Statistical Analysis Using Structural Equation Models

EPsy 8266

Christopher David Desjardins

Research Methodology Consulting Center

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Modeling strategies for fully latent SR models

1. Two-Step
2. Four-Step

Two-Step Modeling

1. Respecify the fully latent SR model as a CFA and assess whether it fits the the data. Needs to fit well.
2. Conditionally on a good fitting CFA, fit the hypothesized SR model
    - The SR model may be nested within the CFA, if so, use a chi-square test of difference
    - If not, fit is identical to CFA
    - Alternative, nested SR models

- If the CFA fits well, then the pattern coefficients should change slightly when moving to a SR model.
- If change a lot, then they depend on the structural paths (**interpretational confounding**).
    - The empirical def'n of the constructs depend on hypotheses about the causal effects.

Four-Step Modeling

Works only when each factor has at least 4 indicators.

1. Perform an EFA where you specify the number of factors in your hypothesized fully latent SR model using the same estimation method
2. Fit the fully latent SR as a CFA (same as Step #1 from the Two-Step approach)
3. Respecifying at least one of the factor covariances as a direct path from Step #2
4. Tests of our a priori hypotheses about the relationships between the factors and their parameters
    - These last two steps are Step #2 from the Two-Step approach

A Structural Equation Model of Parental Involvement, Motivational and Aptitudinal Characteristics, and Academic Achievement

Gonzalez-Pienda, et al. (2002). Journal of Experimental Education

The authors used the structural equation model (SEM) approach to test a model hypothesizing the influence of parental involvement on students' academic aptitudes, self-concept, and causal attributions, as well as the influence of the 3 variables on academic achievement. The theoretical model was contrasted in a group of 12- to 18-year-old adolescents ($N = 261$) attending various educational centers.

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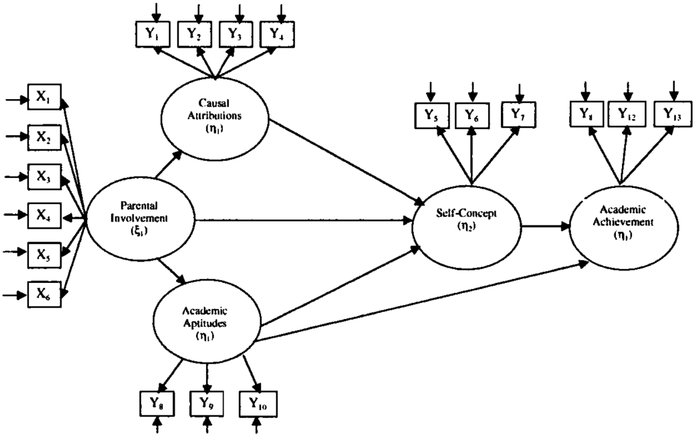
A structural equation model of parental involvement, motivational and aptitudinal characteristics, and academic achievement

JA Gonzalez-Pienda, JC Nunez… - The Journal of …, 2002 - Taylor & Francis

The authors used the structural equation model (SEM) approach to test a model hypothesizing the influence of parental involvement on students' academic aptitudes, self-concept, and causal attributions, as well as the influence of the 3 variables on academic achievement. The theoretical model was contrasted in a group of 12-to 18-year-old adolescents (N= 261) attending various educational centers. The results indicate that (a) parental involvement had a positive and significant influence on the participant's measured …

☆ ⁹⁹ Cited by 293 Related articles All 6 versions

FIGURE 1. A priori model of causal paths among parental involvement, aptitudinal and motivational characteristics, and academic achievement.



Note. Family variables: X_1 = achievement expectations, X_2 = help, X_3 = interest, X_4 = capacity expectations, X_5 = satisfaction, X_6 = reinforcement. Personal variables: Y_1 = capacity as cause of success in mathematical tasks, Y_2 = effort as cause of success in mathematical tasks, Y_3 = capacity as cause of success in verbal tasks, Y_4 = effort as cause of success in verbal tasks, Y_5 = mathematical self-concept, Y_6 = verbal self-concept, Y_7 = self-concept in remaining areas, Y_8 = verbal aptitude, Y_9 = reasoning aptitude, Y_{10} = calculus aptitude. Achievement variables: Y_{11} = mathematical achievement, Y_{12} = verbal achievement, Y_{13} = global achievement in remaining areas.

Methodology

- In the initial model, no relationship was assumed between the measurement errors of the observed variables or indicators, but these correlations were included in the respecifications carried out on the model. We did this because the indicators of each of the latent variables were obtained from our using the same instrument (e.g., the total score of the subscales).
- Considering that some data support the hypothesis of causal relationship in directions opposite to those established in the model presented in Figure 1 and even reciprocal relations (e.g., between causal attributions and self-concept, or between self-concept and academic achievement) we proceeded to contrast two alternative models involving these other possible causal relations after we contrasted the initial theoretical model.
- They presented goodness-of-fit index (GFI) and adjusted version (AGI), CFI, TLI, SRMR, and RMSEA

TABLE 1
Correlation Matrix, Means, and Standard Deviations for Model a

	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11	Y12	Y13	X1	X2	X3	X4	X5	X6
Y1	—																		
Y2	.60	—																	
Y3	.51	.38	—																
Y4	.27	.56	.48	—															
Y5	.58	.41	.15	.00	—														
Y6	.28	.26	.54	.30	.28	—													
Y7	.41	.36	.44	.23	.58	.63	—												
Y8	.24	.12	.10	.07	.37	.27	.32	—											
Y9	.29	.20	.10	.04	.39	.20	.38	.48	—										
Y10	.35	.27	.19	.13	.44	.22	.42	.47	.60	—									
Y11	.44	.31	.25	.05	.55	.34	.60	.41	.46	.46	—								
Y12	.38	.29	.37	.17	.48	.52	.67	.35	.48	.44	.77	—							
Y13	.39	.26	.26	.07	.52	.42	.64	.43	.52	.48	.82	.86	—						
X1	.32	.35	.30	.16	.43	.32	.57	.18	.30	.38	.50	.50	.47	—					
X2	.16	.30	.25	.32	.07	.19	.25	−.01	−.06	−.04	.10	.13	.05	.23	—				
X3	.15	.24	.25	.28	.12	.23	.31	.07	−.03	.06	.07	.15	.06	.27	.71	—			
X4	.40	.37	.37	.20	.53	.45	.73	.20	.30	.31	.54	.57	.56	.65	.43	.41	—		
X5	.30	.27	.24	.13	.42	.37	.65	.12	.31	.23	.49	.50	.51	.47	.41	.42	.75	—	
X6	−.01	−.01	−.00	.02	.02	.07	.08	−.12	−.11	−.12	−.05	.00	−.07	.14	.43	.44	.31	.40	—
M	2.93	3.38	3.42	3.74	3.45	3.89	4.25	27.92	19.61	18.27	2.82	3.05	3.15	4.32	3.93	4.02	3.59	3.92	3.21
SD	1.17	.95	.93	.87	1.33	.91	1.00	6.56	6.88	6.05	1.04	1.01	1.00	.48	.62	.61	.64	.62	.72

Note. Family variables: X1 = achievement expectations, X2 = help, X3 = interest, X4 = capacity expectations, X5 = satisfaction, X6 = reinforcement. Personal variables: Y1 = capacity as cause of success in mathematical tasks, Y2 = effort as cause of success in mathematical tasks, Y3 = capacity as cause of success in verbal tasks, Y4 = effort as cause of success in verbal tasks, Y5 = mathematical self-concept, Y6 = verbal self-concept, Y7 = self-concept in remaining areas, Y8 = verbal aptitude, Y9 = reasoning aptitude, Y10 = calculus aptitude. Achievement Variables: Y11 = mathematical achievement, Y12 = verbal achievement, Y13 = global achievement in remaining areas.

```r
library(lavaan)
lowerTri <- '
1
.60 1
.51 .38 1
.27 .56 .48 1
.58 .41 .15 .00 1
.28 .26 .54 .30 .28 1
.41 .36 .44 .23 .58 .63 1
.24 .12 .10 .07 .37 .27 .32 1
.29 .20 .10 .04 .39 .20 .38 .48 1
.35 .27 .19 .13 .44 .22 .42 .47 .60 1
.44 .31 .25 .05 .55 .34 .60 .41 .46 .46 1
.38 .29 .37 .17 .48 .52 .67 .35 .48 .44 .77 1
.39 .26 .26 .07 .52 .42 .64 .43 .52 .48 .82 .86 1
.32 .35 .30 .16 .43 .32 .57 .18 .30 .38 .50 .50 .47 1
.16 .30 .25 .32 .07 .19 .25 -.01 -.06 -.04 .10 .13 .05 .23 1
.15 .24 .25 .28 .12 .23 .31 .07 -.03 .06 .07 .15 .06 .27 .71 1
.40 .37 .37 .20 .53 .45 .73 .20 .30 .31 .54 .57 .56 .65 .43 .41 1
.30 .27 .24 .13 .42 .37 .65 .12 .31 .23 .49 .50 .51 .47 .41 .42 .75 1
-.01 -.01 -0 .02 .02 .07 .08 -.12 -.11 -.12 -.05 0 -.07 .14 .43 .44 .31 .4 1
'
corMat <- getCov(lowerTri,
                 names = c(paste0("y", 1:13), paste0("x", 1:6)),
                 sd = c(1.17, .95, .93, .87, 1.33, .91, 1.00, 6.56, 6.88, 6.05,
                        1.04, 1.01, 1.00, .48, .62, .61, .64, .62, .72))
```

Four Step Modeling, Step 1: EFA

```
fa.soln <- factanal(covmat = corMat, factors = 5, n.obs = 261, rotation = "promax")
print(loadings(fa.soln), cutoff = .3)

## Loadings:
##     Factor1 Factor2 Factor3 Factor4 Factor5
## y1                   0.574           0.537
## y2                   0.387           0.700
## y3                           0.604   0.436
## y4                                   0.630
## y5                   0.871
## y6                           0.854
## y7                   0.331   0.604
## y8   0.376
## y9   0.452
## y10  0.303           0.333
## y11  0.885
## y12  0.959
## y13  1.061
## x1                   0.325
## x2           0.912
## x3           0.785
## x4           0.394   0.379
## x5           0.484
## x6           0.653
##
##                Factor1 Factor2 Factor3 Factor4 Factor5
## SS loadings      3.394   2.451   2.052   1.740   1.545
## Proportion Var   0.179   0.129   0.108   0.092   0.081
## Cumulative Var   0.179   0.308   0.416   0.507   0.588
```

Four Step Modeling - Step 2

```
one.fact <- "
f1 =~ x1 + x2 + x3 + x4 + x5 + x6 + y1 + y2 + y3 +
      y4 + y5 + y6 + y7 + y8 + y9 + y10 +y11 + y12 + y13
"
one.fit <- cfa(one.fact, sample.cov = corMat, sample.nobs = 261)
```

```r
fitmeasures(one.fit, c("chisq", "df", "pvalue", "cfi",
                       "tli", "rmsea", "srmr"))
```

```
##    chisq       df   pvalue      cfi      tli    rmsea     srmr
## 1442.125  152.000    0.000    0.576    0.524    0.180    0.133
```

```r
meas.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13
"
meas.fit <- cfa(meas.mod, sample.cov = corMat, sample.nobs = 261)

# chi-square test of difference, discriminant validity
anova(meas.fit, one.fit)

## Chi Square Difference Test
##
##           Df   AIC   BIC   Chisq Chisq diff Df diff Pr(>Chisq)
## meas.fit 142 13154 13325  767.34
## one.fit  152 13808 13944 1442.12     674.78      10  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
fitmeasures(meas.fit, c("chisq", "df", "pvalue", "cfi",
                        "tli", "rmsea", "srmr", "gfi", "agfi"))
```

```
##   chisq      df  pvalue     cfi     tli   rmsea    srmr     gfi
## 767.343 142.000   0.000   0.795   0.753   0.130   0.106   0.744
##    agfi
##   0.658
```

Reported pattern coefficients

TABLE 3
Pattern of Estimated Parameters for Measurement Model of Hypothesized Model

Measure	Error/ Uniqueness	Parental involvement (ξ_1)		Causal attribution (η_1)		Self-concept (η_2)		Academic aptitudes (η_3)		Academic achievement (η_4)	
Lambda *X* (λx)											
PIN1	.51 (.51)	.70	(.70)								
PIN2	.84 (.85(	.40*	(.39*)								
PIN3	.81 (.82)	.43*	(.43*)								
PIN4	.16 (.15)	.92**	(.92**)								
PIN5	.33 (.34)	.82**	(.81**)								
PIN6	.98 (.98)	.15	(.15)								
Lambda *Y* (λy)											
CAT1	.24 (.22)			.87	(.86)	.000	(.000)	.000	(.000)	.000	(.000)
CAT2	.52 (.79)			.69**	(.45**)	.000	(.000)	.000	(.000)	.000	(.000)
CAT3	.63 (.94)			.61**	(.24**)	.000	(.000)	.000	(.000)	.000	(.000)
CAT4	.91 (.95)			.30**	(.22**)	.000	(.000)	.000	(.000)	.000	(.000)
ASC1	.53 (.55)			.000	(.000)	.69	(.67)	.000	(.000)	.000	(.000)
ASC2	.75 (.73)			.000	(.000)	.50**	(.52**)	.000	(.000)	.000	(.000)
ASC3	.23 (.24)			.000	(.000)	.87**	(.87**)	.000	(.000)	.000	(.000)
AAP1	.61 (.61)			.000	(.000)	.000	(.000)	.63	(.62)	.000	(.000)
AAP2	.40 (.40)			.000	(.000)	.000	(.000)	.77**	(.78**)	.000	(.000)
AAP3	.41 (.41)			.000	(.000)	.000	(.000)	.77**	(.77**)	.000	(.000)
ACH1	.25 (.25)			.000	(.000)	.000	(.000)	.000	(.000)	.87	(.87)
ACH2	.19 (.19)			.000	(.000)	.000	(.000)	.000	(.000)	.90**	(.90**)
ACH3	.11 (.10)			.000	(.000)	.000	(.000)	.000	(.000)	.95**	(.95**)

Note. Standardized solution. Values without parentheses correspond to the model of attribution of success. Values in parentheses correspond to the model of attribution of failure (see SAS). The first value of each factor is fixed as a reference variable (they were fixed at 1.00), which means that we were unable to estimate their significance (*t* values). The measurement errors of the observed variables (uniqueness) were all at the significance level of $p > .001$. Significant correlated uniqueness are not presented here because of lack of space. PIN = Parental Involvement. CAT = Causal Attributions. ASC = Academic Self-Concept. AAP = Academic Aptitudes. ACH = Academic Achievement (in Figure 2 the nature of the 19 observed variables is described).
$^*p < .01$. $^{**}p < .001$.

```r
params <- parameterestimates(meas.fit, standardized = TRUE)
subset(params, op == "=~", select = c(lhs, op, rhs, std.all))
```

```
##    lhs op rhs std.all
## 1  pin =~  x1   0.671
## 2  pin =~  x2   0.476
## 3  pin =~  x3   0.475
## 4  pin =~  x4   0.938
## 5  pin =~  x5   0.805
## 6  pin =~  x6   0.342
## 7  cat =~  y1   0.743
## 8  cat =~  y2   0.768
## 9  cat =~  y3   0.641
## 10 cat =~  y4   0.573
## 11 asc =~  y5   0.643
## 12 asc =~  y6   0.638
## 13 asc =~  y7   0.928
## 14 aap =~  y8   0.626
## 15 aap =~  y9   0.774
## 16 aap =~ y10   0.765
## 17 ach =~ y11   0.862
## 18 ach =~ y12   0.908
## 19 ach =~ y13   0.945
```

Correlation Residuals

```
round(lavResiduals(meas.fit, type = "cor")$cov, 2)

##        x1    x2    x3    x4    x5    x6    y1
## x1   0.00
## x2  -0.09  0.00
## x3  -0.05  0.48  0.00
## x4   0.02 -0.02 -0.04  0.00
## x5  -0.07  0.03  0.04  0.00  0.00
## x6  -0.09  0.27  0.28 -0.01  0.12  0.00
## y1   0.06 -0.03 -0.04  0.03 -0.02 -0.14  0.00
## y2   0.08  0.11  0.05 -0.01 -0.06 -0.15  0.03
## y3   0.07  0.09  0.09  0.05 -0.03 -0.12  0.03
## y4  -0.04  0.18  0.14 -0.08 -0.11 -0.08 -0.16
## y5   0.07 -0.18 -0.13  0.03 -0.01 -0.16  0.29
## y6  -0.03 -0.06 -0.02 -0.04 -0.05 -0.11  0.00
## y7   0.06 -0.11 -0.05  0.01  0.04 -0.18  0.00
## y8   0.02 -0.13 -0.05 -0.03 -0.08 -0.20  0.06
## y9   0.10 -0.20 -0.17  0.02  0.07 -0.21  0.07
## y10  0.18 -0.18 -0.08  0.03 -0.01 -0.22  0.13
## y11  0.14 -0.16 -0.19  0.03  0.05 -0.24  0.15
## y12  0.12 -0.14 -0.12  0.03  0.04 -0.20  0.08
## y13  0.07 -0.23 -0.22  0.00  0.03 -0.27  0.08
```

Correlation Residuals

```
round(lavResiduals(meas.fit, type = "cor")$cov, 2)

##      y2    y3    y4    y5    y6    y7    y8     y9    y10   y11   y12   y13
## y2   0.00
## y3  -0.11  0.00
## y4   0.12  0.11  0.00
## y5   0.11 -0.10 -0.22  0.00
## y6  -0.03  0.29  0.08 -0.13  0.00
## y7  -0.07  0.08 -0.09 -0.02  0.04  0.00
## y8  -0.07 -0.06 -0.07  0.14  0.04 -0.02  0.00  0.00
## y9  -0.03 -0.09 -0.13  0.10 -0.09 -0.03  0.00  0.01  0.00
## y10  0.04  0.00 -0.04  0.16 -0.06  0.01 -0.01  0.00  0.01  0.00
## y11  0.02  0.00 -0.17  0.13 -0.08 -0.01  0.04  0.00  0.01  0.00
## y12 -0.02  0.11 -0.06  0.04  0.08  0.03 -0.04  0.00 -0.04 -0.01  0.00
## y13 -0.06 -0.01 -0.17  0.06 -0.04 -0.03  0.03  0.02 -0.01  0.00  0.00  0.00
```

Standardized Residuals

```
round(lavResiduals(meas.fit, type = "cor")$cov.z, 2)

##        x1    x2    x3    x4    x5    x6    y1
## x1   0.00
## x2  -2.36  0.00
## x3  -1.29  8.46  0.00
## x4   2.25 -1.53 -3.57  0.00
## x5  -3.26  0.94  1.31 -1.08  0.00
## x6  -2.18  4.98  5.15 -0.91  3.72  0.00
## y1   1.27 -0.53 -0.73  1.08 -0.42 -2.68  0.00
## y2   1.77  2.13  0.94 -0.40 -1.54 -2.76  2.07
## y3   1.54  1.72  1.72  1.44 -0.74 -2.08  1.58
## y4  -0.87  3.18  2.47 -2.18 -2.45 -1.42 -7.40
## y5   1.89 -3.70 -2.73  1.30 -0.17 -3.13  6.50
## y6  -0.82 -1.23 -0.41 -1.75 -1.56 -2.11 -0.11
## y7   2.05 -3.67 -1.73  1.75  1.81 -5.25 -0.14
## y8   0.33 -2.19 -0.80 -0.70 -1.61 -3.37  1.27
## y9   2.12 -3.74 -3.19  0.64  1.77 -3.73  1.65
## y10  3.86 -3.36 -1.54  1.08 -0.23 -3.87  3.20
## y11  3.41 -3.46 -4.04  1.27  1.60 -4.75  4.05
## y12  3.07 -3.33 -2.88  1.74  1.32 -4.24  2.23
## y13  1.85 -5.26 -5.04  0.06  1.07 -5.69  2.27
```

Standardized Residuals

```
round(lavResiduals(meas.fit, type = "cor")$cov.z, 2)
```

```
##        y2    y3    y4    y5    y6    y7    y8     y9    y10   y11   y12   y13
## y2   0.00
## y3  -7.73  0.00
## y4   4.39  3.13  0.00
## y5   2.62 -2.09 -4.29  0.00
## y6  -0.81  6.17  1.66 -3.96  0.00
## y7  -2.95  2.33 -2.48 -1.98  3.94  0.00
## y8  -1.45 -1.11 -1.31  2.93  0.82 -0.43  0.00
## y9  -0.85 -2.06 -2.74  2.36 -2.03 -1.54 -0.26  0.00
## y10  1.09 -0.02 -0.86  3.59 -1.47  0.42 -0.48  0.74  0.00
## y11  0.43  0.09 -3.68  3.71 -2.30 -0.51  1.16  0.13  0.32  0.00
## y12 -0.66  2.76 -1.48  1.13  2.57  1.79 -1.16 -0.03 -1.47 -1.89  0.00
## y13 -2.22 -0.25 -4.04  1.83 -1.34 -2.98  0.85  1.01 -0.75  1.19  0.67  0.00
```

Modification Indices

```
head(modificationindices(meas.fit, sort. = TRUE))

##     lhs op rhs      mi    epc sepc.lv sepc.all sepc.nox
## 148  x2 ~~  x3 107.562  0.192   0.192    0.659    0.659
## 226  y1 ~~  y5  60.071  0.450   0.450    0.566    0.566
## 87  asc =~  x6  41.706 -0.698  -0.596   -0.829   -0.829
## 248  y3 ~~  y6  41.309  0.219   0.219    0.440    0.440
## 225  y1 ~~  y4  41.275 -0.310  -0.310   -0.557   -0.557
## 119 ach =~  x6  36.341 -0.394  -0.353   -0.491   -0.491
```

What to do/What did they do???

Because of the poor fit of the two initial models, we respecified and reestimated the goodness of fit of the alternative models (sensitivity analysis). An essential criterion at this point was that the critical hypotheses of the initial model not be affected. Given that **most** of the respecifications carried out on the initial models referred to the estimation of the correlation between some measurement errors in the observed variables (measurement model), the final models did not differ significantly from the initial models.

Unfortunately, we don't know what they did and their results are not replicable!

Let's fish our way to a model AKA don't ever do this in your own research!

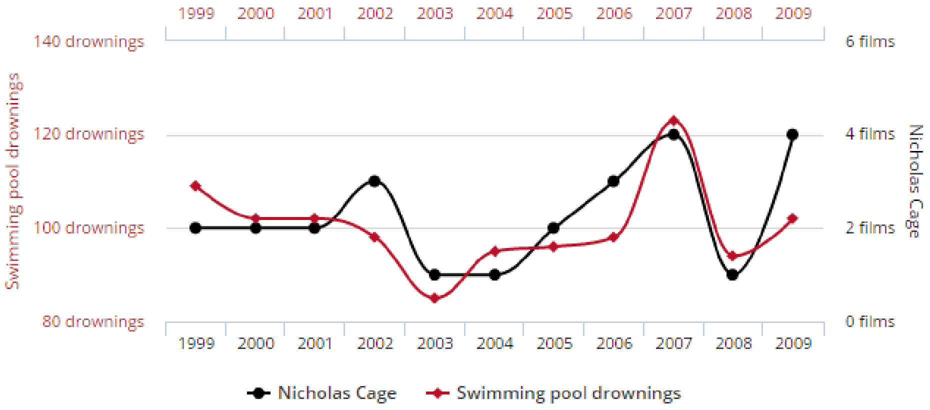
Number of people who drowned by falling into a pool

correlates with

Films Nicolas Cage appeared in

Correlation: 66.6% (r=0.666004)

Data sources: Centers for Disease Control & Prevention and Internet Movie Database



```r
r1.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x2 ~~ x3
y1 ~~ y5
"
r1.fit <- cfa(r1.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r1.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 557.586 140.000   0.000   0.863   0.833   0.107

head(modificationindices(r1.fit, sort. = T, standardized = F))

##     lhs op rhs     mi    epc
## 248  y3 ~~  y6 35.038  0.184
## 235  y2 ~~  y3 34.958 -0.249
## 121 ach =~  x6 34.677 -0.391
## 89  asc =~  x6 33.318 -0.622
## 236  y2 ~~  y4 30.800  0.210
## 105 aap =~  x6 30.172 -0.071
```

```r
r2.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x2 ~~ x3
y1 ~~ y5
y3 ~~ y6
"
r2.fit <- cfa(r2.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r2.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 519.363 139.000   0.000   0.875   0.846   0.102

head(modificationindices(r2.fit, sort. = T, standardized = F))

##     lhs op rhs     mi    epc
## 90  asc =~  x6 34.999 -0.649
## 122 ach =~  x6 34.607 -0.391
## 237  y2 ~~  y4 32.700  0.216
## 106 aap =~  x6 30.384 -0.071
## 236  y2 ~~  y3 28.446 -0.209
## 238  y2 ~~  y5 21.973  0.218
```

```r
r3.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x2 ~~ x3
y1 ~~ y5
y2 ~~ y4
y3 ~~ y6
"
r3.fit <- cfa(r3.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r3.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 487.453 138.000   0.000   0.885   0.858   0.098

head(modificationindices(r3.fit, sort. = T, standardized = F))

##     lhs op rhs     mi    epc
## 91  asc =~  x6 35.238 -0.624
## 123 ach =~  x6 34.689 -0.391
## 107 aap =~  x6 30.379 -0.071
## 238  y2 ~~  y5 24.022  0.213
## 237  y2 ~~  y3 20.478 -0.158
## 247  y3 ~~  y4 20.290  0.138
```

```r
r4.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x2 ~~ x3
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6
"
r4.fit <- cfa(r4.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r4.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 458.813 137.000   0.000   0.894   0.868   0.095

head(modificationindices(r4.fit, sort. = T, standardized = F))

##     lhs op rhs     mi    epc
## 124 ach =~  x6 34.840 -0.392
## 92  asc =~  x6 34.033 -0.593
## 108 aap =~  x6 30.378 -0.071
## 247  y3 ~~  y4 29.168  0.166
## 238  y2 ~~  y3 28.271 -0.195
## 227  y1 ~~  y2 26.859  0.336
```

```r
r5.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x2 ~~ x3
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y4 + y6
"
r5.fit <- cfa(r5.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r5.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 424.057 136.000   0.000   0.905   0.881   0.090

head(modificationindices(r5.fit, sort. = T, standardized = F))

##     lhs op rhs     mi    epc
## 125 ach =~  x6 34.889 -0.392
## 93  asc =~  x6 33.540 -0.580
## 109 aap =~  x6 30.317 -0.071
## 201  x5 ~~  x6 18.422  0.073
## 114 aap =~  y5 11.585  0.075
## 278  y6 ~~ y12 11.543  0.069
```

```r
r6.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x2 ~~ x3
x5 ~~ x6
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y4 + y6

"
r6.fit <- cfa(r6.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r6.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 405.309 135.000   0.000   0.911   0.888   0.088

head(modificationindices(r6.fit, sort. = T, standardized = F))

##     lhs op rhs     mi    epc
## 126 ach =~  x6 36.818 -0.397
## 94  asc =~  x6 33.012 -0.580
## 110 aap =~  x6 30.394 -0.069
## 278  y6 ~~ y12 11.630  0.070
## 115 aap =~  y5 11.615  0.075
## 273  y6 ~~  y7 11.407  0.106
```

```r
r7.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x2 ~~ x3
x5 ~~ x6
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y4 + y6
y6 ~~ y12
"
r7.fit <- cfa(r7.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r7.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 392.724 134.000   0.000   0.915   0.892   0.086

head(modificationindices(r7.fit, sort. = T, standardized = F))

##     lhs op rhs     mi    epc
## 127 ach =~  x6 36.937 -0.397
## 95  asc =~  x6 33.496 -0.586
## 111 aap =~  x6 30.490 -0.070
## 107 aap =~  x2 11.378 -0.028
## 255  y3 ~~ y12 11.267  0.069
## 116 aap =~  y5 11.241  0.074
```

```r
r8.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x2 ~~ x3
x5 ~~ x6
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12
y6 ~~ y12
"
r8.fit <- cfa(r8.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r8.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 380.729 133.000   0.000   0.919   0.895   0.084

modind <- modificationindices(r8.fit, sort. = T, standardized = F)
head(subset(modind, op == "~~"), 1)

##     lhs op rhs     mi   epc
## 274  y6 ~~  y7 11.321 0.104
```

```r
r9.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x2 ~~ x3
x5 ~~ x6
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12
y6 ~~ y7 + y12
"
r9.fit <- cfa(r9.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r9.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 369.014 132.000   0.000   0.922   0.899   0.083

modind <- modificationindices(r9.fit, sort. = T, standardized = F)
head(subset(modind, op == "~~"), 1)

##     lhs op rhs     mi  epc
## 252  y3 ~~  y7 12.793 0.09
```

```r
r10.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x2 ~~ x3
x5 ~~ x6
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9
y6 ~~ y7 + y12
"
r10.fit <- cfa(r10.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r10.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 366.344 131.000   0.000   0.923   0.899   0.083

modind <- modificationindices(r10.fit, sort. = T, standardized = F)
head(subset(modind, op == "~~"), 1)

##     lhs op rhs     mi   epc
## 192  x4 ~~  x6 11.301 0.055
```

```r
r11.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x2 ~~ x3
x4 ~~ x6
x5 ~~ x6
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9
y6 ~~ y7 + y12
"
r11.fit <- cfa(r11.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r11.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 352.055 130.000   0.000   0.927   0.904   0.081

modind <- modificationindices(r11.fit, sort. = T, standardized = F)
head(subset(modind, op == "~~"), 1)

##     lhs op rhs     mi    epc
## 145  x1 ~~  x5 12.032 -0.033
```

```r
r12.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x1 ~~ x5
x2 ~~ x3
x4 ~~ x6
x5 ~~ x6
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9
y6 ~~ y7 + y12
"
r12.fit <- cfa(r12.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r12.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))
```

```
##   chisq      df  pvalue     cfi     tli   rmsea
## 337.978 129.000   0.000   0.931   0.909   0.079
```

```r
modind <- modificationindices(r12.fit, sort. = T, standardized = F)
head(subset(modind, op == "~~"), 1)
```

```
##     lhs op rhs     mi   epc
## 178  x3 ~~  x6 10.183 0.054
```

```r
r13.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x1 ~~ x5
x3 ~~ x2 + x6
x4 ~~ x6
x5 ~~ x6
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9
y6 ~~ y7 + y12
"
r13.fit <- cfa(r13.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r13.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 325.400 128.000   0.000   0.935   0.913   0.077

modind <- modificationindices(r13.fit, sort. = T, standardized = F)
head(subset(modind, op == "~~"), 1)

##     lhs op rhs     mi   epc
## 163  x2 ~~  x6 30.105 0.128
```

```r
r14.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x1 ~~ x5
x3 ~~ x2
x6 ~~ x2 + x3 + x4 + x5
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9
y6 ~~ y7 + y12
"
r14.fit <- cfa(r14.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r14.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 292.230 127.000   0.000   0.946   0.927   0.071

modind <- modificationindices(r14.fit, sort. = T, standardized = F)
head(subset(modind, op == "~~"), 1)

##     lhs op rhs    mi   epc
## 253  y3 ~~  y7 9.872 0.077
```

```r
r15.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x1 ~~ x5
x3 ~~ x2
x6 ~~ x2 + x3 + x4 + x5
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9 + y7
y6 ~~ y7 + y12
"
r15.fit <- cfa(r15.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r15.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 281.945 126.000   0.000   0.949   0.931   0.069

modind <- modificationindices(r15.fit, sort. = T, standardized = F)
head(subset(modind, op == "~~"), 1)

##     lhs op rhs    mi   epc
## 275  y6 ~~  y8 9.376 0.672
```

```r
r16.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x1 ~~ x5
x3 ~~ x2
x6 ~~ x2 + x3 + x4 + x5
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9 + y7
y6 ~~ y7 + y8 + y12
"
r16.fit <- cfa(r16.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r16.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 272.131 125.000   0.000   0.952   0.934   0.067

modind <- modificationindices(r16.fit, sort. = T, standardized = F)
head(subset(modind, op == "~~"), 1)

##     lhs op rhs    mi   epc
## 216  x5 ~~  y9 8.747 0.354
```

```
r17.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x3 ~~ x2
x5 ~~ x1 + y9
x6 ~~ x2 + x3 + x4 + x5
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9 + y7
y6 ~~ y7 + y8 + y12
"
r17.fit <- cfa(r17.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r17.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 262.912 124.000   0.000   0.954   0.937   0.066

modind <- modificationindices(r17.fit, sort. = T, standardized = F)
head(subset(modind, op == "~~"), 1)

##     lhs op rhs    mi   epc
## 284  y7 ~~ y12 9.016 0.054
```

```r
r18.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x3 ~~ x2
x5 ~~ x1 + y9
x6 ~~ x2 + x3 + x4 + x5
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9 + y7
y6 ~~ y7 + y8 + y12
y7 ~~ y12
"
r18.fit <- cfa(r18.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r18.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 253.700 123.000   0.000   0.957   0.940   0.064

modind <- modificationindices(r18.fit, sort. = T, standardized = F)
head(subset(modind, op == "~~"), 1)

##     lhs op rhs    mi    epc
## 260  y4 ~~  y5 8.149 -0.134
```

```r
r19.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x3 ~~ x2
x5 ~~ x1 + y9
x6 ~~ x2 + x3 + x4 + x5
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9 + y7
y4 ~~ y5
y6 ~~ y7 + y8 + y12
y7 ~~ y12
"
r19.fit <- cfa(r19.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r19.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 245.343 122.000   0.000   0.960   0.943   0.062

modind <- modificationindices(r19.fit, sort. = T, standardized = F)
head(subset(modind, op == "~~"), 1)

##     lhs op rhs    mi   epc
## 163  x1 ~~ y10 6.706 0.259
```

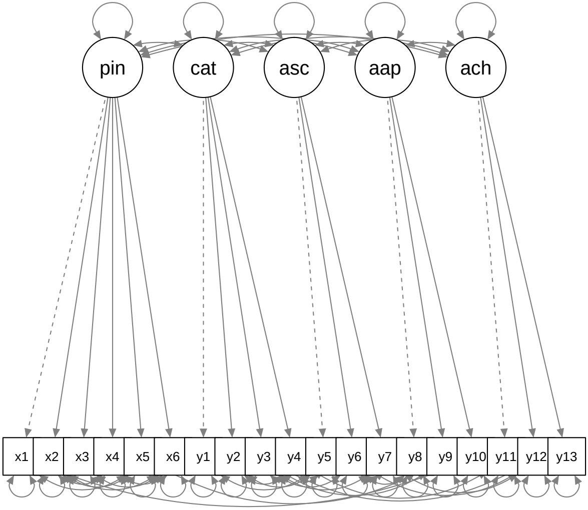
```r
r20.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x1 ~~ y10
x3 ~~ x2
x5 ~~ x1 + y9
x6 ~~ x2 + x3 + x4 + x5
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9 + y7
y4 ~~ y5
y6 ~~ y7 + y8 + y12
y7 ~~ y12
"
r20.fit <- cfa(r20.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r20.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 238.438 121.000   0.000   0.961   0.946   0.061

modind <- modificationindices(r20.fit, sort. = T, standardized = F)
head(subset(modind, op == "~~"), 1)

##     lhs op rhs    mi   epc
## 167  x2 ~~  x4 5.708 0.022
```

```r
r21.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x1 ~~ y10
x2 ~~ x4
x3 ~~ x2
x5 ~~ x1 + y9
x6 ~~ x2 + x3 + x4 + x5
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9 + y7
y4 ~~ y5
y6 ~~ y7 + y8 + y12
y7 ~~ y12
"
r21.fit <- cfa(r21.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r21.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 232.707 120.000   0.000   0.963   0.947   0.060

modind <- modificationindices(r21.fit, sort. = T, standardized = F)
head(subset(modind, op == "~~"), 1)

##     lhs op rhs    mi    epc
## 266  y4 ~~ y11 5.244 -0.052
```

```r
r22.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x1 ~~ y10
x2 ~~ x4
x3 ~~ x2
x5 ~~ x1 + y9
x6 ~~ x2 + x3 + x4 + x5
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9 + y7
y4 ~~ y5 + y11
y6 ~~ y7 + y8 + y12
y7 ~~ y12
"
r22.fit <- cfa(r22.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r22.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 227.164 119.000   0.000   0.964   0.949   0.059

modind <- modificationindices(r22.fit, sort. = T, standardized = F)
head(subset(modind, op == "~~"), 1)

##     lhs op rhs    mi   epc
## 169  x2 ~~  x5 5.094 0.029
```

```r
r23.mod <- "
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# residual correlations
x1 ~~ y10
x2 ~~ x4 + x5
x3 ~~ x2
x5 ~~ x1 + y9
x6 ~~ x2 + x3 + x4 + x5
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9 + y7
y4 ~~ y5 + y11
y6 ~~ y7 + y8 + y12
y7 ~~ y12
"
r23.fit <- cfa(r23.mod, sample.cov = corMat, sample.nobs = 261)
fitmeasures(r23.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 221.655 118.000   0.000   0.966   0.951   0.058
```

Maybe this was there model?



At first glance, the results indicated that the correlation between some measurement errors of certain observed variables of the measurement model lead to a poor fit of the hypothesized model (see Figure 1) and the data obtained in the sample. After the respecifications, the final models (Models a and b with respecifications) were obtained.

Wait ... did they do this on their SR model or their CFA?

I obtained similar RMSE and TLI but probably a different model.

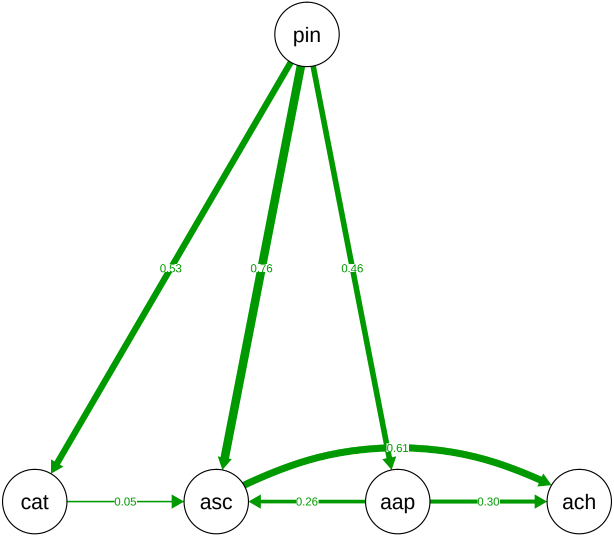
Step 3/4

```
step4.mod <- "
# define measurement models
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# structural paths
cat ~ pin
aap ~ pin
asc ~ cat + aap + pin
ach ~ asc + aap

# residual correlations
x1 ~~ y10
x2 ~~ x4 + x5
x3 ~~ x2
x5 ~~ x1 + y9
x6 ~~ x2 + x3 + x4 + x5
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9 + y7
y4 ~~ y5 + y11
y6 ~~ y7 + y8 + y12
y7 ~~ y12
"
step4.fit <- sem(step4.mod, sample.cov = corMat, sample.nobs = 261)
```

Step 4 - fit

```
fitmeasures(step4.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 229.957 121.000   0.000   0.964   0.949   0.059

anova(step4.fit, r23.fit)

## Chi Square Difference Test
##
##            Df   AIC   BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## r23.fit   118 12656 12913 221.65
## step4.fit 121 12658 12904 229.96     8.3023       3    0.04016 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

But, I used up 3 more df than they did and 261 participants, I estimated 69 parameters or 3.78 participants/parameter estimated.



pin
cat
asc
aap
ach
0.53
0.76
0.46
0.61
0.05
0.26
0.30

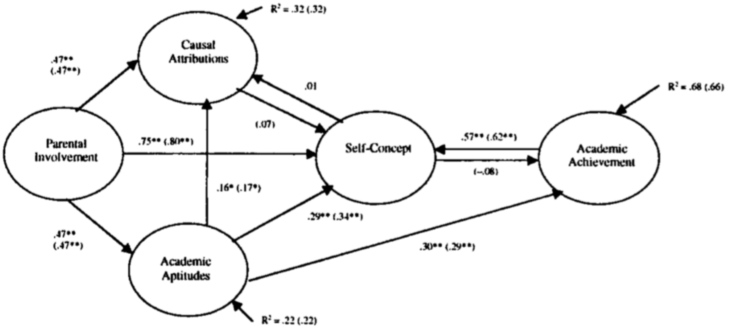
Alternate paths

```
alt1.mod <- "
# define measurement models
pin =~ x1 + x2 + x3 + x4 + x5 + x6
cat =~ y1 + y2 + y3 + y4
asc =~ y5 + y6 + y7
aap =~ y8 + y9 + y10
ach =~ y11 + y12 + y13

# structural paths
cat ~ pin + aap + asc
aap ~ pin
asc ~ cat + aap + pin + ach
ach ~ asc + aap

# residual correlations
x1 ~~ y10
x2 ~~ x4 + x5
x3 ~~ x2
x5 ~~ x1 + y9
x6 ~~ x2 + x3 + x4 + x5
y1 ~~ y5
y2 ~~ y4 + y5
y3 ~~ y6 + y4 + y12 + y9 + y7
y4 ~~ y5 + y11
y6 ~~ y7 + y8 + y12
y7 ~~ y12
"
alt1.fit <- sem(alt1.mod, sample.cov = corMat, sample.nobs = 261)
```

```r
fitmeasures(alt1.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 221.655 118.000   0.000   0.966   0.951   0.058

fitmeasures(r23.fit, c("chisq", "df", "pvalue", "cfi", "tli", "rmsea"))

##   chisq      df  pvalue     cfi     tli   rmsea
## 221.655 118.000   0.000   0.966   0.951   0.058
```

Alternative model

FIGURE 2. Path coefficients of critical causal paths for latent variable model when the causal attributions are made about successful situations (in the SAS).



Their results

TABLE 4
Goodness-of-Fit Indexes for Latent Variable Models

Model	X^2	*df*	X^2/df	*p*	GFI	AGFI	CFI	TLI	RMR	RMSEA
				Model a (attributions in successful situations)						
Null model	3,204.87	171	18.70							
Initial theoretical model	849.07	$\boxed{143}$	5.93	.00	.74	.66	.79	.72	.11	.14
Final model	233.08	124	1.87	.00	.91	.87	.96	.95	.07	.05
Alternative model (a1)	233.08	124	1.87	.00	.91	.87	.96	.95	.07	.05
Alternative model (a2)	233.08	124	1.87	.00	.91	.87	.96	.95	.07	.05