AFC & SEM

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As you may have seen in the previous steps of our analysis, the model including all variables did not perform as well as expected within the theoretical framework. Therefore, I have chosen to examine three theoretical models based on Cho & Jang's (2016) article and compare their structures with the observations from my large survey.

```
library("semPlot")
library("readr")
library("lavaan")
```

```
## This is lavaan 0.6-11
## lavaan is FREE software! Please report any bugs.
```

```
library("readxl")
library("dplyr")
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

SO now I am calling my dataframe and take a look into the variables I will use.

```
setwd("/home/alrier/Descargas")
datos2 = read_excel("/home/alrier/Descargas/Variables Cho & Yang.xlsx")
datos2 %>% head()
```

```
## # A tibble: 6 x 30
##   utilitario1 utilitar~1 utili~2 ries_~3 ries_~4 ries_~5 Hedón~6 Hedón~7 Hedón~8
##         <dbl>      <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
## 1           4          5       3       5       5       5       6       5       4
## 2           4          5       3       5       5       5       6       5       4
## 3           4          5       3       5       5       5       6       5       4
## 4           4          5       3       5       5       5       6       5       4
## 5           6          4       4       6       6       6       7       7       7
## 6           5          5       5       6       5       5       5       5       5
## # ... with 21 more variables: busq_sens1 <dbl>, busq_sens2 <dbl>,
## #   busq_sens3 <dbl>, social1 <dbl>, social2 <dbl>, social3 <dbl>,
## #   val_social1 <dbl>, val_social2 <dbl>, val_social3 <dbl>,
## #   uso_r_sociales1 <dbl>, uso_r_sociales2 <dbl>, uso_r_sociales3 <dbl>,
## #   uso_r_sociales4 <dbl>, uso_r_sociales5 <dbl>, Int_busq_info1 <dbl>,
```

```
## #   Int_busq_info2 <dbl>, Int_busq_info3 <dbl>, int_visita1 <dbl>,
## #   int_visita2 <dbl>, int_visita3 <dbl>, int_visita4 <dbl>, and ...
```

Now I will create a slice of my Data frame to choose only the variables that are useful in the study.

```r
datos2 = datos2[1:18]
datos2 %>% head()
```

```
## # A tibble: 6 x 18
##   utilitario1 utilitar~1 utili~2 ries_~3 ries_~4 ries_~5 Hedón~6 Hedón~7 Hedón~8
##         <dbl>      <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
## 1           4          5       3       5       5       5       6       5       4
## 2           4          5       3       5       5       5       6       5       4
## 3           4          5       3       5       5       5       6       5       4
## 4           4          5       3       5       5       5       6       5       4
## 5           6          4       4       6       6       6       7       7       7
## 6           5          5       5       6       5       5       5       5       5
## # ... with 9 more variables: busq_sens1 <dbl>, busq_sens2 <dbl>,
## #   busq_sens3 <dbl>, social1 <dbl>, social2 <dbl>, social3 <dbl>,
## #   val_social1 <dbl>, val_social2 <dbl>, val_social3 <dbl>, and abbreviated
## #   variable names 1: utilitario2, 2: utilitario3, 3: ries_perc1,
## #   4: ries_perc2, 5: ries_perc3, 6: Hedónico1, 7: Hedónico2, 8: Hedónico3
```

Now I will create the first model with all the first group of variables. In this model all the variables are together without ny distinction.

```r
modelo_confir1 <- 'vp =~ utilitario1    + utilitario2   + utilitario3   + ries_perc1    + ries_perc2
```

Now I will proceed to analyse the information and take a look into the summary of the model.

```r
modelo1 <- cfa(modelo_confir1, data = datos2)
summary(modelo1, fit.measures=TRUE, rsq=TRUE)
```

```
## lavaan 0.6-11 ended normally after 34 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        36
##
##   Number of observations                           821
##
## Model Test User Model:
##
##   Test statistic                              5889.638
##   Degrees of freedom                               135
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
##   Test statistic                             13813.124
##   Degrees of freedom                               153
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.579
##   Tucker-Lewis Index (TLI)                       0.523
```

```
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)             -25451.289
##   Loglikelihood unrestricted model (H1)     -22506.470
##
##   Akaike (AIC)                               50974.578
##   Bayesian (BIC)                             51144.157
##   Sample-size adjusted Bayesian (BIC)        51029.835
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.228
##   90 Percent confidence interval - lower         0.223
##   90 Percent confidence interval - upper         0.233
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.124
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   vp =~
##     utilitario1       1.000
##     utilitario2       1.028    0.051   20.344    0.000
##     utilitario3       0.955    0.048   19.805    0.000
##     ries_perc1        0.331    0.046    7.226    0.000
##     ries_perc2        0.212    0.047    4.469    0.000
##     ries_perc3        0.243    0.047    5.149    0.000
##     Hedónico1         1.131    0.048   23.477    0.000
##     Hedónico2         1.257    0.050   25.210    0.000
##     Hedónico3         0.899    0.044   20.505    0.000
##     busq_sens1        1.169    0.048   24.321    0.000
##     busq_sens2        1.074    0.046   23.408    0.000
##     busq_sens3        0.915    0.043   21.096    0.000
##     social1           0.995    0.047   21.297    0.000
##     social2           0.994    0.045   22.034    0.000
##     social3           1.042    0.048   21.866    0.000
##     val_social1       0.858    0.046   18.466    0.000
##     val_social2       0.664    0.048   13.781    0.000
##     val_social3       0.698    0.048   14.455    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .utilitario1       1.687    0.087   19.300    0.000
##    .utilitario2       1.737    0.090   19.275    0.000
##    .utilitario3       1.668    0.086   19.375    0.000
```

```
##    .ries_perc1        2.728    0.135   20.196    0.000
##    .ries_perc2        3.037    0.150   20.237    0.000
##    .ries_perc3        2.975    0.147   20.229    0.000
##    .Hedónico1         1.035    0.057   18.254    0.000
##    .Hedónico2         0.750    0.045   16.831    0.000
##    .Hedónico3         1.286    0.067   19.243    0.000
##    .busq_sens1        0.871    0.049   17.711    0.000
##    .busq_sens2        0.951    0.052   18.291    0.000
##    .busq_sens3        1.181    0.062   19.111    0.000
##    .social1           1.339    0.070   19.061    0.000
##    .social2           1.136    0.060   18.850    0.000
##    .social3           1.297    0.069   18.902    0.000
##    .val_social1       1.739    0.089   19.575    0.000
##    .val_social2       2.463    0.123   19.972    0.000
##    .val_social3       2.401    0.120   19.932    0.000
##     vp                1.764    0.151   11.684    0.000
##
## R-Square:
##                    Estimate
##     utilitario1       0.511
##     utilitario2       0.517
##     utilitario3       0.491
##     ries_perc1        0.066
##     ries_perc2        0.025
##     ries_perc3        0.034
##     Hedónico1         0.685
##     Hedónico2         0.788
##     Hedónico3         0.526
##     busq_sens1        0.734
##     busq_sens2        0.681
##     busq_sens3        0.556
##     social1           0.566
##     social2           0.605
##     social3           0.596
##     val_social1       0.428
##     val_social2       0.240
##     val_social3       0.264
```

```
parameterestimates(modelo1, standardized = TRUE)
```

```
##             lhs op         rhs   est    se      z pvalue ci.lower ci.upper
## 1            vp =~ utilitario1 1.000 0.000     NA     NA    1.000    1.000
## 2            vp =~ utilitario2 1.028 0.051 20.344      0    0.929    1.127
## 3            vp =~ utilitario3 0.955 0.048 19.805      0    0.860    1.049
## 4            vp =~  ries_perc1 0.331 0.046  7.226      0    0.242    0.421
## 5            vp =~  ries_perc2 0.212 0.047  4.469      0    0.119    0.305
## 6            vp =~  ries_perc3 0.243 0.047  5.149      0    0.150    0.335
## 7            vp =~   Hedónico1 1.131 0.048 23.477      0    1.036    1.225
## 8            vp =~   Hedónico2 1.257 0.050 25.210      0    1.159    1.355
## 9            vp =~   Hedónico3 0.899 0.044 20.505      0    0.813    0.985
## 10           vp =~  busq_sens1 1.169 0.048 24.321      0    1.074    1.263
## 11           vp =~  busq_sens2 1.074 0.046 23.408      0    0.984    1.164
## 12           vp =~  busq_sens3 0.915 0.043 21.096      0    0.830    1.000
## 13           vp =~     social1 0.995 0.047 21.297      0    0.904    1.087
## 14           vp =~     social2 0.994 0.045 22.034      0    0.905    1.082
```

```
## 15          vp =~     social3 1.042 0.048 21.866      0    0.949    1.135
## 16          vp =~ val_social1 0.858 0.046 18.466      0    0.767    0.949
## 17          vp =~ val_social2 0.664 0.048 13.781      0    0.569    0.758
## 18          vp =~ val_social3 0.698 0.048 14.455      0    0.603    0.793
## 19 utilitario1 ~~ utilitario1 1.687 0.087 19.300      0    1.516    1.859
## 20 utilitario2 ~~ utilitario2 1.737 0.090 19.275      0    1.561    1.914
## 21 utilitario3 ~~ utilitario3 1.668 0.086 19.375      0    1.499    1.837
## 22  ries_perc1 ~~  ries_perc1 2.728 0.135 20.196      0    2.463    2.993
## 23  ries_perc2 ~~  ries_perc2 3.037 0.150 20.237      0    2.743    3.331
## 24  ries_perc3 ~~  ries_perc3 2.975 0.147 20.229      0    2.687    3.263
## 25   Hedónico1 ~~   Hedónico1 1.035 0.057 18.254      0    0.924    1.146
## 26   Hedónico2 ~~   Hedónico2 0.750 0.045 16.831      0    0.663    0.837
## 27   Hedónico3 ~~   Hedónico3 1.286 0.067 19.243      0    1.155    1.417
## 28  busq_sens1 ~~  busq_sens1 0.871 0.049 17.711      0    0.775    0.968
## 29  busq_sens2 ~~  busq_sens2 0.951 0.052 18.291      0    0.849    1.053
## 30  busq_sens3 ~~  busq_sens3 1.181 0.062 19.111      0    1.060    1.303
## 31     social1 ~~     social1 1.339 0.070 19.061      0    1.201    1.477
## 32     social2 ~~     social2 1.136 0.060 18.850      0    1.018    1.254
## 33     social3 ~~     social3 1.297 0.069 18.902      0    1.163    1.431
## 34 val_social1 ~~ val_social1 1.739 0.089 19.575      0    1.565    1.913
## 35 val_social2 ~~ val_social2 2.463 0.123 19.972      0    2.221    2.705
## 36 val_social3 ~~ val_social3 2.401 0.120 19.932      0    2.165    2.637
## 37          vp ~~          vp 1.764 0.151 11.684      0    1.468    2.060
##    std.lv std.all std.nox
## 1   1.328   0.715   0.715
## 2   1.365   0.719   0.719
## 3   1.268   0.701   0.701
## 4   0.440   0.258   0.258
## 5   0.281   0.159   0.159
## 6   0.322   0.184   0.184
## 7   1.501   0.828   0.828
## 8   1.670   0.888   0.888
## 9   1.194   0.725   0.725
## 10  1.552   0.857   0.857
## 11  1.426   0.825   0.825
## 12  1.216   0.745   0.745
## 13  1.322   0.752   0.752
## 14  1.320   0.778   0.778
## 15  1.384   0.772   0.772
## 16  1.140   0.654   0.654
## 17  0.881   0.490   0.490
## 18  0.927   0.513   0.513
## 19  1.687   0.489   0.489
## 20  1.737   0.483   0.483
## 21  1.668   0.509   0.509
## 22  2.728   0.934   0.934
## 23  3.037   0.975   0.975
## 24  2.975   0.966   0.966
## 25  1.035   0.315   0.315
## 26  0.750   0.212   0.212
## 27  1.286   0.474   0.474
## 28  0.871   0.266   0.266
## 29  0.951   0.319   0.319
## 30  1.181   0.444   0.444
```

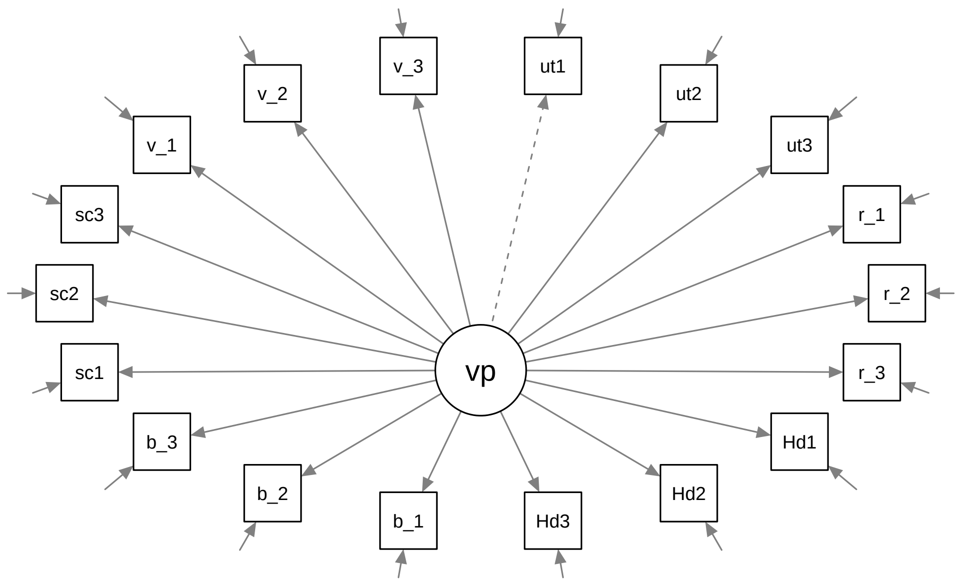
```
## 31   1.339   0.434   0.434
## 32   1.136   0.395   0.395
## 33   1.297   0.404   0.404
## 34   1.739   0.572   0.572
## 35   2.463   0.760   0.760
## 36   2.401   0.736   0.736
## 37   1.000   1.000   1.000
```

As you can see the fit indexes are not the best and the relation between variables are not the best too.

I will try the next model.

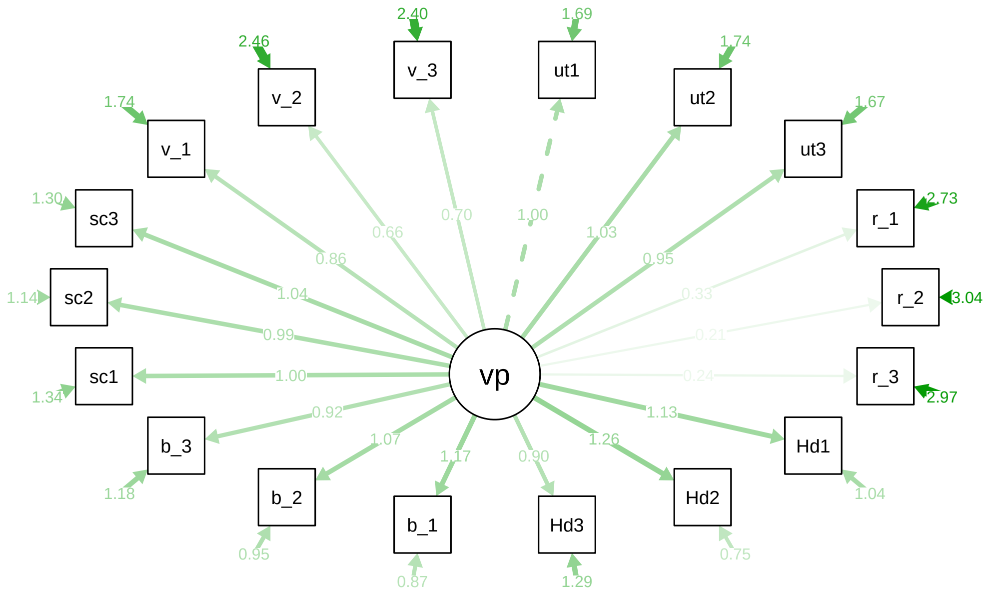
```r
semPaths(modelo1, what = "paths", layout = "circle", title = TRUE, style = "LISREL")
```

```
## Warning in abbreviate(Labels, nCharNodes): abbreviate used with non-ASCII chars
```




```r
semPaths(modelo1, what = "est", layout = "circle", title = TRUE, style = "LISREL")
```

```
## Warning in abbreviate(Labels, nCharNodes): abbreviate used with non-ASCII chars
```



MODEL 2

This is a model with 2 latent variables correlated, so, lets take a look into the model and see if the variables adjust or not with it.

```
modelo_confir2 <- 'V.util =~ utilitario1    + utilitario2   + utilitario3   + ries_perc1    + ries_perc
V.espx =~ Hedónico1 + Hedónico2 + Hedónico3 + busq_sens1    + busq_sens2    + busq_sens3    + social1
V.util~~V.espx'
```

```
modelo2 <- cfa(modelo_confir2, data = datos2)
summary(modelo2, fit.measures=TRUE, rsq=TRUE)
```

```
## lavaan 0.6-11 ended normally after 39 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        37
##
##   Number of observations                           821
##
## Model Test User Model:
##
##   Test statistic                              4351.652
##   Degrees of freedom                               134
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
```

```
##   Test statistic                               13813.124
##   Degrees of freedom                                 153
##   P-value                                          0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                      0.691
##   Tucker-Lewis Index (TLI)                         0.647
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)              -24682.296
##   Loglikelihood unrestricted model (H1)      -22506.470
##
##   Akaike (AIC)                                49438.592
##   Bayesian (BIC)                              49612.882
##   Sample-size adjusted Bayesian (BIC)         49495.384
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                            0.196
##   90 Percent confidence interval - lower           0.191
##   90 Percent confidence interval - upper           0.201
##   P-value RMSEA <= 0.05                            0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                             0.126
##
## Parameter Estimates:
##
##   Standard errors                               Standard
##   Information                                   Expected
##   Information saturated (h1) model            Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   V.util =~
##     utilitario1       1.000
##     utilitario2       1.128    0.026   44.191    0.000
##     utilitario3       1.049    0.025   42.024    0.000
##     ries_perc1        0.135    0.037    3.624    0.000
##     ries_perc2        0.059    0.039    1.517    0.129
##     ries_perc3        0.236    0.038    6.250    0.000
##   V.espx =~
##     Hedónico1         1.000
##     Hedónico2         1.090    0.035   30.942    0.000
##     Hedónico3         0.826    0.033   24.923    0.000
##     busq_sens1        1.054    0.034   31.182    0.000
##     busq_sens2        0.998    0.032   30.768    0.000
##     busq_sens3        0.851    0.032   26.363    0.000
##     social1           0.900    0.035   25.665    0.000
##     social2           0.903    0.033   27.151    0.000
##     social3           0.933    0.036   26.273    0.000
```

```
##     val_social1       0.737    0.037   19.849    0.000
##     val_social2       0.549    0.041   13.489    0.000
##     val_social3       0.578    0.041   14.251    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   V.util ~~
##     V.espx            1.646    0.116   14.129    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .utilitario1       0.811    0.047   17.444    0.000
##    .utilitario2       0.241    0.030    7.939    0.000
##    .utilitario3       0.373    0.031   12.204    0.000
##    .ries_perc1        2.874    0.142   20.248    0.000
##    .ries_perc2        3.107    0.153   20.259    0.000
##    .ries_perc3        2.931    0.145   20.221    0.000
##    .Hedónico1         1.056    0.058   18.175    0.000
##    .Hedónico2         0.885    0.051   17.299    0.000
##    .Hedónico3         1.186    0.062   18.996    0.000
##    .busq_sens1        0.797    0.046   17.182    0.000
##    .busq_sens2        0.762    0.044   17.380    0.000
##    .busq_sens3        1.041    0.056   18.731    0.000
##    .social1           1.277    0.068   18.867    0.000
##    .social2           1.055    0.057   18.559    0.000
##    .social3           1.267    0.068   18.749    0.000
##    .val_social1       1.825    0.093   19.609    0.000
##    .val_social2       2.568    0.128   20.004    0.000
##    .val_social3       2.514    0.126   19.970    0.000
##     V.util            2.640    0.167   15.784    0.000
##     V.espx            2.234    0.156   14.328    0.000
##
## R-Square:
##                    Estimate
##     utilitario1       0.765
##     utilitario2       0.933
##     utilitario3       0.886
##     ries_perc1        0.016
##     ries_perc2        0.003
##     ries_perc3        0.048
##     Hedónico1         0.679
##     Hedónico2         0.750
##     Hedónico3         0.563
##     busq_sens1        0.757
##     busq_sens2        0.745
##     busq_sens3        0.609
##     social1           0.586
##     social2           0.633
##     social3           0.606
##     val_social1       0.399
##     val_social2       0.207
##     val_social3       0.229
```

It goes a little bit better, the CFI and the RMSEA are a little bit better, however lets tke a look into the next model.

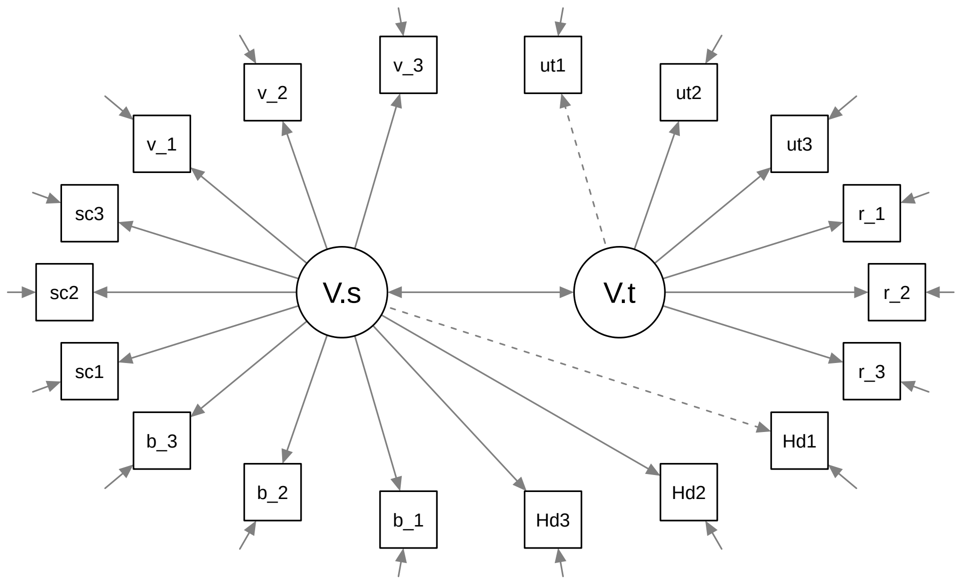
```
parameterestimates(modelo2, standardized = TRUE)
```

```
##            lhs op         rhs   est    se      z pvalue ci.lower ci.upper
## 1       V.util =~ utilitario1 1.000 0.000     NA     NA    1.000    1.000
## 2       V.util =~ utilitario2 1.128 0.026 44.191  0.000    1.078    1.178
## 3       V.util =~ utilitario3 1.049 0.025 42.024  0.000    1.000    1.098
## 4       V.util =~  ries_perc1 0.135 0.037  3.624  0.000    0.062    0.208
## 5       V.util =~  ries_perc2 0.059 0.039  1.517  0.129   -0.017    0.134
## 6       V.util =~  ries_perc3 0.236 0.038  6.250  0.000    0.162    0.310
## 7       V.espx =~   Hedónico1 1.000 0.000     NA     NA    1.000    1.000
## 8       V.espx =~   Hedónico2 1.090 0.035 30.942  0.000    1.021    1.159
## 9       V.espx =~   Hedónico3 0.826 0.033 24.923  0.000    0.761    0.891
## 10      V.espx =~  busq_sens1 1.054 0.034 31.182  0.000    0.988    1.121
## 11      V.espx =~  busq_sens2 0.998 0.032 30.768  0.000    0.934    1.061
## 12      V.espx =~  busq_sens3 0.851 0.032 26.363  0.000    0.788    0.914
## 13      V.espx =~     social1 0.900 0.035 25.665  0.000    0.831    0.969
## 14      V.espx =~     social2 0.903 0.033 27.151  0.000    0.838    0.968
## 15      V.espx =~     social3 0.933 0.036 26.273  0.000    0.864    1.003
## 16      V.espx =~ val_social1 0.737 0.037 19.849  0.000    0.664    0.810
## 17      V.espx =~ val_social2 0.549 0.041 13.489  0.000    0.469    0.628
## 18      V.espx =~ val_social3 0.578 0.041 14.251  0.000    0.498    0.657
## 19      V.util ~~      V.espx 1.646 0.116 14.129  0.000    1.417    1.874
## 20 utilitario1 ~~ utilitario1 0.811 0.047 17.444  0.000    0.720    0.903
## 21 utilitario2 ~~ utilitario2 0.241 0.030  7.939  0.000    0.182    0.301
## 22 utilitario3 ~~ utilitario3 0.373 0.031 12.204  0.000    0.313    0.433
## 23  ries_perc1 ~~  ries_perc1 2.874 0.142 20.248  0.000    2.596    3.152
## 24  ries_perc2 ~~  ries_perc2 3.107 0.153 20.259  0.000    2.806    3.407
## 25  ries_perc3 ~~  ries_perc3 2.931 0.145 20.221  0.000    2.647    3.215
## 26   Hedónico1 ~~   Hedónico1 1.056 0.058 18.175  0.000    0.942    1.169
## 27   Hedónico2 ~~   Hedónico2 0.885 0.051 17.299  0.000    0.784    0.985
## 28   Hedónico3 ~~   Hedónico3 1.186 0.062 18.996  0.000    1.063    1.308
## 29  busq_sens1 ~~  busq_sens1 0.797 0.046 17.182  0.000    0.706    0.888
## 30  busq_sens2 ~~  busq_sens2 0.762 0.044 17.380  0.000    0.676    0.848
## 31  busq_sens3 ~~  busq_sens3 1.041 0.056 18.731  0.000    0.932    1.150
## 32     social1 ~~     social1 1.277 0.068 18.867  0.000    1.144    1.410
## 33     social2 ~~     social2 1.055 0.057 18.559  0.000    0.943    1.166
## 34     social3 ~~     social3 1.267 0.068 18.749  0.000    1.134    1.399
## 35 val_social1 ~~ val_social1 1.825 0.093 19.609  0.000    1.643    2.008
## 36 val_social2 ~~ val_social2 2.568 0.128 20.004  0.000    2.316    2.820
## 37 val_social3 ~~ val_social3 2.514 0.126 19.970  0.000    2.268    2.761
## 38      V.util ~~      V.util 2.640 0.167 15.784  0.000    2.312    2.968
## 39      V.espx ~~      V.espx 2.234 0.156 14.328  0.000    1.928    2.539
##    std.lv std.all std.nox
## 1   1.625   0.875   0.875
## 2   1.833   0.966   0.966
## 3   1.704   0.941   0.941
## 4   0.219   0.128   0.128
## 5   0.095   0.054   0.054
## 6   0.384   0.219   0.219
## 7   1.495   0.824   0.824
## 8   1.629   0.866   0.866
## 9   1.235   0.750   0.750
## 10  1.576   0.870   0.870
```

```
## 11  1.491   0.863   0.863
## 12  1.272   0.780   0.780
## 13  1.345   0.766   0.766
## 14  1.350   0.796   0.796
## 15  1.395   0.778   0.778
## 16  1.101   0.632   0.632
## 17  0.820   0.455   0.455
## 18  0.863   0.478   0.478
## 19  0.678   0.678   0.678
## 20  0.811   0.235   0.235
## 21  0.241   0.067   0.067
## 22  0.373   0.114   0.114
## 23  2.874   0.984   0.984
## 24  3.107   0.997   0.997
## 25  2.931   0.952   0.952
## 26  1.056   0.321   0.321
## 27  0.885   0.250   0.250
## 28  1.186   0.437   0.437
## 29  0.797   0.243   0.243
## 30  0.762   0.255   0.255
## 31  1.041   0.391   0.391
## 32  1.277   0.414   0.414
## 33  1.055   0.367   0.367
## 34  1.267   0.394   0.394
## 35  1.825   0.601   0.601
## 36  2.568   0.793   0.793
## 37  2.514   0.771   0.771
## 38  1.000   1.000   1.000
## 39  1.000   1.000   1.000
```

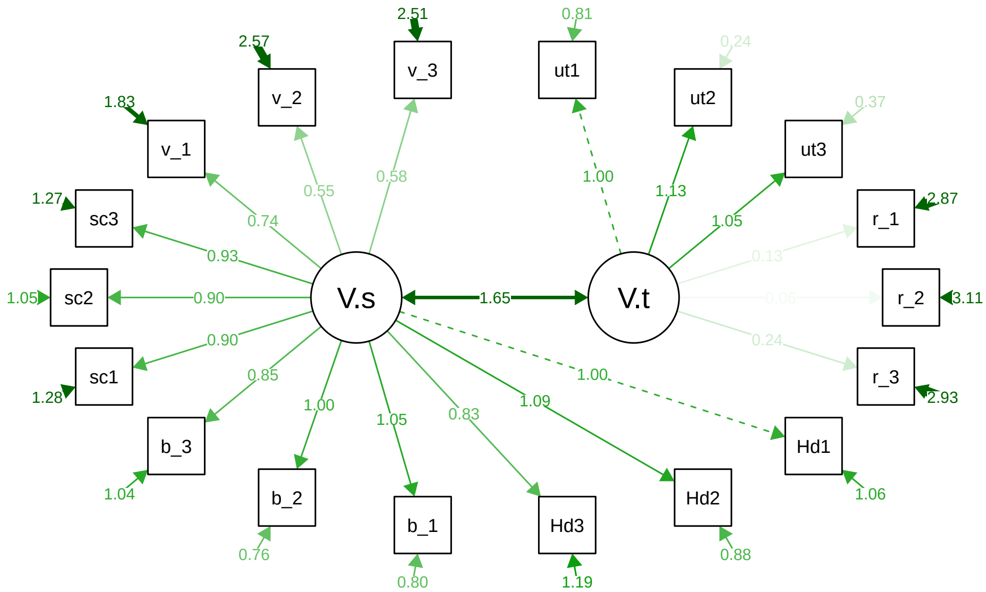
```
semPaths(modelo2, what = "paths", layout = "circle", title = TRUE, style = "LISREL")
```

```
## Warning in abbreviate(Labels, nCharNodes): abbreviate used with non-ASCII chars
```




```
semPaths(modelo2, what = "est", layout = "circle", title = TRUE, style = "LISREL")
```

```
## Warning in abbreviate(Labels, nCharNodes): abbreviate used with non-ASCII chars
```



I really dislike the Hd3, Hd1, b_2, b_1, all the r variables… it makes me think that this model could be improved.

```
modelo_confir3 <- '
V.util =~ utilitario1   + utilitario2   + utilitario3   +
ries_perc1  + ries_perc2    + ries_perc3
V.espx =~ Hedónico1 + Hedónico2 + Hedónico3 + busq_sens1    +
busq_sens2  + busq_sens3    + social1   + social2   + social3   + val_social1   +
val_social2 + val_social3

V.espx ~~ 0* V.util
'
```

```
modelo3 <- cfa(modelo_confir3, data = datos2)
summary(modelo3, fit.measures=TRUE, rsq=TRUE)
```

```
## lavaan 0.6-11 ended normally after 49 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        36
##
##   Number of observations                           821
##
## Model Test User Model:
##
##   Test statistic                              4791.903
```

```
##   Degrees of freedom                               135
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
##   Test statistic                             13813.124
##   Degrees of freedom                               153
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.659
##   Tucker-Lewis Index (TLI)                       0.614
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)             -24902.422
##   Loglikelihood unrestricted model (H1)     -22506.470
##
##   Akaike (AIC)                               49876.844
##   Bayesian (BIC)                             50046.423
##   Sample-size adjusted Bayesian (BIC)        49932.100
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.205
##   90 Percent confidence interval - lower         0.200
##   90 Percent confidence interval - upper         0.210
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.263
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   V.util =~
##     utilitario1       1.000
##     utilitario2       1.137    0.026   43.422    0.000
##     utilitario3       1.054    0.025   41.417    0.000
##     ries_perc1        0.126    0.037    3.367    0.001
##     ries_perc2        0.051    0.039    1.317    0.188
##     ries_perc3        0.235    0.038    6.195    0.000
##   V.espx =~
##     Hedónico1         1.000
##     Hedónico2         1.077    0.036   29.666    0.000
##     Hedónico3         0.841    0.034   25.071    0.000
##     busq_sens1        1.062    0.034   30.797    0.000
```

```
##     busq_sens2        1.021    0.033   31.133    0.000
##     busq_sens3        0.872    0.033   26.772    0.000
##     social1           0.909    0.036   25.535    0.000
##     social2           0.915    0.034   27.093    0.000
##     social3           0.939    0.036   25.994    0.000
##     val_social1       0.726    0.038   19.218    0.000
##     val_social2       0.530    0.041   12.844    0.000
##     val_social3       0.559    0.041   13.581    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   V.util ~~
##     V.espx            0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .utilitario1       0.837    0.048   17.479    0.000
##    .utilitario2       0.223    0.033    6.775    0.000
##    .utilitario3       0.374    0.032   11.509    0.000
##    .ries_perc1        2.880    0.142   20.250    0.000
##    .ries_perc2        3.109    0.153   20.259    0.000
##    .ries_perc3        2.934    0.145   20.222    0.000
##    .Hedónico1         1.086    0.060   18.194    0.000
##    .Hedónico2         0.980    0.056   17.600    0.000
##    .Hedónico3         1.153    0.061   18.887    0.000
##    .busq_sens1        0.793    0.046   17.058    0.000
##    .busq_sens2        0.691    0.041   16.867    0.000
##    .busq_sens3        0.983    0.053   18.526    0.000
##    .social1           1.266    0.067   18.798    0.000
##    .social2           1.034    0.056   18.446    0.000
##    .social3           1.269    0.068   18.704    0.000
##    .val_social1       1.876    0.096   19.633    0.000
##    .val_social2       2.621    0.131   20.022    0.000
##    .val_social3       2.571    0.129   19.990    0.000
##     V.util            2.614    0.167   15.651    0.000
##     V.espx            2.203    0.155   14.172    0.000
##
## R-Square:
##                    Estimate
##     utilitario1       0.757
##     utilitario2       0.938
##     utilitario3       0.886
##     ries_perc1        0.014
##     ries_perc2        0.002
##     ries_perc3        0.047
##     Hedónico1         0.670
##     Hedónico2         0.723
##     Hedónico3         0.575
##     busq_sens1        0.758
##     busq_sens2        0.769
##     busq_sens3        0.630
##     social1           0.590
##     social2           0.641
##     social3           0.605
```

```
##     val_social1       0.383
##     val_social2       0.191
##     val_social3       0.211
```

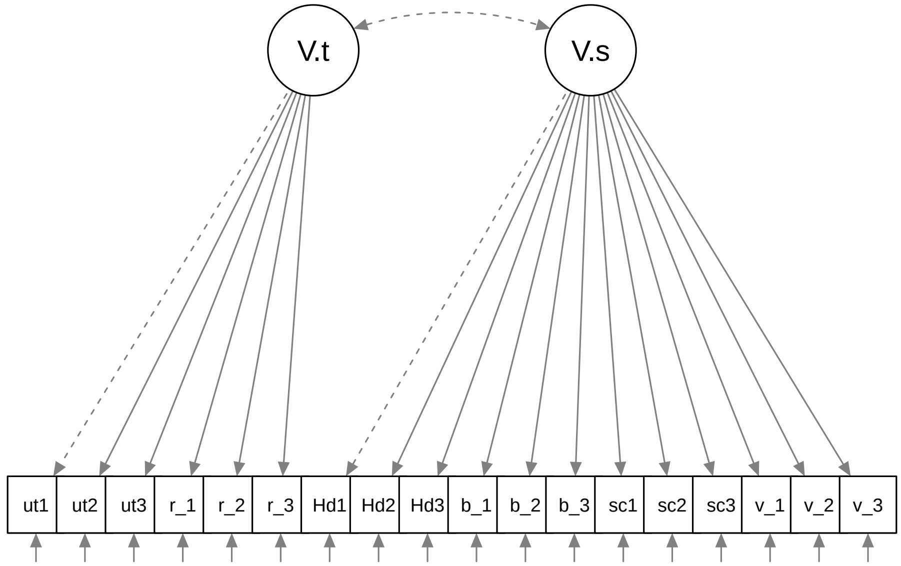
```r
parameterestimates(modelo3, standardized = TRUE)
```

```
##            lhs op         rhs   est    se      z pvalue ci.lower ci.upper
## 1       V.util =~ utilitario1 1.000 0.000     NA     NA    1.000    1.000
## 2       V.util =~ utilitario2 1.137 0.026 43.422  0.000    1.085    1.188
## 3       V.util =~ utilitario3 1.054 0.025 41.417  0.000    1.004    1.104
## 4       V.util =~  ries_perc1 0.126 0.037  3.367  0.001    0.053    0.199
## 5       V.util =~  ries_perc2 0.051 0.039  1.317  0.188   -0.025    0.127
## 6       V.util =~  ries_perc3 0.235 0.038  6.195  0.000    0.161    0.310
## 7       V.espx =~   Hedónico1 1.000 0.000     NA     NA    1.000    1.000
## 8       V.espx =~   Hedónico2 1.077 0.036 29.666  0.000    1.006    1.148
## 9       V.espx =~   Hedónico3 0.841 0.034 25.071  0.000    0.775    0.907
## 10      V.espx =~  busq_sens1 1.062 0.034 30.797  0.000    0.995    1.130
## 11      V.espx =~  busq_sens2 1.021 0.033 31.133  0.000    0.956    1.085
## 12      V.espx =~  busq_sens3 0.872 0.033 26.772  0.000    0.808    0.936
## 13      V.espx =~     social1 0.909 0.036 25.535  0.000    0.839    0.979
## 14      V.espx =~     social2 0.915 0.034 27.093  0.000    0.849    0.981
## 15      V.espx =~     social3 0.939 0.036 25.994  0.000    0.868    1.010
## 16      V.espx =~ val_social1 0.726 0.038 19.218  0.000    0.652    0.800
## 17      V.espx =~ val_social2 0.530 0.041 12.844  0.000    0.449    0.611
## 18      V.espx =~ val_social3 0.559 0.041 13.581  0.000    0.478    0.640
## 19      V.util ~~      V.espx 0.000 0.000     NA     NA    0.000    0.000
## 20 utilitario1 ~~ utilitario1 0.837 0.048 17.479  0.000    0.743    0.931
## 21 utilitario2 ~~ utilitario2 0.223 0.033  6.775  0.000    0.159    0.288
## 22 utilitario3 ~~ utilitario3 0.374 0.032 11.509  0.000    0.310    0.438
## 23  ries_perc1 ~~  ries_perc1 2.880 0.142 20.250  0.000    2.602    3.159
## 24  ries_perc2 ~~  ries_perc2 3.109 0.153 20.259  0.000    2.808    3.410
## 25  ries_perc3 ~~  ries_perc3 2.934 0.145 20.222  0.000    2.649    3.218
## 26   Hedónico1 ~~   Hedónico1 1.086 0.060 18.194  0.000    0.969    1.203
## 27   Hedónico2 ~~   Hedónico2 0.980 0.056 17.600  0.000    0.871    1.089
## 28   Hedónico3 ~~   Hedónico3 1.153 0.061 18.887  0.000    1.033    1.272
## 29  busq_sens1 ~~  busq_sens1 0.793 0.046 17.058  0.000    0.702    0.884
## 30  busq_sens2 ~~  busq_sens2 0.691 0.041 16.867  0.000    0.610    0.771
## 31  busq_sens3 ~~  busq_sens3 0.983 0.053 18.526  0.000    0.879    1.087
## 32     social1 ~~     social1 1.266 0.067 18.798  0.000    1.134    1.398
## 33     social2 ~~     social2 1.034 0.056 18.446  0.000    0.924    1.144
## 34     social3 ~~     social3 1.269 0.068 18.704  0.000    1.136    1.402
## 35 val_social1 ~~ val_social1 1.876 0.096 19.633  0.000    1.689    2.063
## 36 val_social2 ~~ val_social2 2.621 0.131 20.022  0.000    2.365    2.878
## 37 val_social3 ~~ val_social3 2.571 0.129 19.990  0.000    2.319    2.824
## 38      V.util ~~      V.util 2.614 0.167 15.651  0.000    2.287    2.941
## 39      V.espx ~~      V.espx 2.203 0.155 14.172  0.000    1.899    2.508
##    std.lv std.all std.nox
## 1   1.617   0.870   0.870
## 2   1.838   0.968   0.968
## 3   1.704   0.941   0.941
## 4   0.204   0.119   0.119
## 5   0.083   0.047   0.047
## 6   0.380   0.217   0.217
## 7   1.484   0.818   0.818
## 8   1.599   0.850   0.850
```

```
## 9   1.248   0.758   0.758
## 10  1.577   0.871   0.871
## 11  1.515   0.877   0.877
## 12  1.295   0.794   0.794
## 13  1.349   0.768   0.768
## 14  1.358   0.800   0.800
## 15  1.394   0.778   0.778
## 16  1.078   0.619   0.619
## 17  0.787   0.437   0.437
## 18  0.830   0.460   0.460
## 19  0.000   0.000   0.000
## 20  0.837   0.243   0.243
## 21  0.223   0.062   0.062
## 22  0.374   0.114   0.114
## 23  2.880   0.986   0.986
## 24  3.109   0.998   0.998
## 25  2.934   0.953   0.953
## 26  1.086   0.330   0.330
## 27  0.980   0.277   0.277
## 28  1.153   0.425   0.425
## 29  0.793   0.242   0.242
## 30  0.691   0.231   0.231
## 31  0.983   0.370   0.370
## 32  1.266   0.410   0.410
## 33  1.034   0.359   0.359
## 34  1.269   0.395   0.395
## 35  1.876   0.617   0.617
## 36  2.621   0.809   0.809
## 37  2.571   0.789   0.789
## 38  1.000   1.000   1.000
## 39  1.000   1.000   1.000
```

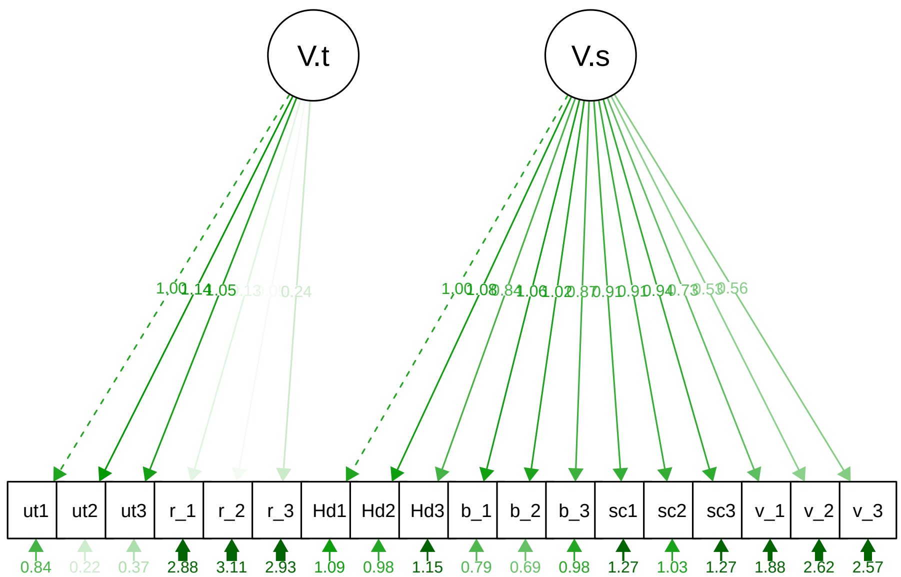
```
semPaths(modelo3, what = "paths", layout = "tree", title = TRUE, style = "LISREL")
```

```
## Warning in abbreviate(Labels, nCharNodes): abbreviate used with non-ASCII chars
```




```r
semPaths(modelo3, what = "est", layout = "tree", title = TRUE, style = "LISREL")
```

```
## Warning in abbreviate(Labels, nCharNodes): abbreviate used with non-ASCII chars
```



This last model is not working too, since the errors are extremely high for some variables and the correlation between latent variables and the dimentions are so high in some cases too.

That's why in the article I published aput this topic, I have created a new model with 4 latent variables.