# Problems with sem

(adapted from Rex Kline: Principals and Practice of Structural Equation Modeling, 2005)

# 44 ways to fool yourself with SEM

I. Specification

II. Data

III. Analysis and Respecification

IV. Interpretation

# Specification

I. Specifying the model after the data are collected (particularly a problem when using archival data)

   A. are key variables omitted

   B. is the model identifiable

# Specification errors (cont)

I. Omitting causes that are correlated with other variables in a structural model

II. Failure to have sufficient number of indicators of latent variables

    A. "Two might be fine, three is better, four is best, and anything more is gravy" (Kenny, 1979)

# Specification errors (cont)

I. Failure to give careful consideration to directionality.

   A. Path techniques are good for estimating strengths if we know the underlying model, but are not good for determining the model (Meehl and Walker, 2002)

# Specification errors (cont)

I. Specifying feedback effects (non-recursive models) as a way to mask uncertainty

II. Overfit the model, ignoring parsimony

III. Add disturbances (measurement error correlations) without substantive reason.

IV. Specifying indicators that are multivocal without substantive reason.

# Data errors

I. Failure to check the accuracy of data input or coding

   A. missing data codes (use a clear missing value)

   B. mistyped, mis-scanned data matrices

   C. improperly reversed items

      1. let the computer do it for you

      2. why reverse when a negative sign will work

# Data errors (continued)

I. Ignoring the pattern of missing data, is it random or systematic?

II. Failure to examine distributional characteristics.

   A. weird data -> weird results

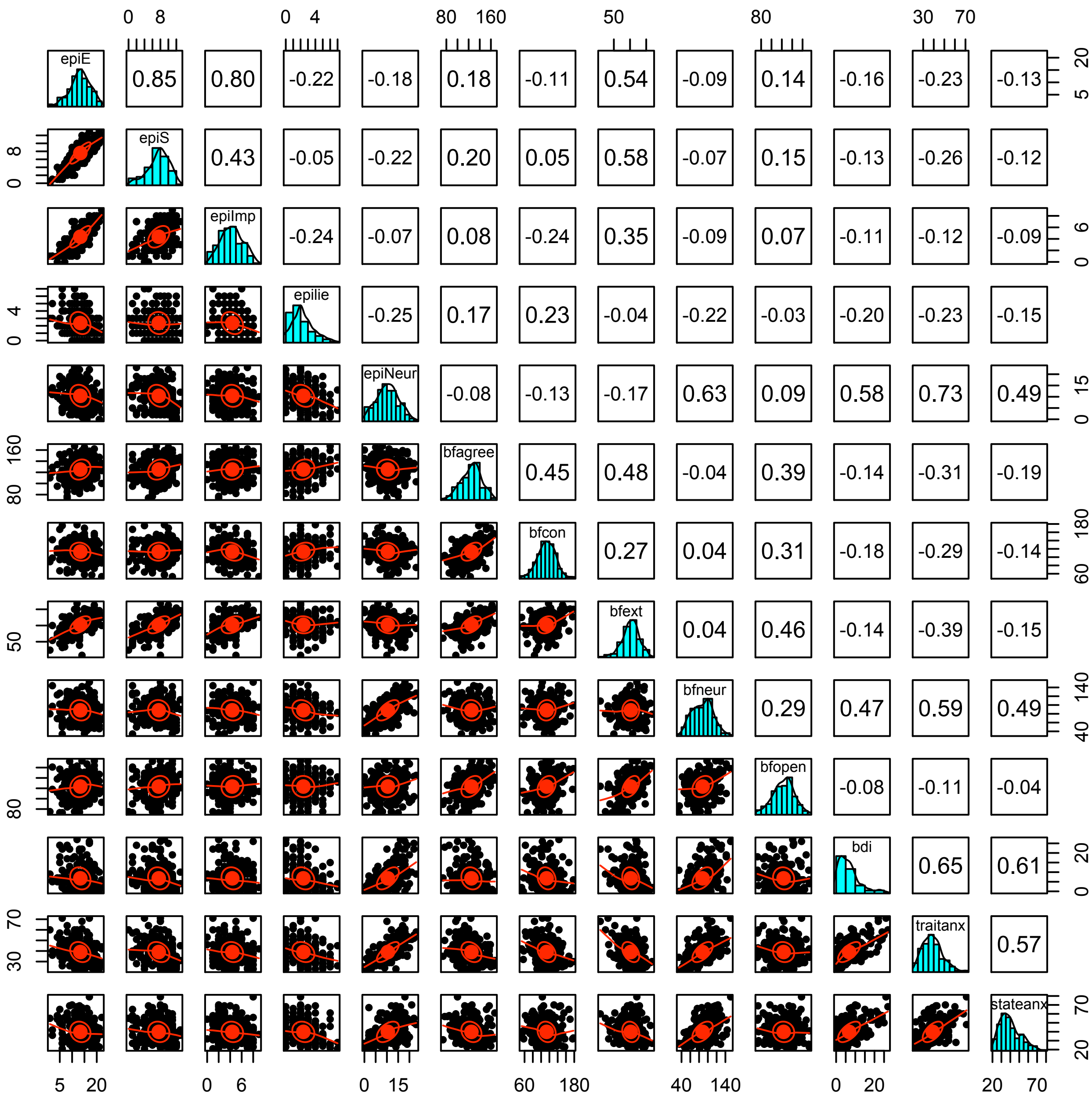
III. Failure to screen for outliers

   A. outliers due to mistakes

   B. outliers due to systematic differences

# Describe the data!

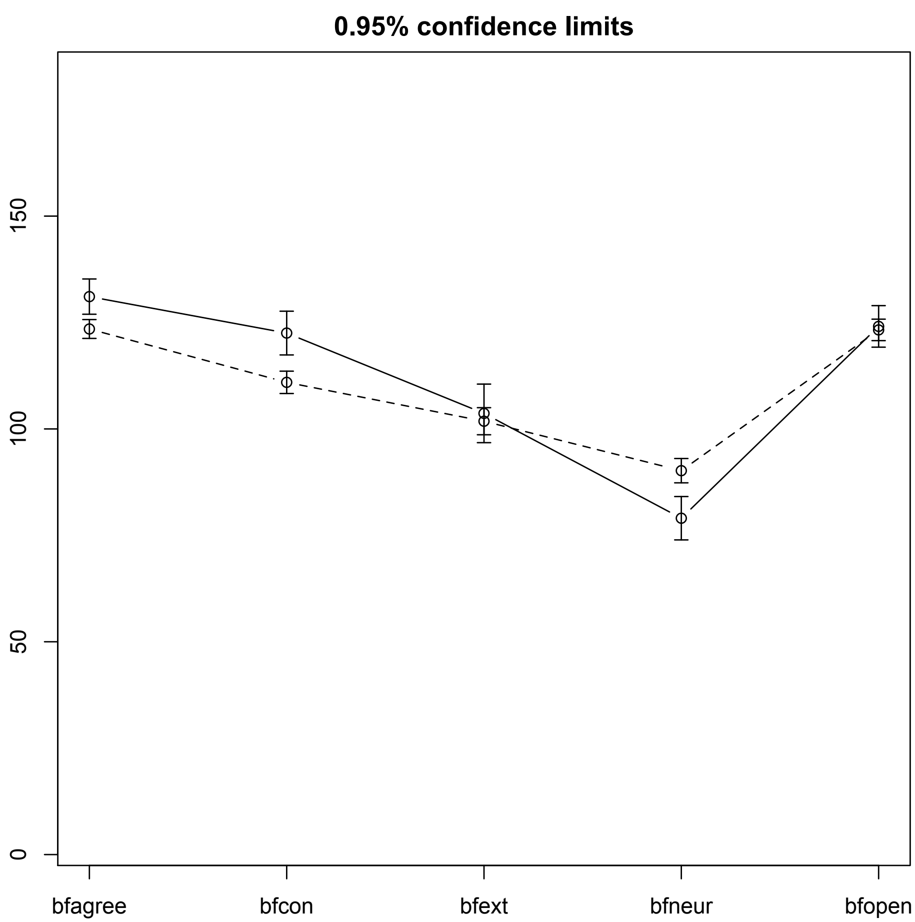
```
> describe(epi.bfi)
         var   n   mean    sd median trimmed   mad min max range  skew kurtosis   se
epiE       1 231  13.33  4.14     14   13.49  4.45   1  22    21 -0.33    -0.06 0.27
epiS       2 231   7.58  2.69      8    7.77  2.97   0  13    13 -0.57    -0.02 0.18
epiImp     3 231   4.37  1.88      4    4.36  1.48   0   9     9  0.06    -0.62 0.12
epilie     4 231   2.38  1.50      2    2.27  1.48   0   7     7  0.66     0.24 0.10
epiNeur    5 231  10.41  4.90     10   10.39  4.45   0  23    23  0.06    -0.50 0.32
bfagree    6 231 125.00 18.14    126  125.26 17.79  74 167    93 -0.21    -0.27 1.19
bfcon      7 231 113.25 21.88    114  113.42 22.24  53 178   125 -0.02     0.23 1.44
bfext      8 231 102.18 26.45    104  102.99 22.24   8 168   160 -0.41     0.51 1.74
bfneur     9 231  87.97 23.34     90   87.70 23.72  34 152   118  0.07    -0.55 1.54
bfopen    10 231 123.43 20.51    125  123.78 20.76  73 173   100 -0.16    -0.16 1.35
bdi       11 231   6.78  5.78      6    5.97  4.45   0  27    27  1.29     1.50 0.38
traitanx  12 231  39.01  9.52     38   38.36  8.90  22  71    49  0.67     0.47 0.63
stateanx  13 231  39.85 11.48     38   38.92 10.38  21  79    58  0.72    -0.01 0.76
```



0 8
0 4
80 160
50
80
30 70
epiE 0.85 0.80 -0.22 -0.18 0.18 -0.11 0.54 -0.09 0.14 -0.16 -0.23 -0.13
epiS 0.43 -0.05 -0.22 0.20 0.05 0.58 -0.07 0.15 -0.13 -0.26 -0.12
epiImp -0.24 -0.07 0.08 -0.24 0.35 -0.09 0.07 -0.11 -0.12 -0.09
epilie -0.25 0.17 0.23 -0.04 -0.22 -0.03 -0.20 -0.23 -0.15
epiNeur -0.08 -0.13 -0.17 0.63 0.09 0.58 0.73 0.49
bfagree 0.45 0.48 -0.04 0.39 -0.14 -0.31 -0.19
bfcon 0.27 0.04 0.31 -0.18 -0.29 -0.14
bfext 0.04 0.46 -0.14 -0.39 -0.15
bfneur 0.29 0.47 0.59 0.49
bfopen -0.08 -0.11 -0.04
bdi 0.65 0.61
traitanx 0.57
stateanx
5 20
0 6
0 15
60 180
40 140
0 20
20 70

# Exclude bad subjects

```
error.bars.by(epi.bfi[,6:10],(epi.bfi$epilie<4))
```




High "Lie" scorers are different

# Data errors (continued)

I. Assuming all relationships are linear without checking (graphical techniques are helpful for non-linearities, but not for interactions)

II. Ignoring lack of independence among observations (nesting of subjects within pairs, classrooms, managers).

# Errors of Analysis and Respecification

I. Failure to check the accuracy of computer syntax.
   A. direction of effects,
   B. error specifications,
   C. paths omitted
II. Respecifying the model based entirely on statistical criteria
III. Failure to check for admissible solutions
   A. Are some of the paths impossible, do you have negative error variances

# Errors of Analysis and Respecification (continued)

I. Reporting only standardized estimates
   A. These are sample based estimates and reflect variances as well as covariances
II. Analyzing a correlation matrix when the covariance matrix is more appropriate
   A. e.g., anything that has a growth or change component to it

# Errors of Analysis and Respecification (continued)

I. Analyzing a data set with extremely high correlations

   A. solution will either be unstable or will not work if variables are too "colinear"

II. Not enough subjects for complexity of the data

   A. This is ambiguous -- what is enough?

   B. Partly reflects se of r = 1/sqrt(n-3)

# Errors of Analysis and Respecification (continued)

I. Setting scales of latent variables inappropriately. (particularly a problem with multiple group comparisons).

II. Ignoring the start values or giving bad ones. Supplying reasonable start values helps a great deal

III. Do different start values lead to different solutions?

# Errors of Analysis and Respecification (continued)

I. Failure to recognize empirical underidentification (for some data sets, the model is underidentified even though there are enough parameters)

II. Failure to separate measurement from structural portion of model

    A. Use the two or four step procedure

# Errors of Analysis and Respecification (continued)

I. Estimating means and intercepts without showing measurement invariance

II. Analyzing parcels without checking if parcels are in fact factorially homogeneous.

   A. Factorial Homogeneous Item Domains (FHID)

   B. Homogenous Item Composites (HIC)

# Errors of Interpretation

I. Looking only at indexes of overall fit

   A. need to examine the residuals to see where there is misfit, even though overall model is fine

II. Interpreting good fit as meaning model is "proved".

   A. consider alternative models

   B. better able to reject alternatives

# Errors of Interpretation (continued)

I. Interpreting good fit as meaning that the endogenous variables are strongly predicted.

   A. What is predicted is the covariance of the variables, not the variables

   B. Are the residual covariances small, not whether the error variance is small

# Consider two data sets

I. cong1 <- sim.congeneric(loads=rep(.8,6))

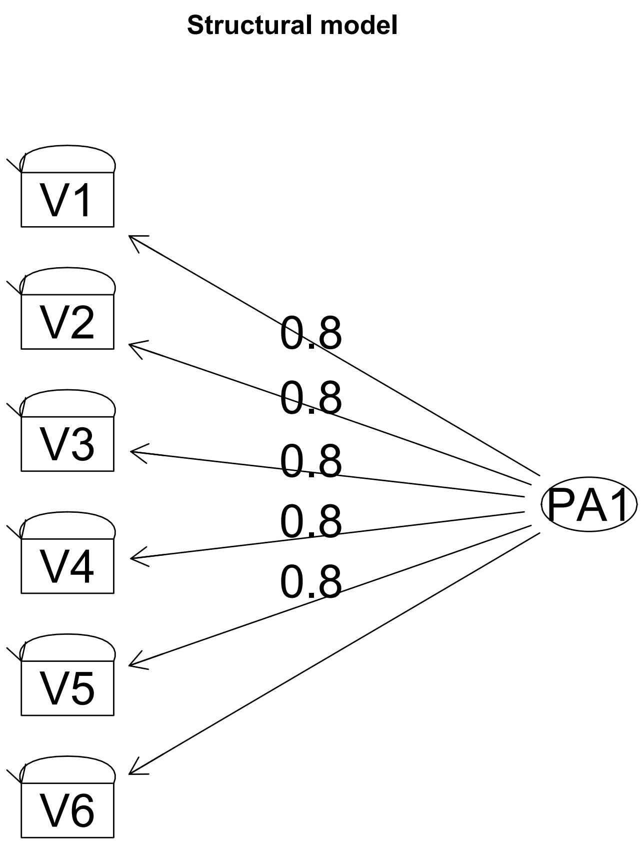
II. cong2 <- sim.congneric(loads=rep(.4,6))

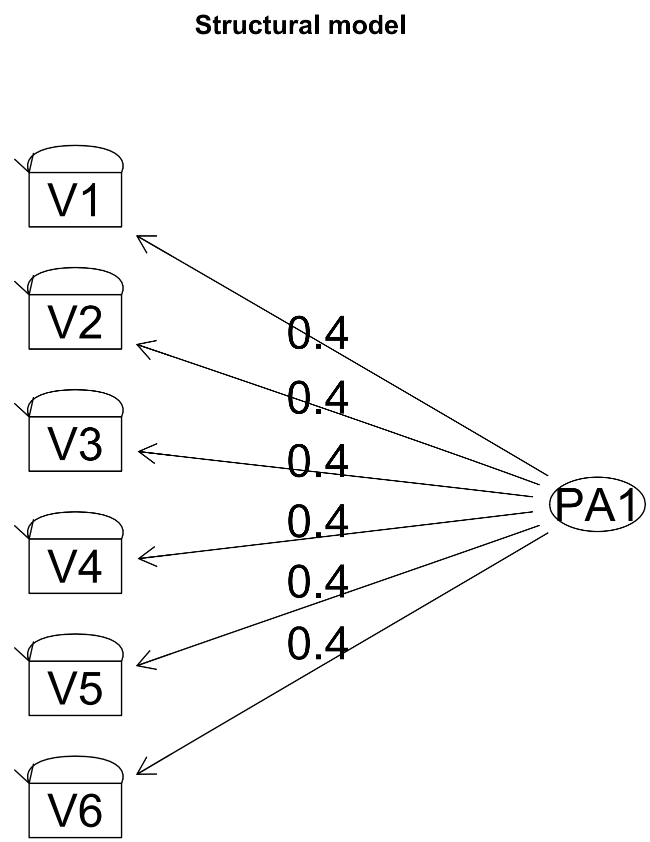
# Data sets 1 and 2

```
> cong1
     V1   V2   V3   V4   V5   V6
V1 1.00 0.64 0.64 0.64 0.64 0.64
V2 0.64 1.00 0.64 0.64 0.64 0.64
V3 0.64 0.64 1.00 0.64 0.64 0.64
V4 0.64 0.64 0.64 1.00 0.64 0.64
V5 0.64 0.64 0.64 0.64 1.00 0.64
V6 0.64 0.64 0.64 0.64 0.64 1.00
```

```
> cong2
     V1   V2   V3   V4   V5   V6
V1 1.00 0.16 0.16 0.16 0.16 0.16
V2 0.16 1.00 0.16 0.16 0.16 0.16
V3 0.16 0.16 1.00 0.16 0.16 0.16
V4 0.16 0.16 0.16 1.00 0.16 0.16
V5 0.16 0.16 0.16 0.16 1.00 0.16
V6 0.16 0.16 0.16 0.16 0.16 1.00
```

# Two structural models



```
> summary(sem1,digits=2)
```

# Set 1

```
 Model Chisquare =  5.4e-11   Df =  9 Pr(>Chisq) = 1
 Chisquare (null model) =  731   Df =  15
 Goodness-of-fit index =  1
 Adjusted goodness-of-fit index =  1
 RMSEA index =  0   90% CI: (NA, NA)
 Bentler-Bonnett NFI =  1
 Tucker-Lewis NNFI =  1.0
 Bentler CFI =  1
 SRMR =  3.6e-07
 BIC =  -48

 Parameter Estimates
    Estimate Std Error z value Pr(>|z|)
V1   0.80     0.060     13.2    0.0e+00  V1 <--- PA1
V2   0.80     0.060     13.2    0.0e+00  V2 <--- PA1
V3   0.80     0.060     13.2    0.0e+00  V3 <--- PA1
V4   0.80     0.060     13.2    0.0e+00  V4 <--- PA1
V5   0.80     0.060     13.2    0.0e+00  V5 <--- PA1
V6   0.80     0.060     13.2    0.0e+00  V6 <--- PA1
x1e  0.36     0.043      8.3    2.2e-16  V1 <--> V1
x2e  0.36     0.043      8.3    2.2e-16  V2 <--> V2
x3e  0.36     0.043      8.3    2.2e-16  V3 <--> V3
x4e  0.36     0.043      8.3    2.2e-16  V4 <--> V4
x5e  0.36     0.043      8.3    2.2e-16  V5 <--> V5
x6e  0.36     0.043      8.3    2.2e-16  V6 <--> V6
```

Set 2

```
> summary(sem2,digits=2)

 Model Chisquare =  4.4e-09   Df =  9 Pr(>Chisq) = 1
 Chisquare (null model) =  57   Df =  15
 Goodness-of-fit index =  1
 Adjusted goodness-of-fit index =  1
 RMSEA index =  0   90% CI: (NA, NA)
 Bentler-Bonnett NFI =  1
 Tucker-Lewis NNFI =  1.4
 Bentler CFI =  1
 SRMR =  2.0e-06
 BIC =  -48

 Normalized Residuals
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-2.5e-05 -2.5e-05 -2.5e-05 -2.5e-05 -2.5e-05 -2.5e-05

 Parameter Estimates
    Estimate Std Error z value Pr(>|z|)
V1  0.40     0.098     4.1     4.5e-05  V1 <--- PA1
V2  0.40     0.098     4.1     4.5e-05  V2 <--- PA1
V3  0.40     0.098     4.1     4.5e-05  V3 <--- PA1
V4  0.40     0.098     4.1     4.5e-05  V4 <--- PA1
V5  0.40     0.098     4.1     4.5e-05  V5 <--- PA1
V6  0.40     0.098     4.1     4.5e-05  V6 <--- PA1
x1e 0.84     0.101     8.3     2.2e-16  V1 <--> V1
x2e 0.84     0.101     8.3     2.2e-16  V2 <--> V2
x3e 0.84     0.101     8.3     2.2e-16  V3 <--> V3
x4e 0.84     0.101     8.3     2.2e-16  V4 <--> V4
x5e 0.84     0.101     8.3     2.2e-16  V5 <--> V5
x6e 0.84     0.101     8.3     2.2e-16  V6 <--> V6
```

# Interpreting the two sets

I. Good fits and reliable parameter estimates in both data sets

II. Both models fit the covariances very well

   A. Residuals are tiny in both cases

III. One model fits the variables better (better variables)

# Errors of Interpretation (continued)

I. Relying solely on statistical criterion in model evaluation

   A. What can the model not explain

   B. What are alternative models

   C. What constraints does the model imply

# Errors of Interpretation (continued)

I. Relying too much on statistical tests

   A. significance of particular path coefficients does not imply effect size or importance

   B. Overall statistical fit (chi square) is sensitive to model misfit as f(N)

# Errors of Interpretation (continued)

I. Misinterpreting the standardized solution in multiple group problems

II. Failure to consider equivalent models

   A. Why is this model better than equivalent models?

III. Failure to consider non-equivalent models

   A. Why is this model better than other, non-equivalent ones?

# Errors of Interpretation (continued)

I. Reifying the latent variables

   A. Latent variables are just models of observed data

   B. “factors are fictions”

II. Believing that naming a factor means it is understood

# Errors of Interpretation (continued)

I. Believing that a strong analytical method like SEM can overcome poor theory or poor design.

II. Failure to report enough so that you can be replicated

III. Interpreting estimates of large effects as evidence for "causality"

# Testing for a general factor in personality

I. A critique of Rushton and Irwing

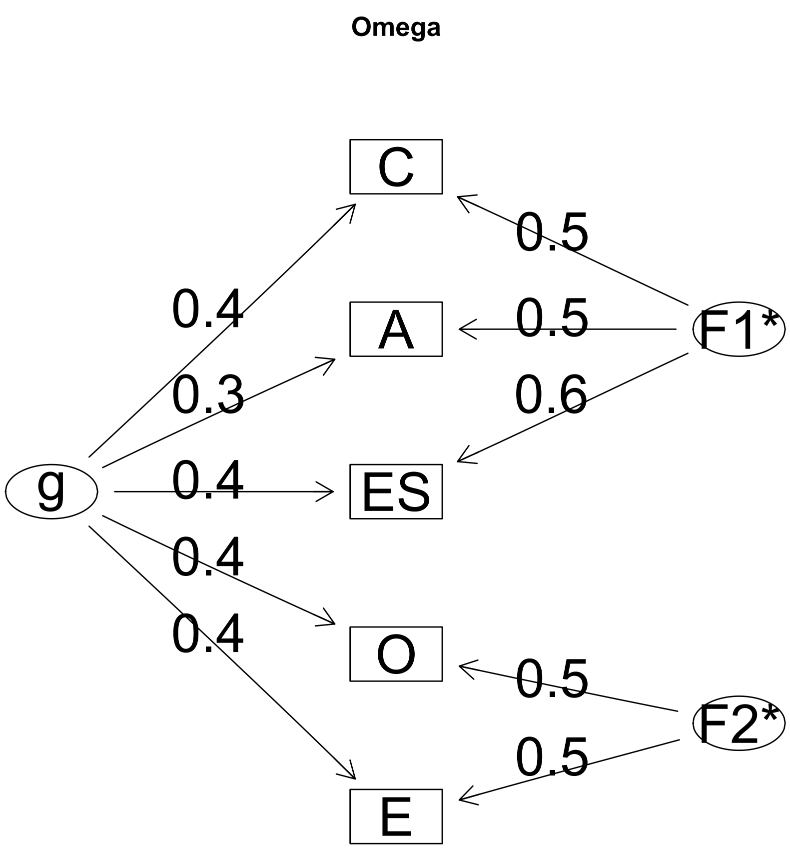
  A. Rushton and Irwing have proposed that there is a general factor personality equivalent to that of the general factor of ability

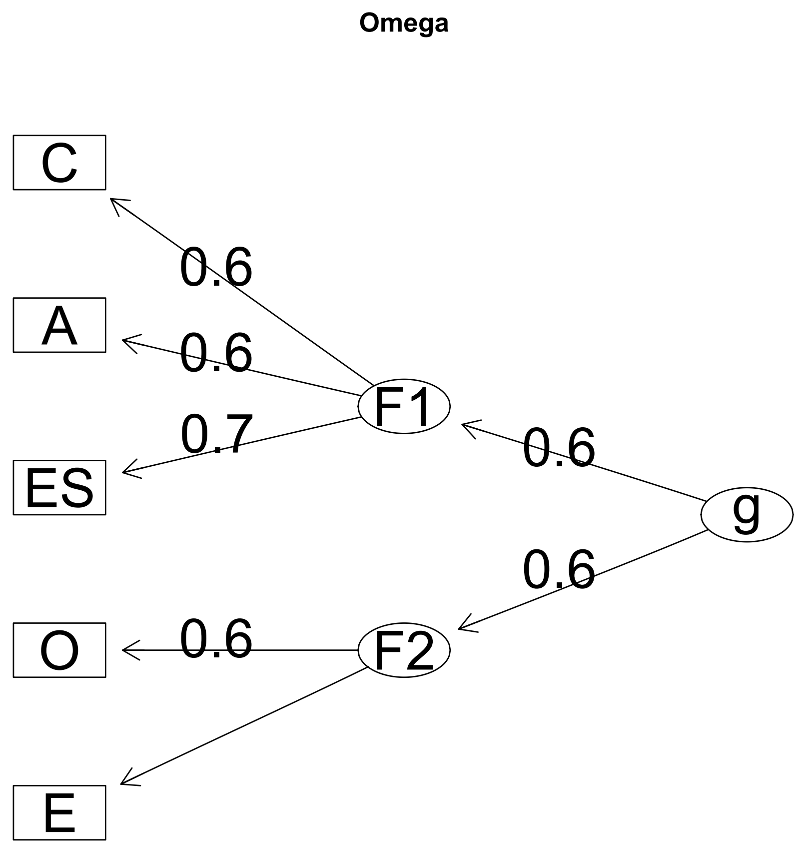
  B. Report higher level factor structure of Big 5 instruments

# Median Big 5 correlation

```
> rush.med <- read.clipboard()
> rush.med
      O     C     E     A    ES
O  1.00 0.190 0.420 0.070 0.120
C  0.19 1.000 0.175 0.350 0.425
E  0.42 0.175 1.000 0.085 0.230
A  0.07 0.350 0.085 1.000 0.410
ES 0.12 0.425 0.230 0.410 1.000
```

# Hierarchical factor solutions



# sem of hierarchical model

```
> med.mod <- edit(om.med$model)
> sem.med <- sem(med.mod,rush.med,1000)
> summary(sem.med,digits=2)


 Model Chisquare =  23   Df =  4 Pr(>Chisq) = 0.00013
 Chisquare (null model) =  704   Df =  10
 Goodness-of-fit index =  1
 Adjusted goodness-of-fit index =  0.97
 RMSEA index =  0.069   90% CI: (0.043, 0.097)
 Bentler-Bonnett NFI =  0.97
 Tucker-Lewis NNFI =  0.93
 Bentler CFI =  0.97
 SRMR =  0.030
 BIC =  -4.7

 Normalized Residuals
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-2.1e+00 -3.6e-01 -3.9e-07 -4.1e-02  2.5e-01  2.2e+00
```

# Loadings match EFA

```
 Parameter Estimates
     Estimate Std Error z value Pr(>|z|)
gF1  0.75     0.078      9.6    0.00000  F1 <--- g
F2O  0.44     0.045      9.9    0.00000  O <--- F2
F1C  0.49     0.034     14.2    0.00000  C <--- F1
F2E  0.61     0.071      8.6    0.00000  E <--- F2
F1A  0.45     0.034     13.1    0.00000  A <--- F1
F1ES 0.58     0.039     14.8    0.00000  ES <--- F1
e1   0.70     0.064     10.9    0.00000  O <--> O
e2   0.63     0.042     14.9    0.00000  C <--> C
e3   0.42     0.109      3.8    0.00013  E <--> E
e4   0.69     0.040     17.3    0.00000  A <--> A
e5   0.48     0.048     10.1    0.00000  ES <--> ES
```

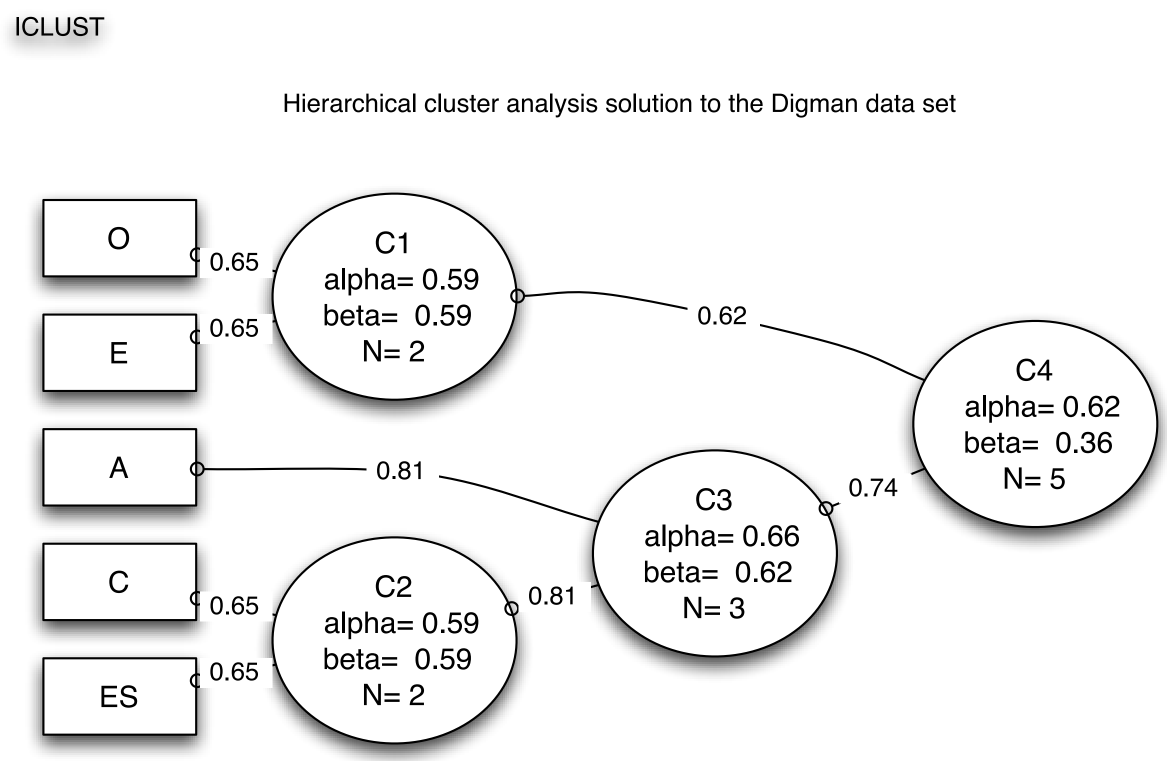
# But omega $_h$ is low

```
> om.med
Omega
Call: omega(m = rush.med, nfactors = 2, sl = FALSE)
Alpha:  0.62
G.6:   0.61
Omega Hierarchical:   0.35
Omega Total   0.71

Schmid Leiman Factor loadings greater than  0.2
   g    F1*  F2*  h2   u2
O  0.36      0.53 0.42 0.58
C  0.38 0.47      0.37 0.63
E  0.40      0.52 0.43 0.57
A  0.30 0.51      0.36 0.64
ES 0.42 0.57      0.50 0.50

With eigenvalues of:
   g  F1*  F2*
0.70 0.81 0.56
```

# Compare with S-L solution fully saturated

```
> summary(sem.med.sl,digits=2)

 Model Chisquare =  12   Df =  0 Pr(>Chisq) = NA
 Chisquare (null model) =  704   Df =  10
 Goodness-of-fit index =  1
 BIC =  12

 Normalized Residuals
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-1.1e+00 -3.0e-05 -1.6e-05  2.3e-02 -1.6e-07  1.5e+00
Parameter Estimates
      Estimate Std Error z value Pr(>|z|)
O      0.33     0.896     0.37    7.1e-01  O <--- g
C      0.44     1.192     0.37    7.1e-01  C <--- g
E      0.45     1.224     0.37    7.1e-01  E <--- g
A      0.20     0.536     0.36    7.2e-01  A <--- g
ES     0.48     1.299     0.37    7.1e-01  ES <--- g
F2*O   0.58     2.073     0.28    7.8e-01  O <--- F2*
F1*C   0.43     1.148     0.37    7.1e-01  C <--- F1*
F2*E   0.47     1.967     0.24    8.1e-01  E <--- F2*
F1*A   0.62     0.586     1.06    2.9e-01  A <--- F1*
F1*ES  0.51     1.294     0.39    6.9e-01  ES <--- F1*
e1     0.55     2.375     0.23    8.2e-01  O <--> O
e2     0.63     0.077     8.15    4.4e-16  C <--> C
e3     0.58     1.549     0.37    7.1e-01  E <--> E
e4     0.58     0.935     0.62    5.4e-01  A <--> A
e5     0.51     0.093     5.54    3.0e-08  ES <--> ES
```

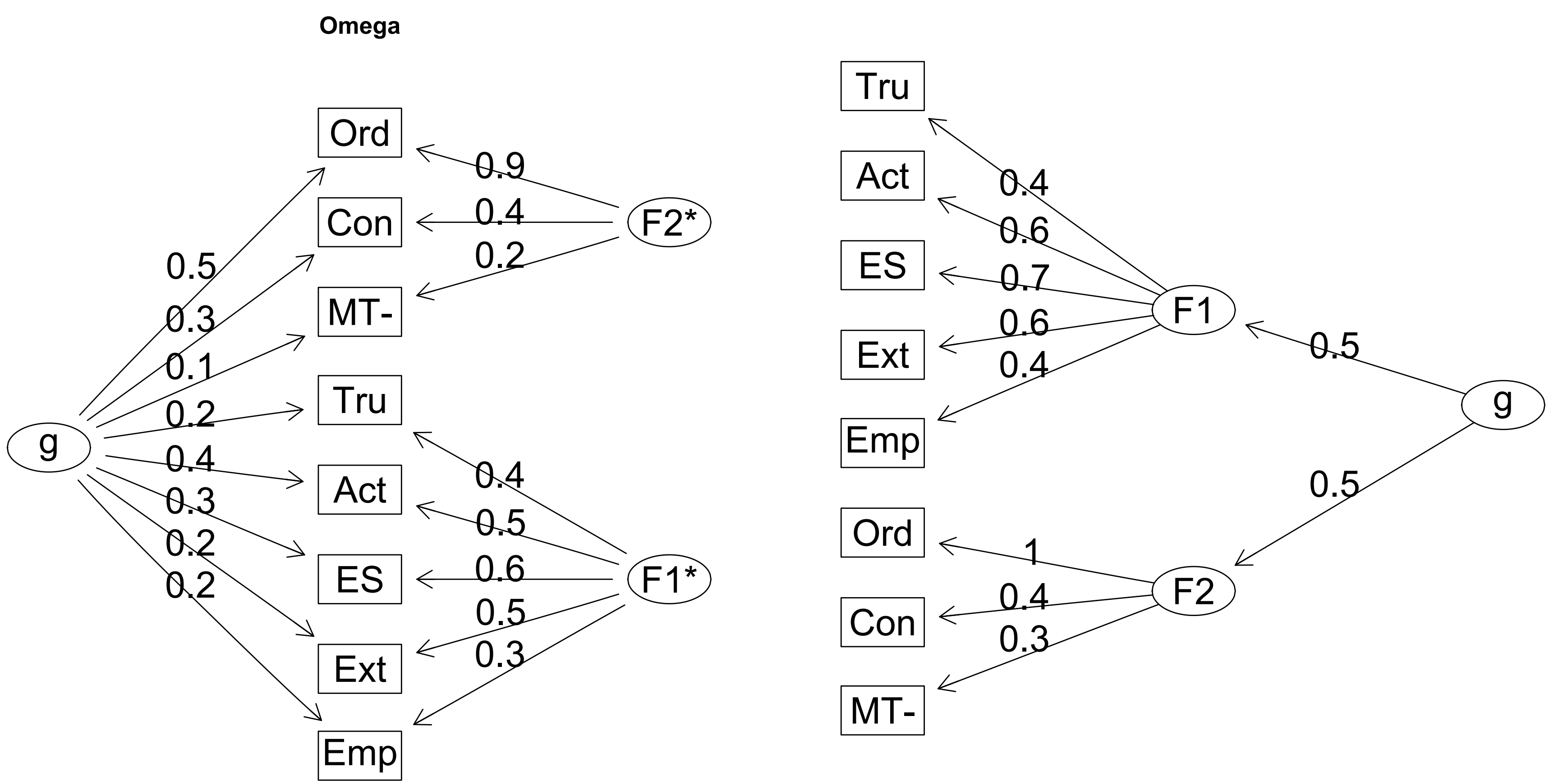
# ICLUST shows structure



# Comrey Personality Inv.

```
> comrey <- read.clipboard()
> comrey
                      Tru   Ord   Con  Act   ES  Ext    MT   Emp
Trust                1.00  0.01  0.14 0.11 0.34 0.12 -0.07  0.33
Orderliness          0.01  1.00  0.48 0.36 0.11 0.01 -0.26  0.05
Conformity           0.14  0.48  1.00 0.20 0.18 0.05 -0.27  0.08
Activity             0.11  0.36  0.20 1.00 0.39 0.35  0.10  0.25
Emotional_stability  0.34  0.11  0.18 0.39 1.00 0.36  0.14  0.15
Extraversion         0.12  0.01  0.05 0.35 0.36 1.00  0.01  0.24
Mental_toughness    -0.07 -0.26 -0.27 0.10 0.14 0.01  1.00 -0.26
Empathy              0.33  0.05  0.08 0.25 0.15 0.24 -0.26  1.00
```

# Bifactor and Hierarchical solutions



# Omega is small

```
> om.c
Omega
Call: omega(m = comrey, nfactors = 2)
Alpha:  0.63
G.6:   0.68
Omega Hierarchical:   0.22
Omega Total   0.71

Schmid Leiman Factor loadings greater than  0.2
    g    F1*  F2*  h2   u2
Tru      0.36           0.85
Ord 0.46      0.88 1.00
Con 0.27      0.40 0.25 0.75
Act 0.37 0.49 0.22 0.42 0.58
ES  0.30 0.60      0.45 0.55
Ext 0.21 0.50      0.30 0.70
MT-           0.25      0.92
Emp      0.33           0.87

With eigenvalues of:
   g  F1*  F2*
0.61 1.11 1.06
```

```
> rownames(comrey) <- colnames(comrey)
> sem.c.sl <- sem(om.c$model,comrey,1000)
> summary(sem.c.sl,digits=2)

 Model Chisquare =  244   Df =  12 Pr(>Chisq) = 0
 Chisquare (null model) =  1431   Df =  28
 Goodness-of-fit index =  0.94
 Adjusted goodness-of-fit index =  0.83
 RMSEA index =  0.14   90% CI: (0.12, 0.15)
 Bentler-Bonnett NFI =  0.83
 Tucker-Lewis NNFI =  0.61
 Bentler CFI =  0.83
 SRMR =  0.076
 BIC =  161
```

# Fit is poor

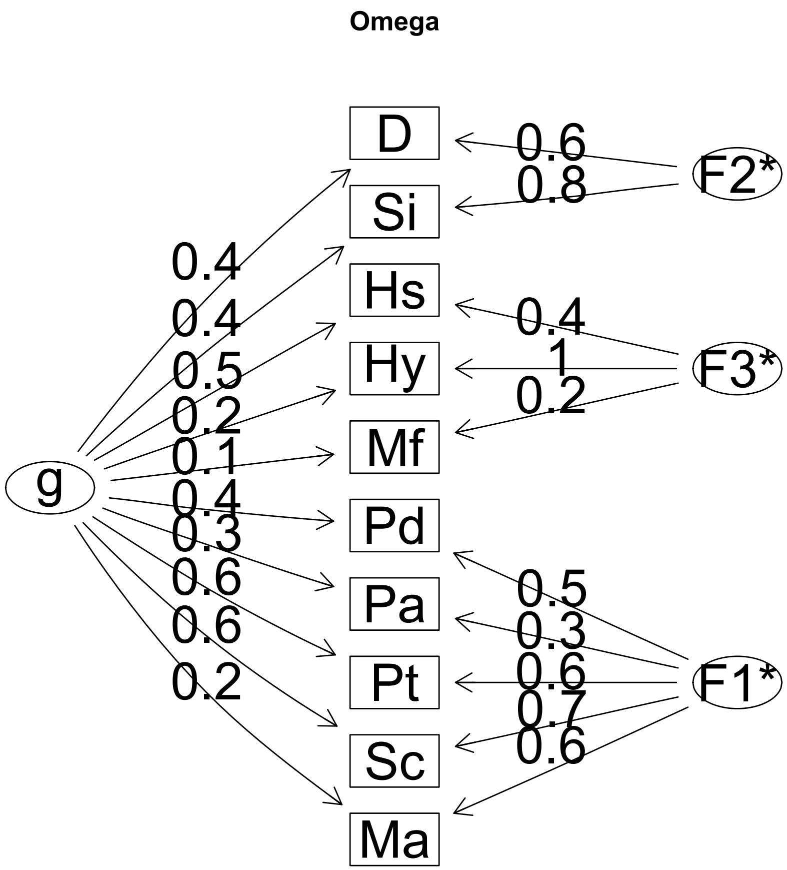
# Parameters do not show g

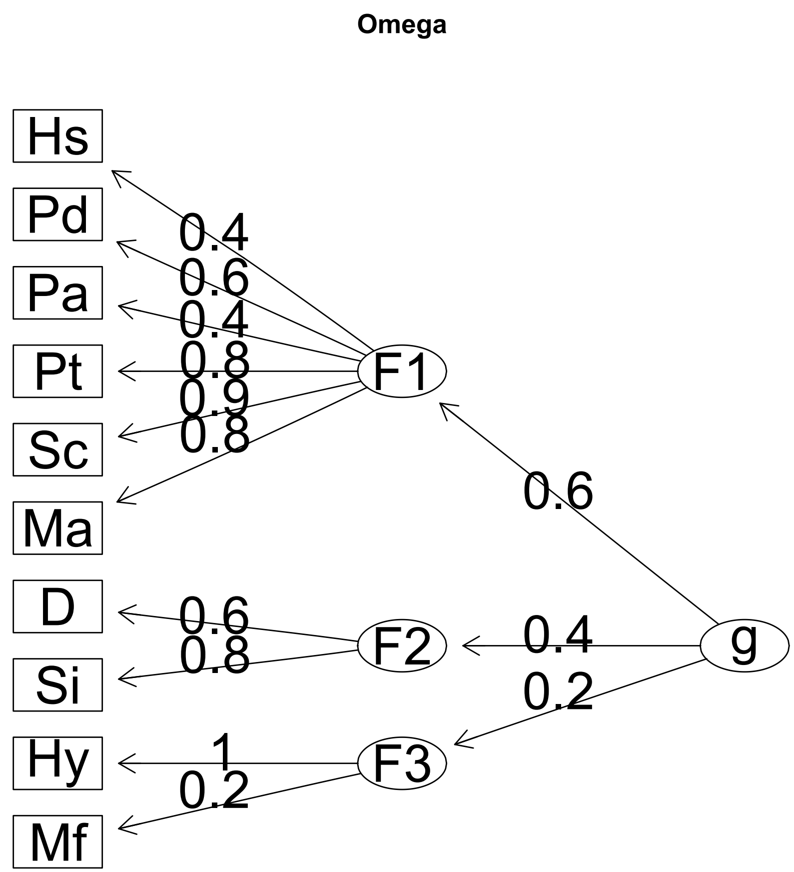
```
 Parameter Estimates
        Estimate Std Error z value Pr(>|z|)
Tru     -0.019   0.047     -0.42   6.8e-01  Tru <--- g
Ord      0.667   0.175      3.81   1.4e-04  Ord <--- g
Con      0.338   0.116      2.91   3.6e-03  Con <--- g
Act      0.380   0.088      4.34   1.5e-05  Act <--- g
ES       0.220   0.063      3.48   5.0e-04  ES <--- g
Ext      0.021   0.038      0.54   5.9e-01  Ext <--- g
MT-      0.574   0.137      4.18   2.9e-05  MT <--- g
Emp     -0.151   0.053     -2.85   4.3e-03  Emp <--- g
F1*Tru   0.407   0.043      9.49   0.0e+00  Tru <--- F1*
F2*Ord   0.594   0.142      4.19   2.8e-05  Ord <--- F2*
F2*Con   0.429   0.122      3.50   4.6e-04  Con <--- F2*
F1*Act   0.543   0.037     14.62   0.0e+00  Act <--- F1*
F1*ES    0.588   0.049     11.97   0.0e+00  ES <--- F1*
F1*Ext   0.557   0.038     14.51   0.0e+00  Ext <--- F1*
F2*MT- -1.082    0.524     -2.07   3.9e-02  MT <--- F2*
F1*Emp   0.477   0.059      8.07   6.7e-16  Emp <--- F1*
e1       0.834   0.045     18.45   0.0e+00  Tru <--> Tru
e2       0.202   0.114      1.76   7.8e-02  Ord <--> Ord
e3       0.702   0.053     13.17   0.0e+00  Con <--> Con
e4       0.561   0.061      9.22   0.0e+00  Act <--> Act
e5       0.606   0.042     14.38   0.0e+00  ES <--> ES
e6       0.690   0.041     16.66   0.0e+00  Ext <--> Ext
e7      -0.501   1.263     -0.40   6.9e-01  MT <--> MT
e8       0.750   0.069     10.87   0.0e+00  Emp <--> Emp
```

# MMPI

```
> mmpi <- read.clipboard()
> mmpi
     Hs     D    Hy   Pd   Mf   Pa   Pt   Sc    Ma    Si
Hs 1.00  0.55  0.47 0.35 0.03 0.24 0.56 0.58  0.20  0.35
D  0.55  1.00  0.35 0.36 0.15 0.29 0.54 0.44 -0.14  0.55
Hy 0.47  0.35  1.00 0.26 0.16 0.27 0.02 0.08 -0.04 -0.17
Pd 0.35  0.36  0.26 1.00 0.12 0.41 0.49 0.60  0.39  0.13
Mf 0.03  0.15  0.16 0.12 1.00 0.21 0.16 0.11  0.01  0.10
Pa 0.24  0.29  0.27 0.41 0.21 1.00 0.39 0.43  0.18  0.10
Pt 0.56  0.54  0.02 0.49 0.16 0.39 1.00 0.84  0.35  0.56
Sc 0.58  0.44  0.08 0.60 0.11 0.43 0.84 1.00  0.49  0.44
Ma 0.20 -0.14 -0.04 0.39 0.01 0.18 0.35 0.49  1.00 -0.20
Si 0.35  0.55 -0.17 0.13 0.10 0.10 0.56 0.44 -0.20  1.00
```

# Omega solutions



# Simple sem does not converge - negative error v

```
> sem.mmpi.sl <- sem(om.mmpi.sl$model,mmpi,1000)
Warning message:
In sem.default(ram = ram, S = S, N = N, param.names = pars, var.names
= vars,  :
  Optimization may not have converged; nlm return code = 4. Consult ?
nlm.

> summary(sem.mmpi.sl,digits=2)

 Model Chisquare =   996   Df =  25 Pr(>Chisq) = 0
 Chisquare (null model) =  5152   Df =  45
 Goodness-of-fit index =  0.83
 Adjusted goodness-of-fit index =  0.63
 RMSEA index =  0.20   90% CI: (NA, NA)
 Bentler-Bonnett NFI =  0.8
 Tucker-Lewis NNFI =  0.66
 Bentler CFI =  0.81
 SRMR =  0.10
 BIC =  823
```

```
-7.22000 -1.07000 -0.00016  0.71800  2.29000  9.17000

 Parameter Estimates
      Estimate Std Error z value Pr(>|z|)
Hs       0.588  0.0322     18.30  0.0e+00  Hs <--- g
D        0.742  0.0313     23.74  0.0e+00  D <--- g
Hy       0.077  0.0362      2.12  3.4e-02  Hy <--- g
Pd       0.324  0.0356      9.10  0.0e+00  Pd <--- g
Mf       0.159  0.0338      4.70  2.6e-06  Mf <--- g
Pa       0.283  0.0355      7.98  1.6e-15  Pa <--- g
Pt       0.758  0.0319     23.79  0.0e+00  Pt <--- g
Sc       0.645  0.0352     18.33  0.0e+00  Sc <--- g
Ma      -0.103  0.0396     -2.61  9.1e-03  Ma <--- g
Si       0.791  0.0310     25.52  0.0e+00  Si <--- g
F3*Hs    0.047  0.0033     14.12  0.0e+00  Hs <--- F3*
F2*D     0.886  0.8665      1.02  3.1e-01  D <--- F2*
F3*Hy    9.381  0.0811    115.69  0.0e+00  Hy <--- F3*
F1*Pd    0.546  0.0313     17.46  0.0e+00  Pd <--- F1*
F3*Mf    0.020  0.0030      6.85  7.3e-12  Mf <--- F3*
F1*Pa    0.346  0.0344     10.06  0.0e+00  Pa <--- F1*
F1*Pt    0.508  0.0290     17.54  0.0e+00  Pt <--- F1*
F1*Sc    0.696  0.0285     24.41  0.0e+00  Sc <--- F1*
F1*Ma    0.803  0.0315     25.53  0.0e+00  Ma <--- F1*
F2*Si   -0.042  0.0491     -0.86  3.9e-01  Si <--- F2*
e1       0.652  0.0337     19.36  0.0e+00  Hs <--> Hs
e2      -0.336  1.5353     -0.22  8.3e-01  D <--> D
e3     -86.990  1.4489    -60.04  0.0e+00  Hy <--> Hy
e4       0.597  0.0285     20.92  0.0e+00  Pd <--> Pd
e5       0.974  0.0438     22.25  0.0e+00  Mf <--> Mf
e6       0.800  0.0365     21.94  0.0e+00  Pa <--> Pa
e7       0.168  0.0123     13.60  0.0e+00  Pt <--> Pt
e8       0.100  0.0125      7.95  2.0e-15  Sc <--> Sc
```

Note the negative error variance

# Omega results

```
> om.mmpi.sl
Omega
Call: omega(m = mmpi)
Alpha:  0.8
G.6:   0.87
Omega Hierarchical:   0.36
Omega Total   0.89

Schmid Leiman Factor loadings greater than  0.2
   g    F1*  F2*  F3*  h2   u2
Hs 0.46 0.36 0.25 0.42 0.59 0.41
D  0.44      0.57 0.32 0.64 0.36
Hy                0.98 1.00
Pd 0.38 0.51      0.21 0.45 0.55
Mf                          0.95
Pa 0.29 0.33      0.23 0.25 0.75
Pt 0.58 0.62 0.34      0.83
Sc 0.58 0.73           0.90
Ma      0.63 0.48      0.68 0.32
Si 0.40      0.75      0.77 0.23

With eigenvalues of:
  g F1* F2* F3*
1.5 1.9 1.3 1.4
```

# Compare with IQ

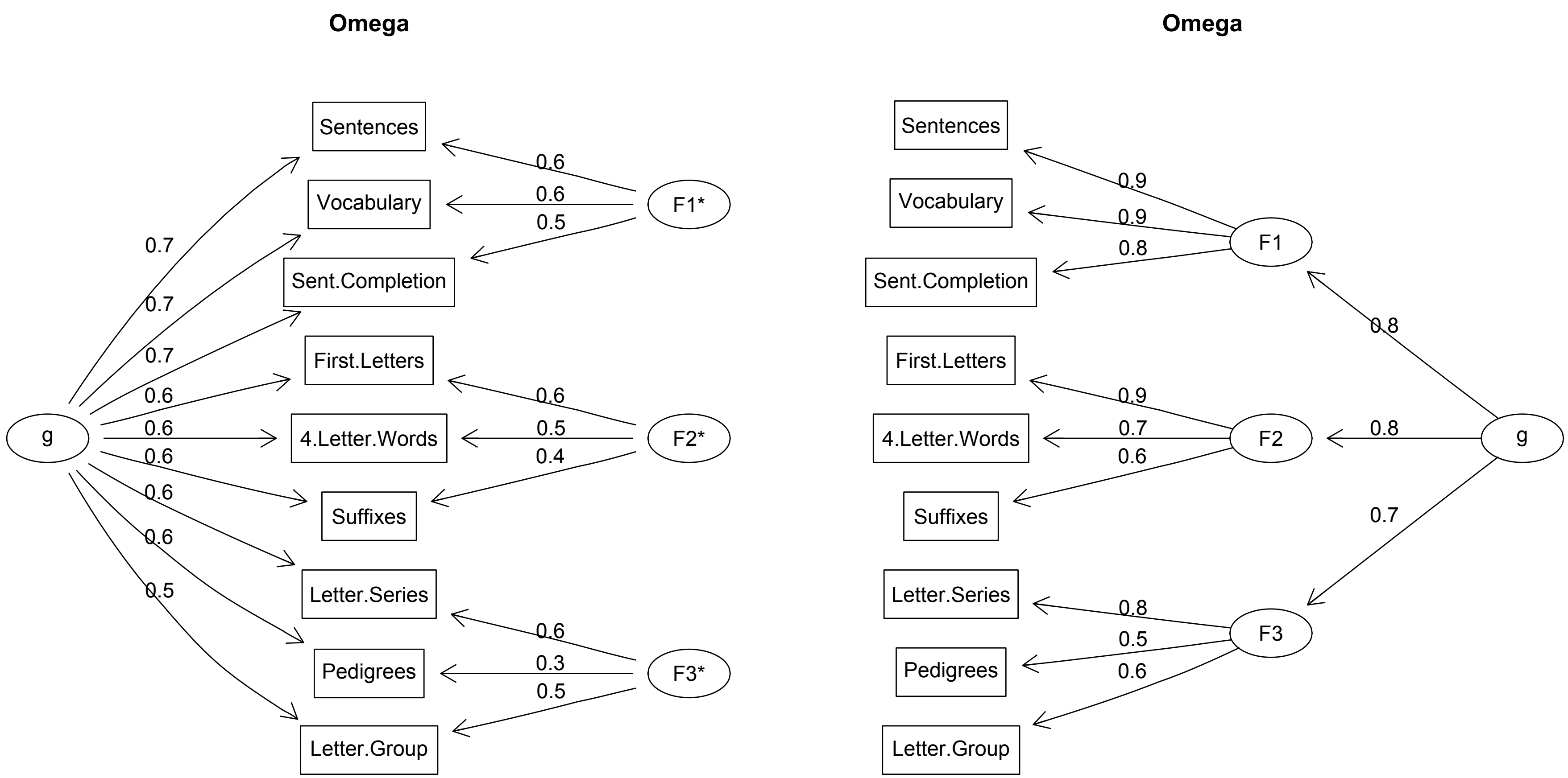
I. Thurstone 9 variable problem

II. Thurston Bechtoldt 17 variables

III. Holzinger-Harman 24 variables

# Thurstone 9 variables

```
data(bifactor)
om.t <- omega(Thurstone,n.obs=213)
```



# Omega is high

```
> om.t <-omega(Thurstone,n.obs=213)
> om.t
Omega
Call: omega(m = Thurstone, n.obs = 213)
Alpha:  0.89
G.6:   0.91
Omega Hierarchical:   0.74
Omega Total   0.93
Schmid Leiman Factor loadings greater than  0.2
                g    F1*  F2*  F3*  h2   u2
Sentences       0.71 0.57           0.83
Vocabulary      0.73 0.55           0.84
Sent.Completion 0.68 0.52           0.73 0.27
First.Letters   0.65      0.56      0.73 0.27
4.Letter.Words  0.62      0.49      0.63 0.37
Suffixes        0.56      0.41      0.50 0.50
Letter.Series   0.59           0.61 0.72 0.28
Pedigrees       0.58 0.23      0.34 0.50 0.50
Letter.Group    0.54           0.46 0.53 0.47
With eigenvalues of:
   g  F1*  F2*  F3*
3.60 0.96 0.74 0.71
general/max  3.73   max/min =   1.36
The degrees of freedom for the model is 12  and the fit was  0.01
The number of observations was  213  with Chi Square =  2.82  with
prob <  1
```

# SEM is very good

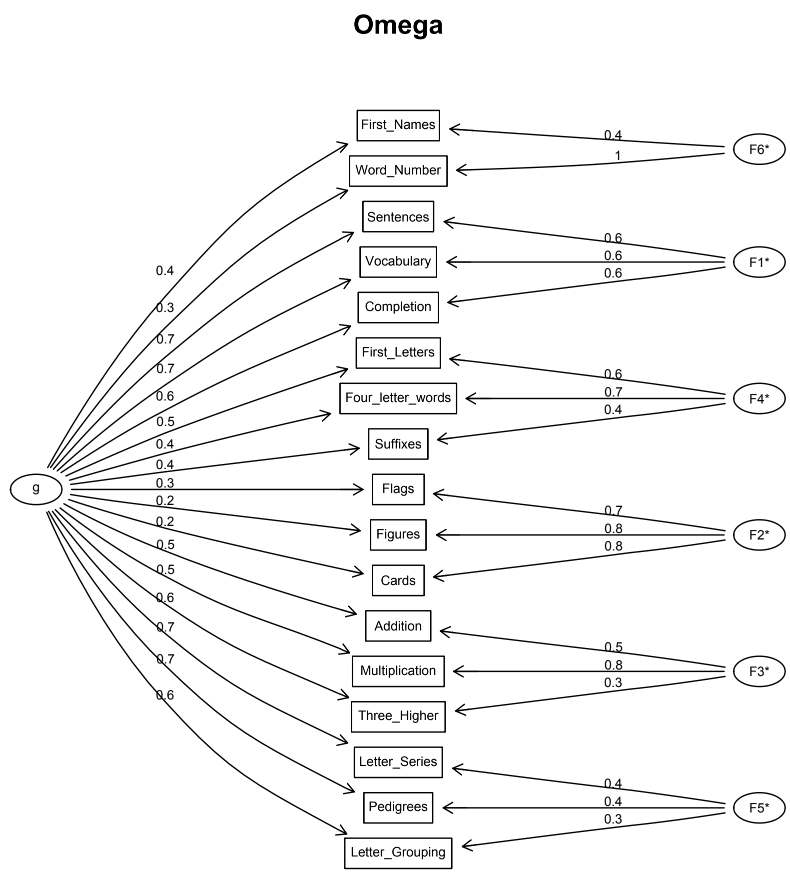
```
> sem.t.sl <- sem(om.t$model,Thurstone,213)
> summary(sem.t.sl,digits=2)

 Model Chisquare =  24   Df =  18 Pr(>Chisq) = 0.15
 Chisquare (null model) =  1102   Df =  36
 Goodness-of-fit index =  0.98
 Adjusted goodness-of-fit index =  0.94
 RMSEA index =  0.04   90% CI: (NA, 0.078)
 Bentler-Bonnett NFI =  0.98
 Tucker-Lewis NNFI =  0.99
 Bentler CFI =  1
 SRMR =  0.035
 BIC =  -72

 Normalized Residuals
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-8.2e-01 -3.3e-01 -8.9e-07  2.8e-02  1.6e-01  1.8e+00
```

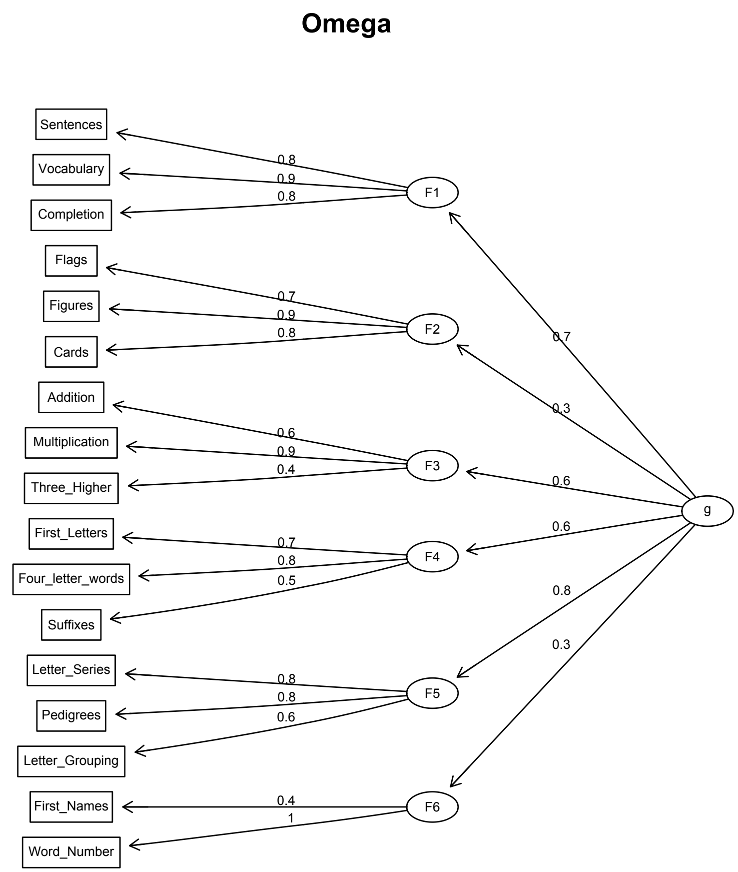
# Parameters show g

Parameter Estimates

| | Estimate | Std Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| Sentences | 0.77 | 0.073 | 10.57 | 0.0e+00 |
| Vocabulary | 0.79 | 0.072 | 10.92 | 0.0e+00 |
| Sent.Completion | 0.75 | 0.073 | 10.27 | 0.0e+00 |
| First.Letters | 0.61 | 0.072 | 8.43 | 0.0e+00 |
| 4.Letter.Words | 0.60 | 0.074 | 8.09 | 6.7e-16 |
| Suffixes | 0.57 | 0.071 | 8.00 | 1.3e-15 |
| Letter.Series | 0.57 | 0.074 | 7.63 | 2.3e-14 |
| Pedigrees | 0.66 | 0.069 | 9.55 | 0.0e+00 |
| Letter.Group | 0.53 | 0.079 | 6.71 | 2.0e-11 |
| F1*Sentences | 0.49 | 0.085 | 5.71 | 1.1e-08 |
| F1*Vocabulary | 0.45 | 0.090 | 5.00 | 5.7e-07 |
| F1*Sent.Completion | 0.40 | 0.093 | 4.33 | 1.5e-05 |
| F2*First.Letters | 0.61 | 0.086 | 7.16 | 8.2e-13 |
| F2*4.Letter.Words | 0.51 | 0.085 | 5.96 | 2.5e-09 |
| F2*Suffixes | 0.39 | 0.078 | 5.04 | 4.7e-07 |
| F3*Letter.Series | 0.73 | 0.159 | 4.56 | 5.1e-06 |
| F3*Pedigrees | 0.25 | 0.089 | 2.77 | 5.6e-03 |
| F3*Letter.Group | 0.41 | 0.122 | 3.35 | 8.1e-04 |
| e1 | 0.17 | 0.034 | 5.05 | 4.4e-07 |
| e2 | 0.17 | 0.030 | 5.65 | 1.6e-08 |
| e3 | 0.27 | 0.033 | 8.09 | 6.7e-16 |
| e4 | 0.25 | 0.079 | 3.18 | 1.5e-03 |
| e5 | 0.39 | 0.063 | 6.13 | 8.8e-10 |
| e6 | 0.52 | 0.060 | 8.68 | 0.0e+00 |
| e7 | 0.15 | 0.223 | 0.67 | 5.0e-01 |
| e8 | 0.50 | 0.060 | 8.39 | 0.0e+00 |
| e9 | 0.55 | 0.085 | 6.51 | 7.4e-11 |

# Bechtoldt 17 variables



# Omega

```
Omega
Call: omega(m = Bechtoldt.1, nfactors = 6, n.obs = 213)
Alpha:  0.89
G.6:   0.93
Omega Hierarchical:   0.72
Omega Total   0.95
Schmid Leiman Factor loadings greater than  0.2
                  g    F1*  F2*  F3*  F4*  F5*  F6*  h2   u2
First_Names       0.40                          0.37 0.33 0.67
Word_Number       0.29                          0.95 1.00
Sentences         0.68 0.58                          0.83
Vocabulary        0.67 0.63                          0.87
Completion        0.65 0.57 0.20                     0.77 0.23
First_Letters     0.53                0.56           0.60 0.40
Four_letter_words 0.45                0.69           0.68 0.32
Suffixes          0.45                0.42           0.43 0.57
Flags             0.33      0.71                     0.63 0.37
Figures           0.20      0.85                     0.76 0.24
Cards             0.24      0.79                     0.69 0.31
Addition          0.52           0.50                0.54 0.46
Multiplication    0.53           0.77                0.86
Three_Higher      0.57           0.33                0.52 0.48
Letter_Series     0.74                     0.42      0.73 0.27
Pedigrees         0.69                     0.39      0.64 0.36
Letter_Grouping   0.64                     0.31      0.53 0.47
With eigenvalues of:
   g  F1*  F2*  F3*  F4*  F5*  F6*
4.78 1.12 1.96 1.00 0.99 0.46 1.07general/max  2.44   max/min =   4.24
The degrees of freedom for the model is 49  and the fit was  0.27
The number of obs was 213 with Chi Square =  54.37  with prob <  0.28
```

# SEM Bechtoldt

```
> sem.b.h <- sem(om.b.h$model,Bechtoldt.1,213)
> summary(sem.b.h,digits=2)

 Model Chisquare =  220   Df =  113 Pr(>Chisq) = 6.5e-09
 Chisquare (null model) =  1983   Df =  136
 Goodness-of-fit index =  0.9
 Adjusted goodness-of-fit index =  0.86
 RMSEA index =  0.067   90% CI: (0.054, 0.08)
 Bentler-Bonnett NFI =  0.89
 Tucker-Lewis NNFI =  0.93
 Bentler CFI =  0.94
 SRMR =  0.064
 BIC =  -386

 Normalized Residuals
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-2.2e+00 -3.5e-01  1.3e-05  1.2e-01  5.3e-01  3.8e+00
```

# Paremeters are non-sensical

Parameter Estimates

| | Estimate | Std Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| gF1 | 1.16 | 0.154 | 7.5 | 6.3e-14 |
| gF2 | 0.30 | 0.087 | 3.4 | 6.6e-04 |
| gF3 | 1.10 | 0.172 | 6.4 | 1.4e-10 |
| gF4 | 0.97 | 0.151 | 6.4 | 1.3e-10 |
| gF5 | 2.02 | 0.449 | 4.5 | 6.8e-06 |
| gF6 | 0.65 | 0.134 | 4.8 | 1.2e-06 |
| F6First_Names | 0.71 | 0.109 | 6.5 | 7.2e-11 |
| F6Word_Number | 0.47 | 0.068 | 6.9 | 4.9e-12 |
| F1Sentences | 0.59 | 0.049 | 12.1 | 0.0e+00 |
| F1Vocabulary | 0.60 | 0.049 | 12.3 | 0.0e+00 |
| F1Completion | 0.55 | 0.048 | 11.5 | 0.0e+00 |
| F4First_Letters | 0.59 | 0.060 | 9.9 | 0.0e+00 |
| F4Four_letter_words | 0.53 | 0.058 | 9.2 | 0.0e+00 |
| F4Suffixes | 0.47 | 0.054 | 8.6 | 0.0e+00 |
| F2Flags | 0.73 | 0.059 | 12.3 | 0.0e+00 |
| F2Figures | 0.85 | 0.059 | 14.4 | 0.0e+00 |
| F2Cards | 0.78 | 0.058 | 13.4 | 0.0e+00 |
| F3Addition | 0.52 | 0.059 | 8.9 | 0.0e+00 |
| F3Multiplication | 0.53 | 0.060 | 8.8 | 0.0e+00 |
| F3Three_Higher | 0.48 | 0.052 | 9.2 | 0.0e+00 |
| F5Letter_Series | 0.38 | 0.071 | 5.3 | 1.1e-07 |
| F5Pedigrees | 0.34 | 0.064 | 5.3 | 9.9e-08 |
| F5Letter_Grouping | 0.32 | 0.060 | 5.3 | 9.7e-08 |

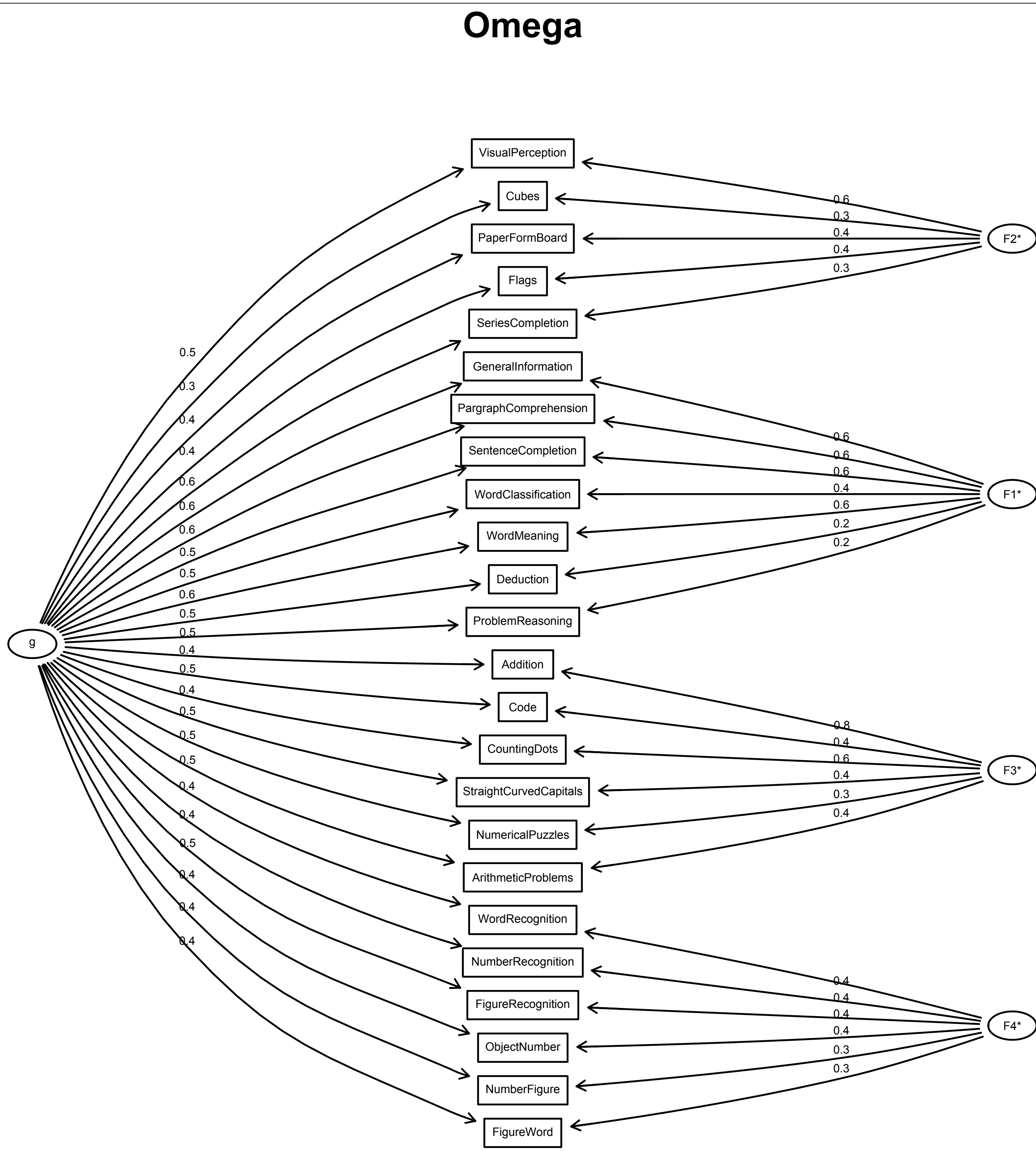
# Bifactor solution

```
> sem.b <- sem(om.b$model,Bechtoldt.1,213)
> summary(sem.b,digits=2)

 Model Chisquare =  189   Df =  102 Pr(>Chisq) = 3.4e-07
 Chisquare (null model) =  1983   Df =  136
 Goodness-of-fit index =  0.9
 Adjusted goodness-of-fit index =  0.86
 RMSEA index =  0.064   90% CI: (0.049, 0.078)
 Bentler-Bonnett NFI =  0.9
 Tucker-Lewis NNFI =  0.94
 Bentler CFI =  0.95
 SRMR =  0.054
 BIC =  -358
```

Clear g solution

Parameter Estimates

| | Estimate | Std Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| First_Names | 0.45 | 0.071 | 6.266 | 3.7e-10 |
| Word_Number | 0.29 | 0.074 | 3.868 | 1.1e-04 |
| Sentences | 0.67 | 0.067 | 10.012 | 0.0e+00 |
| Vocabulary | 0.68 | 0.067 | 10.147 | 0.0e+00 |
| Completion | 0.68 | 0.067 | 10.215 | 0.0e+00 |
| First_Letters | 0.56 | 0.069 | 8.150 | 4.4e-16 |
| Four_letter_words | 0.47 | 0.072 | 6.491 | 8.6e-11 |
| Suffixes | 0.50 | 0.072 | 6.923 | 4.4e-12 |
| Flags | 0.37 | 0.073 | 5.116 | 3.1e-07 |
| Figures | 0.22 | 0.075 | 2.908 | 3.6e-03 |
| Cards | 0.26 | 0.075 | 3.479 | 5.0e-04 |
| Addition | 0.55 | 0.070 | 7.873 | 3.6e-15 |
| Multiplication | 0.53 | 0.071 | 7.526 | 5.2e-14 |
| Three_Higher | 0.64 | 0.067 | 9.496 | 0.0e+00 |
| Letter_Series | 0.76 | 0.065 | 11.547 | 0.0e+00 |
| Pedigrees | 0.70 | 0.068 | 10.333 | 0.0e+00 |
| Letter_Grouping | 0.67 | 0.069 | 9.789 | 0.0e+00 |
| F6*First_Names | 0.53 | 3.155 | 0.167 | 8.7e-01 |
| F6*Word_Number | 0.65 | 3.925 | 0.167 | 8.7e-01 |
| F1*Sentences | 0.61 | 0.058 | 10.625 | 0.0e+00 |
| F1*Vocabulary | 0.62 | 0.058 | 10.686 | 0.0e+00 |
| F1*Completion | 0.50 | 0.060 | 8.301 | 0.0e+00 |
| F4*First_Letters | 0.59 | 0.082 | 7.215 | 5.4e-13 |
| F4*Four_letter_words | 0.62 | 0.086 | 7.191 | 6.4e-13 |
| F4*Suffixes | 0.40 | 0.076 | 5.304 | 1.1e-07 |
| F2*Flags | 0.67 | 0.061 | 11.013 | 0.0e+00 |
| F2*Figures | 0.88 | 0.060 | 14.751 | 0.0e+00 |
| F2*Cards | 0.76 | [illegible] | 12.358 | 0.0e+00 |




# Holzinger-Harman 24 tests

# HH omega

```
> om.hh.sl <- omega(hh,4,n.obs=231)
> om.hh.sl
Omega
Call: omega(m = hh, nfactors = 4, n.obs = 231)
Alpha:  0.91
G.6:   0.94
Omega Hierarchical:   0.65
Omega Total   0.93

Schmid Leiman Factor loadings greater than  0.2
                       g    F1*  F2*  F3*  F4*  h2   u2
VisualPerception       0.50      0.55           0.56 0.44
Cubes                  0.31      0.34           0.22 0.78
PaperFormBoard         0.35      0.45           0.36 0.64
Flags                  0.40      0.41           0.35 0.65
GeneralInformation     0.55 0.58                0.65 0.35
PargraphComprehension  0.56 0.61                0.69 0.31
SentenceCompletion     0.53 0.65                0.72 0.28
WordClassification     0.54 0.42                0.51 0.49
WordMeaning            0.56 0.65                0.74 0.26
Addition               0.37           0.77      0.76 0.24
Code                   0.47           0.41 0.23 0.45 0.55
CountingDots           0.38           0.62      0.56 0.44
StraightCurvedCapitals 0.48      0.35 0.39      0.51 0.49
WordRecognition        0.38                0.44 0.35 0.65
NumberRecognition      0.36                0.42 0.30 0.70
FigureRecognition      0.46      0.25      0.41 0.45 0.55
ObjectNumber           0.42                0.45 0.40 0.60
NumberFigure           0.45           0.22 0.33 0.41 0.59
FigureWord             0.39                0.26 0.24 0.76
Deduction              0.52 0.25 0.23           0.41 0.59
NumericalPuzzles       0.49      0.28 0.31      0.42 0.58
```