

Basics (and advanced stuff) of questionnaire development and analysis

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This is an R Markdown document. Instructions for writing these documents and background information can be found in the book R Markdown: The Definitive Guide. When you execute code within the document, the results appear beneath the code.

show data set

Datensatz ist der Campus-File des IQB-Ländervergleichs 2011 der Primarstufe (Zugang über <https://www.iqb.hu-berlin.de/fdz/Datenzugang>), Bedeutung Variablen einsichtig über Suchfunktion Skalenhandbuch.

```
dim(datenLV)
```

```
## [1] 3005 33
```

```
knitr::kable(datenLV[1:4,], digits = 2)
```

[illegible]

```

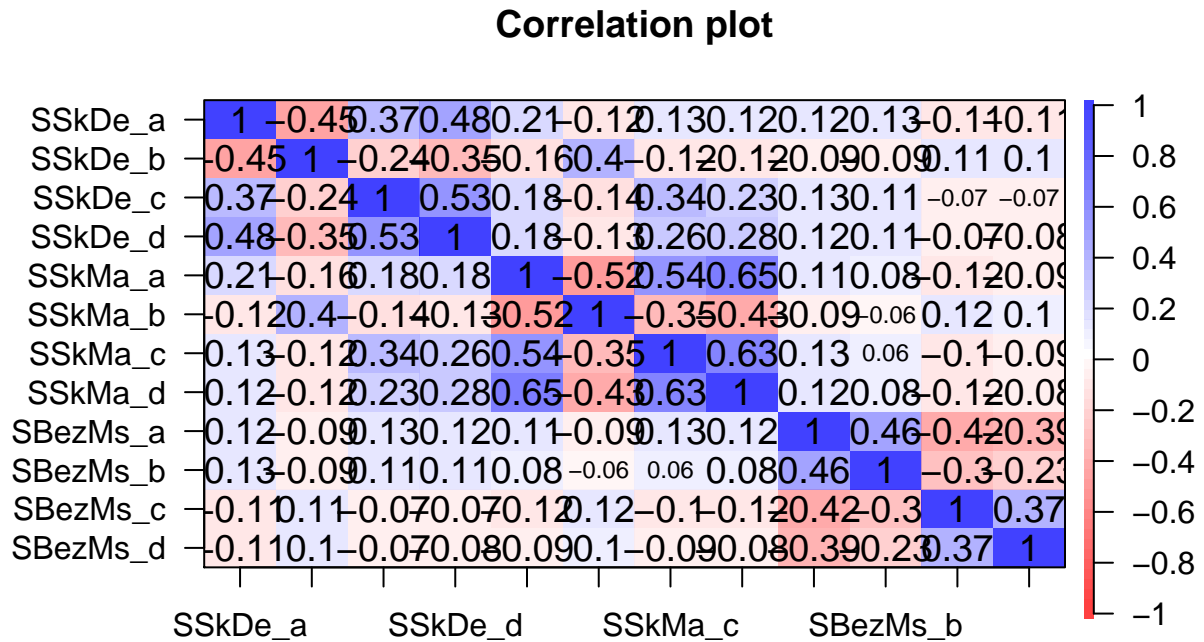
##
##
##      EHisei      EHiscde_akt      SBuecher
## Min.    :10.00    ISCED level 1 : 23    10 Buecher      : 153
## 1st Qu.:37.00    ISCED level 2 : 81    25 Buecher      : 557
## Median :48.00    ISCED level 3A: 10    100 Buecher     :1112
## Mean    :49.57    ISCED level 5B:1556    200 Buecher     : 563
## 3rd Qu.:61.00    ISCED level 5A: 724    mehr 200 Buecher: 550
## Max.    :89.00    ISCED level 6 : 126    NA's            : 70
## NA's    :622      NA's      : 485
##
##              SLesZt      tr_NotDe      tr_NotMa
## weniger als 30 Minuten      : 862    Min.    :1.00    Min.    :1.000
## 30 Minuten bis zu einer Stunde:1173    1st Qu.:2.00    1st Qu.:2.000
## 1-2 Stunden      : 475    Median :2.00    Median :2.000
## 2 Stunden oder mehr      : 398    Mean    :2.46    Mean    :2.509
## NA's      : 97    3rd Qu.:3.00    3rd Qu.:3.000
##
##              Max.    :5.00    Max.    :5.000
##              NA's    :131    NA's    :127
##
## tr_Wdh_r      SSkDe_a      SSkDe_b      SSkDe_c      SSkDe_d
## nein:2830    Min.    :1.000    Min.    :1.000    Min.    :1.000    Min.    :1.000
## ja : 168    1st Qu.:3.000    1st Qu.:1.000    1st Qu.:3.000    1st Qu.:3.000
## NA's: 7    Median :3.000    Median :2.000    Median :3.000    Median :3.000
##
##              Mean    :3.116    Mean    :2.126    Mean    :3.303    Mean    :3.334
##              3rd Qu.:4.000    3rd Qu.:3.000    3rd Qu.:4.000    3rd Qu.:4.000
##              Max.    :4.000    Max.    :4.000    Max.    :4.000    Max.    :4.000
##              NA's    :92      NA's    :121      NA's    :126      NA's    :123
##
##      SSkMa_a      SSkMa_b      SSkMa_c      SSkMa_d      SBezMs_a
## Min.    :1.00    Min.    :1.000    Min.    :1.000    Min.    :1.000    Min.    :1.000
## 1st Qu.:3.00    1st Qu.:1.000    1st Qu.:3.000    1st Qu.:3.000    1st Qu.:3.000
## Median :3.00    Median :2.000    Median :3.000    Median :4.000    Median :3.000
## Mean    :3.17    Mean    :2.065    Mean    :3.314    Mean    :3.331    Mean    :3.365
## 3rd Qu.:4.00    3rd Qu.:3.000    3rd Qu.:4.000    3rd Qu.:4.000    3rd Qu.:4.000
## Max.    :4.00    Max.    :4.000    Max.    :4.000    Max.    :4.000    Max.    :4.000
## NA's    :82      NA's    :115      NA's    :121      NA's    :102      NA's    :164
##
##      SBezMs_b      SBezMs_c      SBezMs_d      SSkDe      SSkMa
## Min.    :1.00    Min.    :1.000    Min.    :1.000    Min.    :1.000    Min.    :1.000
## 1st Qu.:3.00    1st Qu.:1.000    1st Qu.:1.000    1st Qu.:2.750    1st Qu.:2.750
## Median :3.00    Median :1.000    Median :1.000    Median :3.250    Median :3.250
## Mean    :3.11    Mean    :1.633    Mean    :1.493    Mean    :3.156    Mean    :3.187
## 3rd Qu.:4.00    3rd Qu.:2.000    3rd Qu.:2.000    3rd Qu.:3.750    3rd Qu.:4.000
## Max.    :4.00    Max.    :4.000    Max.    :4.000    Max.    :4.000    Max.    :4.000
## NA's    :199      NA's    :173      NA's    :172      NA's    :95      NA's    :85
##
##      SBezMs      wle_lesen      wle hoeren      wle_mathe
## Min.    :1.000    Min.    : -5.06686    Min.    : -5.8078    Min.    : -3.4768
## 1st Qu.:3.000    1st Qu.: -0.68091    1st Qu.: -0.5796    1st Qu.: -0.6384
## Median :3.500    Median : 0.12715    Median : 0.1526    Median : 0.1035
## Mean    :3.335    Mean    : 0.09367    Mean    : 0.1094    Mean    : 0.1061
## 3rd Qu.:3.750    3rd Qu.: 0.88132    3rd Qu.: 0.8188    3rd Qu.: 0.8379
## Max.    :4.000    Max.    : 4.24000    Max.    : 3.5043    Max.    : 4.7832
## NA's    :145
##
##              schoolEconDis      schoolMiganteil
## <33% oekonomisch benachteiligt: 175    < 20% Miganteil:1645
## 33-66% oekonomisch mittel      :2320    > 20% Miganteil:1360
## >66% oekonomisch bevorzugt      : 510

```

```
##
##
##
##
```

tidy and transform data

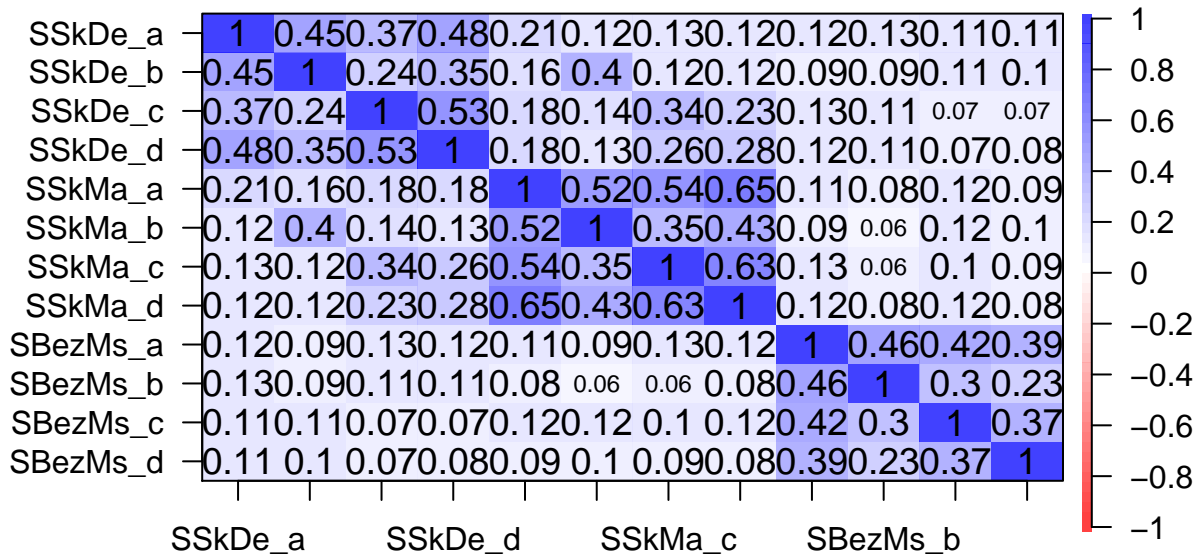
```
psych::corPlot(r = datenLV[,str_subset(string = colnames(datenLV), pattern = "^SSkMa_|^SSkDe_|^SBezMs_")]
```



```
# recode
datenLV$SSkMa_b <- 5 - datenLV$SSkMa_b
datenLV$SSkDe_b <- 5 - datenLV$SSkDe_b
datenLV$SBezMs_c <- 5 - datenLV$SBezMs_c
datenLV$SBezMs_d <- 5 - datenLV$SBezMs_d

psych::corPlot(r = datenLV[,str_subset(string = colnames(datenLV), pattern = "^SSkMa_|^SSkDe_|^SBezMs_")]
```

Correlation plot



describe, visualize your data and get a first impression using R base functions

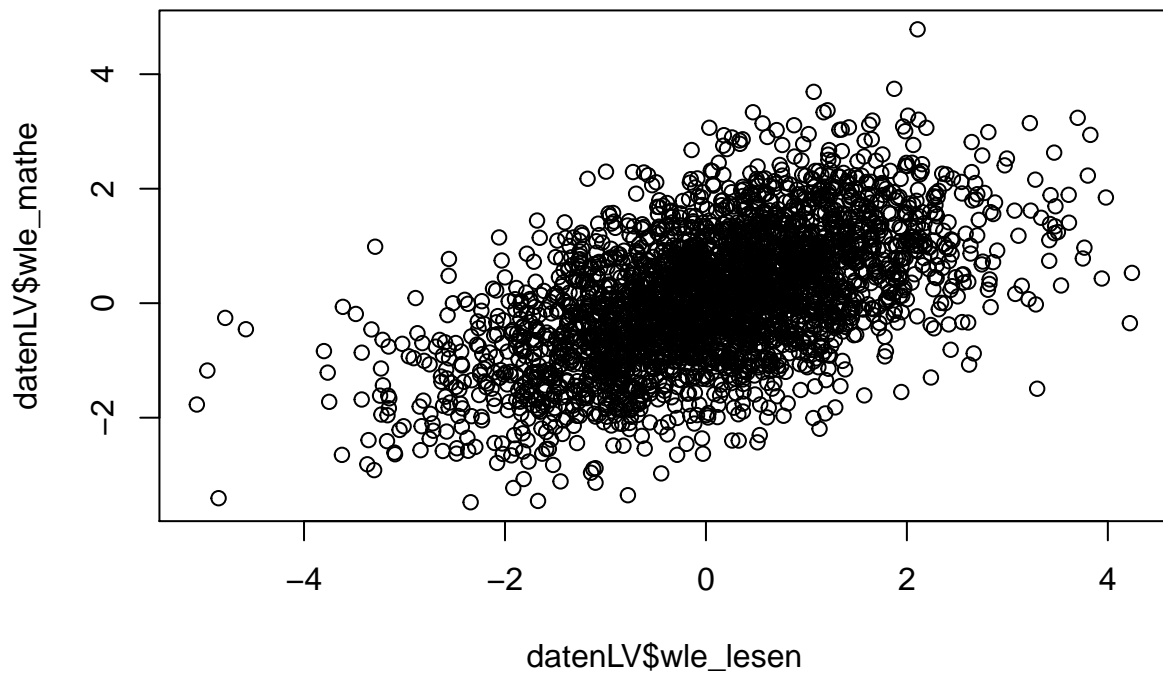
Insgesamt weist der Datensatz N=3005 Schüler/innen in 201 Schulen auf. Die Schulen weisen folgende Anzahl von Schüler/innen auf:

```
proSchule <- aggregate(datenLV$idsch_FDZ,by=list(datenLV$idsch_FDZ),FUN=length) # using base functions
summary(proSchule$x)
```

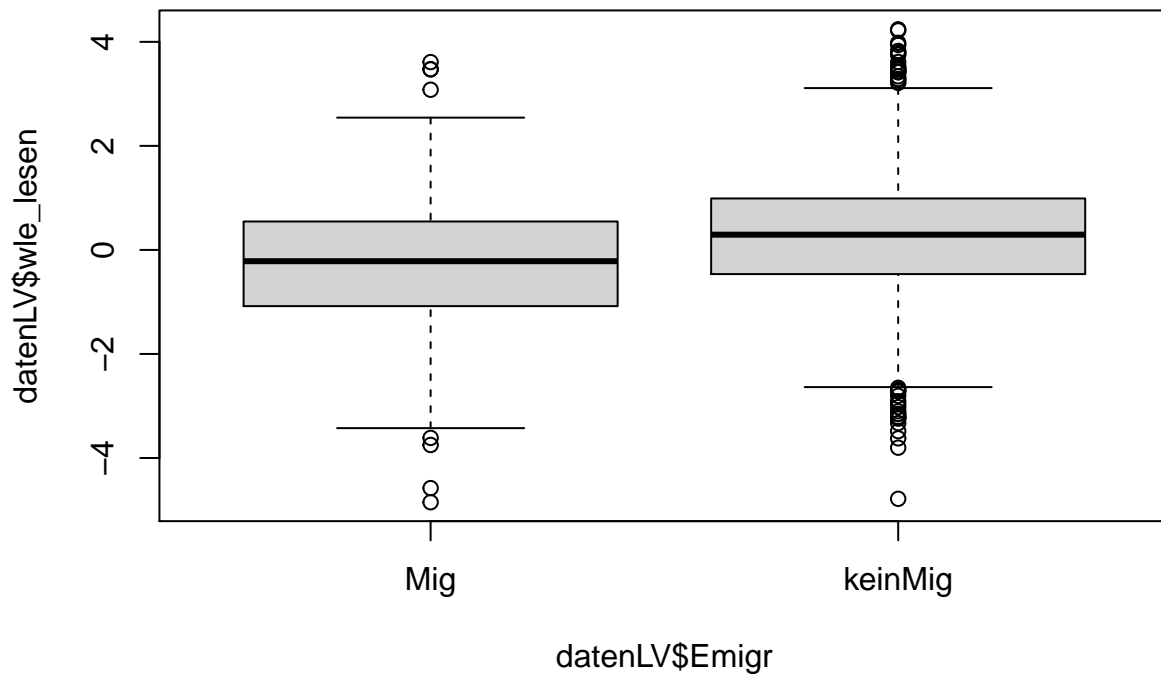
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      5.00   10.00   15.00   14.95   20.00   20.00
```

```
rm(proSchule)
```

```
plot(datenLV$wle_lesen, datenLV$wle_mathe)
```



```
boxplot(datenLV$wle_lesen ~ datenLV$Emigr)
```



```
t.test(datenLV$wle_lesen ~ datenLV$Emigr) # = unequal variances t-test
```

```
##
## Welch Two Sample t-test
##
## data: datenLV$wle_lesen by datenLV$Emigr
## t = -8.6373, df = 720.46, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.6554145 -0.4126442
## sample estimates:
## mean in group Mig mean in group keinMig
## -0.2612065 0.2728229
```

Bestehen lineare Zusammenhänge mit einer (normalverteilten) numerischen Variablen?

```
## linear regression
summary(lm(formula = wle_lesen ~ Emigr*tr_sex + SSkMa, data = datenLV))
```

```
##
## Call:
## lm(formula = wle_lesen ~ Emigr * tr_sex + SSkMa, data = datenLV)
##
## Residuals:
## Min 1Q Median 3Q Max
## -4.3692 -0.7007 0.0184 0.7098 3.8719
##
## Coefficients:
```

```
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -1.98582    0.12494 -15.894 < 2e-16 ***
## EmigrkeinMig       0.39521    0.07802   5.065 4.38e-07 ***
## tr_sexweiblich     0.30605    0.10250   2.986 0.00286 **
## SSkMa              0.52233    0.03229  16.174 < 2e-16 ***
## EmigrkeinMig:tr_sexweiblich 0.04767    0.11380   0.419 0.67535
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## Residual standard error: 1.108 on 2399 degrees of freedom
```

```
## (601 observations deleted due to missingness)
```

```
## Multiple R-squared:  0.1324, Adjusted R-squared:  0.1309
```

```
## F-statistic: 91.49 on 4 and 2399 DF,  p-value: < 2.2e-16
```

Bestehen lineare Zusammenhänge mit einer binären Variablen? empfohlene Seite: https://www.methodenberatung.uzh.ch/de/datenanalyse_spss/zusammenhaenge/lreg.html

```
## logistic regression (if > 2 -> ordinal logistic regression)
```

```
summary(glm(Emigr ~ wle_lesen+wle_hoeren+wle_mathe,
             data = datenLV, family = binomial))
```

```
##
```

```
## Call:
```

```
## glm(formula = Emigr ~ wle_lesen + wle_hoeren + wle_mathe, family = binomial,
```

```
##      data = datenLV)
```

```
##
```

```
## Deviance Residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -2.3848  0.4196  0.5748  0.6953  1.4128
```

```
##
```

```
## Coefficients:
```

```
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  1.36913    0.05226  26.198 < 2e-16 ***
## wle_lesen    0.17045    0.05383   3.167 0.00154 **
## wle_hoeren   0.12008    0.05871   2.045 0.04081 *
## wle_mathe    0.33122    0.05930   5.585 2.33e-08 ***
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## (Dispersion parameter for binomial family taken to be 1)
```

```
##
```

```
##      Null deviance: 2464.3  on 2458  degrees of freedom
```

```
## Residual deviance: 2338.4  on 2455  degrees of freedom
```

```
## (546 observations deleted due to missingness)
```

```
## AIC: 2346.4
```

```
##
```

```
## Number of Fisher Scoring iterations: 4
```

```
exp(coef(glm(Emigr ~ wle_lesen+wle_hoeren+wle_mathe,
             data = datenLV, family = binomial))) - 1
```

```
## (Intercept)  wle_lesen  wle_hoeren  wle_mathe
```

```
##  2.9319093  0.1858348  0.1275879  0.3926618
```

Anmerkung: Hypothesentest, logistische Regression sind die zentralen Verfahren für die **deduktive Methode** der Itementwicklung

missing data patterns

```
mdpattern[match(x = sort(x = as.numeric(rownames(mdpattern))), decreasing = TRUE), table = as.numeric(row
```

9

[illegible]

```
## generate dummy of missing variable to identify potential helper variables
datenLV$missing_SSkMa_a <- ifelse(test = is.na(datenLV$SSkMa_a), yes = 1, no = 0)
helpervars <- c("wle_lesen", "wle_hoeren", "SSkDe") # include normally many more
for(v in helpervars){
  tmp <- t.test(datenLV[[v]] ~ datenLV$missing_SSkMa_a)
  if(tmp$p.value < .05){
    print(v)
    print(tmp)
  }
}
```

```
## [1] "wle_lesen"
##
## Welch Two Sample t-test
##
## data: datenLV[[v]] by datenLV$missing_SSkMa_a
## t = 4.0297, df = 84.449, p-value = 0.0001217
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## 0.3177873 0.9369377
## sample estimates:
```

```
## mean in group 0 mean in group 1
##      0.1107931      -0.5165693
##
## [1] "wle_hoeren"
##
## Welch Two Sample t-test
##
## data: datenLV[[v]] by datenLV$missing_SSkMa_a
## t = 4.4992, df = 83.294, p-value = 2.193e-05
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.4094216 1.0581596
## sample estimates:
## mean in group 0 mean in group 1
##      0.1294574      -0.6043332

## overall missing for each single variable
round(x = sort(x = colSums(x = is.na(datenLV), na.rm = TRUE), decreasing = TRUE) / nrow(datenLV) * 100,

##      EHisei      Emigr      EHiscd_akt      EDezh      SBezMs_b
##      20.70      18.17      16.14      15.57      6.62
##      SBezMs_c      SBezMs_d      SBezMs_a      SBezMs      tr_NotDe
##      5.76      5.72      5.46      4.83      4.36
##      tr_NotMa      SSkDe_c      SSkDe_d      SSkDe_b      SSkMa_c
##      4.23      4.19      4.09      4.03      4.03
##      SSkMa_b      SSkMa_d      SLesZt      SSkDe      SSkDe_a
##      3.83      3.39      3.23      3.16      3.06
##      SSkMa      SSkMa_a      SBuecher      tr_age      tr_Wdh_r
##      2.83      2.73      2.33      0.23      0.23
##      idsch_FDZ      idstud_FDZ      tr_sex      wle_lesen      wle_hoeren
##      0.00      0.00      0.00      0.00      0.00
##      wle_mathe      schoolEconDis      schoolMiganteil      missing_SSkMa_a
##      0.00      0.00      0.00      0.00
```

Es ist zentral fehlende Daten zu ersetzen bzw. modellbasiert zu schätzen. Die zwei modernsten Ansätze, um fehlende Daten zu ersetzen sind:

- multiple imputation, introductory book: <https://stefvanbuuren.name/fimd/>, Grund, Lüdtke, and Robitzsch (2018)
- full information maximum likelihood (aktuell in Mplus, aber nicht in R implementiert)

outlier analysis

Es wird unterschieden in uni- und multivariate Ausreißer, da *structural equation modelling* / *CFA* multivariate Verfahren sind (mehrere UVs und AVs), ist es notwendig die Daten auf multivariate Ausreißer zu kontrollieren. Dafür eignet sich die **Mahalanobis Distance**:

```
## exemplify Mahalanobis Distance
sigma <- matrix(c(4,1,2,1,5,4,2,4,6), ncol = 3)
cov2cor(sigma)
```

```
##      [,1]      [,2]      [,3]
## [1,] 1.0000000 0.2236068 0.4082483
## [2,] 0.2236068 1.0000000 0.7302967
## [3,] 0.4082483 0.7302967 1.0000000
```

```

means <- c(0, 0, 0)
set.seed(42)
n <- 1000
x <- rmvnorm(n = n, mean = means, sigma = sigma)
d <- data.frame(x)
p4 <- plot_ly(d, x = ~ X1, y = ~ X2, z = ~ X3,
             marker = list(color = ~ X2,
                           showscale = TRUE)) %>%
  add_markers()
p4

```

WebGL is not
 supported by your
 browser - visit
<https://get.webgl.org>
 for more info

```

## identify multivariate outliers
d$mahal <- mahalanobis(d, colMeans(d), cov(d))
d$p_mahal <- pchisq(d$mahal, df=2, lower.tail=FALSE)
d[d$p_mahal < .001, ]

##           X1           X2           X3      mahal      p_mahal
## 274  5.759481 -4.929943 -1.450310 16.41275 0.0002729077
## 330  7.398060  3.344539  4.741212 14.50380 0.0007088271
## 980 -6.295530 -5.365858 -4.367558 14.17879 0.0008339001

datenLV$mahal_SSkMa <- mahalanobis(datenLV[,str_subset(string = colnames(datenLV), pattern = "^SSkMa_")],
datenLV$p_mahal_SSkMa <- pchisq(datenLV$mahal_SSkMa, df=3, lower.tail=FALSE)

## identify multivariate outliers
head(datenLV[datenLV$p_mahal_SSkMa < .001 & !is.na(datenLV$p_mahal_SSkMa), c("SSkMa_a", "SSkMa_b", "SSkMa_c")])

```

```
##      SSkMa_a SSkMa_b SSkMa_c SSkMa_d mahal_SSkMa p_mahal_SSkMa
## 8          1          1          4          1    22.80886 4.426227e-05
## 9          1          3          1          4    29.61531 1.662648e-06
## 15         1          1          4          4    17.85799 4.705288e-04
## 25         4          4          1          4    22.55417 5.001386e-05
## 46         4          1          1          4    28.13860 3.396688e-06
## 58         2          4          1          1    17.17129 6.516648e-04
```

```
sum(datenLV$p_mahal_SSkMa < .001, na.rm = TRUE)
```

```
## [1] 112
```

```
datenLV$intravariability_SSkMa <- apply(datenLV[,str_subset(string = colnames(datenLV), pattern = "~SSkMa_"),
## identify insufficient item responding using variability of answering patterns
head(datenLV[datenLV$intravariability_SSkMa == 0 & !is.na(datenLV$intravariability_SSkMa), c("SSkMa_a"
```

```
##      SSkMa_a SSkMa_b SSkMa_c SSkMa_d mahal_SSkMa p_mahal_SSkMa
## 4          4          4          4          4    1.3060837 0.727689
## 5          3          3          3          3    0.2810342 0.963555
## 6          4          4          4          4    1.3060837 0.727689
## 7          4          4          4          4    1.3060837 0.727689
## 11         4          4          4          4    1.3060837 0.727689
## 13         3          3          3          3    0.2810342 0.963555
```

```
sum(datenLV$intravariability_SSkMa == 0, na.rm = TRUE)
```

```
## [1] 1049
```

[simulation study: standardized residuals, reliability]

Using the R-Package `simstudy` it is possible to generate all kinds of data:

I have generated a data set with 3 items (y1-y3) and a data set with 7 items (m1-m7) for different sample sizes. The variables `latentvar` and `errorvar` are unknown and for example important in the context of classical test theory as these correspond to the true and error variance):

```
##      varname      formula      variance      dist      link
## 1: latentvar      20          0.5 normal identity
## 2: errorvar       4          0.5 normal identity
## 3:      y1 latentvar errorvar / 4 normal identity
## 4:      y2 latentvar errorvar / 4 normal identity
## 5:      y3 latentvar errorvar / 4 normal identity
## 6:      m1 latentvar errorvar / 4 normal identity
## 7:      m2 latentvar errorvar / 4 normal identity
## 8:      m3 latentvar errorvar / 4 normal identity
## 9:      m4 latentvar errorvar / 4 normal identity
## 10:     m5 latentvar errorvar / 4 normal identity
## 11:     m6 latentvar errorvar / 4 normal identity
## 12:     m7 latentvar errorvar / 4 normal identity
```

```
set.seed(111)
```

```
dt_50 <- genData(50, def); dt_50 <- as.data.frame(dt_50)
dt_200 <- genData(200, def); dt_200 <- as.data.frame(dt_200)
dt_500 <- genData(500, def); dt_500 <- as.data.frame(dt_500)
dt_100000 <- genData(100000, def); dt_100000 <- as.data.frame(dt_100000)
```

```
round(x = cor(dt_50[, str_subset(string = colnames(dt_50), pattern = "m")]), digits = 2)
```

```
##      m1  m2  m3  m4  m5  m6  m7
## m1 1.00 0.45 0.39 0.34 0.35 0.43 0.24
## m2 0.45 1.00 0.52 0.34 0.56 0.40 0.49
## m3 0.39 0.52 1.00 0.25 0.44 0.39 0.57
## m4 0.34 0.34 0.25 1.00 0.19 0.30 0.35
## m5 0.35 0.56 0.44 0.19 1.00 0.20 0.37
## m6 0.43 0.40 0.39 0.30 0.20 1.00 0.49
## m7 0.24 0.49 0.57 0.35 0.37 0.49 1.00
```

```
round(x = cor(dt_100000[, str_subset(string = colnames(dt_100000), pattern = "m")]), digits = 2)
```

```
##      m1  m2  m3  m4  m5  m6  m7
## m1 1.00 0.34 0.33 0.34 0.33 0.33 0.34
## m2 0.34 1.00 0.33 0.34 0.34 0.34 0.34
## m3 0.33 0.33 1.00 0.33 0.33 0.33 0.34
## m4 0.34 0.34 0.33 1.00 0.33 0.34 0.34
## m5 0.33 0.34 0.33 0.33 1.00 0.33 0.33
## m6 0.33 0.34 0.33 0.34 0.33 1.00 0.34
## m7 0.34 0.34 0.34 0.34 0.33 0.34 1.00
```

```
round(x = cor(dt_50[, str_subset(string = colnames(dt_50), pattern = "m")]), digits = 2) - round(x = cor(dt_100000[, str_subset(string = colnames(dt_100000), pattern = "m")]), digits = 2)
```

```
##      m1  m2  m3  m4  m5  m6  m7
## m1 0.00 0.11 0.06 0.00 0.02 0.10 -0.10
## m2 0.11 0.00 0.19 0.00 0.22 0.06 0.15
## m3 0.06 0.19 0.00 -0.08 0.11 0.06 0.23
## m4 0.00 0.00 -0.08 0.00 -0.14 -0.04 0.01
## m5 0.02 0.22 0.11 -0.14 0.00 -0.13 0.04
## m6 0.10 0.06 0.06 -0.04 -0.13 0.00 0.15
## m7 -0.10 0.15 0.23 0.01 0.04 0.15 0.00
```

```
sd(dt_50$m1) / sqrt(x = length(dt_50$m1))
```

```
## [1] 0.18367
```

```
sd(dt_100000$m1) / sqrt(x = length(dt_100000$m1))
```

```
## [1] 0.003876399
```

```
psych::alpha(cor(dt_50[, str_subset(string = colnames(dt_50), pattern = "m")]))$total
```

```
## raw_alpha std.alpha G6(smc) average_r S/N median_r
## 0.8132445 0.8132445 0.8146988 0.3835094 4.354593 0.3878958
```

```
psych::alpha(cor(dt_200[, str_subset(string = colnames(dt_200), pattern = "m")]))$total
```

```
## raw_alpha std.alpha G6(smc) average_r S/N median_r
## 0.7631399 0.7631399 0.7410928 0.3151959 3.221902 0.3114825
```

```
psych::alpha(cor(dt_100000[, str_subset(string = colnames(dt_100000), pattern = "m")]))$total
```

```
## raw_alpha std.alpha G6(smc) average_r S/N median_r
## 0.7781921 0.7781921 0.7504623 0.3338666 3.508406 0.3353357
```

```
psych::alpha(cor(dt_50[, str_subset(string = colnames(dt_50), pattern = "y")]))$total
```

```
## raw_alpha std.alpha G6(smc) average_r S/N median_r
## 0.6202657 0.6202657 0.5319161 0.3525301 1.63342 0.3163457
```

```

psych::alpha(cor(dt_200[, str_subset(string = colnames(dt_200), pattern = "y")]))$total

## raw_alpha std.alpha G6(smc) average_r S/N median_r
## 0.5365776 0.5365776 0.4427281 0.2784747 1.157858 0.3205137
psych::alpha(cor(dt_100000[, str_subset(string = colnames(dt_100000), pattern = "y")]))$total

## raw_alpha std.alpha G6(smc) average_r S/N median_r
## 0.5972012 0.5972012 0.4971001 0.3307499 1.482629 0.3324383
psych::omega(m = dt_100000[, str_subset(string = colnames(dt_100000), pattern = "y")], nfactors = 1, plot = FALSE)

## Loading required namespace: GPArotation
## Omega_h for 1 factor is not meaningful, just omega_t
## Warning in schmid(m, nfactors, fm, digits, rotate = rotate, n.obs = n.obs, :
## Omega_h and Omega_asymptotic are not meaningful with one factor
## Warning in cov2cor(t(w) %*% r %*% w): diag(.) had 0 or NA entries; non-finite
## result is doubtful
## Omega
## Call: omegah(m = m, nfactors = nfactors, fm = fm, key = key, flip = flip,
## digits = digits, title = title, sl = sl, labels = labels,
## plot = plot, n.obs = n.obs, rotate = rotate, Phi = Phi, option = option,
## covar = covar)
## Alpha: 0.6
## G.6: 0.5
## Omega Hierarchical: 0.6
## Omega H asymptotic: 1
## Omega Total 0.6
##
## Schmid Leiman Factor loadings greater than 0.2
## g F1* h2 u2 p2
## y1 0.58 0.34 0.66 1
## y2 0.57 0.33 0.67 1
## y3 0.57 0.33 0.67 1
##
## With eigenvalues of:
## g F1*
## 0.99 0.00
##
## general/max Inf max/min = NaN
## mean percent general = 1 with sd = 0 and cv of 0
## Explained Common Variance of the general factor = 1
##
## The degrees of freedom are 0 and the fit is 0
## The number of observations was 100000 with Chi Square = 0 with prob < NA
## The root mean square of the residuals is 0
## The df corrected root mean square of the residuals is NA
##
## Compare this with the adequacy of just a general factor and no group factors
## The degrees of freedom for just the general factor are 0 and the fit is 0
## The number of observations was 100000 with Chi Square = 0 with prob < NA
## The root mean square of the residuals is 0
## The df corrected root mean square of the residuals is NA

```

```
##
## Measures of factor score adequacy
##
## Correlation of scores with factors      g F1*      0.77  0
## Multiple R square of scores with factors      0.60  0
## Minimum correlation of factor score estimates 0.19 -1
##
## Total, General and Subset omega for each subset
##
## Omega total for total scores and subscales      g F1*      0.6 0.6
## Omega general for total scores and subscales      0.6 0.6
## Omega group for total scores and subscales      0.0 0.0
```

Zusammenfassung:

- die Kovarianzmatrix der Population ist unbekannt und wird durch unsere Daten geschätzt (wenn N gegen unendlich geht, können wir unseren Parameterschätzungen vertrauen -> Konzept des Standardfehlers des Mittelwerts)
- Reliabilität ist abhängig von der Anzahl der Items: unter Zunahme der Anzahl der Items bei gleicher mittlerer Interkorrelation steigt die Reliabilität
- Cronbachs Alpha sollte nur unter Bedingung eines tau-äquivalenten Messmodells und vorheriger Testung auf Eindimensionalität verwendet werden (Sijtsma (2009)), sonst empfiehlt sich immer modell-basierte Reliabilitätsschätzer wie McDonald's Omega

developing a questionnaire scale

descriptive analysis using classical test theory

orientiert sich an Buchkapitel 7, 13 in Moosbrugger and Kelava (2020)

$y_i = \tau_i + \epsilon_i$, aus der Messfehlertheorie folgt die Definition der Reliabilität: $Rel(Y) = \frac{Var(T)}{Var(T) + Var(E)}$

$$E(y_i) = E(\tau_i) + E(\epsilon_i)$$

$$E(y_i) = E(\tau_i) + 0$$

über mehrere Items einer Skala lässt sich ein Punktschätzer für den wahren Wert τ_i wie folgt berechnen als Summenscore: $Y = \sum_{i=1}^p y_i$ oder besser interpretierbar als Personmittelwertmittelwert: $\bar{Y} = \frac{\sum_{i=1}^p y_i}{n}$!
vorläufige Testwertermittlung (*Eindimensionalität, tau-äquivalenten Messmodells muss an sich gegeben sein*)

Schwierigkeitsindex

$$P_i = \frac{\sum_{v=1}^n y_{vi}}{n * max(y_i)} * 100$$

folgende Zahlen geben die Leichtigkeit des Items an:

```
datenLV[,str_subset(string = colnames(datenLV), pattern = "^SBezMs_")] <- datenLV[,str_subset(string = colnames(datenLV), pattern = "^SBezMs_")]
datenLV$failitem <- rbinom(n = nrow(datenLV), size = 3, prob = .95)
head(datenLV[, c(str_subset(string = colnames(datenLV), pattern = "^SBezMs_"), "failitem")])
```

```
##   SBezMs_a SBezMs_b SBezMs_c SBezMs_d failitem
## 1      3      2      3      3      2
## 2      2      2      3      3      3
## 3      3      0      3      2      3
## 4      0      3      0      0      3
## 5      3      2      0      0      3
## 6      3      3      3      3      3
```



```

sum(datenLV$SBezMs_a, na.rm = TRUE) / (sum(!is.na(datenLV$SBezMs_a)) * max(datenLV$SBezMs_a, na.rm = TRUE))
## [1] 78.82201
sum(datenLV$SBezMs_b, na.rm = TRUE) / (sum(!is.na(datenLV$SBezMs_b)) * max(datenLV$SBezMs_b, na.rm = TRUE))
## [1] 70.34925
sum(datenLV$SBezMs_c, na.rm = TRUE) / (sum(!is.na(datenLV$SBezMs_c)) * max(datenLV$SBezMs_c, na.rm = TRUE))
## [1] 78.88418
sum(datenLV$SBezMs_d, na.rm = TRUE) / (sum(!is.na(datenLV$SBezMs_d)) * max(datenLV$SBezMs_d, na.rm = TRUE))
## [1] 83.55101
sum(datenLV$failitem, na.rm = TRUE) / (sum(!is.na(datenLV$failitem)) * max(datenLV$failitem, na.rm = TRUE))
## [1] 95.50749
datenLV[,str_subset(string = colnames(datenLV), pattern = "SBezMs_")] <- datenLV[,str_subset(string = "SBezMs_", pattern = "SBezMs_")]

```

Itemvarianz

$$Var(y_i) = \frac{\sum_{v=1}^n (y_{vi} - \bar{y}_i)^2}{n}$$

```

sum((datenLV$SBezMs_a - mean(datenLV$SBezMs_a, na.rm = TRUE))^2, na.rm = TRUE) / sum(!is.na(datenLV$SBezMs_a))
## [1] 0.5393213
sum((datenLV$SBezMs_b - mean(datenLV$SBezMs_b, na.rm = TRUE))^2, na.rm = TRUE) / sum(!is.na(datenLV$SBezMs_b))
## [1] 0.8131689
sum((datenLV$SBezMs_c - mean(datenLV$SBezMs_c, na.rm = TRUE))^2, na.rm = TRUE) / sum(!is.na(datenLV$SBezMs_c))
## [1] 0.8543597
sum((datenLV$SBezMs_d - mean(datenLV$SBezMs_d, na.rm = TRUE))^2, na.rm = TRUE) / sum(!is.na(datenLV$SBezMs_d))
## [1] 0.6580054
sum((datenLV$failitem - mean(datenLV$failitem, na.rm = TRUE))^2, na.rm = TRUE) / sum(!is.na(datenLV$failitem))
## [1] 0.1325844

```

Trennschärfe

part-whole korrigierte Trennschärfe $r_{it(i)}$: $r_{it(i)} = r_{(y_i, y(i))}$

```

cor(datenLV$SBezMs_a, rowSums(datenLV[, c("SBezMs_b", "SBezMs_c", "SBezMs_d")], na.rm = TRUE), use = "c")
## [1] 0.5407678
cor(datenLV$SBezMs_b, rowSums(datenLV[, c("SBezMs_a", "SBezMs_c", "SBezMs_d")], na.rm = TRUE), use = "c")
## [1] 0.4083451
cor(datenLV$SBezMs_c, rowSums(datenLV[, c("SBezMs_a", "SBezMs_b", "SBezMs_d")], na.rm = TRUE), use = "c")
## [1] 0.4591703
cor(datenLV$SBezMs_d, rowSums(datenLV[, c("SBezMs_a", "SBezMs_b", "SBezMs_c")], na.rm = TRUE), use = "c")

```

```
## [1] 0.3990633
```

```
cor(datenLV$failitem, rowSums(datenLV[, c("SBezMs_a", "SBezMs_b", "SBezMs_c", "SBezMs_d")], na.rm = TRUE))
```

```
## [1] 0.006453734
```

Testwertverteilung

orientiert sich an Buchkapitel 8 in Moosbrugger and Kelava (2020)

```
## liegt bereits in Daten vor
```

```
cor(rowMeans(x = datenLV[, str_subset(string = colnames(datenLV), pattern = "^SBezMs_")]), datenLV$SBezMs)
```

```
## [1] 1
```

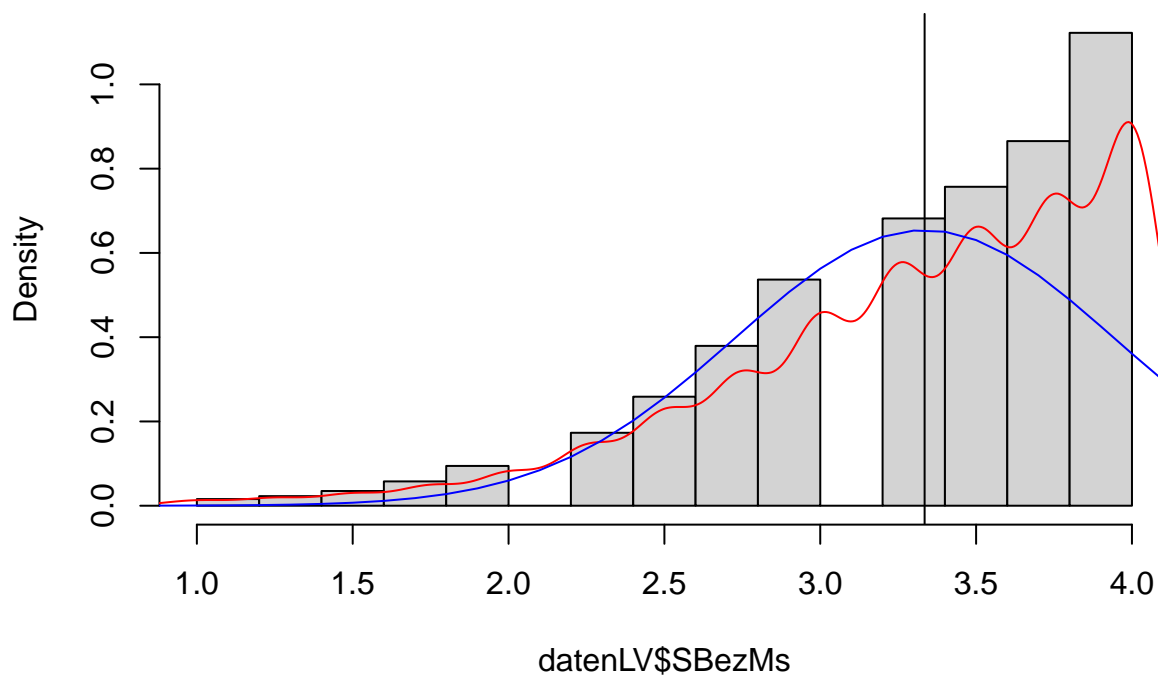
```
hist(datenLV$SBezMs, freq = FALSE)
```

```
abline(v = mean(datenLV$SBezMs, na.rm = TRUE))
```

```
lines(density(datenLV$SBezMs[!is.na(datenLV$SBezMs)]), col="red") # empirical density
```

```
lines(seq(0, 5, by=.1), dnorm(seq(0, 5, by=.1),  
    mean(datenLV$SBezMs, na.rm = TRUE), sd(datenLV$SBezMs, na.rm = TRUE)), col="blue") # normal density
```

Histogram of datenLV\$SBezMs



```
sd(x = datenLV$SBezMs, na.rm = TRUE)
```

```
## [1] 0.6099304
```

```
moments::skewness(x = datenLV$SBezMs, na.rm = TRUE)
```

```
## [1] -1.013992
```

```
moments::kurtosis(x = datenLV$SBezMs, na.rm = TRUE) - 3 # = SPSS output
```

```
## [1] 0.7847189
```

```
shapiro.test(x = datenLV$SBezMs)
```

```
##
```

```
## Shapiro-Wilk normality test
```

```
##
```

```
## data: datenLV$SBezMs
```

```
## W = 0.89501, p-value < 2.2e-16
```

für ein normorientierten Vergleich bietet sich eine z-Standardisierung $\frac{Y_v - \bar{Y}}{SD(Y)}$ an:

```
datenLV$Zstand_SBezMs <- scale(x = datenLV$SBezMs, center = TRUE, scale = TRUE)
```

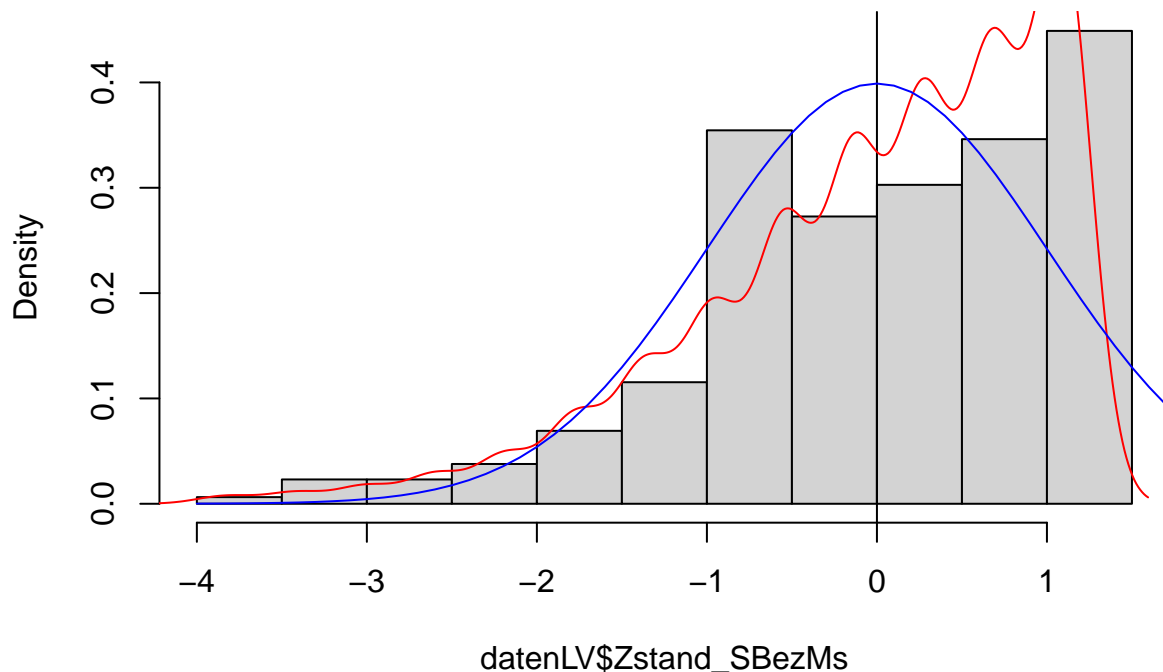
```
hist(datenLV$Zstand_SBezMs, freq = FALSE)
```

```
abline(v = mean(datenLV$Zstand_SBezMs, na.rm = TRUE))
```

```
lines(density(datenLV$Zstand_SBezMs[!is.na(datenLV$Zstand_SBezMs)]), col="red")
```

```
lines(seq(-4, 4, by=.1), dnorm(seq(-4, 4, by=.1),  
    mean(datenLV$Zstand_SBezMs, na.rm = TRUE), sd(datenLV$Zstand_SBezMs, na.rm = TRUE)), col="blue")
```

Histogram of datenLV\$Zstand_SBezMs



exploratory factor analysis

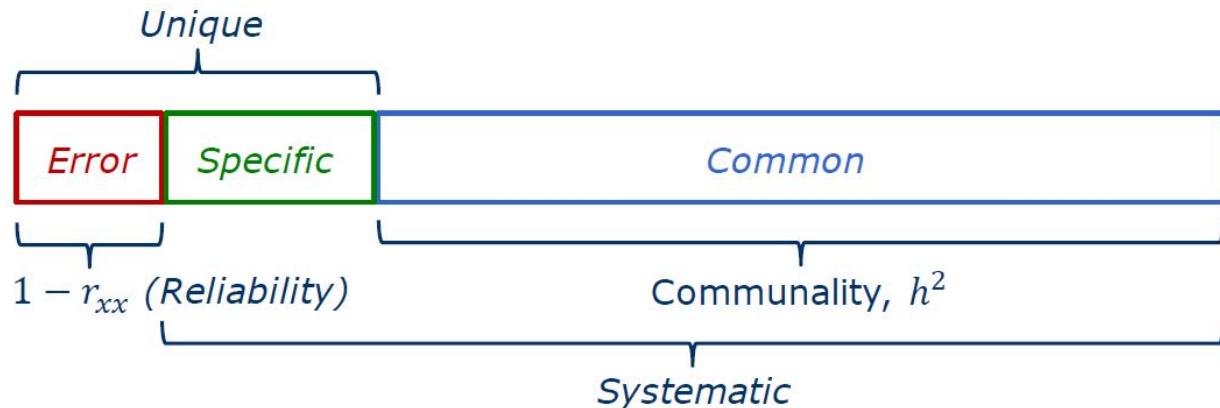
induktive Methode

an sich gehört zur KTT Testung auf Messinvarianz über die klassischen Testmodelle, jedoch muss für diese Eindimensionalität gegeben sein, hierfür eignet sich eine sogenannte EFA

Verwendung des **psych** Paketes in R (siehe <http://personality-project.org/r/psych/HowTo/factor.pdf>), Alternativ eignet sich auch das Statistikprogramm JASP für EFA / CFA: (<https://jasp-stats.org/>)

einführende Artikel in EFA: Costello and Osborne (2005), Mvududu and Sink (2013) (Anmerkung: es gibt Mischformen zwischen EFA und CFA, wie beispielsweise ESEM: Marsh et al. (2014))

! wichtig es sollte keine principal component analysis gerechnet werden (Relikt der Vergangenheit, Grundprinzipien mit EFA gleich), da hier keine **Varianzzerlegung** stattfindet.



Ziele der explorativen Faktorenanalyse sind

- die Reduktion der Dimension der Kovarianz- bzw. Korrelationsmatrix
- die Identifizierung von latenten Variablen (z.B. über die Hauptachsenanalyse (Principal Axes Analyses)) und
- die Ausdifferenzierung eines komplexen Merkmalsbereichs in homogene Teilbereiche, d.h. die Variablen werden so gruppiert, dass sie innerhalb der Gruppe möglichst hoch korreliert sind (homogen) und die Gruppen der Variablen zueinander möglichst heterogen sind. Hier wird das gleiche Ziel wie mit einer Clusteranalyse (Latente Klassenanalyse) verfolgt

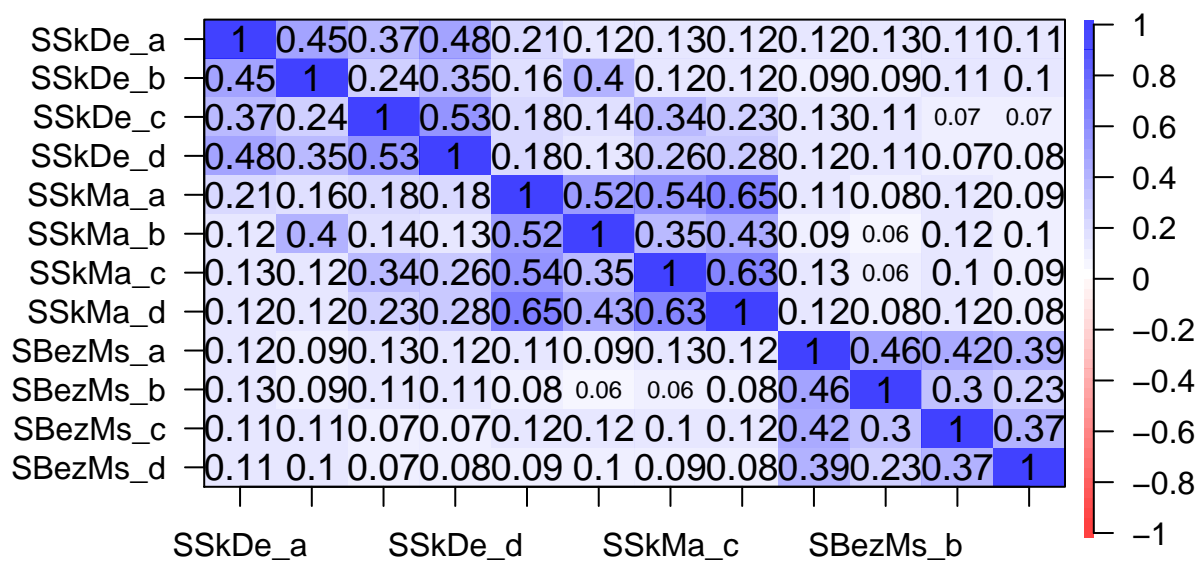
EFA läuft in vier Schritten ab:

1. vorbetrachtende Tests
2. die Wahl der Extraktionsmethode
3. die Wahl eines Abbruchkriteriums und zuletzt
4. die Wahl der Rotationsmethode

zur eigenen Interpretation der Ergebnisse siehe Blog von Michael Clark: <https://m-clark.github.io/posts/2020-04-10-psych-explained/>

```
psych::corPlot(r = datenLV[,str_subset(string = colnames(datenLV), pattern = "^SSkMa_|^SSkDe_|^SBezMs_")]
```

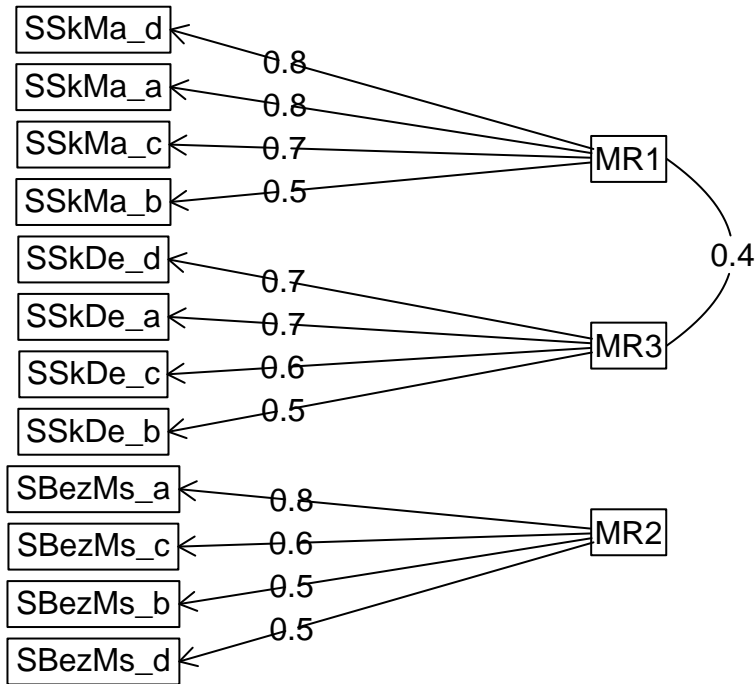
Correlation plot



not accounting for the non-normal / skewed data

```
efa1 = fa(r = datenLV[,str_subset(string = colnames(datenLV), pattern = "^SSkMa_|^SSkDe_|^SBezMs_")], n = 10)
fa.diagram(efa1)
```

Factor Analysis



efal

```

## Factor Analysis using method = minres
## Call: fa(r = datenLV[, str_subset(string = colnames(datenLV), pattern = "^SSkMa_|^SSkDe_|^SBezMs_")]
##       nfactors = 3, rotate = "oblimin")
## Standardized loadings (pattern matrix) based upon correlation matrix
##           MR1   MR3   MR2   h2   u2 com
## SSkDe_a -0.07  0.70  0.04 0.47 0.53  1
## SSkDe_b  0.04  0.51  0.03 0.28 0.72  1
## SSkDe_c  0.09  0.57 -0.01 0.37 0.63  1
## SSkDe_d  0.02  0.75 -0.03 0.56 0.44  1
## SSkMa_a  0.80 -0.02  0.01 0.63 0.37  1
## SSkMa_b  0.53  0.07  0.03 0.32 0.68  1
## SSkMa_c  0.69  0.06  0.00 0.51 0.49  1
## SSkMa_d  0.84 -0.03 -0.01 0.70 0.30  1
## SBezMs_a  0.00 -0.01  0.76 0.57 0.43  1
## SBezMs_b -0.04  0.05  0.53 0.29 0.71  1
## SBezMs_c  0.04 -0.02  0.59 0.35 0.65  1
## SBezMs_d  0.01  0.00  0.53 0.28 0.72  1
##
##           MR1   MR3   MR2
## SS loadings      2.16 1.68 1.50
## Proportion Var    0.18 0.14 0.13
## Cumulative Var    0.18 0.32 0.44
## Proportion Explained 0.40 0.31 0.28
## Cumulative Proportion 0.40 0.72 1.00
##

```

```

## With factor correlations of
##      MR1  MR3  MR2
## MR1 1.00 0.36 0.20
## MR3 0.36 1.00 0.24
## MR2 0.20 0.24 1.00
##
## Mean item complexity = 1
## Test of the hypothesis that 3 factors are sufficient.
##
## The degrees of freedom for the null model are 66 and the objective function was 3.47 with Chi Squ
## The degrees of freedom for the model are 33 and the objective function was 0.43
##
## The root mean square of the residuals (RMSR) is 0.05
## The df corrected root mean square of the residuals is 0.07
##
## The harmonic number of observations is 2811 with the empirical chi square 868.15 with prob < 4.6
## The total number of observations was 3005 with Likelihood Chi Square = 1288.18 with prob < 1.3e
##
## Tucker Lewis Index of factoring reliability = 0.757
## RMSEA index = 0.113 and the 90 % confidence intervals are 0.107 0.118
## BIC = 1023.92
## Fit based upon off diagonal values = 0.97
## Measures of factor score adequacy
##
##                                     MR1  MR3  MR2
## Correlation of (regression) scores with factors 0.92 0.88 0.86
## Multiple R square of scores with factors        0.85 0.77 0.73
## Minimum correlation of possible factor scores    0.70 0.53 0.47

### accounting partly for the non-normal / skewed data using choric correlations (limited information a
efa2choric <- fa(r = datenLV[,str_subset(string = colnames(datenLV), pattern = "^SSkMa_|^SSkDe_|^SBezMs_")
efa2choric

## Factor Analysis using method = wls
## Call: fa(r = datenLV[, str_subset(string = colnames(datenLV), pattern = "^SSkMa_|^SSkDe_|^SBezMs_")
##      nfactors = 3, rotate = "oblimin", scores = "Bartlett", max.iter = 500,
##      fm = "wls", cor = "poly")
## Standardized loadings (pattern matrix) based upon correlation matrix
##
##      WLS1  WLS3  WLS2  h2  u2 com
## SSkDe_a -0.09  0.76  0.04 0.55 0.45 1.0
## SSkDe_b  0.04  0.57  0.03 0.36 0.64 1.0
## SSkDe_c  0.10  0.66 -0.01 0.49 0.51 1.1
## SSkDe_d  0.03  0.82 -0.03 0.67 0.33 1.0
## SSkMa_a  0.86 -0.03  0.01 0.72 0.28 1.0
## SSkMa_b  0.62  0.06  0.02 0.43 0.57 1.0
## SSkMa_c  0.77  0.07  0.00 0.64 0.36 1.0
## SSkMa_d  0.90 -0.02  0.00 0.80 0.20 1.0
## SBezMs_a  0.00 -0.01  0.83 0.68 0.32 1.0
## SBezMs_b -0.05  0.05  0.59 0.36 0.64 1.0
## SBezMs_c  0.04 -0.02  0.69 0.48 0.52 1.0
## SBezMs_d  0.00  0.01  0.63 0.40 0.60 1.0
##
##
##      WLS1  WLS3  WLS2
## SS loadings      2.60 2.06 1.92
## Proportion Var    0.22 0.17 0.16
## Cumulative Var     0.22 0.39 0.55

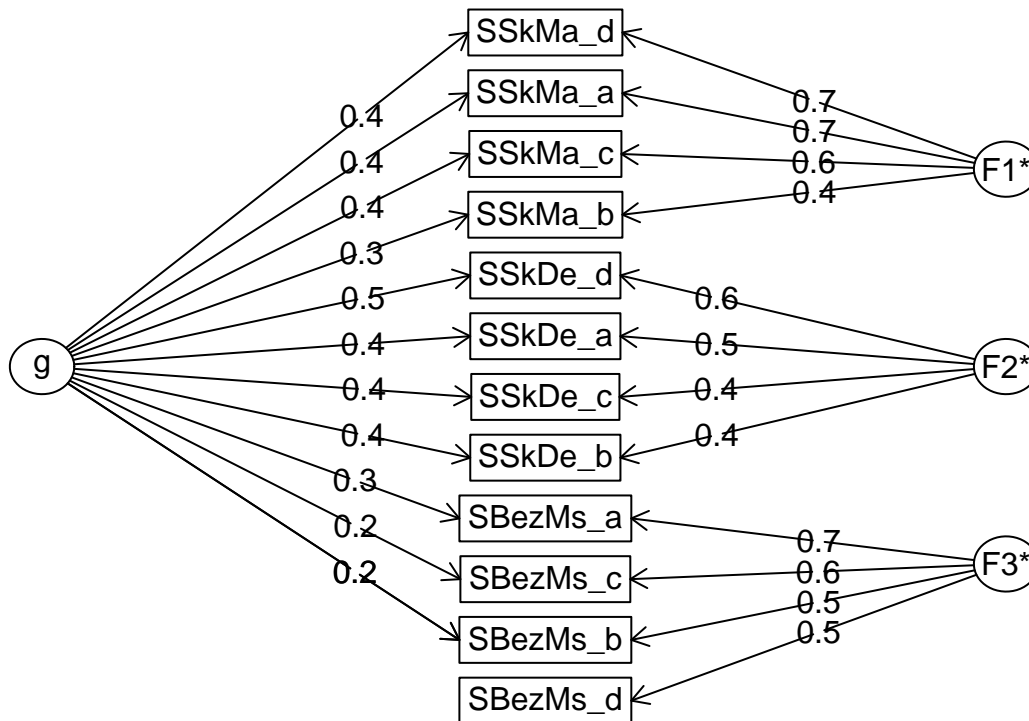
```

```

## Proportion Explained  0.39 0.31 0.29
## Cumulative Proportion 0.39 0.71 1.00
##
## With factor correlations of
##      WLS1 WLS3 WLS2
## WLS1 1.00 0.41 0.23
## WLS3 0.41 1.00 0.27
## WLS2 0.23 0.27 1.00
##
## Mean item complexity = 1
## Test of the hypothesis that 3 factors are sufficient.
##
## The degrees of freedom for the null model are 66 and the objective function was 5.63 with Chi Square = 5.63
## The degrees of freedom for the model are 33 and the objective function was 0.89
##
## The root mean square of the residuals (RMSR) is 0.06
## The df corrected root mean square of the residuals is 0.08
##
## The harmonic number of observations is 2811 with the empirical chi square 1148.38 with prob < 5e-16
## The total number of observations was 3005 with Likelihood Chi Square = 2678.78 with prob < 0
##
## Tucker Lewis Index of factoring reliability = 0.685
## RMSEA index = 0.163 and the 90 % confidence intervals are 0.158 0.169
## BIC = 2414.51
## Fit based upon off diagonal values = 0.97
## Measures of factor score adequacy
##
## Correlation of (regression) scores with factors      WLS1 WLS3 WLS2
## Multiple R square of scores with factors             0.95 0.91 0.90
## Minimum correlation of possible factor scores        0.91 0.84 0.81
## Minimum correlation of possible factor scores        0.81 0.67 0.62
##
### model based reliability score
omega(datenLV[,str_subset(string = colnames(datenLV), pattern = "^SSkMa_|^SSkDe_|^SBezMs_")])

```


Omega



```
## Omega
## Call: omegah(m = m, nfactors = nfactors, fm = fm, key = key, flip = flip,
##   digits = digits, title = title, sl = sl, labels = labels,
##   plot = plot, n.obs = n.obs, rotate = rotate, Phi = Phi, option = option,
##   covar = covar)
## Alpha:          0.76
## G.6:            0.81
## Omega Hierarchical: 0.45
## Omega H asymptotic: 0.54
## Omega Total      0.83
##
## Schmid Leiman Factor loadings greater than 0.2
##      g    F1*   F2*   F3*   h2   u2   p2
## SSkDe_a 0.43      0.53      0.47 0.53 0.40
## SSkDe_b 0.37      0.38      0.28 0.72 0.48
## SSkDe_c 0.42      0.43      0.37 0.63 0.48
## SSkDe_d 0.49      0.56      0.56 0.44 0.43
## SSkMa_a 0.43 0.67      0.63 0.37 0.29
## SSkMa_b 0.35 0.44      0.32 0.68 0.38
## SSkMa_c 0.42 0.57      0.51 0.49 0.35
## SSkMa_d 0.45 0.70      0.70 0.30 0.28
## SBezMs_a 0.27      0.71 0.57 0.43 0.13
## SBezMs_b 0.20      0.50 0.29 0.71 0.14
## SBezMs_c 0.22      0.55 0.35 0.65 0.14
## SBezMs_d 0.20      0.49 0.28 0.72 0.14
##
```

```

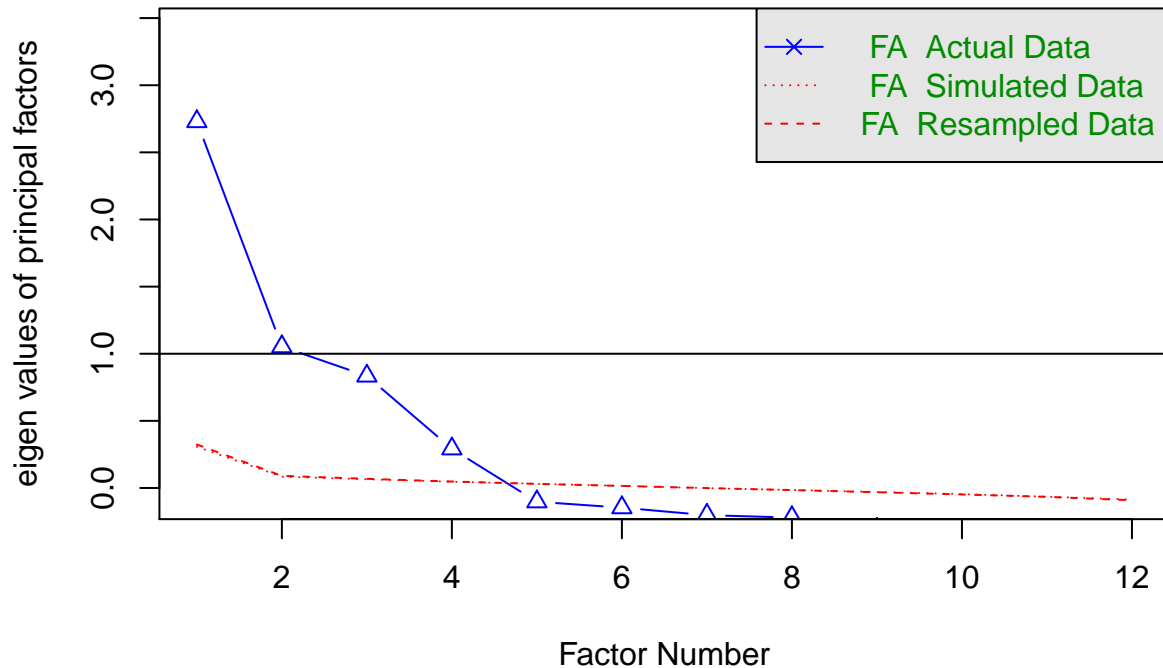
## With eigenvalues of:
##   g  F1*  F2*  F3*
## 1.63 1.48 0.93 1.30
##
## general/max 1.1  max/min = 1.59
## mean percent general = 0.3  with sd = 0.14 and cv of 0.45
## Explained Common Variance of the general factor = 0.31
##
## The degrees of freedom are 33  and the fit is 0.43
## The number of observations was 3005  with Chi Square = 1288.18  with prob < 1.3e-249
## The root mean square of the residuals is 0.05
## The df corrected root mean square of the residuals is 0.07
## RMSEA index = 0.113  and the 10 % confidence intervals are 0.107 0.118
## BIC = 1023.92
##
## Compare this with the adequacy of just a general factor and no group factors
## The degrees of freedom for just the general factor are 54  and the fit is 2.02
## The number of observations was 3005  with Chi Square = 6062.27  with prob < 0
## The root mean square of the residuals is 0.17
## The df corrected root mean square of the residuals is 0.19
##
## RMSEA index = 0.192  and the 10 % confidence intervals are 0.188 0.197
## BIC = 5629.84
##
## Measures of factor score adequacy
##
##           g  F1*  F2*  F3*
## Correlation of scores with factors      0.70 0.81 0.69 0.81
## Multiple R square of scores with factors 0.49 0.65 0.48 0.66
## Minimum correlation of factor score estimates -0.03 0.30 -0.05 0.32
##
## Total, General and Subset omega for each subset
##
##           g  F1*  F2*  F3*
## Omega total for total scores and subscales 0.83 0.82 0.74 0.70
## Omega general for total scores and subscales 0.45 0.26 0.33 0.10
## Omega group for total scores and subscales 0.36 0.56 0.41 0.61

```

Wenn die Anzahl der zu bestimmenden Faktoren unklar ist bietet sich die Verwendung von Scree plots an:

```
efa3 <- fa.parallel(x = datenLV[,str_subset(string = colnames(datenLV), pattern = "^SSkMa_|^SSkDe_|^SBe
```

Parallel Analysis Scree Plots



```
## Parallel analysis suggests that the number of factors = 4 and the number of components = NA
efa3
```

```
## Call: fa.parallel(x = datenLV[, str_subset(string = colnames(datenLV),
##   pattern = "^SSkMa_|^SSkDe_|^SBezMs_")], fa = "fa", n.iter = 50)
## Parallel analysis suggests that the number of factors = 4 and the number of components = NA
##
## Eigen Values of
##
## eigen values of factors
## [1] 2.73 1.05 0.83 0.29 -0.10 -0.15 -0.20 -0.22 -0.31 -0.36 -0.42 -0.42
##
## eigen values of simulated factors
## [1] 0.31 0.08 0.06 0.05 0.03 0.02 0.00 -0.01 -0.03 -0.05 -0.06 -0.09
##
## eigen values of components
## [1] 3.43 1.89 1.60 1.04 0.78 0.62 0.61 0.49 0.47 0.45 0.33 0.28
##
## eigen values of simulated components
## [1] NA
```

classical test models / measurement invariance

Im Folgenden wollen wir die Items zu dem Matheselbstkonzept genauer analysieren - ohne die Testung von tau-äquivalentem Modell, sowie Eindimensionalität berechnen wir vorläufig nur McDonald's Omega:

```

psych::omega(datenLV[,str_subset(string = colnames(datenLV), pattern = "^SSkMa_")], nfactors = 1)

## Omega_h for 1 factor is not meaningful, just omega_t

## Warning in schmid(m, nfactors, fm, digits, rotate = rotate, n.obs = n.obs, :
## Omega_h and Omega_asymptotic are not meaningful with one factor

## Omega
## Call: omegah(m = m, nfactors = nfactors, fm = fm, key = key, flip = flip,
##   digits = digits, title = title, sl = sl, labels = labels,
##   plot = plot, n.obs = n.obs, rotate = rotate, Phi = Phi, option = option,
##   covar = covar)
## Alpha:                0.81
## G.6:                  0.78
## Omega Hierarchical:    0.82
## Omega H asymptotic:    1
## Omega Total            0.82
##
## Schmid Leiman Factor loadings greater than 0.2
##      g  F1*   h2   u2 p2
## SSkMa_a 0.81    0.65 0.35 1
## SSkMa_b 0.56    0.31 0.69 1
## SSkMa_c 0.70    0.49 0.51 1
## SSkMa_d 0.83    0.69 0.31 1
##
## With eigenvalues of:
##      g  F1*
## 2.1 0.0
##
## general/max 3.862933e+16 max/min = 1
## mean percent general = 1 with sd = 0 and cv of 0
## Explained Common Variance of the general factor = 1
##
## The degrees of freedom are 2 and the fit is 0.05
## The number of observations was 3005 with Chi Square = 143.45 with prob < 7.1e-32
## The root mean square of the residuals is 0.04
## The df corrected root mean square of the residuals is 0.07
## RMSEA index = 0.153 and the 10 % confidence intervals are 0.133 0.175
## BIC = 127.43
##
## Compare this with the adequacy of just a general factor and no group factors
## The degrees of freedom for just the general factor are 2 and the fit is 0.05
## The number of observations was 3005 with Chi Square = 143.45 with prob < 7.1e-32
## The root mean square of the residuals is 0.04
## The df corrected root mean square of the residuals is 0.07
##
## RMSEA index = 0.153 and the 10 % confidence intervals are 0.133 0.175
## BIC = 127.43
##
## Measures of factor score adequacy
##
##      g  F1*
## Correlation of scores with factors    0.92  0
## Multiple R square of scores with factors    0.85  0
## Minimum correlation of factor score estimates 0.69 -1
##

```

```
## Total, General and Subset omega for each subset
##
##              g    F1*
## Omega total for total scores and subscales    0.82 0.82
## Omega general for total scores and subscales  0.82 0.82
## Omega group for total scores and subscales    0.00 0.00
```

Um auf Messinvarianz zu testen, müssen wir das Messmodell über eine sogenannte Modellsyntax eingeben, um darauf folgend das R Paket lavaan verwenden zu können:

Achtung: CFAs werden geschätzt mittels maximum likelihood (ML), weiter unten in Abschnitt CFA / SEM für die Daten besser geeignete Schätzmethode (jedoch ist ML hier zielführend da hiermit über den likelihood ratio test ein Modellvergleich gerechnet werden kann):

classical test models (Voraussetzung Reliabilitätsanalysen, Sparsamkeit des Modells; gleiches Prinzip wie Messinvarianz weiter unten)

```
cong.model <- '
SSmath =~ lam1*SSkMa_a + lam2*SSkMa_b + lam3*SSkMa_c + lam4*SSkMa_d

SSkMa_a ~~ var1*SSkMa_a
SSkMa_b ~~ var2*SSkMa_b
SSkMa_c ~~ var3*SSkMa_c
SSkMa_d ~~ var4*SSkMa_d

SSkMa_a ~ mean1*1
SSkMa_b ~ mean2*1
SSkMa_c ~ mean3*1
SSkMa_d ~ mean4*1
'

# identification: Fixed factor
cong.fit <- sem(cong.model, data = datenLV, std.lv = TRUE)
summary(cong.fit, standardized = TRUE, fit.measures=TRUE)
```

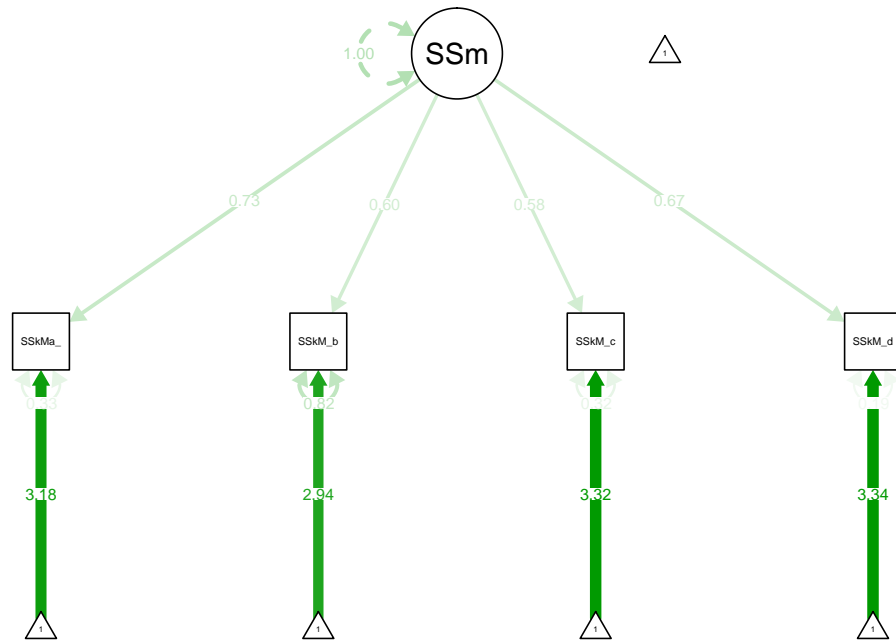
```
## lavaan 0.6-8 ended normally after 16 iterations
##
##      Estimator              ML
##      Optimization method    NLMINB
##      Number of model parameters    12
##
##                               Used      Total
##      Number of observations    2843      3005
##
## Model Test User Model:
##
##      Test statistic    124.430
##      Degrees of freedom      2
##      P-value (Chi-square)    0.000
##
## Model Test Baseline Model:
##
##      Test statistic    4111.594
##      Degrees of freedom      6
##      P-value          0.000
##
## User Model versus Baseline Model:
```

```

##
## Comparative Fit Index (CFI) 0.970
## Tucker-Lewis Index (TLI) 0.911
##
## Loglikelihood and Information Criteria:
##
## Loglikelihood user model (H0) -12967.449
## Loglikelihood unrestricted model (H1) -12905.234
##
## Akaike (AIC) 25958.898
## Bayesian (BIC) 26030.329
## Sample-size adjusted Bayesian (BIC) 25992.201
##
## Root Mean Square Error of Approximation:
##
## RMSEA 0.147
## 90 Percent confidence interval - lower 0.125
## 90 Percent confidence interval - upper 0.169
## P-value RMSEA <= 0.05 0.000
##
## Standardized Root Mean Square Residual:
##
## SRMR 0.028
##
## Parameter Estimates:
##
## Standard errors Standard
## Information Expected
## Information saturated (h1) model Structured
##
## Latent Variables:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## SSmath =~
## SSkMa_a (lam1) 0.733 0.016 45.845 0.000 0.733 0.786
## SSkMa_b (lam2) 0.603 0.020 29.672 0.000 0.603 0.554
## SSkMa_c (lam3) 0.582 0.014 40.830 0.000 0.582 0.717
## SSkMa_d (lam4) 0.674 0.013 49.973 0.000 0.674 0.841
##
## Intercepts:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .SSkMa_a (men1) 3.177 0.017 181.586 0.000 3.177 3.406
## .SSkMa_b (men2) 2.943 0.020 144.193 0.000 2.943 2.704
## .SSkMa_c (men3) 3.319 0.015 217.876 0.000 3.319 4.086
## .SSkMa_d (men4) 3.337 0.015 221.820 0.000 3.337 4.160
## SSmath 0.000 0.000 0.000
##
## Variances:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .SSkMa_a (var1) 0.332 0.013 25.253 0.000 0.332 0.382
## .SSkMa_b (var2) 0.820 0.024 34.594 0.000 0.820 0.693
## .SSkMa_c (var3) 0.320 0.011 29.946 0.000 0.320 0.486
## .SSkMa_d (var4) 0.189 0.009 19.857 0.000 0.189 0.293
## SSmath 1.000 1.000

```

```
semPlot::semPaths(object = cong.fit, what = "est")
```



```
tauequi.model <- '
SSmath =~ lam1*SSkMa_a + lam2*SSkMa_b + lam3*SSkMa_c + lam4*SSkMa_d

SSkMa_a ~~ var1*SSkMa_a
SSkMa_b ~~ var2*SSkMa_b
SSkMa_c ~~ var3*SSkMa_c
SSkMa_d ~~ var4*SSkMa_d

SSkMa_a ~ mean1*1
SSkMa_b ~ mean2*1
SSkMa_c ~ mean3*1
SSkMa_d ~ mean4*1

# fix variance of SSmath factor
SSmath ~~ 1*SSmath

# constraints
lam1 == lam2
lam2 == lam3
lam3 == lam4
'

# identification: Fixed factor
tauequi.fit <- sem(tauequi.model, data = datenLV, std.lv = TRUE)
```

```
summary(tauequi.fit, standardized = TRUE, fit.measures=TRUE)
```

```
## lavaan 0.6-8 ended normally after 12 iterations
##
##      Estimator                      ML
##      Optimization method          NLMINB
##      Number of model parameters      12
##      Number of equality constraints     3
##
##                               Used      Total
##      Number of observations          2843      3005
##
## Model Test User Model:
##
##      Test statistic                209.808
##      Degrees of freedom              5
##      P-value (Chi-square)           0.000
##
## Model Test Baseline Model:
##
##      Test statistic                4111.594
##      Degrees of freedom              6
##      P-value                        0.000
##
## User Model versus Baseline Model:
##
##      Comparative Fit Index (CFI)      0.950
##      Tucker-Lewis Index (TLI)         0.940
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)      -13010.138
##      Loglikelihood unrestricted model (H1) -12905.234
##
##      Akaike (AIC)                     26038.276
##      Bayesian (BIC)                    26091.849
##      Sample-size adjusted Bayesian (BIC) 26063.253
##
## Root Mean Square Error of Approximation:
##
##      RMSEA                            0.120
##      90 Percent confidence interval - lower 0.106
##      90 Percent confidence interval - upper 0.134
##      P-value RMSEA <= 0.05              0.000
##
## Standardized Root Mean Square Residual:
##
##      SRMR                            0.065
##
## Parameter Estimates:
##
##      Standard errors                  Standard
##      Information                      Expected
##      Information saturated (h1) model  Structured
```



```
##
## Latent Variables:
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##   SSmath =~
##     SSkMa_a (lam1)   0.655   0.010  63.090   0.000   0.655   0.734
##     SSkMa_b (lam2)   0.655   0.010  63.090   0.000   0.655   0.586
##     SSkMa_c (lam3)   0.655   0.010  63.090   0.000   0.655   0.767
##     SSkMa_d (lam4)   0.655   0.010  63.090   0.000   0.655   0.830
##
## Intercepts:
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##   .SSkMa_a (men1)   3.177   0.017 189.961   0.000   3.177   3.563
##   .SSkMa_b (men2)   2.943   0.021 140.437   0.000   2.943   2.634
##   .SSkMa_c (men3)   3.319   0.016 207.225   0.000   3.319   3.886
##   .SSkMa_d (men4)   3.337   0.015 225.422   0.000   3.337   4.228
##   SSmath           0.000           0.000   0.000
##
## Variances:
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##   .SSkMa_a (var1)   0.366   0.012  30.452   0.000   0.366   0.461
##   .SSkMa_b (var2)   0.820   0.024  34.536   0.000   0.820   0.657
##   .SSkMa_c (var3)   0.300   0.010  28.781   0.000   0.300   0.412
##   .SSkMa_d (var4)   0.194   0.008  23.975   0.000   0.194   0.312
##   SSmath           1.000           1.000   1.000
##
## Constraints:
##                                     |Slack|
##   lam1 - (lam2)                   0.000
##   lam2 - (lam3)                   0.000
##   lam3 - (lam4)                   0.000
```

```
anova(cong.fit, tauequi.fit) # LRT
```

```
## Chi-Squared Difference Test
##
##           Df   AIC   BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## cong.fit      2 25959 26030 124.43
## tauequi.fit   5 26038 26092 209.81      85.378      3 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
fit.stats <- rbind(fitmeasures(cong.fit, fit.measures = c("chisq", "df", "rmsea", "tli", "cfi", "aic")),
fitmeasures(tauequi.fit, fit.measures = c("chisq", "df", "rmsea", "tli", "cfi", "aic")))
rownames(fit.stats) <- c("configural", "weak invariance")
fit.stats
```

```
##           chisq df   rmsea      tli      cfi      aic
## configural 124.4304  2 0.1467375 0.9105389 0.9701796 25958.90
## weak invariance 209.8084  5 0.1200330 0.9401377 0.9501148 26038.28
```

```
parallel.model <- '
SSmath =~ lam1*SSkMa_a + lam2*SSkMa_b + lam3*SSkMa_c + lam4*SSkMa_d

SSkMa_a ~~ var1*SSkMa_a
SSkMa_b ~~ var2*SSkMa_b
SSkMa_c ~~ var3*SSkMa_c
```

```

SSkMa_d ~~ var4*SSkMa_d

SSkMa_a ~ mean1*1
SSkMa_b ~ mean2*1
SSkMa_c ~ mean3*1
SSkMa_d ~ mean4*1

# fix variance of SSmath factor
SSmath ~~ 1*SSmath

# constraints
lam1 == lam2
lam2 == lam3
lam3 == lam4

var1 == var2
var2 == var3
var3 == var4
'

# identification: Fixed factor
parallel.fit <-sem(parallel.model, data = datenLV, std.lv = TRUE)
summary(parallel.fit, standardized = TRUE, fit.measures=TRUE)

## lavaan 0.6-8 ended normally after 4 iterations
##
##      Estimator                      ML
##      Optimization method          NLMINB
##      Number of model parameters          12
##      Number of equality constraints          6
##
##                                     Used      Total
##      Number of observations          2843      3005
##
## Model Test User Model:
##
##      Test statistic          1157.170
##      Degrees of freedom          8
##      P-value (Chi-square)          0.000
##
## Model Test Baseline Model:
##
##      Test statistic          4111.594
##      Degrees of freedom          6
##      P-value          0.000
##
## User Model versus Baseline Model:
##
##      Comparative Fit Index (CFI)          0.720
##      Tucker-Lewis Index (TLI)          0.790
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)          -13483.819

```

```

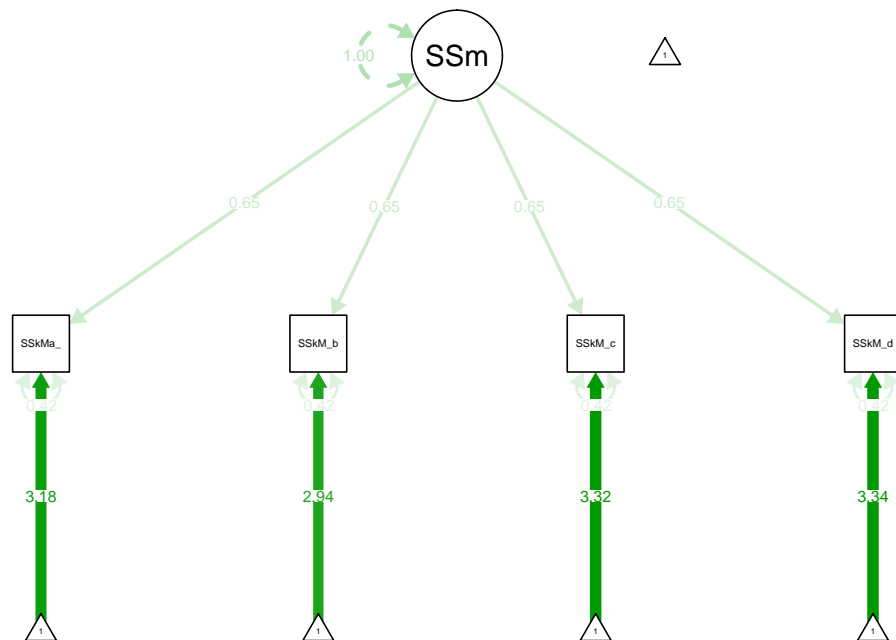
## Loglikelihood unrestricted model (H1)      -12905.234
##
## Akaike (AIC)                               26979.637
## Bayesian (BIC)                             27015.353
## Sample-size adjusted Bayesian (BIC)       26996.289
##
## Root Mean Square Error of Approximation:
##
## RMSEA                                       0.225
## 90 Percent confidence interval - lower     0.214
## 90 Percent confidence interval - upper     0.236
## P-value RMSEA <= 0.05                     0.000
##
## Standardized Root Mean Square Residual:
##
## SRMR                                       0.144
##
## Parameter Estimates:
##
## Standard errors                           Standard
## Information                               Expected
## Information saturated (h1) model          Structured
##
## Latent Variables:
##
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## SSmath =~
##   SSkMa_a (lam1)   0.648   0.011  59.955   0.000   0.648   0.708
##   SSkMa_b (lam2)   0.648   0.011  59.955   0.000   0.648   0.708
##   SSkMa_c (lam3)   0.648   0.011  59.955   0.000   0.648   0.708
##   SSkMa_d (lam4)   0.648   0.011  59.955   0.000   0.648   0.708
##
## Intercepts:
##
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##   .SSkMa_a (men1)   3.177   0.017 184.882   0.000   3.177   3.467
##   .SSkMa_b (men2)   2.943   0.017 171.290   0.000   2.943   3.213
##   .SSkMa_c (men3)   3.319   0.017 193.132   0.000   3.319   3.622
##   .SSkMa_d (men4)   3.337   0.017 194.196   0.000   3.337   3.642
##   SSmath             0.000             0.000   0.000
##
## Variances:
##
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##   .SSkMa_a (var1)   0.419   0.006  65.303   0.000   0.419   0.499
##   .SSkMa_b (var2)   0.419   0.006  65.303   0.000   0.419   0.499
##   .SSkMa_c (var3)   0.419   0.006  65.303   0.000   0.419   0.499
##   .SSkMa_d (var4)   0.419   0.006  65.303   0.000   0.419   0.499
##   SSmath             1.000             1.000   1.000
##
## Constraints:
##
##                               |Slack|
##   lam1 - (lam2)              0.000
##   lam2 - (lam3)              0.000
##   lam3 - (lam4)              0.000
##   var1 - (var2)              0.000
##   var2 - (var3)              0.000

```

```
##      var3 - (var4)                                0.000
anova(cong.fit, tauequi.fit, parallel.fit) # LRT

## Chi-Squared Difference Test
##
##           Df    AIC    BIC   Chisq Chisq diff Df diff Pr(>Chisq)
## cong.fit      2 25959 26030  124.43
## tauequi.fit   5 26038 26092  209.81      85.38      3 < 2.2e-16 ***
## parallel.fit  8 26980 27015 1157.17     947.36      3 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

semPlot::semPaths(object = parallel.fit, what = "est")
```



measurment invariance (longitudinal data, multi-group analysis)

zur eigenen Interpretation der Ergebnisse siehe: https://rstudio-pubs-static.s3.amazonaws.com/194879_192b64ad567743d392b559d650b95a3b.html

```
CFAmoel <- ' SSmath =~ SSkMa_a + SSkMa_b + SSkMa_c + SSkMa_d'
fit <- cfa(CFAmoel, data=datenLV) # ! ML
summary(fit, fit.measures=TRUE)
```

```
## lavaan 0.6-8 ended normally after 19 iterations
##
##      Estimator                                ML
##      Optimization method                    NLMINB
##      Number of model parameters              8
```

```

##
##
##      Used      Total
##      Number of observations      2843      3005
##
## Model Test User Model:
##
##      Test statistic      124.430
##      Degrees of freedom      2
##      P-value (Chi-square)      0.000
##
## Model Test Baseline Model:
##
##      Test statistic      4111.594
##      Degrees of freedom      6
##      P-value      0.000
##
## User Model versus Baseline Model:
##
##      Comparative Fit Index (CFI)      0.970
##      Tucker-Lewis Index (TLI)      0.911
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)      -12967.449
##      Loglikelihood unrestricted model (H1)      -12905.234
##
##      Akaike (AIC)      25950.898
##      Bayesian (BIC)      25998.519
##      Sample-size adjusted Bayesian (BIC)      25973.100
##
## Root Mean Square Error of Approximation:
##
##      RMSEA      0.147
##      90 Percent confidence interval - lower      0.125
##      90 Percent confidence interval - upper      0.169
##      P-value RMSEA <= 0.05      0.000
##
## Standardized Root Mean Square Residual:
##
##      SRMR      0.033
##
## Parameter Estimates:
##
##      Standard errors      Standard
##      Information      Expected
##      Information saturated (h1) model      Structured
##
## Latent Variables:
##      Estimate Std.Err z-value P(>|z|)
##      SSmath =~
##      SSkMa_a      1.000
##      SSkMa_b      0.823      0.029      28.041      0.000
##      SSkMa_c      0.794      0.022      36.756      0.000
##      SSkMa_d      0.920      0.023      40.728      0.000

```

```

##
## Variances:
##           Estimate Std.Err z-value P(>|z|)
##   .SSkMa_a      0.332   0.013  25.253   0.000
##   .SSkMa_b      0.820   0.024  34.594   0.000
##   .SSkMa_c      0.320   0.011  29.946   0.000
##   .SSkMa_d      0.189   0.009  19.857   0.000
##   SSmath        0.538   0.023  22.923   0.000
table(datenLV$Emigr)

##
##   Mig keinMig
##   493    1966
configural <- cfa(CFAModel, data=datenLV, group = "Emigr")

## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: group vari
summary(configural, fit.measures=TRUE)

## lavaan 0.6-8 ended normally after 35 iterations
##
##   Estimator                      ML
##   Optimization method          NLMINB
##   Number of model parameters      24
##
##   Number of observations per group:      Used      Total
##   keinMig                          1878      1966
##   Mig                              465       493
##
## Model Test User Model:
##
##   Test statistic                  98.189
##   Degrees of freedom                4
##   P-value (Chi-square)              0.000
##   Test statistic for each group:
##   keinMig                          72.077
##   Mig                              26.112
##
## Model Test Baseline Model:
##
##   Test statistic                  3389.720
##   Degrees of freedom                12
##   P-value                          0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)      0.972
##   Tucker-Lewis Index (TLI)        0.916
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)    -10511.368
##   Loglikelihood unrestricted model (H1) -10462.274
##

```

```

## Akaike (AIC) 21070.736
## Bayesian (BIC) 21208.957
## Sample-size adjusted Bayesian (BIC) 21132.704
##
## Root Mean Square Error of Approximation:
##
## RMSEA 0.142
## 90 Percent confidence interval - lower 0.118
## 90 Percent confidence interval - upper 0.167
## P-value RMSEA <= 0.05 0.000
##
## Standardized Root Mean Square Residual:
##
## SRMR 0.027
##
## Parameter Estimates:
##
## Standard errors Standard
## Information Expected
## Information saturated (h1) model Structured
##
##
## Group 1 [keinMig]:
##
## Latent Variables:
## Estimate Std.Err z-value P(>|z|)
## SSmath =~
## SSkMa_a 1.000
## SSkMa_b 0.865 0.037 23.226 0.000
## SSkMa_c 0.814 0.027 29.652 0.000
## SSkMa_d 0.931 0.028 32.753 0.000
##
## Intercepts:
## Estimate Std.Err z-value P(>|z|)
## .SSkMa_a 3.238 0.021 155.739 0.000
## .SSkMa_b 3.013 0.025 122.777 0.000
## .SSkMa_c 3.356 0.018 184.052 0.000
## .SSkMa_d 3.377 0.018 189.921 0.000
## SSmath 0.000
##
## Variances:
## Estimate Std.Err z-value P(>|z|)
## .SSkMa_a 0.324 0.015 21.236 0.000
## .SSkMa_b 0.766 0.027 27.915 0.000
## .SSkMa_c 0.301 0.012 24.207 0.000
## .SSkMa_d 0.171 0.011 15.854 0.000
## SSmath 0.488 0.027 18.289 0.000
##
##
## Group 2 [Mig]:
##
## Latent Variables:
## Estimate Std.Err z-value P(>|z|)
## SSmath =~

```

```
##      SSkMa_a          1.000
##      SSkMa_b          0.758    0.066    11.542    0.000
##      SSkMa_c          0.699    0.050    14.064    0.000
##      SSkMa_d          0.916    0.053    17.127    0.000
```

```
##
## Intercepts:
##              Estimate Std.Err z-value P(>|z|)
##      .SSkMa_a          3.069    0.044    69.482    0.000
##      .SSkMa_b          2.798    0.051    55.224    0.000
##      .SSkMa_c          3.239    0.039    82.839    0.000
##      .SSkMa_d          3.241    0.040    80.897    0.000
##      SSmath            0.000
```

```
##
## Variances:
##              Estimate Std.Err z-value P(>|z|)
##      .SSkMa_a          0.280    0.033     8.428    0.000
##      .SSkMa_b          0.833    0.059    14.087    0.000
##      .SSkMa_c          0.404    0.031    13.177    0.000
##      .SSkMa_d          0.219    0.027     8.049    0.000
##      SSmath            0.628    0.063     9.963    0.000
```

```
weak.invariance <- cfa(CFAmodel, data=datenLV, group = "Emigr", group.equal = "loadings")
```

```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: group vari
```

```
summary(weak.invariance, fit.measures = TRUE)
```

```
## lavaan 0.6-8 ended normally after 27 iterations
```

```
##
##      Estimator                      ML
##      Optimization method          NLMINB
##      Number of model parameters          24
##      Number of equality constraints          3
##
##      Number of observations per group:      Used      Total
##      keinMig                          1878      1966
##      Mig                              465      493
##
```

```
## Model Test User Model:
```

```
##
##      Test statistic          104.031
##      Degrees of freedom          7
##      P-value (Chi-square)          0.000
##      Test statistic for each group:
##      keinMig          73.273
##      Mig              30.758
##
```

```
## Model Test Baseline Model:
```

```
##
##      Test statistic          3389.720
##      Degrees of freedom          12
##      P-value          0.000
##
```

```
## User Model versus Baseline Model:
```

```
##
```



```

## Comparative Fit Index (CFI) 0.971
## Tucker-Lewis Index (TLI) 0.951
##
## Loglikelihood and Information Criteria:
##
## Loglikelihood user model (H0) -10514.289
## Loglikelihood unrestricted model (H1) -10462.274
##
## Akaike (AIC) 21070.578
## Bayesian (BIC) 21191.521
## Sample-size adjusted Bayesian (BIC) 21124.800
##
## Root Mean Square Error of Approximation:
##
## RMSEA 0.109
## 90 Percent confidence interval - lower 0.091
## 90 Percent confidence interval - upper 0.128
## P-value RMSEA <= 0.05 0.000
##
## Standardized Root Mean Square Residual:
##
## SRMR 0.032
##
## Parameter Estimates:
##
## Standard errors Standard
## Information Expected
## Information saturated (h1) model Structured
##
##
## Group 1 [keinMig]:
##
## Latent Variables:
## Estimate Std.Err z-value P(>|z|)
## SSmath =~
## SSkMa_a 1.000
## SSkMa_b (.p2.) 0.840 0.032 25.944 0.000
## SSkMa_c (.p3.) 0.790 0.024 32.950 0.000
## SSkMa_d (.p4.) 0.927 0.025 37.016 0.000
##
## Intercepts:
## Estimate Std.Err z-value P(>|z|)
## .SSkMa_a 3.238 0.021 154.981 0.000
## .SSkMa_b 3.013 0.024 123.393 0.000
## .SSkMa_c 3.356 0.018 185.466 0.000
## .SSkMa_d 3.377 0.018 189.351 0.000
## SSmath 0.000
##
## Variances:
## Estimate Std.Err z-value P(>|z|)
## .SSkMa_a 0.322 0.015 21.310 0.000
## .SSkMa_b 0.768 0.027 28.123 0.000
## .SSkMa_c 0.304 0.012 24.751 0.000
## .SSkMa_d 0.169 0.011 16.002 0.000

```

```
##      SSmath          0.498    0.026    19.451    0.000
##
##
## Group 2 [Mig]:
##
## Latent Variables:
##           Estimate Std.Err  z-value  P(>|z|)
##      SSmath =~
##      SSkMa_a      1.000
##      SSkMa_b (.p2.)  0.840    0.032    25.944    0.000
##      SSkMa_c (.p3.)  0.790    0.024    32.950    0.000
##      SSkMa_d (.p4.)  0.927    0.025    37.016    0.000
##
## Intercepts:
##           Estimate Std.Err  z-value  P(>|z|)
##      .SSkMa_a      3.069    0.043    70.625    0.000
##      .SSkMa_b      2.798    0.052    54.123    0.000
##      .SSkMa_c      3.239    0.040    80.088    0.000
##      .SSkMa_d      3.241    0.040    81.950    0.000
##      SSmath        0.000
##
## Variances:
##           Estimate Std.Err  z-value  P(>|z|)
##      .SSkMa_a      0.292    0.029    10.086    0.000
##      .SSkMa_b      0.829    0.059    14.044    0.000
##      .SSkMa_c      0.395    0.030    12.983    0.000
##      .SSkMa_d      0.223    0.024     9.499    0.000
##      SSmath        0.586    0.049    11.977    0.000
```

```
anova(weak.invariance, configural) # LRT
```

```
## Chi-Squared Difference Test
```

```
##
##           Df   AIC   BIC   Chisq Chisq diff Df diff Pr(>Chisq)
## configural    4 21071 21209  98.189
## weak.invariance 7 21071 21192 104.031    5.8415    3    0.1196
```

```
fit.stats <- rbind(fitmeasures(configural, fit.measures = c("chisq", "df", "rmsea", "tli", "cfi", "aic"),
fitmeasures(weak.invariance, fit.measures = c("chisq", "df", "rmsea", "tli", "cfi", "aic")))
rownames(fit.stats) <- c("configural", "weak invariance")
fit.stats
```

```
##           chisq df    rmsea    tli    cfi    aic
## configural    98.18934  4 0.1417750 0.9163436 0.9721145 21070.74
## weak invariance 104.03081  7 0.1087764 0.9507542 0.9712733 21070.58
```

```
strong.invariance <- cfa(CFModel, data=datenLV, group = "Emigr", group.equal = c( "loadings", "intercept"))
```

```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: group variables
```

```
summary(strong.invariance, fit.measures = TRUE)
```

```
## lavaan 0.6-8 ended normally after 39 iterations
```

```
##
##      Estimator                      ML
##      Optimization method          NLMINB
##      Number of model parameters    25
```

```

## Number of equality constraints          7
##
## Number of observations per group:      Used      Total
##   keinMig                             1878      1966
##   Mig                                 465       493
##
## Model Test User Model:
##
## Test statistic                         107.336
## Degrees of freedom                     10
## P-value (Chi-square)                   0.000
## Test statistic for each group:
##   keinMig                             73.780
##   Mig                                 33.556
##
## Model Test Baseline Model:
##
## Test statistic                         3389.720
## Degrees of freedom                     12
## P-value                                0.000
##
## User Model versus Baseline Model:
##
## Comparative Fit Index (CFI)            0.971
## Tucker-Lewis Index (TLI)              0.965
##
## Loglikelihood and Information Criteria:
##
## Loglikelihood user model (H0)          -10515.941
## Loglikelihood unrestricted model (H1)   -10462.274
##
## Akaike (AIC)                          21067.883
## Bayesian (BIC)                         21171.548
## Sample-size adjusted Bayesian (BIC)    21114.359
##
## Root Mean Square Error of Approximation:
##
## RMSEA                                 0.091
## 90 Percent confidence interval - lower  0.076
## 90 Percent confidence interval - upper  0.107
## P-value RMSEA <= 0.05                  0.000
##
## Standardized Root Mean Square Residual:
##
## SRMR                                 0.032
##
## Parameter Estimates:
##
## Standard errors                       Standard
## Information                           Expected
## Information saturated (h1) model      Structured
##
## Group 1 [keinMig]:

```

```

##
## Latent Variables:
##      Estimate   Std.Err   z-value   P(>|z|)
##      SSmath =~
##      SSkMa_a      1.000
##      SSkMa_b (.p2.) 0.844    0.032   26.189    0.000
##      SSkMa_c (.p3.) 0.788    0.024   33.102    0.000
##      SSkMa_d (.p4.) 0.925    0.025   37.264    0.000
##
## Intercepts:
##      Estimate   Std.Err   z-value   P(>|z|)
##      .SSkMa_a (.10.) 3.237    0.020  159.328    0.000
##      .SSkMa_b (.11.) 2.999    0.023  130.339    0.000
##      .SSkMa_c (.12.) 3.358    0.017  192.037    0.000
##      .SSkMa_d (.13.) 3.380    0.018  192.150    0.000
##      SSmath      0.000
##
## Variances:
##      Estimate   Std.Err   z-value   P(>|z|)
##      .SSkMa_a      0.321    0.015   21.285    0.000
##      .SSkMa_b      0.767    0.027   28.090    0.000
##      .SSkMa_c      0.304    0.012   24.775    0.000
##      .SSkMa_d      0.170    0.011   16.109    0.000
##      SSmath      0.499    0.026   19.521    0.000
##
##
## Group 2 [Mig]:
##
## Latent Variables:
##      Estimate   Std.Err   z-value   P(>|z|)
##      SSmath =~
##      SSkMa_a      1.000
##      SSkMa_b (.p2.) 0.844    0.032   26.189    0.000
##      SSkMa_c (.p3.) 0.788    0.024   33.102    0.000
##      SSkMa_d (.p4.) 0.925    0.025   37.264    0.000
##
## Intercepts:
##      Estimate   Std.Err   z-value   P(>|z|)
##      .SSkMa_a (.10.) 3.237    0.020  159.328    0.000
##      .SSkMa_b (.11.) 2.999    0.023  130.339    0.000
##      .SSkMa_c (.12.) 3.358    0.017  192.037    0.000
##      .SSkMa_d (.13.) 3.380    0.018  192.150    0.000
##      SSmath     -0.164    0.042   -3.867    0.000
##
## Variances:
##      Estimate   Std.Err   z-value   P(>|z|)
##      .SSkMa_a      0.291    0.029   10.062    0.000
##      .SSkMa_b      0.832    0.059   14.035    0.000
##      .SSkMa_c      0.395    0.030   12.989    0.000
##      .SSkMa_d      0.224    0.024    9.543    0.000
##      SSmath      0.587    0.049   11.990    0.000

```

```
anova(strong.invariance, weak.invariance, configural)
```

```
## Chi-Squared Difference Test
```

```
##
##               Df    AIC    BIC    Chisq Chisq diff Df diff Pr(>Chisq)
## configural      4 21071 21209   98.189
## weak.invariance  7 21071 21192 104.031      5.8415      3    0.1196
## strong.invariance 10 21068 21172 107.336      3.3049      3    0.3470

strict.invariance <- cfa(CFModel, data=datenLV, group = "Emigr", group.equal = c( "loadings", "intercept"))

## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: group variable not used
anova(strict.invariance, strong.invariance, weak.invariance, configural)

## Chi-Squared Difference Test
##
##               Df    AIC    BIC    Chisq Chisq diff Df diff Pr(>Chisq)
## configural      4 21071 21209   98.189
## weak.invariance  7 21071 21192 104.031      5.8415      3    0.119583
## strong.invariance 10 21068 21172 107.336      3.3049      3    0.346958
## strict.invariance 14 21077 21158 124.388     17.0527      4    0.001888 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

confirmatory factor analysis

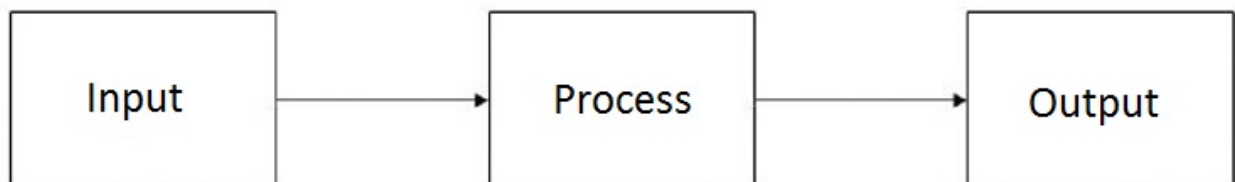
Verwendung des `lavaan` Paketes in R (siehe <https://lavaan.ugent.be/>), google group lavaan (<https://groups.google.com/g/lavaan>); es empfiehlt sich jedoch für komplexe Analysen Mplus zu verwenden (FIML, Bayesian SEM, ...)

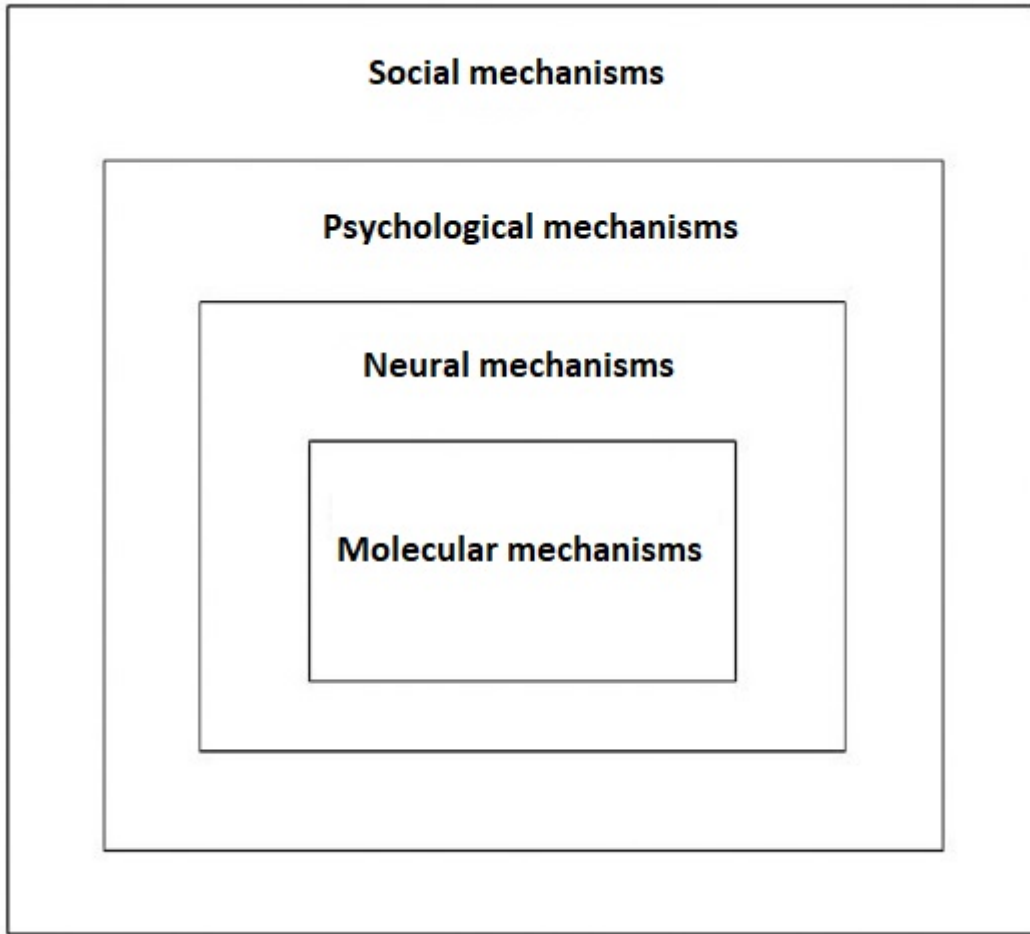
wichtigstes Grundlagenbuch zu SEM: Bollen (1989)

short theoretical: focus the structural modelling perspective

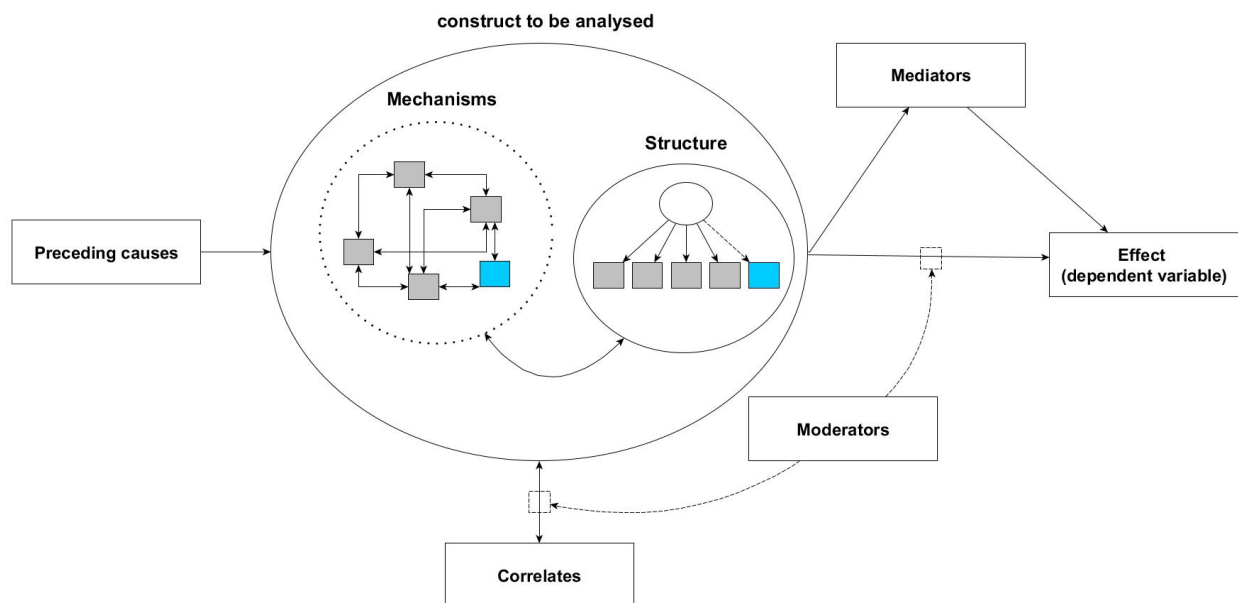
deduktive Methode

Context-Process-Input-Output model (bekannt in deutschsprachigen Raum durch Ditton (2000), entwickelt von Stufflebeam (1971); klare Ausführungen in Keller (2014)):





Dies lässt sich zusammenbauen zu einem nomologischen Netzwerk (= Testung Konstruktvalidität):



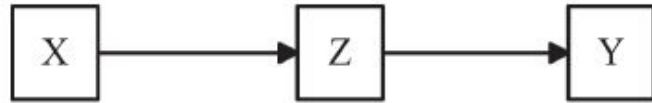
Welche möglicherweise Variablen interessant sind lässt sich aus einer graphischen theoretischen Ausarbeitung

(Pfaddiagramm) schrittweise aufbauen (Kapitel 7 “causal models” in Jaccard and Jacoby (2020)):

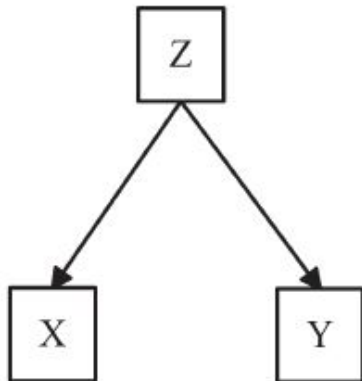
Direct Causal Relationship



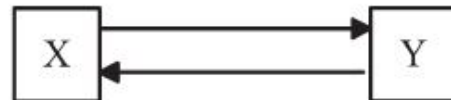
Indirect Causal Relationship



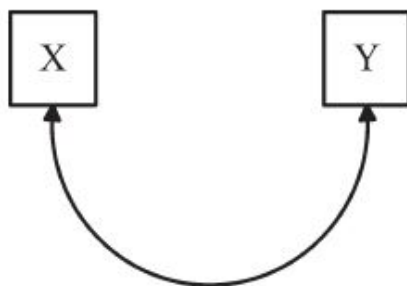
Spurious Relationship



Bidirectional Causal Relationship



Unanalyzed Relationship



Moderated Causal Relationship

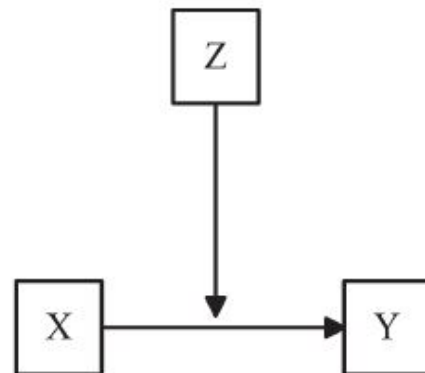


FIGURE 7.1. Relationships in causal models.

CFA (measurement model)

Abschnitt CFA / SEM orientiert sich an Kapitel 9-12 in Hair et al. (2019):

an sich sollten die einzelnen Messmodelle (CFAs) getrennt berechnet werden, hier wird jedoch aus Zeitdrücken direkt eine CFA erster Ordnung (*first order CFA*) für alle Messmodelle, die im Strukturgleichungsmodell verwendet werden gerechnet:

```

firstorderCFA <- '
SSmath =~ SSkMa_a + SSkMa_b + SSkMa_c + SSkMa_d
SSgerman =~ SSkDe_a + SSkDe_b + SSkDe_c + SSkDe_d

SozInt =~ SBezMs_a + SBezMs_b + SBezMs_c + SBezMs_d

Abilities =~ wle_lesen + wle_hoeren + wle_mathe
'

# identification: Fixed factor
fit <-sem(firstorderCFA, data = datenLV, std.lv = TRUE)
summary(fit, standardized = TRUE, fit.measures=TRUE)

## lavaan 0.6-8 ended normally after 24 iterations
##
##      Estimator                      ML
##      Optimization method          NLMINB
##      Number of model parameters          36
##
##                                     Used      Total
##      Number of observations          2566      3005
##
## Model Test User Model:
##
##      Test statistic          1514.039
##      Degrees of freedom           84
##      P-value (Chi-square)        0.000
##
## Model Test Baseline Model:
##
##      Test statistic          11646.307
##      Degrees of freedom          105
##      P-value                  0.000
##
## User Model versus Baseline Model:
##
##      Comparative Fit Index (CFI)          0.876
##      Tucker-Lewis Index (TLI)           0.845
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)        -45769.003
##      Loglikelihood unrestricted model (H1) -45011.984
##
##      Akaike (AIC)                      91610.007
##      Bayesian (BIC)                    91820.610
##      Sample-size adjusted Bayesian (BIC) 91706.228
##
## Root Mean Square Error of Approximation:
##
##      RMSEA                      0.081
##      90 Percent confidence interval - lower 0.078
##      90 Percent confidence interval - upper 0.085
##      P-value RMSEA <= 0.05            0.000

```



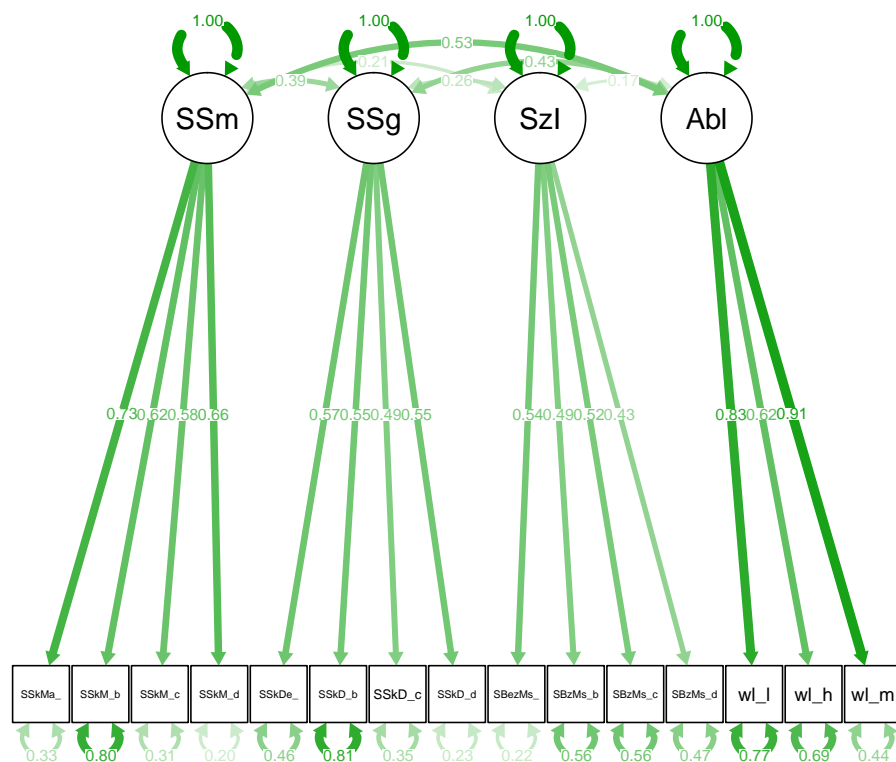
```

##
## Standardized Root Mean Square Residual:
##
## SRMR                                0.054
##
## Parameter Estimates:
##
## Standard errors                      Standard
## Information                          Expected
## Information saturated (h1) model      Structured
##
## Latent Variables:
##      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
## SSmath =~
##   SSkMa_a      0.733   0.017  44.281   0.000   0.733   0.789
##   SSkMa_b      0.618   0.021  29.186   0.000   0.618   0.569
##   SSkMa_c      0.584   0.015  39.403   0.000   0.584   0.722
##   SSkMa_d      0.661   0.014  47.284   0.000   0.661   0.828
## SSgerman =~
##   SSkDe_a      0.568   0.018  31.610   0.000   0.568   0.643
##   SSkDe_b      0.553   0.022  24.924   0.000   0.553   0.523
##   SSkDe_c      0.494   0.016  31.469   0.000   0.494   0.640
##   SSkDe_d      0.553   0.015  38.039   0.000   0.553   0.758
## SozInt =~
##   SBezMs_a     0.544   0.016  34.545   0.000   0.544   0.757
##   SBezMs_b     0.495   0.019  25.382   0.000   0.495   0.553
##   SBezMs_c     0.524   0.020  26.359   0.000   0.524   0.573
##   SBezMs_d     0.429   0.018  24.247   0.000   0.429   0.530
## Abilities =~
##   wle_lesen    0.830   0.024  34.203   0.000   0.830   0.687
##   wle_hoeren   0.618   0.021  29.300   0.000   0.618   0.597
##   wle_mathe    0.909   0.022  40.680   0.000   0.909   0.809
##
## Covariances:
##      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
## SSmath ~~
##   SSgerman      0.392   0.022  18.006   0.000   0.392   0.392
##   SozInt        0.212   0.024   8.711   0.000   0.212   0.212
##   Abilities     0.529   0.019  27.358   0.000   0.529   0.529
## SSgerman ~~
##   SozInt        0.263   0.025  10.370   0.000   0.263   0.263
##   Abilities     0.427   0.023  18.929   0.000   0.427   0.427
## SozInt ~~
##   Abilities     0.167   0.026   6.448   0.000   0.167   0.167
##
## Variances:
##      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   .SSkMa_a     0.326   0.013  24.737   0.000   0.326   0.378
##   .SSkMa_b     0.798   0.024  32.781   0.000   0.798   0.676
##   .SSkMa_c     0.313   0.011  28.688   0.000   0.313   0.478
##   .SSkMa_d     0.200   0.009  21.359   0.000   0.200   0.314
##   .SSkDe_a     0.457   0.016  27.929   0.000   0.457   0.587
##   .SSkDe_b     0.815   0.026  31.736   0.000   0.815   0.727
##   .SSkDe_c     0.350   0.012  28.040   0.000   0.350   0.590

```

```
##      .SSkDe_d      0.227      0.011      20.899      0.000      0.227      0.426
##      .SBezMs_a      0.221      0.013      17.345      0.000      0.221      0.427
##      .SBezMs_b      0.555      0.019      29.542      0.000      0.555      0.694
##      .SBezMs_c      0.560      0.019      28.764      0.000      0.560      0.671
##      .SBezMs_d      0.472      0.016      30.322      0.000      0.472      0.719
##      .wle_lesen      0.770      0.030      25.848      0.000      0.770      0.528
##      .wle_hoeren      0.690      0.023      30.039      0.000      0.690      0.643
##      .wle_mathe      0.437      0.027      16.471      0.000      0.437      0.346
##      SSmath          1.000
##      SSgerman        1.000
##      SozInt          1.000
##      Abilities       1.000
```

```
semPlot::semPaths(object = fit, what = "est")
```



To account for the non-normal distribution of the questionnaire items and the small sample, the DWLS estimator was used and the X^2 statistic was mean and variance adjusted (e.g. chapter 11 in Hancock and Mueller (2013)):

! limited information approach; FIML, Bayesian SEM is possible in Mplus

```
datenLV[,c("SSkMa_a",
  "SSkMa_b",
  "SSkMa_c",
  "SSkMa_d",
  "SSkDe_a",
  "SSkDe_b",
  "SSkDe_c",
```

```

      "SSkDe_d",
      "SBezMs_a",
      "SBezMs_b",
      "SBezMs_c",
      "SBezMs_d")] <-
lapply(datenLV[,c("SSkMa_a",
      "SSkMa_b",
      "SSkMa_c",
      "SSkMa_d",
      "SSkDe_a",
      "SSkDe_b",
      "SSkDe_c",
      "SSkDe_d",
      "SBezMs_a",
      "SBezMs_b",
      "SBezMs_c",
      "SBezMs_d")], ordered)

head(datenLV$SSkMa_a)

## [1] 3 3 3 4 3 4
## Levels: 1 < 2 < 3 < 4

firstorderCFA <- '
SSmath =~ SSkMa_a + SSkMa_b + SSkMa_c + SSkMa_d
SSgerman =~ SSkDe_a + SSkDe_b + SSkDe_c + SSkDe_d

SozInt =~ SBezMs_a + SBezMs_b + SBezMs_c + SBezMs_d

Abilities =~ wle_lesen + wle_hoeren + wle_mathe
'

# identification: Marker variable method
fit <- sem(firstorderCFA, data = datenLV,
      ordered = c("SSkMa_a",
      "SSkMa_b",
      "SSkMa_c",
      "SSkMa_d",
      "SSkDe_a",
      "SSkDe_b",
      "SSkDe_c",
      "SSkDe_d",
      "SBezMs_a",
      "SBezMs_b",
      "SBezMs_c",
      "SBezMs_d"))

summary(fit, standardized = TRUE, fit.measures=TRUE)

## lavaan 0.6-8 ended normally after 37 iterations
##
##      Estimator                      DWLS
##      Optimization method           NLMINB
##      Number of model parameters      63
##

```

```

##                               Used      Total
##   Number of observations      2566      3005
##
## Model Test User Model:
##                               Standard    Robust
##   Test Statistic      1091.263    1391.590
##   Degrees of freedom         84         84
##   P-value (Chi-square)      0.000      0.000
##   Scaling correction factor          0.795
##   Shift parameter          19.352
##   simple second-order correction
##
## Model Test Baseline Model:
##
##   Test statistic      39677.932    22840.150
##   Degrees of freedom      105         105
##   P-value              0.000      0.000
##   Scaling correction factor          1.741
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)      0.975      0.942
##   Tucker-Lewis Index (TLI)        0.968      0.928
##
##   Robust Comparative Fit Index (CFI)          NA
##   Robust Tucker-Lewis Index (TLI)          NA
##
## Root Mean Square Error of Approximation:
##
##   RMSEA      0.068      0.078
##   90 Percent confidence interval - lower      0.065      0.074
##   90 Percent confidence interval - upper      0.072      0.082
##   P-value RMSEA <= 0.05      0.000      0.000
##
##   Robust RMSEA          NA
##   90 Percent confidence interval - lower      NA
##   90 Percent confidence interval - upper      NA
##
## Standardized Root Mean Square Residual:
##
##   SRMR      0.057      0.057
##
## Parameter Estimates:
##
##   Standard errors      Robust.sem
##   Information          Expected
##   Information saturated (h1) model      Unstructured
##
## Latent Variables:
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   SSmath =~
##     SSkMa_a      1.000
##     SSkMa_b      0.837    0.018   46.522   0.000    0.701    0.701
##     SSkMa_c      0.965    0.015   66.163   0.000    0.807    0.807

```

```

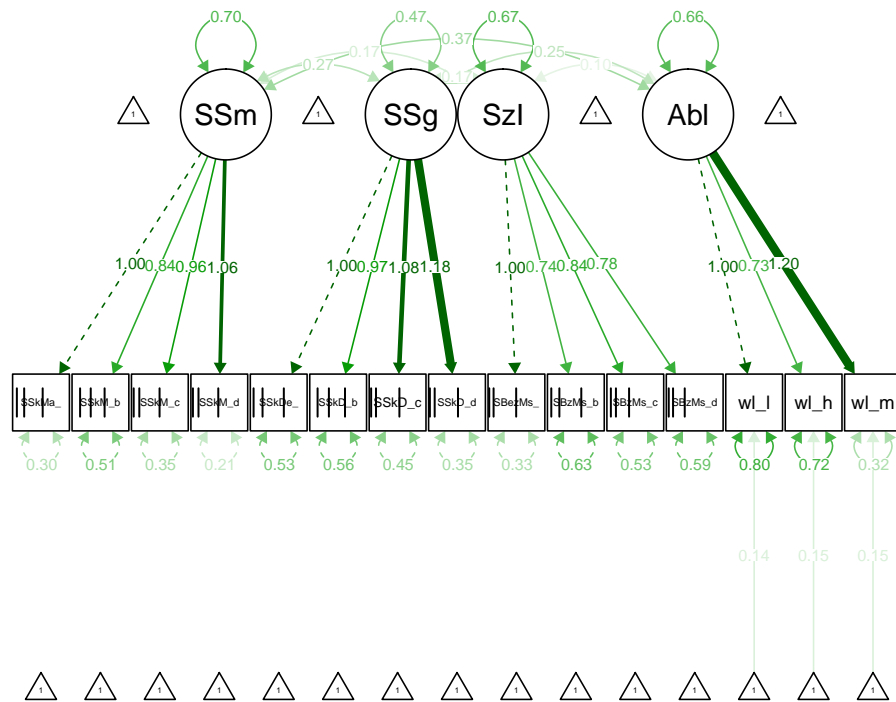
##      SSkMa_d      1.059      0.015      70.858      0.000      0.886      0.886
##      SSgerman =~
##      SSkDe_a      1.000      0.000      0.000      0.682      0.682
##      SSkDe_b      0.975      0.031      31.326      0.000      0.665      0.665
##      SSkDe_c      1.084      0.029      37.812      0.000      0.740      0.740
##      SSkDe_d      1.184      0.029      40.916      0.000      0.808      0.808
##      SozInt =~
##      SBezMs_a      1.000      0.000      0.000      0.821      0.821
##      SBezMs_b      0.745      0.030      25.241      0.000      0.611      0.611
##      SBezMs_c      0.836      0.032      26.338      0.000      0.686      0.686
##      SBezMs_d      0.781      0.031      24.827      0.000      0.641      0.641
##      Abilities =~
##      wle_lesen      1.000      0.000      0.000      0.811      0.672
##      wle_hoeren      0.731      0.035      20.902      0.000      0.593      0.573
##      wle_mathe      1.196      0.048      24.758      0.000      0.970      0.863
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      SSmath ~~
##      SSgerman      0.273      0.014      19.965      0.000      0.478      0.478
##      SozInt      0.166      0.017      9.494      0.000      0.241      0.241
##      Abilities      0.367      0.018      19.885      0.000      0.541      0.541
##      SSgerman ~~
##      SozInt      0.165      0.015      10.840      0.000      0.295      0.295
##      Abilities      0.253      0.016      16.022      0.000      0.457      0.457
##      SozInt ~~
##      Abilities      0.103      0.018      5.751      0.000      0.155      0.155
##
## Intercepts:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      .SSkMa_a      0.000      0.000      0.000      0.000      0.000      0.000
##      .SSkMa_b      0.000      0.000      0.000      0.000      0.000      0.000
##      .SSkMa_c      0.000      0.000      0.000      0.000      0.000      0.000
##      .SSkMa_d      0.000      0.000      0.000      0.000      0.000      0.000
##      .SSkDe_a      0.000      0.000      0.000      0.000      0.000      0.000
##      .SSkDe_b      0.000      0.000      0.000      0.000      0.000      0.000
##      .SSkDe_c      0.000      0.000      0.000      0.000      0.000      0.000
##      .SSkDe_d      0.000      0.000      0.000      0.000      0.000      0.000
##      .SBezMs_a      0.000      0.000      0.000      0.000      0.000      0.000
##      .SBezMs_b      0.000      0.000      0.000      0.000      0.000      0.000
##      .SBezMs_c      0.000      0.000      0.000      0.000      0.000      0.000
##      .SBezMs_d      0.000      0.000      0.000      0.000      0.000      0.000
##      .wle_lesen      0.144      0.024      6.032      0.000      0.144      0.119
##      .wle_hoeren      0.148      0.021      7.186      0.000      0.148      0.143
##      .wle_mathe      0.151      0.022      6.788      0.000      0.151      0.134
##      SSmath      0.000      0.000      0.000      0.000      0.000      0.000
##      SSgerman      0.000      0.000      0.000      0.000      0.000      0.000
##      SozInt      0.000      0.000      0.000      0.000      0.000      0.000
##      Abilities      0.000      0.000      0.000      0.000      0.000      0.000
##
## Thresholds:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      SSkMa_a|t1      -1.438      0.037      -39.175      0.000      -1.438      -1.438
##      SSkMa_a|t2      -0.828      0.028      -29.478      0.000      -0.828      -0.828

```

##	SSkMa_a t3	0.074	0.025	3.000	0.003	0.074	0.074
##	SSkMa_b t1	-1.072	0.031	-34.946	0.000	-1.072	-1.072
##	SSkMa_b t2	-0.442	0.026	-17.229	0.000	-0.442	-0.442
##	SSkMa_b t3	0.185	0.025	7.417	0.000	0.185	0.185
##	SSkMa_c t1	-1.758	0.045	-38.947	0.000	-1.758	-1.758
##	SSkMa_c t2	-1.088	0.031	-35.229	0.000	-1.088	-1.088
##	SSkMa_c t3	-0.014	0.025	-0.553	0.581	-0.014	-0.014
##	SSkMa_d t1	-1.801	0.047	-38.664	0.000	-1.801	-1.801
##	SSkMa_d t2	-1.109	0.031	-35.599	0.000	-1.109	-1.109
##	SSkMa_d t3	-0.044	0.025	-1.776	0.076	-0.044	-0.044
##	SSkDe_a t1	-1.575	0.040	-39.504	0.000	-1.575	-1.575
##	SSkDe_a t2	-0.787	0.028	-28.379	0.000	-0.787	-0.787
##	SSkDe_a t3	0.228	0.025	9.111	0.000	0.228	0.228
##	SSkDe_b t1	-1.090	0.031	-35.260	0.000	-1.090	-1.090
##	SSkDe_b t2	-0.420	0.026	-16.448	0.000	-0.420	-0.420
##	SSkDe_b t3	0.308	0.025	12.218	0.000	0.308	0.308
##	SSkDe_c t1	-1.816	0.047	-38.552	0.000	-1.816	-1.816
##	SSkDe_c t2	-1.175	0.032	-36.630	0.000	-1.175	-1.175
##	SSkDe_c t3	0.081	0.025	3.276	0.001	0.081	0.081
##	SSkDe_d t1	-2.003	0.055	-36.643	0.000	-2.003	-2.003
##	SSkDe_d t2	-1.244	0.033	-37.544	0.000	-1.244	-1.244
##	SSkDe_d t3	0.043	0.025	1.737	0.082	0.043	0.043
##	SBezMs_a t1	-2.033	0.056	-36.257	0.000	-2.033	-2.033
##	SBezMs_a t2	-1.294	0.034	-38.099	0.000	-1.294	-1.294
##	SBezMs_a t3	-0.012	0.025	-0.474	0.636	-0.012	-0.012
##	SBezMs_b t1	-1.495	0.038	-39.394	0.000	-1.495	-1.495
##	SBezMs_b t2	-0.808	0.028	-28.930	0.000	-0.808	-0.808
##	SBezMs_b t3	0.243	0.025	9.702	0.000	0.243	0.243
##	SBezMs_c t1	-1.475	0.037	-39.329	0.000	-1.475	-1.475
##	SBezMs_c t2	-0.999	0.030	-33.512	0.000	-0.999	-0.999
##	SBezMs_c t3	-0.278	0.025	-11.078	0.000	-0.278	-0.278
##	SBezMs_d t1	-1.723	0.044	-39.140	0.000	-1.723	-1.723
##	SBezMs_d t2	-1.183	0.032	-36.742	0.000	-1.183	-1.183
##	SBezMs_d t3	-0.456	0.026	-17.735	0.000	-0.456	-0.456
##							
##	Variances:						
##		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
##	.SSkMa_a	0.300				0.300	0.300
##	.SSkMa_b	0.509				0.509	0.509
##	.SSkMa_c	0.348				0.348	0.348
##	.SSkMa_d	0.214				0.214	0.214
##	.SSkDe_a	0.535				0.535	0.535
##	.SSkDe_b	0.558				0.558	0.558
##	.SSkDe_c	0.453				0.453	0.453
##	.SSkDe_d	0.348				0.348	0.348
##	.SBezMs_a	0.326				0.326	0.326
##	.SBezMs_b	0.626				0.626	0.626
##	.SBezMs_c	0.530				0.530	0.530
##	.SBezMs_d	0.588				0.588	0.588
##	.wle_lesen	0.801	0.032	25.318	0.000	0.801	0.549
##	.wle_hoeren	0.720	0.025	28.933	0.000	0.720	0.672
##	.wle_mathe	0.323	0.033	9.688	0.000	0.323	0.255
##	SSmath	0.700	0.015	47.431	0.000	1.000	1.000
##	SSgerman	0.465	0.019	24.768	0.000	1.000	1.000

```
##      SozInt          0.674    0.028   24.229    0.000    1.000    1.000
##      Abilities      0.658    0.039   16.728    0.000    1.000    1.000
##
## Scales y*:
##              Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      SSkMa_a          1.000
##      SSkMa_b          1.000
##      SSkMa_c          1.000
##      SSkMa_d          1.000
##      SSkDe_a          1.000
##      SSkDe_b          1.000
##      SSkDe_c          1.000
##      SSkDe_d          1.000
##      SBezMs_a          1.000
##      SBezMs_b          1.000
##      SBezMs_c          1.000
##      SBezMs_d          1.000
```

```
semPlot::semPaths(object = fit, what = "est")
```



SEM (measurement model + structural model)

```
SEMmodel <- '
# measurement models
SSmath =~ SSkMa_a + SSkMa_b + SSkMa_c + SSkMa_d
SSgerman =~ SSkDe_a + SSkDe_b + SSkDe_c + SSkDe_d
```

```

SozInt =~ SBezMs_a + SBezMs_b + SBezMs_c + SBezMs_d

Abilities =~ wle_lesen + wle hoeren + wle_mathe

# regressions (+2 dummies)
Abilities ~ SSmath + SSgerman + SozInt + Emigr + tr_sex + EHisei
,

# identification: Marker variable method
fit <- sem(SEMmodel, data = datenLV,
          ordered = c("SSkMa_a",
                      "SSkMa_b",
                      "SSkMa_c",
                      "SSkMa_d",
                      "SSkDe_a",
                      "SSkDe_b",
                      "SSkDe_c",
                      "SSkDe_d",
                      "SBezMs_a",
                      "SBezMs_b",
                      "SBezMs_c",
                      "SBezMs_d"))

summary(fit, standardized = TRUE, fit.measures=TRUE)

## lavaan 0.6-8 ended normally after 39 iterations
##
##      Estimator                      DWLS
##      Optimization method          NLMINB
##      Number of model parameters          66
##
##                                     Used      Total
##      Number of observations          1973      3005
##
## Model Test User Model:
##                                     Standard      Robust
##      Test Statistic          1505.862      1548.544
##      Degrees of freedom           126           126
##      P-value (Chi-square)          0.000           0.000
##      Scaling correction factor              0.994
##      Shift parameter              33.596
##      simple second-order correction
##
## Model Test Baseline Model:
##                                     Standard      Robust
##      Test statistic          27860.196      16284.077
##      Degrees of freedom           105           105
##      P-value          0.000           0.000
##      Scaling correction factor              1.715
##
## User Model versus Baseline Model:
##                                     Standard      Robust
##      Comparative Fit Index (CFI)          0.950           0.912

```



```

## Tucker-Lewis Index (TLI)                0.959      0.927
##
## Robust Comparative Fit Index (CFI)                NA
## Robust Tucker-Lewis Index (TLI)                NA
##
## Root Mean Square Error of Approximation:
##
## RMSEA                0.075      0.076
## 90 Percent confidence interval - lower      0.071      0.072
## 90 Percent confidence interval - upper      0.078      0.079
## P-value RMSEA <= 0.05      0.000      0.000
##
## Robust RMSEA                NA
## 90 Percent confidence interval - lower      NA
## 90 Percent confidence interval - upper      NA
##
## Standardized Root Mean Square Residual:
##
## SRMR                0.055      0.055
##
## Parameter Estimates:
##
## Standard errors                Robust.sem
## Information                Expected
## Information saturated (h1) model      Unstructured
##
## Latent Variables:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## SSmath =~
##   SSkMa_a      1.000          0.828      0.828
##   SSkMa_b      0.830      0.021  38.856      0.000      0.688      0.688
##   SSkMa_c      0.958      0.018  54.715      0.000      0.794      0.794
##   SSkMa_d      1.072      0.018  59.008      0.000      0.887      0.887
## SSgerman =~
##   SSkDe_a      1.000          0.681      0.681
##   SSkDe_b      0.983      0.035  27.891      0.000      0.669      0.669
##   SSkDe_c      1.063      0.033  32.359      0.000      0.724      0.724
##   SSkDe_d      1.181      0.034  35.089      0.000      0.804      0.804
## SozInt =~
##   SBezMs_a      1.000          0.828      0.828
##   SBezMs_b      0.768      0.034  22.361      0.000      0.636      0.636
##   SBezMs_c      0.808      0.036  22.713      0.000      0.669      0.669
##   SBezMs_d      0.766      0.035  21.863      0.000      0.634      0.634
## Abilities =~
##   wle_lesen      1.000          0.814      0.693
##   wle_hoeren      0.706      0.039  17.878      0.000      0.574      0.572
##   wle_mathe      1.130      0.051  21.943      0.000      0.919      0.841
##
## Regressions:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## Abilities ~
##   SSmath      0.383      0.031  12.450      0.000      0.389      0.389
##   SSgerman      0.248      0.038   6.571      0.000      0.207      0.207
##   SozInt     -0.039      0.027  -1.449      0.147     -0.040     -0.040

```

```

##      Emigr          0.369    0.051    7.206    0.000    0.454    0.178
##      tr_sex        -0.076    0.039   -1.937    0.053   -0.093   -0.046
##      EHisei         0.017    0.001   12.552    0.000    0.021    0.327
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      SSmath ~~
##      SSgerman      0.279    0.016   17.807    0.000    0.495    0.495
##      SozInt         0.168    0.020    8.468    0.000    0.245    0.245
##      SSgerman ~~
##      SozInt         0.164    0.018    9.265    0.000    0.290    0.290
##
## Intercepts:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      .SSkMa_a      0.000
##      .SSkMa_b      0.000
##      .SSkMa_c      0.000
##      .SSkMa_d      0.000
##      .SSkDe_a      0.000
##      .SSkDe_b      0.000
##      .SSkDe_c      0.000
##      .SSkDe_d      0.000
##      .SBezMs_a     0.000
##      .SBezMs_b     0.000
##      .SBezMs_c     0.000
##      .SBezMs_d     0.000
##      .wle_lesen    -1.602    0.152  -10.511    0.000   -1.602   -1.364
##      .wle_hoeren   -0.980    0.123   -7.956    0.000   -0.980   -0.976
##      .wle_mathe    -0.892    0.132   -6.777    0.000   -0.892   -0.816
##      SSmath        0.000
##      SSgerman      0.000
##      SozInt         0.000
##      .Abilities    0.000
##
## Thresholds:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      SSkMa_a|t1    -1.467    0.152   -9.631    0.000   -1.467   -1.467
##      SSkMa_a|t2    -0.859    0.151   -5.700    0.000   -0.859   -0.859
##      SSkMa_a|t3     0.121    0.150    0.805    0.421    0.121    0.121
##      SSkMa_b|t1    -0.723    0.148   -4.881    0.000   -0.723   -0.723
##      SSkMa_b|t2    -0.084    0.147   -0.572    0.567   -0.084   -0.084
##      SSkMa_b|t3     0.586    0.148    3.961    0.000    0.586    0.586
##      SSkMa_c|t1    -1.553    0.154  -10.081    0.000   -1.553   -1.553
##      SSkMa_c|t2    -0.882    0.151   -5.852    0.000   -0.882   -0.882
##      SSkMa_c|t3     0.225    0.151    1.492    0.136    0.225    0.225
##      SSkMa_d|t1    -1.786    0.157  -11.392    0.000   -1.786   -1.786
##      SSkMa_d|t2    -1.070    0.153   -7.005    0.000   -1.070   -1.070
##      SSkMa_d|t3     0.041    0.152    0.267    0.789    0.041    0.041
##      SSkDe_a|t1    -0.456    0.150   -3.050    0.002   -0.456   -0.456
##      SSkDe_a|t2     0.292    0.148    1.975    0.048    0.292    0.292
##      SSkDe_a|t3     1.367    0.150    9.100    0.000    1.367    1.367
##      SSkDe_b|t1     0.211    0.144    1.461    0.144    0.211    0.211
##      SSkDe_b|t2     0.899    0.144    6.249    0.000    0.899    0.899
##      SSkDe_b|t3     1.672    0.146   11.481    0.000    1.672    1.672

```

##	SSkDe_c t1	-1.090	0.158	-6.886	0.000	-1.090	-1.090
##	SSkDe_c t2	-0.456	0.152	-3.008	0.003	-0.456	-0.456
##	SSkDe_c t3	0.857	0.153	5.611	0.000	0.857	0.857
##	SSkDe_d t1	-1.218	0.161	-7.542	0.000	-1.218	-1.218
##	SSkDe_d t2	-0.515	0.152	-3.382	0.001	-0.515	-0.515
##	SSkDe_d t3	0.831	0.153	5.418	0.000	0.831	0.831
##	SBezMs_a t1	-1.361	0.160	-8.500	0.000	-1.361	-1.361
##	SBezMs_a t2	-0.596	0.152	-3.917	0.000	-0.596	-0.596
##	SBezMs_a t3	0.722	0.154	4.697	0.000	0.722	0.722
##	SBezMs_b t1	-0.772	0.144	-5.354	0.000	-0.772	-0.772
##	SBezMs_b t2	-0.076	0.143	-0.529	0.597	-0.076	-0.076
##	SBezMs_b t3	1.019	0.146	6.996	0.000	1.019	1.019
##	SBezMs_c t1	-1.196	0.154	-7.759	0.000	-1.196	-1.196
##	SBezMs_c t2	-0.728	0.153	-4.752	0.000	-0.728	-0.728
##	SBezMs_c t3	0.034	0.154	0.223	0.824	0.034	0.034
##	SBezMs_d t1	-1.203	0.164	-7.316	0.000	-1.203	-1.203
##	SBezMs_d t2	-0.650	0.160	-4.056	0.000	-0.650	-0.650
##	SBezMs_d t3	0.091	0.161	0.568	0.570	0.091	0.091

##

Variances:

##		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
##	.SSkMa_a	0.314				0.314	0.314
##	.SSkMa_b	0.527				0.527	0.527
##	.SSkMa_c	0.370				0.370	0.370
##	.SSkMa_d	0.213				0.213	0.213
##	.SSkDe_a	0.536				0.536	0.536
##	.SSkDe_b	0.552				0.552	0.552
##	.SSkDe_c	0.476				0.476	0.476
##	.SSkDe_d	0.354				0.354	0.354
##	.SBezMs_a	0.315				0.315	0.315
##	.SBezMs_b	0.596				0.596	0.596
##	.SBezMs_c	0.553				0.553	0.553
##	.SBezMs_d	0.598				0.598	0.598
##	.wle_lesen	0.718	0.031	22.816	0.000	0.718	0.520
##	.wle_hoeren	0.679	0.026	25.904	0.000	0.679	0.673
##	.wle_mathe	0.350	0.031	11.178	0.000	0.350	0.293
##	SSmath	0.686	0.017	39.302	0.000	1.000	1.000
##	SSgerman	0.464	0.022	21.511	0.000	1.000	1.000
##	SozInt	0.685	0.032	21.401	0.000	1.000	1.000
##	.Abilities	0.378	0.028	13.341	0.000	0.571	0.571

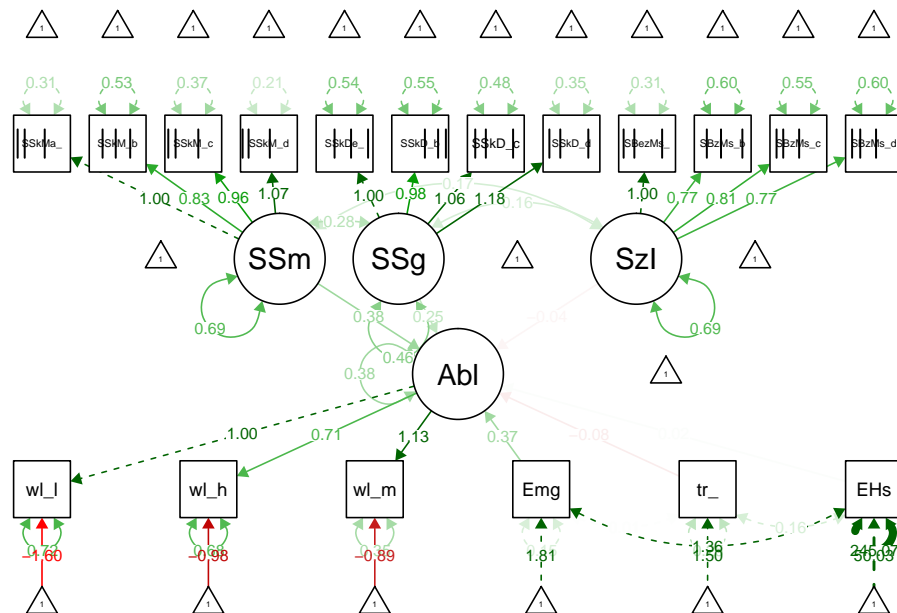
##

Scales y*:

##		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
##	SSkMa_a	1.000				1.000	1.000
##	SSkMa_b	1.000				1.000	1.000
##	SSkMa_c	1.000				1.000	1.000
##	SSkMa_d	1.000				1.000	1.000
##	SSkDe_a	1.000				1.000	1.000
##	SSkDe_b	1.000				1.000	1.000
##	SSkDe_c	1.000				1.000	1.000
##	SSkDe_d	1.000				1.000	1.000
##	SBezMs_a	1.000				1.000	1.000
##	SBezMs_b	1.000				1.000	1.000
##	SBezMs_c	1.000				1.000	1.000

```
##      SBezMs_d      1.000      1.000      1.000
```

```
semPlot::semPaths(object = fit, what = "est")
```



short: item response theory

wörtliche Anmerkungen, wenn Zeit übrig

short: longitudinal data / multi-group analysis

wörtliche Anmerkungen, wenn Zeit übrig

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