

Introduction to Structural Equation Modeling using lavaan

Exploratory and Confirmatory Factor Analysis

R. M. Kuiper (and many others)

Department of Methodology & Statistics
Utrecht University

Outline of this lecture

SAPI

EFA and CFA

EFA in R

CFA in R

Scaling

The end

Extra

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Extra

Example: South African Personality Inventory Project (SAPI)



Carin Hill
Leon Jackson
Deon Meiring
J. Aleweyn Nel

Ian Rothmann
Michael Temane
Velichko H. Valchev
Fons J. R. van de Vijver

SAPI details

- 1216 participants from 11 official language groups
- From about 50,000 descriptive responses to 262 personality items
- Nine personality clusters:
 - Conscientiousness
 - Emotional Stability
 - Extraversion
 - Facilitating
 - Integrity
 - Intellect
 - Openness
 - Relationship Harmony
 - Soft-Heartedness (Ubuntu)
- Our data: selection of 1000 participants

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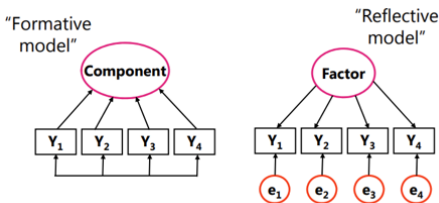
Extra

Factor Analysis

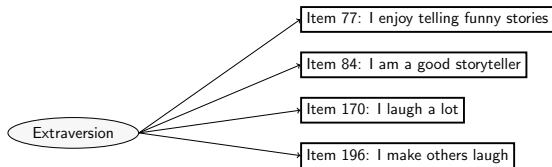
Factor Analysis: Modeling measurement of a latent variable

- EFA: Exploratory Factor Analysis.
- CFA: Confirmatory Factor Analysis.

Both EFA and CFA use a “reflective” measurement model, not a “formative” model.

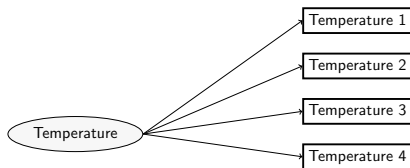


Reflective measurement model



- Items are dependent variables, caused by the factor!
- Latent variable 'extraversion' explains item correlations:
The factor is the reason for the covariances/correlations.

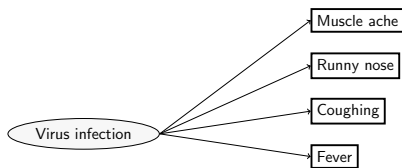
Reflective measurement model



Note:

Thermometer readings are the dependent variables,
caused by the temperature!

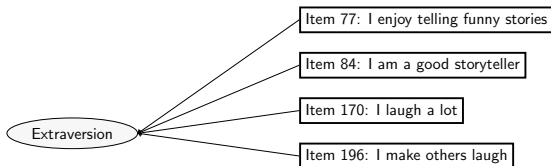
Reflective measurement model



Note:
symptoms are the dependent variables,
caused by the virus infection!

Formative measurement model

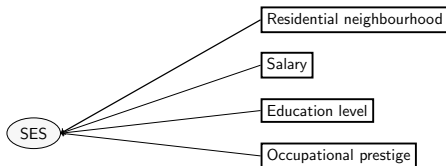
If formative measurement model:



Note:

- Extraversion is the dependent variable, predicted by the items.
- **Extraversion is defined as a (weighted) sum of the items:**
This is not a testable measurement model, but a definition.

Formative measurement model



Note:

SES is defined as a (weighted) sum of the items.

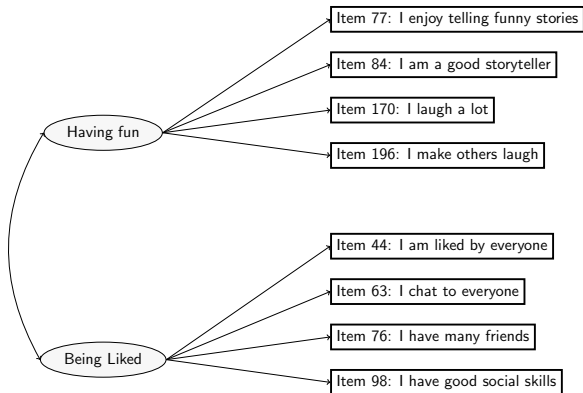
Interesting read

Interesting read on theory & latent variables:

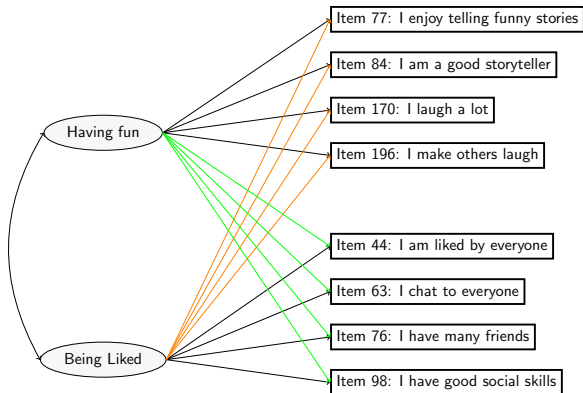
Borsboom, D., Mellenbergh, G.J., & Van Heerden, J. (2003). The theoretical status of latent variables. *Psychological review*, 110(2), 203.

Confirmatory or exploratory?

Two sub-scales of extraversion



EFA: all loadings including cross-loadings



CFA: only hypothesized loadings

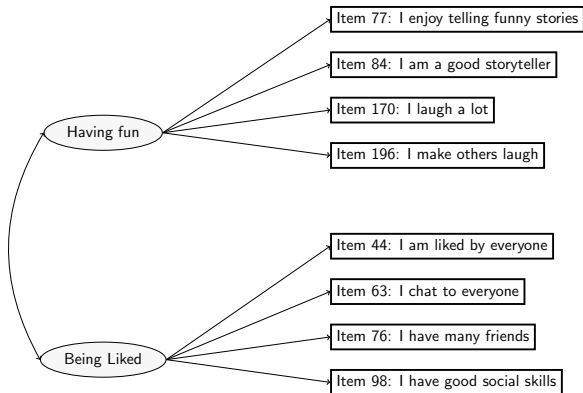


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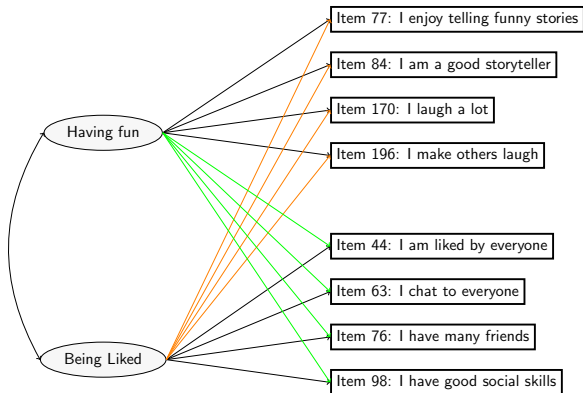
Extra

Step 1: Loading data into R

```
data_sapi <- read.table("Sapi.txt", header = T)

data_sapi[sapply(data_sapi,
  function(x) as.character(x) %in% c("-999") )] <- NA
```

Step 3: Draw your model



Step 4: Specify EFA in lavaan (general case)

In factor analysis (EFA and CFA):

- \rightarrow is latent variable definition ('is measured by'): $=\sim$
- \leftrightarrow is covariance. By default, factors are related.
- In EFA: use `efa("efa")*` in front of the latent variable / factor.

```
# 1-factor model
f1 <- '
efa("efa")*f1 =~ y1 + y2 + y3 + ...
'

# 2-factor model
f2 <- '
efa("efa")*f1 +
efa("efa")*f2 =~ y1 + y2 + y3 + ...
'

# 3-factor model
f3 <- '
efa("efa")*f1 +
efa("efa")*f2 +
efa("efa")*f3 =~ y1 + y2 + y3 + ...
```

Step 4: Specify our SAPI EFA model

In factor analysis (EFA and CFA):

- \rightarrow is latent variable definition ('is measured by'): $=\sim$
- \leftrightarrow is covariance. By default, factors related.
- Use `efa("efa")*` in front of the latent variable / factor.

```
# two-factor EFA
model.2EFA <- "
  efa('block1')*Having fun  =~ Q77 + Q84 + Q170 + Q196 +
                                Q44 + Q63 + Q76  + Q98
  efa('block1')*Being liked =~ Q77 + Q84 + Q170 + Q196 +
                                Q44 + Q63 + Q76  + Q98
"
```

Step 5: Fit the model

Use the `cfa()` function in lavaan.

```
fit_2EFA <- cfa(model.2EFA, data=data_sapi,  
               missing='fiml', fixed.x=F) # use FIML  
# Note: FIML will be discusses in the Missing Data lecture.
```

Step 5. Fit the EFA model: All code

```
# Data
data_sapi <- read.table("Sapi.txt", header = T)
data_sapi[sapply(data_sapi,
  function(x) as.character(x) %in% c("-999") )] <- NA

# Model: two-factor EFA
model.2EFA <- "
  efa('block1')*Having fun  =~ Q77 + Q84 + Q170 + Q196 +
                                Q44 + Q63 + Q76  + Q98
  efa('block1')*Being liked =~ Q77 + Q84 + Q170 + Q196 +
                                Q44 + Q63 + Q76  + Q98
"

# Fit model
fit_2EFA <- cfa(model.2EFA, data=data_sapi,
  missing='fiml', fixed.x=F) # use FIML
```

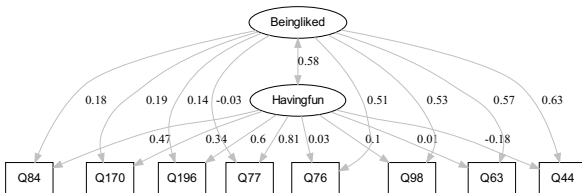

Step 6: Plot the lavaan model in R

```
if (!require("lavaanPlot")) install.packages("lavaanPlot")  
library(lavaanPlot)
```

```
lavaanPlot(model = fit_2EFA,  
            node_options = list(shape = "box",  
                                fontname = "Helvetica"),  
            edge_options = list(color = "grey"),  
            coefs = T,  
            stand = T, # standardized  
            covs = T)
```

Step 6: Plot the lavaan model in R Ctd.

```
lavaanPlot(model = fit_2EFA,  
  node_options = list(shape = "box",  
                       fontname = "Helvetica"),  
  edge_options = list(color = "grey"),  
  coefs = T, stand = T, covs = T)
```



Step 9: Acquiring the summary

```
summary(fit_2EFA)

parameterEstimates(fit_2EFA)

fitMeasures(fit_2EFA, c("chisq", "df", "pvalue",
                        "cfi", "tli",
                        "rmsea", "srmr"))

# As an example, there are more.
```

Step 9: Acquiring the summary

```
parameterEstimates(fit_2EFA)[1:16,1:5][,-4]
```

```
##           lhs op   rhs    est
## 1   Havingfun =~  Q77  0.884
## 2   Havingfun =~  Q84  0.493
## 3   Havingfun =~ Q170  0.336
## 4   Havingfun =~ Q196  0.523
## 5   Havingfun =~  Q44 -0.163
## 6   Havingfun =~  Q63  0.014
## 7   Havingfun =~  Q76  0.031
## 8   Havingfun =~  Q98  0.085
## 9   Beingliked =~  Q77 -0.028
## 10  Beingliked =~  Q84  0.186
## 11  Beingliked =~ Q170  0.187
## 12  Beingliked =~ Q196  0.119
## 13  Beingliked =~  Q44  0.576
## 14  Beingliked =~  Q63  0.632
## 15  Beingliked =~  Q76  0.595
```

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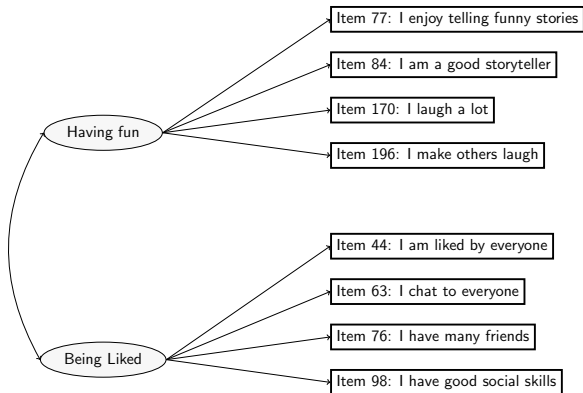
Extra

Step 1: Loading data into R

```
data_sapi <- read.table("Sapi.txt", header = T)

data_sapi[sapply(data_sapi,
  function(x) as.character(x) %in% c("-999") )] <- NA
```

Step 3: Draw your model



Step 4: Specify CFA in lavaan (general case)

- \rightarrow is latent variable definition ('is measured by'): $=\sim$
- \leftrightarrow is covariance. By default, factors are related.

```
# k-factor model
model.kCFA <- '
latent variable_1 =~ indicator11 + indicator12 + ...
latent variable_2 =~ indicator21 + indicator22 + ...
...
latent variable_k =~ indicatork1 + indicatork2 + ...
'
```


Step 4: Specify our SAPI CFA model

CFA: Only hypothesized loadings.

CFA vs EFA: force cross-loadings to zero.

In lavaan:

one can fix loadings to zero, BUT instead:

let manifest variables only appear in the equation of their factor.

```
# two-factor CFA
model.2CFA <- "
  Having fun =~ Q77 + Q84 + Q170 + Q196
  Being liked =~ Q44 + Q63 + Q76 + Q98
"
```

Step 5: Fit the model

Use the `cfa()` function in lavaan.

```
fit_2CFA <- cfa(model.2CFA, data=data_sapi,  
               missing='fiml', fixed.x=F) # use FIML  
# Note: FIML will be discusses in the Missing Data lecture.
```

5. Fit the CFA model: All code

```
# Data
data_sapi <- read.table("Sapi.txt", header = T)
data_sapi[sapply(data_sapi,
  function(x) as.character(x) %in% c("-999") )] <- NA

# Model: two-factor CFA
model.2CFA <- "
  Having fun =~ Q77 + Q84 + Q170 + Q196
  Being liked =~ Q44 + Q63 + Q76 + Q98
"

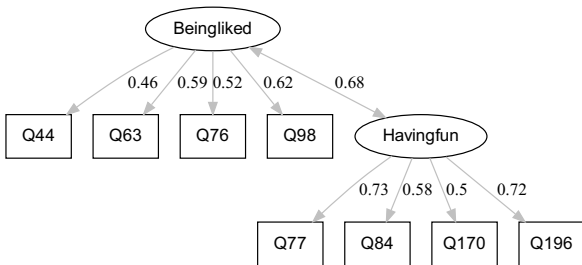
# Fit model
fit_2CFA <- cfa(model.2CFA, data=data_sapi,
  missing='fiml', fixed.x=F) # use FIML
```

Step 6: Plot the lavaan model in R

```
if (!require("lavaanPlot")) install.packages("lavaanPlot")  
library(lavaanPlot)
```

```
lavaanPlot(model = fit_2CFA,  
            node_options = list(shape = "box",  
                                fontname = "Helvetica"),  
            edge_options = list(color = "grey"),  
            coefs = T,  
            stand = T,  
            covs = T)
```

```
lavaanPlot(model = fit_2CFA,
            node_options = list(shape = "box",
                                fontname = "Helvetica"),
            edge_options = list(color = "grey"), coefs = T,
            stand = T, covs = T)
```



Step 9: Acquiring the summary

```
summary(fit_2CFA)

parameterEstimates(fit_2CFA)

fitMeasures(fit_2CFA, c("chisq", "df", "pvalue",
                        "cfi", "tli",
                        "rmsea", "srmr"))

# As an example, there are more.
```

```
#The factors scores for each subject can be required via:
predict(fit_2CFA)
```

CFA: modification indices - lavaan commands

Remark: Blending confirmatory and exploratory!
Make sure it makes sense!

In lavaan, modification indices can be requested

- within the summary call:

```
summary(fit_2CFA, modindices = TRUE)
```

- directly:

```
modindices(fit_2CFA, sort = TRUE)
```

- for specific parameters, say, factor loadings:

```
mi <- modindices(fit)  
mi[mi$op == "=~",]
```

Also, have a look at the `lavTestScore()` function.

CFA: modification indices - interpretation

```
#modindices(fit, sort = TRUE, maximum.number = 7) # or:
modindices(fit_2CFA, sort = TRUE)[1:7,] # first 7 rows
```

| ## | | lhs | op | rhs | mi | epc | sepc.lv | sepc.all | sepc.nox |
|-------|------------|------|----|------|--------|--------|---------|----------|----------|
| ## 51 | | Q170 | ~~ | Q196 | 36.273 | 0.138 | 0.138 | 0.271 | 0.271 |
| ## 38 | | Q77 | ~~ | Q84 | 35.431 | 0.194 | 0.194 | 0.305 | 0.305 |
| ## 46 | | Q84 | ~~ | Q196 | 31.126 | -0.143 | -0.143 | -0.276 | -0.276 |
| ## 45 | | Q84 | ~~ | Q170 | 20.426 | -0.123 | -0.123 | -0.170 | -0.170 |
| ## 50 | | Q84 | ~~ | Q98 | 16.530 | 0.092 | 0.092 | 0.156 | 0.156 |
| ## 35 | Beingliked | = | ~ | Q84 | 13.085 | 0.552 | 0.234 | 0.222 | 0.222 |
| ## 39 | | Q77 | ~~ | Q170 | 12.876 | -0.104 | -0.104 | -0.166 | -0.166 |

- mi: If parameter freely estimated, overall Chi-square statistic could decrease by approximately this amount.
- epc (= expected parameter change): Approximate value that a parameter is expected to attain.

CFA: modification indices - cross-loadings

Cross-loadings:

| | lhs | op | rhs | mi | epc | sepc.lv | sepc.all | sepc.nox |
|------------|------|----|------|--------|--------|---------|----------|----------|
| | Q170 | ~~ | Q196 | 36.273 | 0.138 | 0.138 | 0.271 | 0.271 |
| | Q77 | ~~ | Q84 | 35.431 | 0.194 | 0.194 | 0.305 | 0.305 |
| | Q84 | ~~ | Q196 | 31.126 | -0.143 | -0.143 | -0.276 | -0.276 |
| | Q84 | ~~ | Q170 | 20.426 | -0.123 | -0.123 | -0.170 | -0.170 |
| | Q84 | ~~ | Q98 | 16.530 | 0.092 | 0.092 | 0.156 | 0.156 |
| beingliked | == | | Q84 | 13.085 | 0.552 | 0.234 | 0.222 | 0.222 |
| | Q77 | ~~ | Q170 | 12.876 | -0.104 | -0.104 | -0.166 | -0.166 |
| beingliked | == | | Q77 | 12.564 | -0.586 | -0.249 | -0.229 | -0.229 |
| Havingfun | == | | Q44 | 11.853 | -0.255 | -0.203 | -0.221 | -0.221 |
| | Q77 | ~~ | Q44 | 10.621 | -0.078 | -0.078 | -0.129 | -0.129 |

CFA: modification indices - residual variances

Residual covariances:

| | lhs | op | rhs | mi | epc | sepc.lv | sepc.all | sepc.nox |
|------------|------|----|------|--------|--------|---------|----------|----------|
| | Q170 | ~~ | Q196 | 36.273 | 0.138 | 0.138 | 0.271 | 0.271 |
| | Q77 | ~~ | Q84 | 35.431 | 0.194 | 0.194 | 0.305 | 0.305 |
| | Q84 | ~~ | Q196 | 31.126 | -0.143 | -0.143 | -0.276 | -0.276 |
| | Q84 | ~~ | Q170 | 20.426 | -0.123 | -0.123 | -0.170 | -0.170 |
| | 084 | ~~ | 098 | 16.530 | 0.092 | 0.092 | 0.156 | 0.156 |
| Beingliked | == | | 084 | 13.085 | 0.552 | 0.234 | 0.222 | 0.222 |
| | Q77 | ~~ | Q170 | 12.876 | -0.104 | -0.104 | -0.166 | -0.166 |
| Beingliked | == | | Q77 | 12.564 | -0.586 | -0.249 | -0.229 | -0.229 |
| Havingfun | == | | Q44 | 11.853 | -0.255 | -0.203 | -0.221 | -0.221 |
| | Q77 | ~~ | Q44 | 10.621 | -0.078 | -0.078 | -0.129 | -0.129 |

CFA: modification indices - be aware!

```
      lhs op rhs      mi      epc sepc.lv sepc.all sepc.noX
51  Q170 ~ Q196 36.273 0.138 0.138 0.271 0.271
38  Q77 ~ Q84 35.431 0.194 0.194 0.305 0.305
46  Q84 ~ Q196 31.126 -0.143 -0.143 -0.276 -0.276
45  Q84 ~ Q170 20.426 -0.123 -0.123 -0.170 -0.170
50  Q84 ~ Q98 16.530 0.092 0.092 0.156 0.156
35  Beingliked ~ Q84 13.600 0.552 0.234 0.222 0.222
39  Q77 ~ Q170 12.000 0.104 -0.104 -0.166 -0.166
34  Beingliked ~ Q77 11.000 0.086 -0.249 -0.229 -0.229
30  Havingfun ~ Q44 10.000 0.005 -0.203 -0.221 -0.221
41  Q77 ~ Q44 10.000 0.000 -0.078 -0.129 -0.129
33  Havingfun ~ Q44 10.000 0.192 0.220 0.220 0.220
61  Q44 ~ Q77 10.000 0.088 0.108 0.108 0.108
60  Q44 ~ Q77 10.000 0.070 0.096 0.096 0.096
44  Q77 ~ Q84 10.000 0.004 -0.087 -0.087 -0.087
49  Q84 ~ Q77 10.000 0.065 0.065 0.065 0.065
55  Q170 ~ Q84 10.000 0.066 0.066 0.066 0.066
65  Q170 ~ Q84 10.000 0.082 -0.082 -0.082 -0.082
36  Beingliked ~ Q170 10.000 0.106 0.106 0.106 0.106
48  Q77 ~ Q84 10.000 0.052 -0.052 -0.052 -0.052
62  Q77 ~ Q84 10.000 0.007 -0.057 -0.057 -0.057
58  Q77 ~ Q84 10.000 0.000 -0.047 -0.047 -0.047
57  Q77 ~ Q84 10.000 0.000 0.038 0.038 0.038
64  Q77 ~ Q84 10.000 0.000 0.045 0.045 0.045
43  Q77 ~ Q76 0.068 0.008 0.008 0.011 0.011
47  Q84 ~ Q44 0.042 0.005 0.005 0.007 0.007
54  Q170 ~ Q76 0.011 0.003 0.003 0.004 0.004
```

DANGER!
Capitalization on
chance

CFA: modification indices - modification

```
modindices(fit_2CFA, sort = TRUE)[1,]
```

```
##      lhs op  rhs      mi    epc sepc.lv sepc.all sepc.nox
## 51 Q170 ~~ Q196 36.273 0.138    0.138    0.271    0.271
```

```
# Allow residuals of Q170 and Q196 to covary
```

```
# Modified model:
```

```
# two-factor CFA + residual covariance Q170 and Q196
```

```
model.2CFA_mod <- "
```

```
  Having fun  =~ Q77 + Q84 + Q170 + Q196
```

```
  Being liked =~ Q44 + Q63 + Q76  + Q98
```

```
  Q170 ~~ Q196
```

```
"
```

```
# Fit model
```

```
fit_2CFA_mod <- cfa(model.2CFA_mod, data=data_sapi,
                    missing='fiml', fixed.x=F) # use FIML
```

CFA: modification indices - test modification

```
anova(fit_2CFA, fit_2CFA_mod)[,-c(2,3)] # without AIC & BIC

##           Df      Chisq Chisq diff Df diff Pr(>Chisq)
## fit_2CFA_mod 18   88.738
## fit_2CFA      19 124.170      35.432      1 2.641e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
modindices(fit_2CFA, sort = TRUE)[1,]

##      lhs op  rhs      mi   epc sepc.lv sepc.all sepc.nox
## 51 Q170 ~~ Q196 36.273 0.138   0.138   0.271   0.271
```

CFA: modification indices - new parameter value

```
parameterEstimates(fit_2CFA_mod)[9,-c(5,6,7)] # no se, z, and p
```

```
##      lhs op  rhs    est ci.lower ci.upper
## 9 Q170 ~~ Q196 0.137    0.089    0.184
```

```
modindices(fit_2CFA, sort = TRUE)[1,1:5] # no sepc
```

```
##      lhs op  rhs    mi    epc
## 51 Q170 ~~ Q196 36.273 0.138
```

CFA: cross-loadings approximately zero

Problem:

- Restricting cross-loadings to exactly zero can be too strict.
- Consequence: rejection of the model, model modifications that capitalise on chance.

(Possible) solution in Bayesian SEM (BSEM) blavaan:

- Replace exact zero restrictions with approximate ones.
- Using Bayesian small-variance priors.

Interesting reading:

- Merkle, E. C., & Rosseel, Y. (2018). blavaan: Bayesian Structural Equation Models via Parameter Expansion. *Journal of Statistical Software*, 85(4), 1–30. <https://doi.org/10.18637/jss.v085.i04>
- Muthén, B., & Asparouhov, T. (2012). Bayesian structural equation modelling: A more flexible representation of substantive theory. *Psychological Methods*, 17(3), 313-335.

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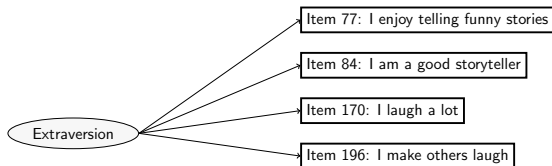
Scaling

The end

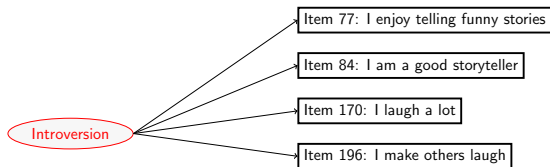
Extra

Latent variable scaling

Latent variables are not observed, thus no inherent scale.



Latent variable scaling Ctd.



Therefore, set up model such that scale of latent variable is clear.

Three common ways

1. Marker-variable method

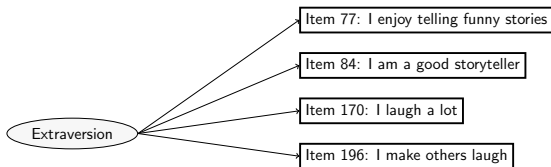
Constrain one of the factor loadings (default).

2. Reference group method:

Constrain the factor variance.

3. Effect coding:

Constrain the average of the loadings.



1. Marker-variable method (default)

Default parameterization:

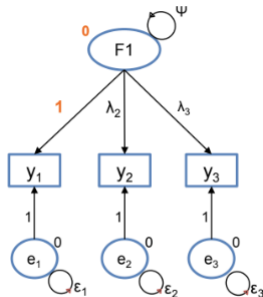
- First factor loading constrained at 1.
- Factor mean constrained at 0.

Other defaults:

- Mean of residuals is by definition 0.
- Residuals have a loading of 1.

Estimated:

- factor variance (Ψ),
- 'other' factor loadings (λ_2, λ_3),
- all item intercepts (ν_1, ν_2, ν_3),
- all residual variances ($\epsilon_1, \epsilon_2, \epsilon_3$).



1. Default marker-variable method - lavaan

```
# Model
model.1CFA <- '
  Extraversion =~ Q77 + Q84 + Q170 + Q196
'

# Fit model
fit_1CFA <- cfa(model.1CFA, data=data_sapi,
                missing='fiml', fixed.x=F) # use FIML
```

- First factor loading constrained at 1:

```
Extraversion =~
  Q77                1.000
```

- Factor mean constrained at 0:

```
Extraversion      0.000
```

1. Default marker-variable method - lavaan Ctd

```
parameterEstimates(fit_1CFA)[1:4,-c(5,6,7)]
```

| ## | | lhs | op | rhs | est | ci.lower | ci.upper |
|------|--------------|-----|----|------|-------|----------|----------|
| ## 1 | Extraversion | =~ | | Q77 | 1.000 | 1.000 | 1.000 |
| ## 2 | Extraversion | =~ | | Q84 | 0.708 | 0.616 | 0.799 |
| ## 3 | Extraversion | =~ | | Q170 | 0.567 | 0.466 | 0.668 |
| ## 4 | Extraversion | =~ | | Q196 | 0.742 | 0.640 | 0.845 |

Factor loading of first indicator fixed to 1.
all other loadings are relative to that.

If reference category changed, other loadings also change.

2. Reference-group method

Parameterization:

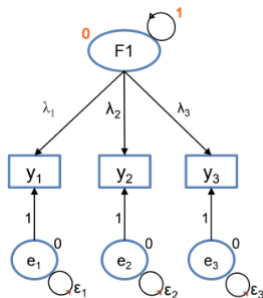
- Factor variance constrained at 1.
- Factor mean constrained at 0.

Defaults:

- Mean of residuals is by definition 0.
- Residuals have a loading of 1.

Estimated:

- all factor loadings ($\lambda_1, \lambda_2, \lambda_3$),
- all item intercepts (ν_1, ν_2, ν_3),
- all residual variances ($\epsilon_1, \epsilon_2, \epsilon_3$).



2. Reference-group method - lavaan

```
# Model
model.1CFA_RefGr <- '
  # Free first factor loading, using: NA*
  Extraversion =~ NA*Q77 + Q84 + Q170 + Q196

  # Set factor variance to 1, using: 1*
  Extraversion ~~ 1*Extraversion
  '

# Fit model
fit_1CFA_RefGr <- cfa(model.1CFA_RefGr, data=data_sapi,
  missing='fiml', fixed.x=F) # use FIML
```

- Factor variance constrained at 1:

Extraversion 1.000

- Factor mean constrained at 0:

Extraversion 0.000

2. Reference-group method - lavaan Ctd

```
parameterEstimates(fit_1CFA_RefGr)[1:4,-c(5,6,7)]
```

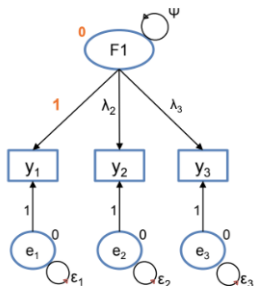
```
##           lhs op   rhs   est ci.lower ci.upper
## 1 Extraversion =~  Q77 0.835    0.759    0.910
## 2 Extraversion =~  Q84 0.591    0.520    0.662
## 3 Extraversion =~  Q170 0.473    0.404    0.543
## 4 Extraversion =~  Q196 0.619    0.559    0.680
```

Advantage:

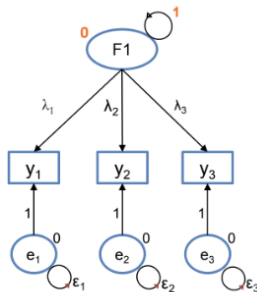
All factor loadings and scores on standardized metric.

Which method to choose?

1. Marker-variable method



2. Reference-group method



Does not matter for substantive conclusions.
Sometimes, pragmatic reasons.

3. Effects-coding method

Parameterization:

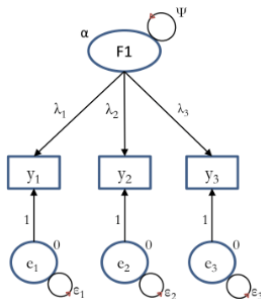
- Constrain the average of the factor loadings to 1: $\frac{1}{3} \sum_{i=1}^3 \lambda_i = 1$.
- Constrain the average of the item intercepts to 0: $\frac{1}{3} \sum_{i=1}^3 \nu_i = 0$.

Defaults:

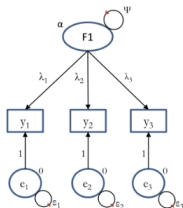
- Mean of residuals is by definition 0.
- Residuals have a loading of 1.

Estimated (subject to the constraints):

- factor variance (Ψ),
- factor mean (α),
- all factor loadings ($\lambda_1, \lambda_2, \lambda_3$),
- all item intercepts (ν_1, ν_2, ν_3),
- all residual variances ($\epsilon_1, \epsilon_2, \epsilon_3$).



3. Effects-coding method Ctd



Interpretations can be intuitive:

- Factor on similar scale as the indicators.
- Factor variance (Ψ): average variance of each indicator that can be explained by the factor.
- Factor mean (α): weighted mean of the indicator means

3. Effects-coding method - lavaan model

```
# Model
model.1CFA_EffC <- '
  # Label parameters, such that they can be constrained
  Extraversion =~ lambda1*Q77 + lambda2*Q84 +
                  lambda3*Q170 + lambda4*Q196

  # intercepts
  Q77 ~ nu1*1
  Q84 ~ nu2*1
  Q170 ~ nu3*1
  Q196 ~ nu4*1

  # Constrain average of loadings to 1, i.e., set sum to 4
  lambda1 == 4 - lambda2 - lambda3 - lambda4
  # Constrain average of item intercepts to 0,
  # i.e., set sum to 0
  nu1 == 0 - nu2 - nu3 - nu4
  '
```

3. Effects-coding method - fit lavaan model

Now, use the `lavaan()` function:

```
# Fit model: Now, use the lavaan() function!  
fit_1CFA_EffC <- lavaan(model.1CFA_EffC, data=data_sapi,  
  missing='fiml', fixed.x=F,  
  auto.var = TRUE,  
  auto.fix.first = FALSE,  
  auto.cov.lv.x = TRUE,  
  int.ov.free = TRUE)
```

3. Effects-coding method - lavaan output

- Constrain the average of the factor loadings to 1: $\frac{1}{4} \sum_{i=1}^4 \lambda_i = 1$.

```
parameterEstimates(fit_1CFA_EffC)[1:4,1:5]
```

```
##           lhs op  rhs  label  est
## 1 Extraversion =~ Q77 lambda1 1.197
## 2 Extraversion =~ Q84 lambda2 1.027
## 3 Extraversion =~ Q170 lambda3 0.879
## 4 Extraversion =~ Q196 lambda4 0.898
```

- Constrain the average of the item intercepts to 0: $\frac{1}{4} \sum_{i=1}^4 \nu_i = 0$.

```
parameterEstimates(fit_1CFA_EffC)[5:8,1:5]
```

```
##    lhs op rhs label  est
## 5  Q77 ~1      nu1 -0.765
## 6  Q84 ~1      nu2 -0.521
## 7  Q170 ~1     nu3  0.738
## 8  Q196 ~1     nu4  0.548
```

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Thanks & How to proceed

Thanks for listening!

Are there any questions?

- Ask fellow participant on course platform.
- Ask teacher during Q&A (or via course platform).
- See if making the lab exercises help.
- Check the lavaan tutorial: e.g.,
<https://lavaan.ugent.be/tutorial/index.html>.
- Do not forget that Google is your best friend :-).

You can start working on the lab exercises.

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Extra:

Categorical/Ordinal or continuous indicators?

Note: in `cfa()` you can, for example use `'ordered = TRUE'`.

Q77

Q84



Q170

Q196



Remark!

Do NOT use a χ^2 test or IC (AIC or BIC)
to compare categorical and continuous models:

- Obviously not nested (so, no χ^2 test anyway).
- AND likelihoods of categorical and continuous indicator models are incomparable!

Note: χ^2 test and IC are based on (log) likelihood (= fit).

Interesting Reading

Muthén, B. (1984). A general structural equation model with dichotomous, ordered categorical, and continuous latent variable indicators. *Psychometrika*, 49(1), 115-132.

Rhemtulla, M., Brosseau-Liard, P.É., & Savalei, V. (2012). When can categorical variables be treated as continuous? A comparison of robust continuous and categorical SEM estimation methods under suboptimal conditions. *Psychological Methods*, 17(3), 354-373.

Sventina, D., Rutkowski, D. (2020). Multiple group invariance with categorical outcomes using updated guidelines: an illustration using Mplus and the lavaan/semtools packages. *Structural Equational Modelling: A Multidisciplinary Journal*, 27(1), 111-130