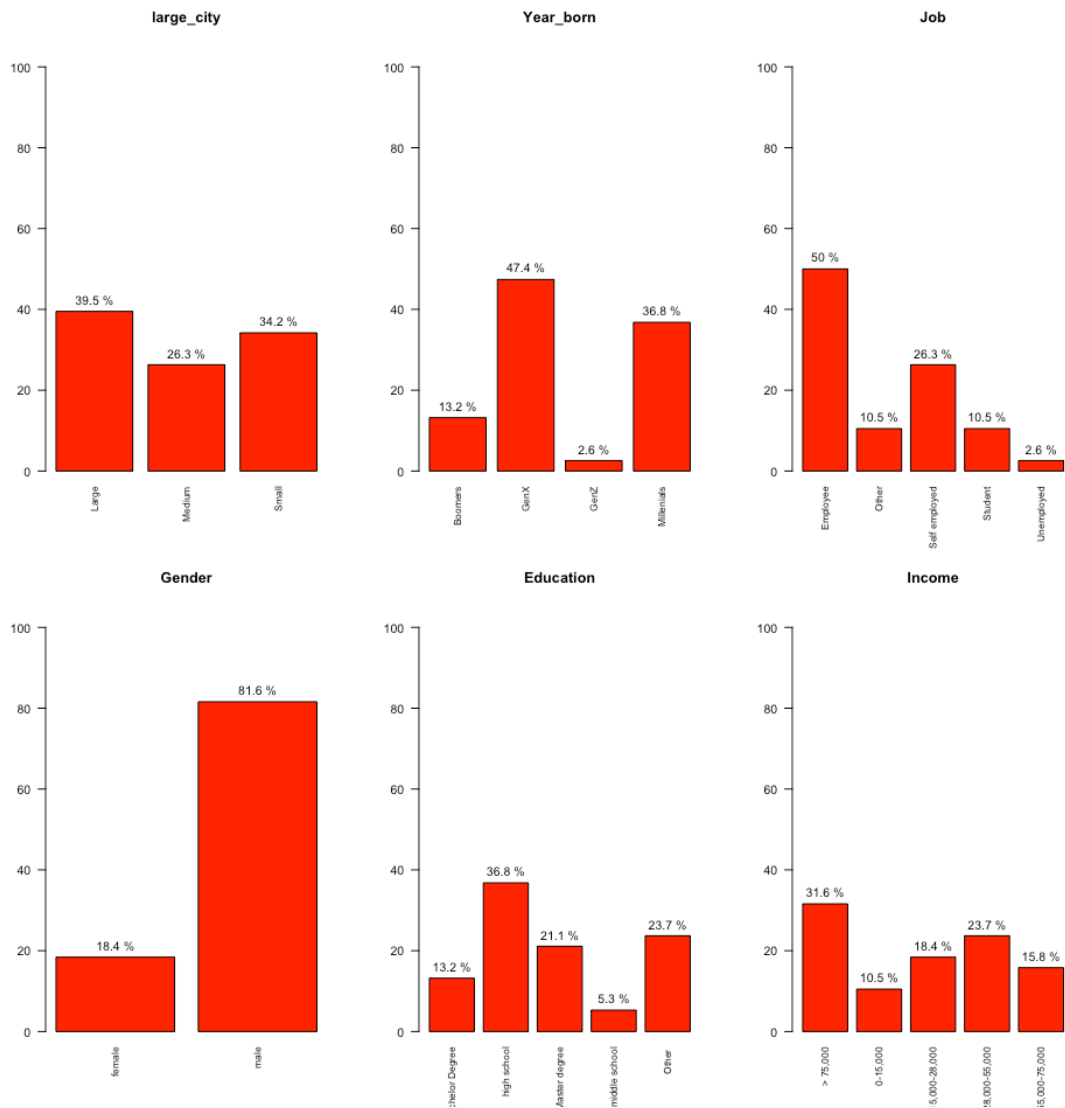
Comparing the two blocks of histogram, we can see that:

The first thing we noticed is that there is not a significant difference between the age of the owners of these two groups. We can see that the two major groups of owners are the Millennials and GenX, in accordance with our secondary research. The owners' education is another area where there aren't any discernible distinctions between the two groups. Another interesting finding is related to the location of the watches' owners. On one hand, who owns both types of watches tend to live in large cities (with more than 200,000 inhabitants). On the other hand, traditional watches users are more likely to live in small cities (with less than 50,000 inhabitants).

Regarding the income, the data shows a small difference between the two groups. People who own both types of watches are more likely to have higher incomes (over $75,000), while traditional watches users have a more equal distribution across income levels. We need to specify that our observed data for traditional watches are slightly different than in our secondary research, what changes was income, which is smaller in our observed data.

The gender of owners also does not significantly differ among the two watches categories, unless smartwatches have just a slightly larger share of female owners. We notice that male is the prominent gender in our observed sample, which is coherent with our secondary research as well. The biggest difference between the two group of owners is found in the job factor. We found that retired people do not possess both types of watches, while people in other professions share a comparable distribution with the traditional owners. In conclusion, our data demonstrates how there is little difference between people who solely own traditional watches and people who possess both kinds. Even if we believe these findings are relevant for TradWatch, we are unable to draw a definitive conclusion on the differences in socio-demographic traits because we were unable to compare owners of traditional watches with owners of smartwatches.

Qusetion 7: Do characteristics and perception of watches affect the willingness to buy of customers?

```
#creating a dataset with the willingness to buy responses for the
three type of watches
wtb <- na.omit(watches[,102:104])
#renaming the column to increase clarity
colnames(wtb) <- c("wtb.MW","wtb.QW","wtb.SW")
```

To answer this question we will use factors on the charactestics that we already developed. Moreover, we decided to develop the factors for the perception of watches (Question 4)

Factor analysis for the perception variables

We start by evaluating if there is any correlation worth exploring among the variable

```
#import library psych to measure the KMO index and perform the Barlett
test of sphericity
library(psych)

#mechanical wathces
KMO(per.MW)
```

```
## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = per.MW)
## Overall MSA =  0.86
## MSA for each item =
## classy_MW status_MW    soph_MW evergr_MW desire_MW     fun_MW
superf_MW gratif_MW
##      0.91      0.89      0.92      0.94      0.92      0.82
0.59      0.79
##    exc_MW trendy_MW sporty_MW
##      0.78      0.81      0.84

cortest.bartlett(per.MW)

## R was not square, finding R from data

## $chisq
## [1] 805.9306
##
## $p.value
## [1] 5.548378e-134
##
## $df
## [1] 55
```

```
# quartz watches
KMO(per.QW)

## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = per.QW)
## Overall MSA =  0.82
## MSA for each item =
## classy_QW status_QW    soph_QW evergr_QW desire_QW     fun_QW
superf_QW gratif_QW
##      0.82      0.83      0.89      0.83      0.89      0.75
0.70      0.80
##    exc_QW trendy_QW sporty_QW
##      0.81      0.91      0.45

cortest.bartlett(per.QW)

## R was not square, finding R from data
```

```
## $chisq
## [1] 780.8364
##
## $p.value
## [1] 6.764467e-129
##
## $df
## [1] 55
```

```
# smartwatches
KMO(per.SW)
```

```
## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = per.SW)
## Overall MSA =  0.81
## MSA for each item =
## classy_SW status_SW   soph_SW evergr_SW desire_SW    fun_SW
superf_SW gratif_SW
##      0.79      0.82      0.89      0.85      0.85      0.83
0.61      0.79
##    exc_SW trendy_SW sporty_SW
##      0.80      0.70      0.80
```

```
cortest.bartlett(per.SW)
```

```
## R was not square, finding R from data
```

```
## $chisq
## [1] 656.6783
##
## $p.value
## [1] 6.365062e-104
##
## $df
## [1] 55
```

It seems it is worthwile to proceed witht the factorial analysis because the variables are correlated, they share common variability since:

- Mecahnical watches are ok : MSA: 0.86, p-value:5.548378e-134

- Quatz watches are ok : MSA: 0.82, p-value: 6.764467e-129

- Smartwatches are ok: MSA: 0.81, p-value:6.365062e-104

Scree plot for mechanical watches

Variance explained by each factor

Number of factors

Scree plot for quartz watches

Variance explained by each factor (y-axis)

Number of factors (x-axis)
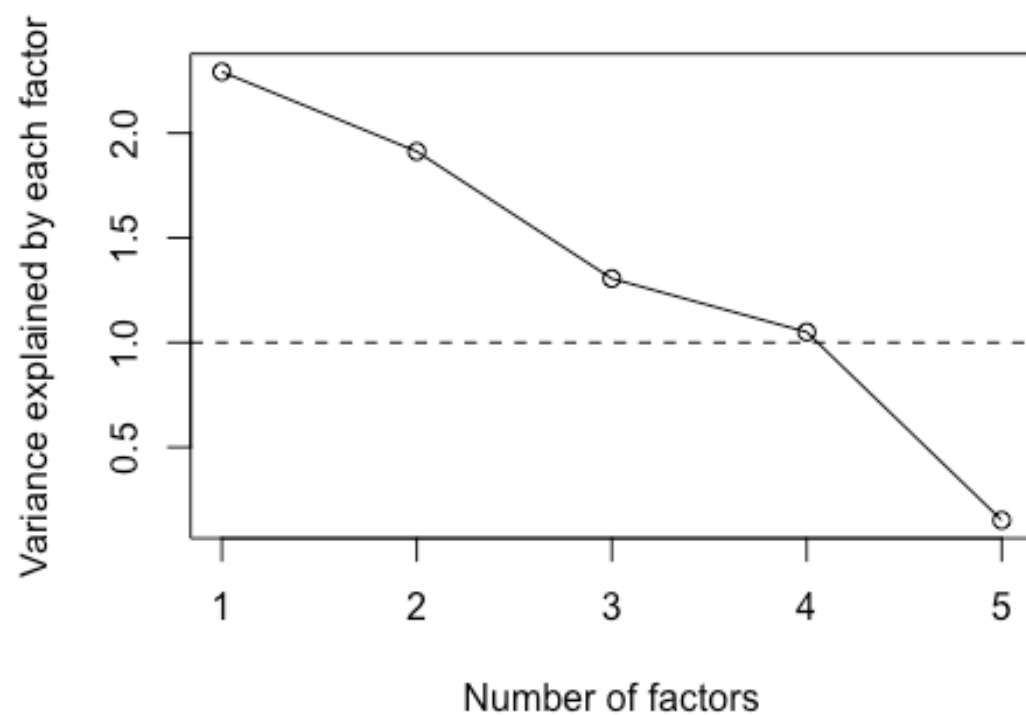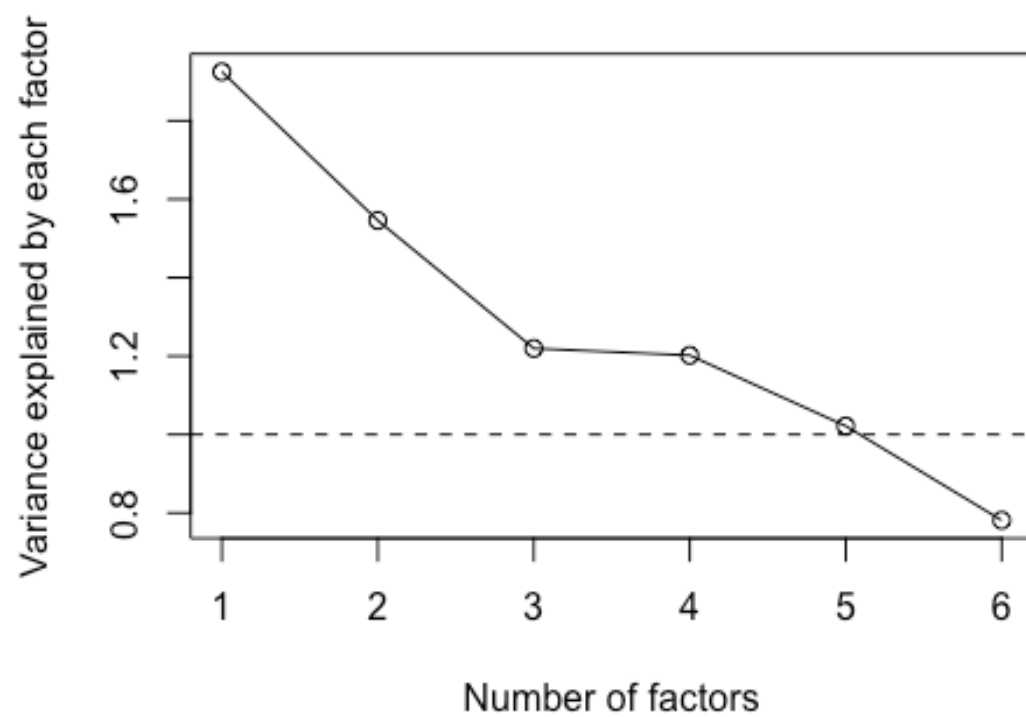
Scree plot for smart watches
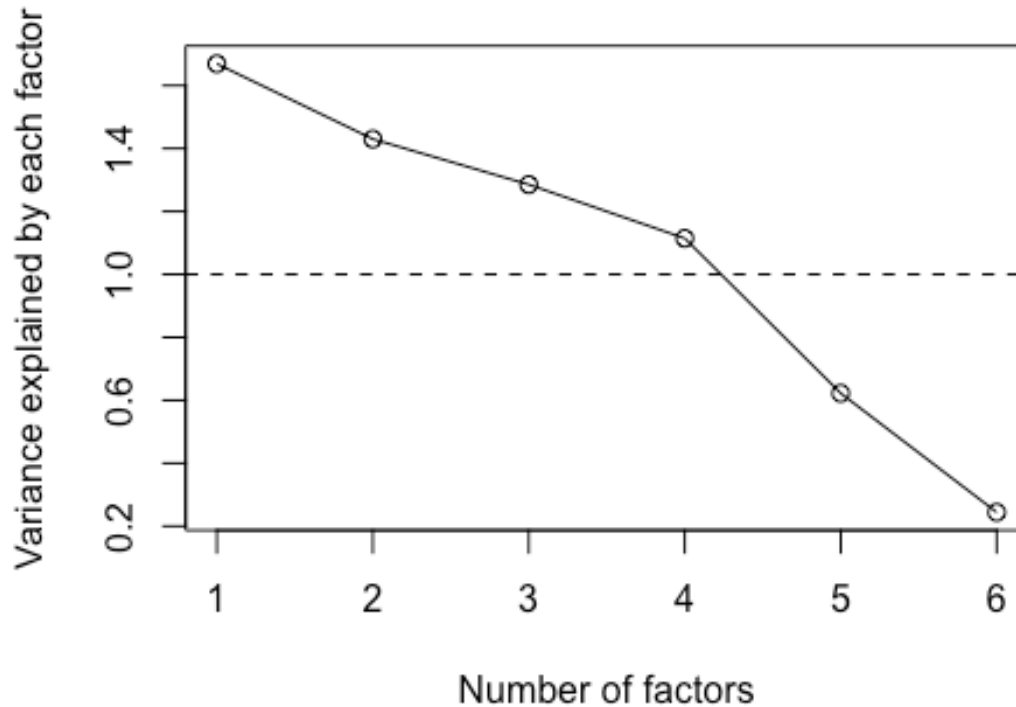

```
##
## Call:
## factanal(x = per2.MW, factors = 3, scores = "regression", rotation
= "varimax")
##
## Uniquenesses:
## classy_MW status_MW    soph_MW evergr_MW desire_MW     fun_MW
gratif_MW    exc_MW
##     0.520     0.408     0.470     0.603     0.388     0.657
0.174     0.171
## trendy_MW sporty_MW
##     0.420     0.652
##
## Loadings:
##            Factor1 Factor2 Factor3
```

```
## classy_MW 0.637    0.232    0.142
## status_MW 0.713    0.166    0.236
## soph_MW   0.632    0.251    0.260
## evergr_MW 0.490    0.331    0.216
## desire_MW 0.552    0.482    0.273
## fun_MW    0.154             0.560
## gratif_MW 0.437    0.771    0.202
## exc_MW    0.263    0.853    0.182
## trendy_MW 0.246    0.104    0.713
## sporty_MW 0.134    0.211    0.534
##
##                 Factor1 Factor2 Factor3
## SS loadings       2.222   1.869   1.446
## Proportion Var    0.222   0.187   0.145
## Cumulative Var    0.222   0.409   0.554
##
## Test of the hypothesis that 3 factors are sufficient.
## The chi square statistic is 18.79 on 18 degrees of freedom.
## The p-value is 0.405

##
## Call:
## factanal(x = per2.QW, factors = 4, scores = "regression", rotation
= "varimax")
##
## Uniquenesses:
## classy_QW status_QW   soph_QW evergr_QW desire_QW     fun_QW
gratif_QW    exc_QW
##     0.513     0.395     0.568     0.005     0.373     0.156
0.061     0.310
## trendy_QW sporty_QW
##     0.628     0.626
##
## Loadings:
##           Factor1 Factor2 Factor3 Factor4
## classy_QW  0.646   0.174           0.176
## status_QW  0.735   0.214           0.122
## soph_QW    0.497   0.384   0.191
## evergr_QW  0.353   0.162   0.187   0.900
## desire_QW  0.630   0.451   0.111   0.120
## fun_QW     0.215   0.123   0.884
```

```
## gratif_QW  0.274    0.902    0.167    0.151
## exc_QW      0.360    0.728    0.125    0.126
## trendy_QW  0.394    0.299    0.294    0.201
## sporty_QW -0.190    0.136    0.479    0.300
##
##                 Factor1 Factor2 Factor3 Factor4
## SS loadings       2.170   1.919   1.237   1.040
## Proportion Var    0.217   0.192   0.124   0.104
## Cumulative Var    0.217   0.409   0.533   0.637
##
## Test of the hypothesis that 4 factors are sufficient.
## The chi square statistic is 24.4 on 11 degrees of freedom.
## The p-value is 0.0111

##
## Call:
## factanal(x = per2.SW, factors = 4, scores = "regression", rotation
= "varimax")
##
## Uniquenesses:
## classy_SW status_SW   soph_SW evergr_SW desire_SW     fun_SW
gratif_SW    exc_SW
##     0.338     0.616     0.608     0.677     0.005     0.552
0.031     0.333
## trendy_SW sporty_SW
##     0.327     0.884
##
## Loadings:
##           Factor1 Factor2 Factor3 Factor4
## classy_SW           0.800   0.128
## status_SW  0.541   0.223           0.200
## soph_SW    0.524   0.304   0.129
## evergr_SW          0.506   0.217   0.138
## desire_SW  0.228   0.239   0.284   0.897
## fun_SW     0.503           0.278   0.343
## gratif_SW  0.336   0.363   0.822   0.221
## exc_SW     0.261   0.370   0.618   0.284
## trendy_SW  0.808           0.134
## sporty_SW  0.316           0.104
##
##                 Factor1 Factor2 Factor3 Factor4
```

```
## SS loadings          1.809   1.367   1.326   1.126
## Proportion Var       0.181   0.137   0.133   0.113
## Cumulative Var       0.181   0.318   0.450   0.563
##
## Test of the hypothesis that 4 factors are sufficient.
## The chi square statistic is 11.26 on 11 degrees of freedom.
## The p-value is 0.422
```

Naming factors

Mechanical watches

- Factor 1: **Elegancy** = classy+ status+ sophisticated+ evergreen+ desire

- Factor 2: **Enjoyable** = gratifying + exciting

- Factor 3: **Sparky** = fun+ sporty+ trendy

Quartz watches

- Factor1: **Fancy** = Classy+ status+ sophisticated+ trendy+ desire

- Factor2: **Enjoyable** = gratifying + exciting

- Factor3: **Playful** = fun+ sporty

- Factor4: **Evergreen** = evergreen

Smartwatches

- Factor1: **Glamour** = Status+ sophisticated+fun+trendy+sporty

- Factor2: **Timeless**= evergreen+classy

- Factor3: **Enjoyable**= gratifying + exciting

- Factor4: **Deside**= desire

#Logistic Regression

Mechanical Watches

```
modelMW <- glm(wtbMW~.,data=testdata, family = binomial(link="logit"))
summary(modelMW)
```

```
##
## Call:
## glm(formula = wtbMW ~ ., family = binomial(link = "logit"), data =
testdata)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.6032   0.2658   0.2981   0.3888   1.7781
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)   2.35174    0.31752   7.407  1.3e-13 ***
## quality      -0.03981    0.43706  -0.091 0.927430
## adaptability  0.19025    0.28539   0.667 0.505022
## reliability   0.05406    0.30439   0.178 0.859041
## elegancy      0.66189    0.38545   1.717 0.085944 .
## enjoyable     1.07574    0.27744   3.877 0.000106 ***
## stylish       0.08853    0.38031   0.233 0.815933
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 125.786  on 164  degrees of freedom
## Residual deviance:  91.932  on 158  degrees of freedom
## AIC: 105.93
##
## Number of Fisher Scoring iterations: 5
```

For mechanical watches, we can see that the relevant variables pushing people to buy a mechanical watch are the enjoyable factor and the elegancy factor, which are both from related to the perception.

We move to the exponential transform to better understand the effects of these factors on the willingness to buy

```
#find the odds-ratios
#mechanical watches
round(exp(modelMW$coefficients),3)

##  (Intercept)      quality adaptability  reliability     elegancy
enjoyable
```

```
##          10.504           0.961           1.210           1.056           1.938
2.932
##         stylish
##           1.093
```

-One point more in the scale of the **enjoyable factor** leads to an increase of **193.2%** $((2.932 - 1) \times 100)$ in the odds of a customer buying a mechanical watch.

- One point more in the scale of the **elegancy** factor leads to an increase of **93.8%** $((1.938 - 1) \times 100)$ in the odds of a customer buying a mechanical watch.

To validate our model we test for the null of the regressors bringing something more with respect to the null model.

```
#building the null model
#mechanical watches
nullmodelMW <- glm(wtbMW~1, data = testdata, family = binomial(link =
"logit"))

# likelihood ratio test
print(paste("model MW likelihood ratio test p-value:",
round(with(modelMW, pchisq(null.deviance-deviance,df.null-df.residual,
lower.tail = F)),6)))

## [1] "model MW likelihood ratio test p-value: 7e-06"
```

Since the p-value is significantly smaller than 0.05, we reject the null hypothesis, meaning that our model "modelMW" with regressors is useful in explaining the dependent variable (willingness to buy MW).

Quartz watches

We follow the same precedure for quartz watches.

```
modelQW <- glm(wtbQW~.,data=testdata, family = binomial(link="logit"))
summary(modelQW)

##
## Call:
## glm(formula = wtbQW ~ ., family = binomial(link = "logit"), data =
testdata)
##
## Deviance Residuals:
##      Min      1Q    Median      3Q      Max
```

```
## -1.7385  -0.7591  -0.5076   0.8659   2.4748
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -1.0958     0.2158  -5.078 3.81e-07 ***
## performance    0.7641     0.2798   2.731  0.00632 **
## craftsmanship  0.2878     0.2146   1.341  0.17991
## fancy          0.4773     0.2446   1.951  0.05105 .
## enjoyable      0.6076     0.2084   2.915  0.00356 **
## playful        0.3297     0.2143   1.538  0.12393
## evergreen      0.2234     0.1956   1.142  0.25335
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 205.64  on 164  degrees of freedom
## Residual deviance: 165.83  on 158  degrees of freedom
## AIC: 179.83
##
## Number of Fisher Scoring iterations: 5
```

For quartz watches, we can see that the relevant variables pushing people to buy a quartz watch are the performance factor, the fancy factor, and the enjoyable factor. We notice that the relevant variables affecting the willingness to buy quartz watches are similar to mechanical watches, highlighting the belonging to the same traditional watches category.

We move to the exponential transform to better understand the effects of these factors on the willingness to buy

```
#find the odds-ratios
#quartz watches
round(exp(modelQW$coefficients),3)

##   (Intercept)   performance craftsmanship         fancy
enjoyable
##         0.334         2.147         1.334         1.612
1.836
##       playful     evergreen
##         1.391         1.250
```

- One point more in the scale of the **performance factor** leads to a increase of **114.7%** $((2.147 - 1) \times 100)$ in the odds of a customer buying a quartz watch.

- One point more in the scale of the **fancy factor** leads to an increase of **61.2%** $\left((1.612 - 1) \times 100\right)$ in the odds of a customer buying a quartz watch.

- One point more in the scale of the **enjoyable factor** leads to an increase of **83.6%** $\left((1.836 - 1) \times 100\right)$ in the odds of a customer buying a quartz watch.

To validate our model we test for the null of the regressors bringing something more with respect to the null model.

```
#building the null model
#mechanical watches
nullmodelQW <- glm(wtbQW~1, data = testdata, family = binomial(link =
"logit"))

# likelihood ratio test
print(paste("model QW likelihood ratio test p-value:",
round(with(modelQW, pchisq(null.deviance-deviance,df.null-df.residual,
lower.tail = F)),9)))

## [1] "model QW likelihood ratio test p-value: 4.95e-07"
```

Since the p-value is significantly smaller than 0.05, we reject the null hypothesis, meaning that our model "modelQW" with regressors is useful in explaining the dependent variable (willingness to buy QW).

Smart watch

```
modelSW <- glm(wtbSW~.,data=testdata, family = binomial(link="logit"))
summary(modelSW)

##
## Call:
## glm(formula = wtbSW ~ ., family = binomial(link = "logit"), data =
testdata)
##
## Deviance Residuals:
##     Min        1Q    Median        3Q       Max
## -1.2256   -0.5582   -0.4331   -0.2633    2.4225
##
```

```
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -2.1297     0.2925  -7.280 3.34e-13 ***
## usability       0.3442     0.3530   0.975   0.3295
## craftsmanship  -0.2312     0.3116  -0.742   0.4582
## value           0.6291     0.3384   1.859   0.0630 .
## glamour         0.2717     0.3084   0.881   0.3784
## timeless        0.2049     0.3006   0.682   0.4955
## enjoyable       0.2641     0.2423   1.090   0.2757
## desire          0.5430     0.2448   2.218   0.0265 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 136.87  on 164  degrees of freedom
## Residual deviance: 121.00  on 157  degrees of freedom
## AIC: 137
##
## Number of Fisher Scoring iterations: 5
```

For smart watches, we can see that the relevant variables pushing people to buy a smartwatch are the performance value and the desire factor.

We move to the exponential transform to better understand the effects of these factors on the willingness to buy.

```
#find the odds-ratios
#smartwatches
round(exp(modelSW$coefficients),3)

##   (Intercept)      usability craftsmanship         value
glamour
##         0.119          1.411         0.794         1.876
1.312
##      timeless      enjoyable        desire
##         1.227          1.302         1.721
```

- One point more in the scale of the **value factor** leads to a increase of **87.6%** $\Big((1.876 - 1) \times 100 \Big)$ in the odds of a customer buying a smartwatch.

- One point more in the scale of the **desire factor** leads to an increase of **72.1%** ($(1.721 - 1) \times 100$) in the odds of a customer buying a smartwatch.

To validate our model we test for the null of the regressors bringing something more with respect to the null model.

```
#building the null model
#smartwatch
nullmodelSW <- glm(wtbSW~1, data = testdata, family = binomial(link =
"logit"))

print(paste("model 1 likelihood ratio test p-value:",
round(with(modelSW, pchisq(null.deviance-deviance,df.null-df.residual,
lower.tail = F)),6)))

## [1] "model 1 likelihood ratio test p-value: 0.026349"
```

Since the p-value is significantly smaller than 0.05, we reject the null hypothesis, meaning that our model "modelSW" with regressors is useful in explaining the dependent variable (willingness to buy SW).

##Conclusion logic regression

From our analysis, we discovered that both perception and characteristic have an impact on the willingness to buy different types of watches. In particular, we noticed that perception factors were more relevant than characteristics. Furthermore, we noticed that this analysis further validated the intrinsic connection between mechanical and quartz watches. In fact, the willingness to buy of the two traditional watches are affected by similar factors (e.g., perception variables such as: classy, sophisticated, exciting). However,we want to underline a difference between the two traditional watches: only the willingness to buy quartz watches is affected by some characteristics variable included in the performance factors (e.g., design, reliability).

Regarding smartwatches we found that the willing to buy is influence mainly by value and desire factors. This signal the different value and lifestyle of smartwatches and traditional buyers. Our final analysis provides interesting opportunities for TradWatches to understand better customer focus its resources to reach the customers they are more interested in.

FINDING OF OUR ANALYSIS

- We found that in general design and brand are those attributes that have a positive impact on the perception of customers on both categories of watches (traditional, smartwatches). Specifically, functionality, design and brand impact the most on the perception of traditional watches; while, desing and brand have the major impact on the perception of smartwatches.

- Thanks to our heatmaps, we observed that the highest ranked variables among all the three types of watches (mechanical, quartz, smartwatch) is the reliability. However, reliability has no significan impact on the perception of customers.

- We can conclude that the characteristics of the watches can be reduced to common factors. This may allow the company to conduct a survey with easier and quicker answers. Moreover, reducing variables to common factors could allow marketing team to in-depth analyze the correlation between some variables.

- We notice some differences in terms of socio-demographic characteristics:

  – Significant difference between the age of the owners of these two groups (the two major groups of owners are the Millennials and GenX, in accordance with our secondary research)
  – People who owns both types of watches tend to live in large cities (< 200,000 inhabitants). Whereas, traditional watches users are more likely to live in small cities (> 50,000 inhabitants).
  – People who own both types of watches are more likely to have higher incomes (over $75,000), whereas traditional watches users have a more equal distribution across income levels.
  – The gender of owners also does not significantly differs between the two watches types, with smartwatches having just a slightly larger share of female owners.
  – The biggest difference can be found in job factor. Retired people seems to not owns both types of watches.
- We identified 11 different clusters of customers who appreciate different types of watches' characteristics. Moreover, we used socio-demographic variables to characterized these 11 clusters in order to allow a deeper segmentation of the market.

- From our analysis, we discovered that both perception and characteristic have an impact on the willingness to buy different types of watches. In particular, we noticed that perception factors were more relevant than characteristics. Furthermore, we

noticed that this analysis further validated the intrinsic connection between mechanical and quartz watches. In fact, the willingness to buy of the two traditional watches are affected by similar factors (e.g., perception variables such as: classy, sophisticated, exciting). However, we want to underline a difference between traditional watches: only the willingness to buy quartz watches is affected by some characteristic's variable included in the performance factors (e.g., design, reliability). Regarding smartwatches we found that the willing to buy is influence mainly by value and desire factors. This signal the different value and lifestyle of smartwatches and traditional buyers.