Structural Equation Modeling with Latent Variables or their and Plausible Values using MLR Mplus 7.11

These data were adapted from my dissertation work in which 152 adults age 63–87 years were measured on visual impairment (distance acuity and five degrees of contrast sensitivity), processing speed, divided visual attention, and selective visual attention (as measured by the Useful Field of View subtests for each), attentional search efficiency (DriverScan), and simulator driving impairment (as measured by six driving performance indicators).

Hoffman, L., Yang, X., Bovaird, J. A., & Embretson, S. E. (2006). Measuring attention in older adults: Development and psychometric evaluation of DriverScan. *Educational and Psychological Measurement, 66*, 984-1000.

Hoffman, L., McDowd, J. M., Atchley, P., & Dubinsky R. A. (2005). The role of visual attention in predicting driving impairment in older adults. *Psychology and Aging, 20*(4), 610-622.

This example will demonstrate how to estimate structural equation models, including models with latent variable interactions. But because simultaneous estimation of all effects of interest may not always be possible, this example will also how to generate, merge, and use plausible values instead. Finally, the example will also demonstrate the optimism of the results when using only a single factor score per person.

Mplus Code to Read in Data:

```
TITLE:      SEM Example for Driverscan
DATA:       FILE = driverscanSEM.dat;     ! FILE is file to be analyzed
            FORMAT IS free;               ! Free is default
            TYPE IS INDIVIDUAL;           ! Individual data is default

VARIABLE:  ! Every variable in data set
      NAMES = PartID sex age75 lncs15 lncs3 lncs6 lncs12 lncs18 far lnps
              lnda lnsa Dscan lane da_task crash stop speed time ticket acc;
      ! Every variable in THIS MODEL
      USEVARIABLES = lncs15 lncs3 lncs6 lncs12 lncs18 far;
      IDVARIABLE IS PartID;               ! Will keep ID variable for merging
      MISSING ARE ALL (-9999);            ! Make sure to specify all missing values

ANALYSIS:   ESTIMATOR IS MLR; ! For continuous items whose residuals may not be normal

OUTPUT:     SAMPSTAT                ! Sample descriptives to verify data
            MODINDICES (4)          ! Voodoo to improve model (at p<.05)
            STDYX                   ! Requests fully standardized solution
            RESIDUAL                ! Requests standardized and normalized residuals
            SVALUES;                ! Write code with estimated parameters
            TECH4;                  ! Latent variable correlation matrix

SAVEDATA:   SAVE = FSCORES; FILE IS FactorScores.dat;  ! Change .dat name by model

MODEL:      (model syntax goes here, to be changed for each model)
```

We will begin by fitting single-factor measurement models for each latent factor. This is for 2 reasons: (1) we need to ensure each factor fits *per se*, and (2) we will generate the plausible values to use later.

Measurement Model for Visual Impairment (including Omega)

Step 1: Estimate model using MLR, generate SVALUES text

```
VARIABLE:  ! Every variable in THIS MODEL
            USEVARIABLES = lncs15 lncs3 lncs6 lncs12 lncs18 far;
ANALYSIS:   ESTIMATOR = MLR;
MODEL:      ! Measurement models
  Vision BY far@1 ! 1 marker loading
            lncs15* lncs3* lncs6* lncs12* lncs18* (L2-L6);
  [far* lncs15* lncs3* lncs6* lncs12* lncs18*];         ! All intercepts
   far* lncs15* lncs3* lncs6* lncs12* lncs18* (E1-E6);   ! Residual variances
  Vision*; [Vision@0];                                  ! Factor M=0, Var=?

MODEL CONSTRAINT: ! TO GET OMEGA
NEW(SumLoad2 SumError SumRCov Omega);
SumLoad2 = (1+L2+L3+L4+L5+L6)^2;
SumError =  E1+E2+E3+E4+E5+E6;
SumRCov = 2*(0);
Omega = SumLoad2 / (SumLoad2+SumError+SumRCov);
```

```
MODEL FIT INFORMATION
Number of Free Parameters                       18

Loglikelihood
          H0 Value                        -747.948
          H0 Scaling Correction Factor      1.1255
            for MLR
          H1 Value                        -739.282
          H1 Scaling Correction Factor      1.1171
            for MLR

Information Criteria
          Akaike (AIC)                    1531.897
          Bayesian (BIC)                  1586.327
          Sample-Size Adjusted BIC        1529.357
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit
          Value                             15.752*
          Degrees of Freedom                     9
          P-Value                           0.0722
          Scaling Correction Factor         1.1003
            for MLR

*   The chi-square value for MLM, MLMV, MLR, ULSMV, WLSM and WLSMV cannot be used
    for chi-square difference testing in the regular way.  MLM, MLR and WLSM
    chi-square difference testing is described on the Mplus website.  MLMV, WLSMV,
    and ULSMV difference testing is done using the DIFFTEST option.

RMSEA (Root Mean Square Error Of Approximation)
          Estimate                           0.070
          90 Percent C.I.                    0.000  0.126
          Probability RMSEA <= .05           0.246

CFI/TLI
          CFI                                0.973
          TLI                                0.955

Chi-Square Test of Model Fit for the Baseline Model
          Value                            264.950
          Degrees of Freedom                    15
          P-Value                           0.0000

SRMR (Standardized Root Mean Square Residual)
          Value                              0.041
```

Measurement Model Results from Step 1 for Vision:

```
MODEL RESULTS
                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value
VISION   BY
    FAR                1.000      0.000    999.000    999.000
    LNCS15             0.497      0.103      4.815      0.000
    LNCS3              0.594      0.118      5.018      0.000
    LNCS6              0.764      0.136      5.628      0.000
    LNCS12             1.296      0.207      6.277      0.000
    LNCS18             1.504      0.237      6.353      0.000

 Means
    VISION             0.000      0.000    999.000    999.000

 Intercepts
    LNCS15            -3.698      0.035   -105.136      0.000
    LNCS3             -3.938      0.035   -113.273      0.000
    LNCS6             -3.730      0.043    -87.639      0.000
    LNCS12            -2.368      0.066    -36.000      0.000
    LNCS18            -1.406      0.081    -17.389      0.000
    FAR                3.026      0.067     45.130      0.000

 Variances
    VISION             0.224      0.067      3.333      0.001

 Residual Variances
    LNCS15             0.133      0.018      7.435      0.000
    LNCS3              0.105      0.014      7.451      0.000
    LNCS6              0.145      0.028      5.231      0.000
    LNCS12             0.282      0.047      5.947      0.000
    LNCS18             0.488      0.062      7.933      0.000
    FAR                0.460      0.055      8.349      0.000

 New/Additional Parameters
    SUMLOAD2          31.983      7.564      4.228      0.000
    SUMERROR           1.613      0.102     15.822      0.000
    SUMRCOV            0.000      0.000      0.000      1.000
    OMEGA              0.952      0.011     88.539      0.000


STANDARDIZED MODEL RESULTS
STDYX Standardization
                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value
VISION   BY
    FAR                0.572      0.062      9.190      0.000
    LNCS15             0.541      0.074      7.305      0.000
    LNCS3              0.656      0.062     10.605      0.000
    LNCS6              0.688      0.057     12.062      0.000
    LNCS12             0.756      0.051     14.815      0.000
    LNCS18             0.713      0.041     17.293      0.000
```

The SVALUES output option provided this code, which we will use to generate plausible values for our factor scores for later.

```
MODEL COMMAND WITH FINAL
ESTIMATES USED AS STARTING
VALUES

 vision BY far@1;
 vision BY lncs15*0.49665 (l2);
 vision BY lncs3*0.59433 (l3);
 vision BY lncs6*0.76361 (l4);
 vision BY lncs12*1.29636 (l5);
 vision BY lncs18*1.50436 (l6);

 [ lncs15*-3.69842 ];
 [ lncs3*-3.93821 ];
 [ lncs6*-3.72997 ];
 [ lncs12*-2.36777 ];
 [ lncs18*-1.40608 ];
 [ far*3.02632 ];
 [ vision@0 ];

 lncs15*0.13297 (e2);
 lncs3*0.10479 (e3);
 lncs6*0.14501 (e4);
 lncs12*0.28191 (e5);
 lncs18*0.48808 (e6);
 far*0.46001 (e1);
 vision*0.22350;
```

For factor score reliability

```
SAMPLE STATISTICS FOR ESTIMATED
FACTOR SCORES

           Means
          VISION        VISION_SE
        ________      ________
           0.000         0.194

         Covariances

          ________      ________
          VISION         0.186
```

$$\rho = \frac{.186}{.186 + .194^2} = .832$$

```
          Normalized Residuals for Covariances/Correlations/Residual Correlations
             LNCS15        LNCS3         LNCS6         LNCS12        LNCS18
             ________      ________      ________      ________      ________
 LNCS15         0.000
 LNCS3          1.651         0.000
 LNCS6         -0.045         0.261         0.000
 LNCS12        -0.455        -0.241         0.021         0.000
 LNCS18        -0.629        -0.458        -0.177         0.353         0.000
 FAR           -0.471        -0.731        -0.062         0.198         0.558
```

Local fit looks good as well…

Now we are ready for Step 2 for the Visual Impairment factor:
Generate plausible values using BAYES estimation of *previous MLR model*

```
ANALYSIS:      ESTIMATOR = BAYES;

MODEL:      ! Parameters from previously estimated measurement model, but all FIXED@

Vision BY far@1;
Vision BY lncs15@0.49665(l2);
Vision BY lncs3@0.59434(l3);
Vision BY lncs6@0.76361(l4);
Vision BY lncs12@1.29636(l5);
Vision BY lncs18@1.50436(l6);

[lncs15@-3.69842];
[lncs3@-3.93821];
[lncs6@-3.72997];
[lncs12@-2.36777];
[lncs18@-1.40608];
[far@3.02632];
[vision@0];

lncs15@0.13296(e2);
lncs3@0.10479(e3);
lncs6@0.14501(e4);
lncs12@0.28191(e5);
lncs18@0.48808(e6);
far@0.46002(e1);
vision@0.22350;

DATA IMPUTATION:                ! Creating plausible values for factor score
    NDATASETS = 100;            ! Number of separate values to create
    SAVE = Vision*.dat;         ! Name of separate datasets with plausible values

SAVEDATA:   FILE = VisionSummary.dat;   ! Summary about plausibles per person
            SAVE = FSCORES (100);       ! Needed to generate 100 factor scores
            FACTORS = Vision;           ! Which factors to save

  Save file
    Vision*.dat

  Order of variables

    LNCS15
    LNCS3
    LNCS6
    LNCS12
    LNCS18
    FAR
    PARTID
    VISION
```

Now we have 100 datasets (named Vision1.dat to Vision100.dat) with these variables in this order. Thus, rather than just using the mean of a person's factor score distribution, we are *sampling* from each person's factor distribution.

In addition, it made a text file called "Visionlist.dat" that lists these individual data files:

```
Vision1.dat
Vision2.dat
Vision3.dat
Vision4.dat
Vision5.dat
…..
```

Later we will use these types of files to tell Mplus to run the same analysis on every single file, then aggregation the results (as in multiple imputation for missing data).

Measurement Model for Driving Impairment (including Omega)

Step 1: Estimate model using MLR, generate SVALUES text

```
VARIABLE:  ! Every variable in THIS MODEL
            USEVARIABLES = lane da_task crash stop speed time;
ANALYSIS:   ESTIMATOR = MLR;
MODEL:      ! Measurement models
  Driving BY crash@1   ! 1 marker loading
              da_task* lane* stop* speed* time* (L2-L6);
  [lane* da_task* crash* stop* speed* time*];            ! All intercepts
   lane* da_task* crash* stop* speed* time* (E1-E6);     ! Residual variances
  Driving*; [Driving@0];                                 ! Factor M=0, Var=?
  speed WITH time* (ResCov);                             ! Residual covariance

MODEL CONSTRAINT: ! TO GET OMEGA
NEW(SumLoad2 SumError SumRCov Omega);
SumLoad2 = (1+L2+L3+L4+L5+L6)^2;
SumError =  E1+E2+E3+E4+E5+E6;
SumRCov = 2*(ResCov);
Omega = SumLoad2 / (SumLoad2+SumError+SumRCov);
```

```
MODEL FIT INFORMATION
Number of Free Parameters                       19
Loglikelihood
          H0 Value                         -37.119
          H0 Scaling Correction Factor      1.1566
            for MLR
          H1 Value                         -30.710
          H1 Scaling Correction Factor      1.1108
            for MLR

Information Criteria
          Akaike (AIC)                     112.239
          Bayesian (BIC)                   167.012
          Sample-Size Adjusted BIC         106.915
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit
          Value                             12.791*
          Degrees of Freedom                     8
          P-Value                           0.1192
          Scaling Correction Factor         1.0021
            for MLR

*   The chi-square value for MLM, MLMV, MLR, ULSMV, WLSM and WLSMV cannot be used
    for chi-square difference testing in the regular way.  MLM, MLR and WLSM
    chi-square difference testing is described on the Mplus website.  MLMV, WLSMV,
    and ULSMV difference testing is done using the DIFFTEST option.

RMSEA (Root Mean Square Error Of Approximation)
          Estimate                           0.067
          90 Percent C.I.                    0.000  0.133
          Probability RMSEA <= .05           0.293

CFI/TLI
          CFI                                0.922
          TLI                                0.854

Chi-Square Test of Model Fit for the Baseline Model
          Value                             76.677
          Degrees of Freedom                    15
          P-Value                           0.0000

SRMR (Standardized Root Mean Square Residual)
          Value                              0.054
```

Measurement Model Results from Step 1 for Driving:

```
MODEL RESULTS
                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value
DRIVING  BY
    CRASH              1.000      0.000    999.000    999.000
    LANE               0.150      0.057      2.608      0.009
    DA_TASK            0.173      0.074      2.348      0.019
    STOP               0.347      0.163      2.124      0.034
    SPEED              0.422      0.138      3.054      0.002
    TIME               0.048      0.043      1.104      0.270

 SPEED    WITH
    TIME              -0.023      0.004     -5.393      0.000

 Means
    DRIVING            0.000      0.000    999.000    999.000

 Intercepts
    LANE               0.815      0.015     53.293      0.000
    DA_TASK            0.256      0.013     20.102      0.000
    CRASH              0.859      0.053     16.292      0.000
    STOP               0.205      0.038      5.349      0.000
    SPEED              0.836      0.042     19.687      0.000
    TIME               3.146      0.009    349.081      0.000

 Variances
    DRIVING            0.159      0.062      2.574      0.010

 Residual Variances
    LANE               0.027      0.004      6.596      0.000
    DA_TASK            0.017      0.004      4.613      0.000
    CRASH              0.209      0.055      3.781      0.000
    STOP               0.174      0.031      5.575      0.000
    SPEED              0.210      0.028      7.391      0.000
    TIME               0.010      0.001      8.639      0.000

 New/Additional Parameters
    SUMLOAD2           4.578      1.185      3.865      0.000
    SUMERROR           0.647      0.067      9.627      0.000
    SUMRCOV           -0.046      0.009     -5.393      0.000
    OMEGA              0.884      0.022     40.166      0.000

STANDARDIZED MODEL RESULTS
STDYX Standardization
                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value
DRIVING  BY
    CRASH              0.657      0.117      5.596      0.000
    LANE               0.340      0.123      2.767      0.006
    DA_TASK            0.470      0.132      3.576      0.000
    STOP               0.315      0.115      2.748      0.006
    SPEED              0.345      0.107      3.226      0.001
    TIME               0.185      0.145      1.275      0.202

SPEED    WITH
    TIME              -0.494      0.090     -5.478      0.000
```

The SVALUES output option provided this code, which we will use to generate plausible values for our factor scores for later.

```
MODEL COMMAND WITH FINAL
ESTIMATES USED AS STARTING VALUES

 driving BY crash@1;
 driving BY lane*0.14977 (l2);
 driving BY da_task*0.17282 (l3);
 driving BY stop*0.34713 (l4);
 driving BY speed*0.42198 (l5);
 driving BY time*0.04799 (l6);

 speed WITH time*-0.02305
(rescov);

 [ lane*0.81538 ];
 [ da_task*0.25614 ];
 [ crash*0.85947 ];
 [ stop*0.20455 ];
 [ speed*0.83636 ];
 [ time*3.14598 ];
 [ driving*0 ];

 lane*0.02734 (e1);
 da_task*0.01669 (e2);
 crash*0.20856 (e3);
 stop*0.17387 (e4);
 speed*0.20994 (e5);
 time*0.01036 (e6);
 driving*0.15881;
```

For factor score reliability

```
SAMPLE STATISTICS FOR ESTIMATED
FACTOR SCORES

           Means
          DRIVING     DRIVING_SE
          ________    ________
           0.000       0.247

        Covariances
           ________    ________
           DRIVING       0.098
```

$$\rho = \frac{.098}{.098 + .247^2} = .616$$

```
         Normalized Residuals for Covariances/Correlations/Residual Correlations
            LANE          DA_TASK       CRASH         STOP          SPEED
            ________      ________      ________      ________      ________
 LANE          0.000
 DA_TASK      -0.487         0.000
 CRASH         0.359        -0.390         0.000
 STOP          0.769         0.503        -0.004         0.000
 SPEED         0.458        -0.836         0.471        -0.482         0.000
 TIME         -1.508         2.067        -0.346        -0.545         0.000
```

Local fit looks mostly ok…

<u>**Now we are ready for Step 2 for the Driving Impairment factor:**</u>
Generate plausible values using BAYES estimation of *previous MLR model*

```
ANALYSIS:      ESTIMATOR = BAYES;

MODEL:      ! Parameters from previously estimated measurement model, but all FIXED

 driving BY crash@1;
 driving BY lane@0.14977 (l2);
 driving BY da_task@0.17282 (l3);
 driving BY stop@0.34713 (l4);
 driving BY speed@0.42198 (l5);
 driving BY time@0.04799 (l6);

 speed WITH time@-0.02305 (rescov);

 [ lane@0.81538 ];
 [ da_task@0.25614 ];
 [ crash@0.85947 ];
 [ stop@0.20455 ];
 [ speed@0.83636 ];
 [ time@3.14598 ];
 [ driving@0 ];

 lane@0.02734 (e1);
 da_task@0.01669 (e2);
 crash@0.20856 (e3);
 stop@0.17387 (e4);
 speed@0.20994 (e5);
 time@0.01036 (e6);
 driving@0.15881;


DATA IMPUTATION:                    ! Creating plausible values for factor score
    NDATASETS = 100;                ! Number of separate values to create
    SAVE = Driving*.dat;            ! Name of separate datasets with plausible values

SAVEDATA:   FILE = DrivingSummary.dat;   ! Summary about plausibles per person
            SAVE = FSCORES (100);        ! Needed to generate 100 factor scores
            FACTORS = Driving;           ! Which factors to save
```

```
  Save file
    Driving*.dat

  Order of variables

    LANE
    DA_TASK
    CRASH
    STOP
    SPEED
    TIME
    PARTID
    DRIVING
```

Now we have 100 datasets (named Driving1.dat to Driving100.dat) with these variables in this order. Thus, rather than just using the mean, we are *sampling* from each person's factor score distribution.

In addition, it made a text file called "Visionlist.dat" that lists these individual data files:

```
Driving1.dat
Driving2.dat
Driving3.dat
Driving4.dat
Driving5.dat
…..
```

Later we will use these types of files to tell Mplus to run the same analysis on every single file, then aggregation the results (as in multiple imputation).

Measurement Model for Attentional Impairment (including Omega)

Step 1: Estimate model using MLR, generate SVALUES text

```
VARIABLE:  ! Every variable in THIS MODEL
            USEVARIABLES = lnda lnsa Dscan;
ANALYSIS:   ESTIMATOR = MLR;

MODEL:       ! Measurement models
  Attn BY lnda@1 ! 1 marker loading
          lnsa* dscan* (L2-L3);
  [lnda* lnsa* dscan*];         ! All intercepts
   lnda* lnsa* dscan* (E1-E3); ! Residual variances
  Attn*; [Attn@0];              ! Factor M=0, Var=?

MODEL CONSTRAINT:  ! TO GET OMEGA
NEW(SumLoad2 SumError SumRCov Omega);
SumLoad2 = (1+L2+L3)^2;
SumError =  E1+E2+E3;
SumRCov = 2*(0);
Omega = SumLoad2 / (SumLoad2+SumError+SumRCov);
```

Can you guess why I didn't include the model fit?

The SVALUES output option provided this code, which we will use to generate plausible values for our factor scores for later.

```
MODEL COMMAND WITH FINAL
ESTIMATES USED AS STARTING VALUES

 attn BY lnda@1;
 attn BY lnsa*0.51567 (l2);
 attn BY dscan*1.10655 (l3);

 [ lnda*4.35396 ];
 [ lnsa*5.58076 ];
 [ dscan*-0.01244 ];
 [ attn*0 ];

 lnda*0.51556 (e1);
 lnsa*0.08112 (e2);
 dscan*0.44855 (e3);
 attn*0.44310;
```

Measurement Model Results from Step 1 for Attention:

```
MODEL RESULTS
                                                   Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value
 ATTN     BY
    LNDA               1.000      0.000    999.000    999.000
    LNSA               0.516      0.071      7.275      0.000
    DSCAN              1.107      0.139      7.933      0.000

 Means
    ATTN               0.000      0.000    999.000    999.000

 Intercepts
    LNDA               4.354      0.079     54.825      0.000
    LNSA               5.581      0.036    154.256      0.000
    DSCAN             -0.012      0.081     -0.154      0.878

 Variances
    ATTN               0.443      0.088      5.008      0.000

 Residual Variances
    LNDA               0.516      0.068      7.597      0.000
    LNSA               0.081      0.017      4.674      0.000
    DSCAN              0.449      0.086      5.243      0.000

 New/Additional Parameters
    SUMLOAD2           6.876      0.960      7.165      0.000
    SUMERROR           1.045      0.102     10.212      0.000
    SUMRCOV            0.000      0.000      0.000      1.000
    OMEGA              0.868      0.017     50.812      0.000

STANDARDIZED MODEL RESULTS
STDYX Standardization
                                                   Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value
 ATTN     BY
    LNDA               0.680      0.055     12.275      0.000
    LNSA               0.770      0.055     14.087      0.000
    DSCAN              0.740      0.056     13.153      0.000
```

For factor score reliability

```
SAMPLE STATISTICS FOR ESTIMATED
FACTOR SCORES
           Means
          ATTN          ATTN_SE
       ________      ________
          0.000         0.313

          Covariances
        ________      ________
           ATTN         0.345
```

$$\rho = \frac{.345}{.345 + .313^2} = .779$$

Now we are ready for Step 2 for the Attentional Impairment factor:
Generate plausible values using BAYES estimation of *previous MLR model*

```
ANALYSIS:      ESTIMATOR = BAYES;

MODEL:      ! Parameters from previously estimated measurement model, but all FIXED

 attn BY lnda@1;
 attn BY lnsa@0.51567 (l2);
 attn BY dscan@1.10655 (l3);

 [ lnda@4.35396 ];
 [ lnsa@5.58076 ];
 [ dscan@-0.01244 ];
 [ attn@0 ];

 lnda@0.51556 (e1);
 lnsa@0.08112 (e2);
 dscan@0.44855 (e3);
 attn@0.44310;

DATA IMPUTATION:                ! Creating plausible values for factor score
    NDATASETS = 100;            ! Number of separate values to create
    SAVE = Attn*.dat;           ! Name of separate datasets with plausible values

SAVEDATA:   FILE = AttnSummary.dat;      ! Summary about plausibles per person
            SAVE = FSCORES (100);        ! Needed to generate 100 factor scores
            FACTORS = Attn;              ! Which factors to save
```

```
  Save file
    Attn*.dat

  Order of variables

    LNDA
    LNSA
    DSCAN
    PARTID
    ATTN
```

Now we have 100 datasets (named Attn1.dat to Attn100.dat) with these variables in this order. Thus, rather than just using the mean of a person's factor score distribution, we are *sampling* from it.

In addition, it made a text file called "Attnlist.dat" that lists these individual data files:

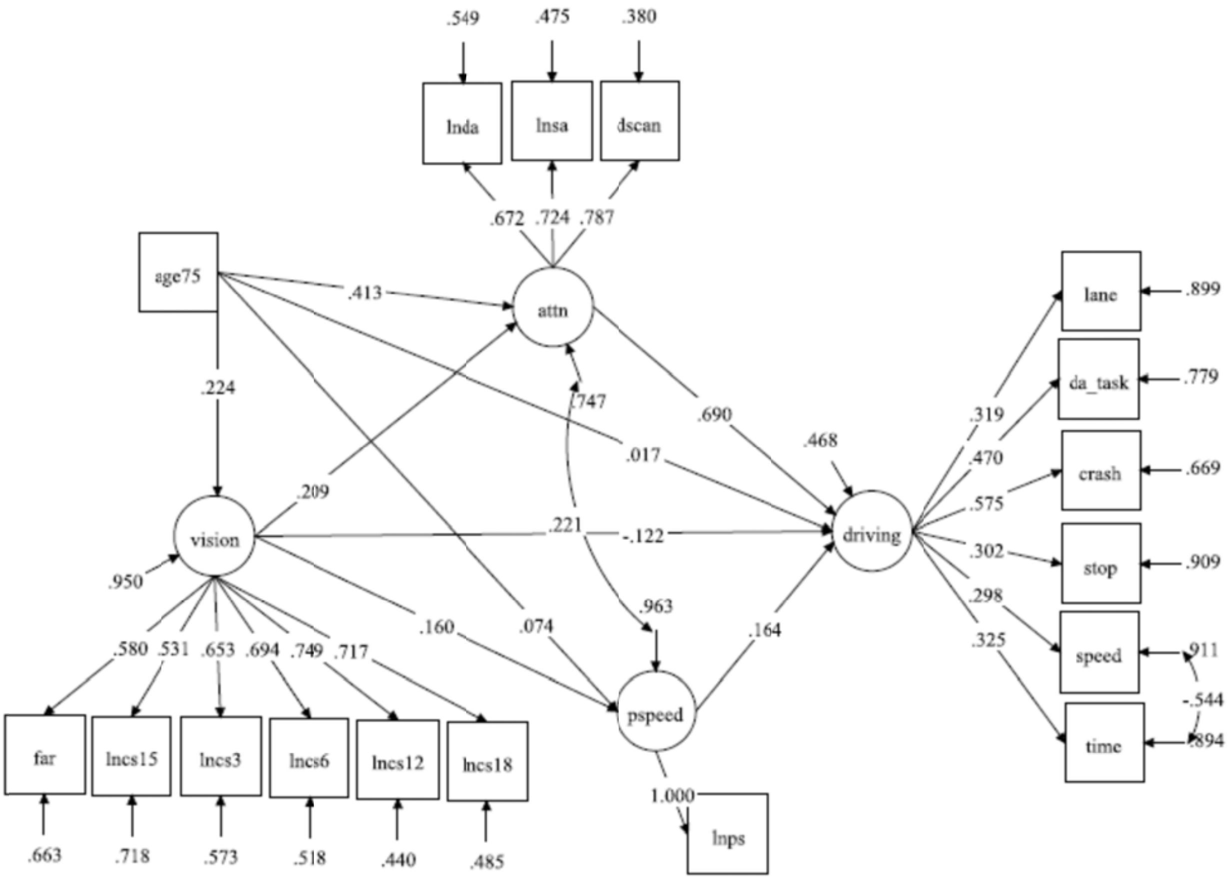
```
Attn1.dat
Attn2.dat
Attn3.dat
Attn4.dat
Attn5.dat
…..
```

Later we will use these types of files to tell Mplus to run the same analysis on every single file, then aggregation the results (as in multiple imputation).

Now we are ready to test the model of interest, as shown below (drawn by Mplus, made prettier by me). We'll begin with a saturated structural model that has main effects of the latent variables only.

```
VARIABLE:  ! Every variable in THIS MODEL
            USEVARIABLES = lncs15 lncs3 lncs6 lncs12 lncs18 far
                           lane da_task crash stop speed time
                           lnda lnsa Dscan age75 lnps;

ANALYSIS:    ESTIMATOR = MLR;
```




```
MODEL:        ! Measurement models
  Vision BY far@1 lncs15* lncs3* lncs6* lncs12* lncs18*;  ! 1 marker loading
  [far* lncs15* lncs3* lncs6* lncs12* lncs18*];           ! All intercepts
   far* lncs15* lncs3* lncs6* lncs12* lncs18*;            ! Residual variances
  Vision*; [Vision@0];                                    ! Factor M=0, Var=?

  Driving BY crash@1 da_task* lane* stop* speed* time*;   ! 1 marker loading
  [lane* da_task* crash* stop* speed* time*];             ! All intercepts
   lane* da_task* crash* stop* speed* time*;              ! Residual variances
  Driving*; [Driving@0];                                  ! Factor M=0, Var=?
  speed WITH time* (ResCov);                              ! Residual covariance

 Attn BY lnda@1 lnsa* dscan*;                             ! 1 marker loading
  [lnda* lnsa* dscan*];                                   ! All intercepts
   lnda* lnsa* dscan*;                                    ! Residual variances
  Driving*; [Driving@0];                                  ! Factor M=0, Var=?

  Pspeed BY lnps@1; lnps@0;          ! Bring proc speed into likelihood
  [lnps* Pspeed@0]; Pspeed*;         ! Move its variance to factor

! Structural model with all possible main effects
  Driving Vision Attn Pspeed ON Age75* (Age1-Age4);  ! Age --> outcomes
  Driving Pspeed Attn ON Vision*       (Vis1-Vis3);  ! Vision --> outcomes
  Attn WITH Pspeed*;                                 ! Res cov for Attn and Pspeed
  Driving ON Pspeed* Attn* (Speed1 Attn1);           ! Pspeed, Attn --> Driving

MODEL CONSTRAINT:
NEW(AgeVis AgeSpeed AgeAttn);
AgeVis   = Age1*Vis1;    ! Indirect effect of age to vision to driving
AgeSpeed = Age1*Speed1;  ! Indirect effect of age to proc speed to driving
AgeAttn  = Age1*Attn1;   ! Indirect effect of age to attention to driving
```

```
MODEL FIT INFORMATION
Number of Free Parameters                       58
Loglikelihood
          H0 Value                       -1310.811
          H0 Scaling Correction Factor      1.1063
            for MLR
          H1 Value                       -1238.221
          H1 Scaling Correction Factor      1.0405
            for MLR

Information Criteria
          Akaike (AIC)                    2737.622
          Bayesian (BIC)                  2913.007
          Sample-Size Adjusted BIC        2729.438
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit
          Value                            144.331*
          Degrees of Freedom                   110
          P-Value                           0.0156
          Scaling Correction Factor         1.0059
            for MLR

*   The chi-square value for MLM, MLMV, MLR, ULSMV, WLSM and WLSMV cannot be used
    for chi-square difference testing in the regular way.  MLM, MLR and WLSM
    chi-square difference testing is described on the Mplus website.  MLMV, WLSMV,
    and ULSMV difference testing is done using the DIFFTEST option.

RMSEA (Root Mean Square Error Of Approximation)
          Estimate                           0.045
          90 Percent C.I.                    0.021  0.064
          Probability RMSEA <= .05           0.635

CFI/TLI
          CFI                                0.936
          TLI                                0.921

Chi-Square Test of Model Fit for the Baseline Model
          Value                            671.031
          Degrees of Freedom                   136
          P-Value                           0.0000

SRMR (Standardized Root Mean Square Residual)
          Value                              0.063

MODEL RESULTS
                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value
 VISION   BY
    FAR                1.000      0.000    999.000    999.000
    LNCS15             0.481      0.099      4.837      0.000
    LNCS3              0.584      0.115      5.076      0.000
    LNCS6              0.759      0.136      5.583      0.000
    LNCS12             1.265      0.203      6.248      0.000
    LNCS18             1.491      0.232      6.416      0.000
DRIVING  BY
    CRASH              1.000      0.000    999.000    999.000
    LANE               0.161      0.066      2.444      0.015
    DA_TASK            0.197      0.065      3.022      0.003
    STOP               0.381      0.164      2.330      0.020
    SPEED              0.418      0.164      2.540      0.011
    TIME               0.097      0.053      1.819      0.069
 ATTN     BY
    LNDA               1.000      0.000    999.000    999.000
    LNSA               0.491      0.061      8.000      0.000
    DSCAN              1.192      0.170      7.022      0.000
 PSPEED   BY
    LNPS               1.000      0.000    999.000    999.000
```

```
 DRIVING  ON
    VISION            -0.089      0.109     -0.814      0.415
    PSPEED             0.114      0.083      1.387      0.165
    ATTN               0.365      0.127      2.884      0.004
 PSPEED   ON
    VISION             0.167      0.100      1.658      0.097
 ATTN     ON
    VISION             0.287      0.137      2.095      0.036
 DRIVING  ON
    AGE75              0.001      0.011      0.119      0.905
 VISION   ON
    AGE75              0.024      0.011      2.187      0.029
 ATTN     ON
    AGE75              0.059      0.014      4.393      0.000
 PSPEED   ON
    AGE75              0.008      0.008      0.988      0.323
 ATTN     WITH
    PSPEED             0.061      0.027      2.292      0.022
 SPEED    WITH
    TIME              -0.025      0.004     -5.512      0.000
 New/Additional Parameters
    AGEVIS             0.000      0.000     -0.119      0.905
    AGESPEED           0.000      0.000      0.119      0.905
    AGEATTN            0.000      0.000      0.123      0.902

STANDARDIZED MODEL RESULTS
STDYX Standardization
                                                       Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value
 VISION   BY
    FAR                0.580      0.062      9.424      0.000
    LNCS15             0.531      0.076      6.999      0.000
    LNCS3              0.653      0.061     10.646      0.000
    LNCS6              0.694      0.059     11.851      0.000
    LNCS12             0.749      0.051     14.647      0.000
    LNCS18             0.717      0.042     17.024      0.000
DRIVING  BY
    CRASH              0.575      0.107      5.378      0.000
    LANE               0.319      0.130      2.446      0.014
    DA_TASK            0.470      0.100      4.694      0.000
    STOP               0.302      0.115      2.630      0.009
    SPEED              0.298      0.102      2.911      0.004
    TIME               0.325      0.132      2.470      0.014
 ATTN     BY
    LNDA               0.672      0.058     11.501      0.000
    LNSA               0.724      0.053     13.543      0.000
    DSCAN              0.787      0.045     17.608      0.000
 PSPEED   BY
    LNPS               1.000      0.000    999.000    999.000
 DRIVING  ON
    VISION            -0.122      0.148     -0.826      0.409
    PSPEED             0.164      0.120      1.368      0.171
    ATTN               0.690      0.149      4.617      0.000
 PSPEED   ON
    VISION             0.160      0.094      1.715      0.086
 ATTN     ON
    VISION             0.209      0.096      2.191      0.028
 DRIVING  ON
    AGE75              0.017      0.148      0.118      0.906
 VISION   ON
    AGE75              0.224      0.087      2.582      0.010
 ATTN     ON
    AGE75              0.413      0.081      5.085      0.000
 PSPEED   ON
    AGE75              0.074      0.075      0.986      0.324
 ATTN     WITH
    PSPEED             0.221      0.088      2.523      0.012
```

```
 SPEED    WITH
    TIME              -0.544      0.090     -6.061      0.000
R-SQUARE
     Latent                                         Two-Tailed
    Variable        Estimate       S.E.  Est./S.E.    P-Value
    VISION             0.050      0.039      1.291      0.197
    DRIVING            0.532      0.151      3.526      0.000
    ATTN               0.253      0.077      3.264      0.001
    PSPEED             0.037      0.032      1.129      0.259
```

```
! Reduced structural model (no age or vision --> driving)
  Vision Attn Pspeed ON Age75* (Age1-Age3);         ! Age --> outcomes
  Pspeed Attn ON Vision*       (Vis1-Vis2);         ! Vision --> outcomes
  Attn WITH Pspeed*;                                ! Res cov for Attn and Pspeed
  Driving ON Pspeed* Attn*  (Speed1 Attn1);         ! Pspeed, Attn --> Driving
```

```
MODEL FIT INFORMATION
Number of Free Parameters                       56
Loglikelihood
          H0 Value                       -1311.286
          H0 Scaling Correction Factor      1.0933
            for MLR
          H1 Value                       -1238.221
          H1 Scaling Correction Factor      1.0405
            for MLR
Information Criteria
          Akaike (AIC)                    2734.572
          Bayesian (BIC)                  2903.909
          Sample-Size Adjusted BIC        2726.670
            (n* = (n + 2) / 24)
Chi-Square Test of Model Fit
          Value                           144.090*
          Degrees of Freedom                   112
          P-Value                           0.0221
          Scaling Correction Factor         1.0142
            for MLR
RMSEA (Root Mean Square Error Of Approximation)
          Estimate                           0.043
          90 Percent C.I.                    0.018  0.063
          Probability RMSEA <= .05           0.691
CFI/TLI
          CFI                                0.940
          TLI                                0.927
SRMR (Standardized Root Mean Square Residual)
          Value                              0.063
```

Did constraining these two paths to 0 make the model worse?
Rescaled −2ΔLL(2) = 0.646, *p* = .72, so no

This is the appropriate way to test a structural model, whose job is to reproduce the covariance among the latent factors and any observed predictors (but not among any observed predictors themselves).

Relying on good global model fit (which will mostly reflect the measurement models) is not sufficient to say a structural model fits.

What if we wanted to test an interaction between latent variables?

```
ANALYSIS:   ESTIMATOR = MLR; TYPE = RANDOM; ALGORITHM = INTEGRATION;
SAVEDATA:   SAVE = FSCORES; FILE IS FactorScores.dat; ! Save mean of plausibles only

! Reduced structural model (no age --> driving, but vision --> driving)
  Vision Attn Pspeed ON Age75*    (Age1-Age3);      ! Age --> outcomes
  Driving Pspeed Attn ON Vision*  (Vis1-Vis3);      ! Vision --> outcomes
  Attn WITH Pspeed*;                                ! Res cov for Attn and Pspeed
  Driving ON Pspeed* Attn*  (Speed1 Attn1);         ! Pspeed, Attn --> Driving

! Interaction between two latent variables (would be same if one was observed)
  VisAttn | Vision XWITH Attn;        ! VisAttn = new latent interaction
  Driving ON VisAttn* (VxA);          ! Interaction --> Driving

MODEL CONSTRAINT: ! latent factor variance of attn = .443, of vision = .224
NEW (V4low V4high A4low A4high);
V4low =  Vis1  - VxA*SQRT(.443);  ! Vision slope for -1SD attn
V4high = Vis1  + VxA*SQRT(.443);  ! Vision slope for +1SD attn
A4low =  Attn1 - VxA*SQRT(.224);  ! Attn slope for -1SD vision
A4high = Attn1 + VxA*SQRT(.224);  ! Attn slope for -+1SD vision
```

```
MODEL FIT INFORMATION
Number of Free Parameters                        58
Loglikelihood
          H0 Value                        -1310.275
          H0 Scaling Correction Factor       1.1008
            for MLR
Information Criteria
          Akaike (AIC)                     2736.549
          Bayesian (BIC)                   2911.934
          Sample-Size Adjusted BIC         2728.365
            (n* = (n + 2) / 24)
```

Model fit has disappeared once we've used numeric integration (no covariance matrix to come back to anymore). STDYX disappears for the same reason.

New structural model output only:

```
DRIVING    ON
    VISION            -0.105      0.116     -0.907      0.365 simple vision slope at attn=0
    PSPEED             0.117      0.084      1.384      0.166
    ATTN               0.372      0.088      4.204      0.000 simple attn slope at vision=0
    VISATTN            0.139      0.143      0.957      0.330
 PSPEED     ON
    VISION             0.168      0.101      1.663      0.096
 ATTN       ON
    VISION             0.304      0.143      2.128      0.033
 VISION     ON
    AGE75              0.024      0.011      2.189      0.029
 ATTN       ON
    AGE75              0.060      0.013      4.453      0.000
 PSPEED     ON
    AGE75              0.008      0.008      0.983      0.326
ATTN     WITH
    PSPEED             0.060      0.027      2.232      0.026
New/Additional Parameters
    V4LOW             -0.198      0.170     -1.166      0.244 simple vision slope at attn=-1SD
    V4HIGH            -0.102      0.127     -0.097      0.923 simple vision slope at attn=+1SD
    A4LOW              0.306      0.105      2.908      0.004 simple attn slope at vision=-1SD
    A4HIGH             0.438      0.117      3.738      0.000 simple attn slope at vision=+1SD
```

What if we wanted to test multiple interactions between latent variables, or the model wouldn't converge (or there are too many latent variables to estimate all at once)? **Plausible values to the rescue!** So far we've done step 1 (run model in MLR) and step 2 (use Bayes estimation to generate plausible values for each latent factor). Now we need steps 3 and 4.

Step 3: Merge the plausible values of different factors together, so that you have 100 complete datasets. Here is a SAS macro to automate that process:

```
**********************************************************************************;
*****                INFO NEEDED TO ENTER TO MERGE PLAUSIBLE VALUES          ******;
**********************************************************************************;

* Folder for plausible files;     %LET filesave = C:\Dropbox\14_Psyc948\DriverScan\PV Files;
* SAS file name of original data; %LET datafile = MyOriginalData;
* Name of person ID variable;     %LET IDvar = PartID;
* Suffix # of FIRST file;         %LET startP = 1;
* Suffix # of LAST file;          %LET endP = 100;
* Total # of sets of files;       %LET total = 3;

%MACRO LabelThem;
* index = count of how many sets of files,
* prefix = name of file prefix;
* # items needed to drop from front of file;
%IF &index. = 1 %THEN %DO; %LET prefix = Vision;  %LET ndrop = 6; %END;
%IF &index. = 2 %THEN %DO; %LET prefix = Driving; %LET ndrop = 6; %END;
%IF &index. = 3 %THEN %DO; %LET prefix = Attn;    %LET ndrop = 3; %END;
**** REPEAT THIS FOR ALL YOUR SETS OF FILES TO BE MERGED ***********;
%MEND LabelThem;
```

```
*********************************************************************************;
*****              NOTHING NEEDS TO BE CHANGED FROM HERE, JUST RUN IT       ******;
*********************************************************************************;
* Sort original data by ID; PROC SORT DATA=&datafile.; BY &IDvar.; RUN;
%GLOBAL index prefix ndrop; %MACRO Import;
%DO num=&startp. %TO &endp.; DATA Merge&num.; SET &datafile.; RUN;
      %DO index=1 %TO &total.; %LabelThem; * Import plausible file;
            DATA &prefix.&num.; INFILE  "&filesave.\&prefix.&num..dat" DLM=TAB LRECL=1000;
            LENGTH  var1-var&ndrop. $3; * Items as string vars given * missing;
            INPUT   var1-var&ndrop. &IDvar. &prefix.; KEEP &IDvar. &prefix.; RUN;
             PROC SORT DATA=&prefix.&num.; BY &IDvar.; RUN;
            * Merge with original data, replace missing values;
            DATA Merge&num.; MERGE Merge&num. &prefix.&num.; BY &IDvar.;
            IF &prefix.=. THEN &prefix.=-9999; IF &IDvar.=. THEN &IDvar.=-9999; RUN;
            * Remove SAS datasets;
            PROC DATASETS LIB=WORK NOLIST; DELETE &prefix.&num.; RUN; QUIT;
      %END; * Export to .csv for use in Mplus;
            PROC EXPORT DATA=Merge&num. OUTFILE= "&filesave.\PV&num..csv"
            DBMS=CSV REPLACE; PUTNAMES=NO; RUN;
      * Remove SAS datasets;
      PROC DATASETS LIB=WORK NOLIST; DELETE Merge&num.; RUN; QUIT;
%END; %MEND Import; * Run macro; %Import;
* Build list of plausible values files;
%MACRO Makelist;
DATA _NULL_; * Name of file to print to;
      FILE "&filesave.\PVFilesList.dat" NOPAD NOTITLES;
      * Print all dataset names;
      %DO i=&startP. %TO &endP.; PUT @1 "PV&i..csv"; %END;
RUN; %MEND Makelist; * Run macro; %Makelist;
*********************************************************************************;
```

When the SAS program is done running, you will have 100 .csv files with all latent variables merged together, as well as a file called “PVFileList.dat” that lists all these files. Now we are ready to analyze!
Step 4: Estimate the same model, but using the plausible values instead of the latent factors to build an observed interaction term. This tells Mplus to do so for all 100 files and then combine the results.

```
TITLE:  SEM Example for Driverscan using Plausible Values;
DATA:
  FILE = PVFilesList.dat;     ! FILE that lists all the data file names
  TYPE = IMPUTATION;          ! Analyze and combine results across files
VARIABLE:
! List of ALL variables in data file
  NAMES = PartID sex age75 lncs15 lncs3 lncs6 lncs12 lncs18 far lnps
               lnda lnsa Dscan lane da_task crash stop speed time ticket acc
          Vision Driving Attn;  ! New factor scores
! Variables to be analyzed in this model
  USEVARIABLE =  age75 lnps Vision Driving Attn VisAttn;
! Missing data identifier
  MISSING ARE ALL (-9999);
! ID variable;
  IDVARIABLE IS PartID;
DEFINE:     VisAttn = Vision * Attn; ! Now interaction is observed variable
ANALYSIS:   ESTIMATOR = MLR;
OUTPUT:     STDYX RESIDUAL;      ! Standardized model, local fit
            SAMPSTAT;            ! Get descriptive stats for variables
MODEL: ! Structural model
  Vision Attn lnps  ON Age75*  (Age1-Age3);   ! Age --> outcomes
  Driving lnps Attn ON Vision* (Vis1-Vis3);   ! Vision --> outcomes
  Attn WITH lnps*;                            ! Res cov for Attn and Pspeed
  lnps Attn Vision ON VisAttn*;               ! Interaction relations
  Driving ON lnps* Attn* (Speed1 Attn1);      ! Obs vars --> Driving
  Driving ON VisAttn* (VxA);                  ! Obs var interaction
MODEL CONSTRAINT: ! Plausible score variance of attn = .441, of vision = .221
NEW (V4low V4high A4low A4high);
V4low =  Vis1  - VxA*SQRT(.441);  ! Vision slope for -1SD attn
V4high = Vis1  + VxA*SQRT(.441);  ! Vision slope for +1SD attn
A4low =  Attn1 - VxA*SQRT(.221);  ! Attn slope for -1SD vision
A4high = Attn1 + VxA*SQRT(.221);  ! Attn slope for -+1SD vision
```

```
Number of Free Parameters                       21
Loglikelihood
    H0 Value
        Mean                               -391.439
        Std Dev                               9.112
    H1 Value
        Mean                               -390.891
        Std Dev                               9.052
Information Criteria
    Akaike (AIC)
        Mean                                824.879
        Std Dev                              18.224
    Bayesian (BIC)
        Mean                                888.380
        Std Dev                              18.224
     Sample-Size Adjusted BIC (n* = (n + 2) / 24)
        Mean                                821.916
        Std Dev                              18.224
Chi-Square Test of Model Fit
        Degrees of freedom                        1
        Mean                                  1.268
        Std Dev                               1.630
RMSEA (Root Mean Square Error Of Approximation)
        Mean                                  0.039
        Std Dev                               0.053
CFI/TLI
    CFI
        Mean                                  0.986
        Std Dev                               0.027
    TLI
        Mean                                  0.914
        Std Dev                               0.443
SRMR (Standardized Root Mean Square Residual)
        Mean                                  0.013
        Std Dev                               0.008
```

Each dataset has its own set of fit statistics, the mean and SD for each are given here (with much other output omitted).

This means that likelihood ratio testing cannot proceed in the usual way.

```
MODEL RESULTS
                                                    Two-Tailed   Rate of
                    Estimate       S.E.  Est./S.E.    P-Value    Missing
 VISION   ON
    AGE75              0.019      0.009      2.137      0.033      0.153
    VISATTN            0.082      0.251      0.325      0.745      0.255
 ATTN     ON
    AGE75              0.042      0.012      3.647      0.000      0.129
    VISION             0.454      0.123      3.700      0.000      0.171
    VISATTN            0.055      0.247      0.222      0.824      0.218
 LNPS     ON
    AGE75              0.009      0.008      1.155      0.248      0.014
    VISION             0.140      0.093      1.502      0.133      0.120
    VISATTN           -0.012      0.144     -0.086      0.931      0.255

 DRIVING  ON
    VISION            -0.060      0.102     -0.589      0.556      0.276
    LNPS               0.095      0.079      1.201      0.230      0.208
    ATTN               0.187      0.066      2.839      0.005      0.279
    VISATTN            0.013      0.133      0.101      0.919      0.320
 ATTN     WITH
    LNPS               0.045      0.023      1.922      0.055      0.111
 New/Additional Parameters
    V4LOW             -0.069      0.133     -0.518      0.605      0.306
    V4HIGH            -0.051      0.136     -0.375      0.708      0.286
    A4LOW              0.180      0.089      2.028      0.043      0.284
    A4HIGH             0.193      0.092      2.087      0.037      0.312
```

What would have happened if we used the mean of each person’s factor score distribution from the single-factor models as a single observed variable instead? Let’s examine two versions.

```
TITLE:  SEM Example for Driverscan using Factor Score Values;
DATA:
  FILE = SEMfactorscores.dat;     ! Mean factor score merged back into data
  TYPE = INDIVIDUAL;              ! Now just a regular analysis
VARIABLE:
! List of ALL variables in data file
  NAMES = PartID sex age75 lnps vision driving attn; ! New factor scores
! Variables to be analyzed in this model
  USEVARIABLE = age75 lnps vision driving attn visattn;
! Missing data identifier
  MISSING ARE ALL (-9999);
! ID variable;
  IDVARIABLE IS PartID;
DEFINE:     VisAttn = Vision * Attn; ! Now interaction is observed variable

ANALYSIS:   ESTIMATOR = MLR;
OUTPUT:     STDYX RESIDUAL;     ! Standardized model, local fit
            SAMPSTAT;           ! Get descriptive stats for variables
MODEL:
! Structural model
  Vision Attn lnps  ON Age75*  (Age1-Age3);   ! Age --> outcomes
  Driving lnps Attn ON Vision* (Vis1-Vis3);   ! Vision --> outcomes
  Attn WITH lnps*;                            ! Res cov for Attn and Pspeed
  lnps Attn Vision ON VisAttn*;               ! Interaction relations
  Driving ON lnps* Attn* (Speed1 Attn1);      ! Obs vars --> Driving
  Driving ON VisAttn* (VxA);                  ! Obs var interaction

MODEL CONSTRAINT: ! New factor score variance of attn = .345, of vision = .186
NEW (V4low V4high A4low A4high);
V4low =  Vis1  - VxA*SQRT(.345);  ! Vision slope for -1SD attn
V4high = Vis1  + VxA*SQRT(.345);  ! Vision slope for +1SD attn
A4low =  Attn1 - VxA*SQRT(.186);  ! Attn slope for -1SD vision
A4high = Attn1 + VxA*SQRT(.186);  ! Attn slope for -+1SD vision

MODEL FIT INFORMATION
Number of Free Parameters                         21
Loglikelihood
          H0 Value                          -323.603
          H0 Scaling Correction Factor        1.1794
            for MLR
          H1 Value                          -323.451
          H1 Scaling Correction Factor        1.1676
            for MLR
Information Criteria
          Akaike (AIC)                       689.207
          Bayesian (BIC)                     752.708
          Sample-Size Adjusted BIC           686.244
            (n* = (n + 2) / 24)
Chi-Square Test of Model Fit
          Value                                0.331*
          Degrees of Freedom                       1
          P-Value                             0.5649
          Scaling Correction Factor           0.9182
           for MLR
*   The chi-square value for MLM, MLMV, MLR, ULSMV, WLSM and WLSMV cannot be used
    for chi-square difference testing in the regular way.  MLM, MLR and WLSM
    chi-square difference testing is described on the Mplus website.  MLMV, WLSMV,
    and ULSMV difference testing is done using the DIFFTEST option.

RMSEA (Root Mean Square Error Of Approximation)
          Estimate                             0.000
          90 Percent C.I.                      0.000  0.178
          Probability RMSEA <= .05             0.633
CFI/TLI
          CFI                                  1.000
          TLI                                  1.172
SRMR (Standardized Root Mean Square Residual)
          Value                                0.007
```

Here's what the code would have looked like to correct for factor score unreliability:

```
! Measurement models for factor score unreliability
Fvision BY Vision@1;  Vision*(ResVis);   [Fvision@0 Vision*];
Fattn   BY Attn@1;    Attn*(ResAttn);    [Fattn@0   Attn*];
Fdrive  BY Driving@1; Driving*(ResDriv); [Fdrive@0  Driving*];

! Structural model with "latent" variables;
  Fvision Fattn lnps  ON Age75* (Age1-Age3);     ! Age --> outcomes
  Fdrive lnps Fattn ON Fvision* (Vis1-Vis3);     ! Vision --> outcomes
  Fattn WITH lnps*;                              ! Res cov for Attn and Pspeed
  lnps Fattn Fvision ON VisAttn*;                ! Interaction relations
  Fdrive ON lnps* Fattn* (Speed1 Attn1);         ! Obs vars --> Driving
  Fdrive ON VisAttn* (VxA);                      ! Obs var interaction

MODEL CONSTRAINT: ! New factor score variance of attn = .345, of vision = .186
NEW (V4low V4high A4low A4high);
V4low =  Vis1  - VxA*SQRT(.345);  ! Vision slope for -1SD attn
V4high = Vis1  + VxA*SQRT(.345);  ! Vision slope for +1SD attn
A4low =  Attn1 - VxA*SQRT(.186);  ! Attn slope for -1SD vision
A4high = Attn1 + VxA*SQRT(.186);  ! Attn slope for -+1SD vision

ResVis =(1-.832)*0.186; ! Fix residual variances to "unreliable" part
ResAttn=(1-.779)*0.345;
ResDriv=(1-.616)*0.097;
```

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value	P-value from Rel	P-value from SEM	P-value from Plaus
VISION ON							
AGE75	0.019	0.007	2.563	0.010	.010	.029	.033
VISATTN	0.170	0.259	0.654	0.513	.513		.745
ATTN ON							
AGE75	0.047	0.010	4.632	0.000	.000	.000	.000
VISION	0.227	0.105	2.165	0.030	.034	.033	.000
VISATTN	0.092	0.240	0.385	0.700	.731		.824
LNPS ON							
AGE75	0.009	0.008	1.094	0.274	.320	.326	.248
VISION	0.168	0.095	1.767	0.077	.077	.096	.133
VISATTN	-0.032	0.146	-0.220	0.826	.796		.931
DRIVING ON							
VISION	-0.022	0.064	-0.343	0.731	.515	.365	.556
LNPS	0.080	0.052	1.538	0.124	.242	.166	.230
ATTN	0.229	0.040	5.791	0.000	.000	.000	.005
VISATTN	0.024	0.090	0.381	0.703	.774	.330	.919
ATTN WITH							
PSPEED	0.052	0.020	2.580	0.010	.012	.026	.055
New/Additional Parameters							
V4LOW	-0.042	0.084	-0.500	0.617	.511	.244	.605
V4HIGH	-0.002	0.082	-0.020	0.984	.689	.923	.708
A4LOW	0.214	0.057	3.789	0.000	.000	.004	.043
A4HIGH	0.244	0.055	4.475	0.000	.000	.000	.047

The p-values from the model treating factor scores as observed variables are compared here with those correcting for factor score unreliability, from SEM, and from using plausible values. As shown, results are similar, although relative to SEM, although slightly more conservative when using plausible values, and slightly more liberal when using factor scores. To the extent that reliability of the sum score or the factor scores is lower, though, these results should diverge more.