

MI in R

```
library(lavaan)
```

```
## This is lavaan 0.6-9  
## lavaan is FREE software! Please report any bugs.
```

```
library(dplyr)
```

```
##  
## Attaching package: 'dplyr'  
  
## The following objects are masked from 'package:stats':  
##  
##   filter, lag  
  
## The following objects are masked from 'package:base':  
##  
##   intersect, setdiff, setequal, union
```

```
habit <- read.table("sem_categorical.dat", header = FALSE)
```

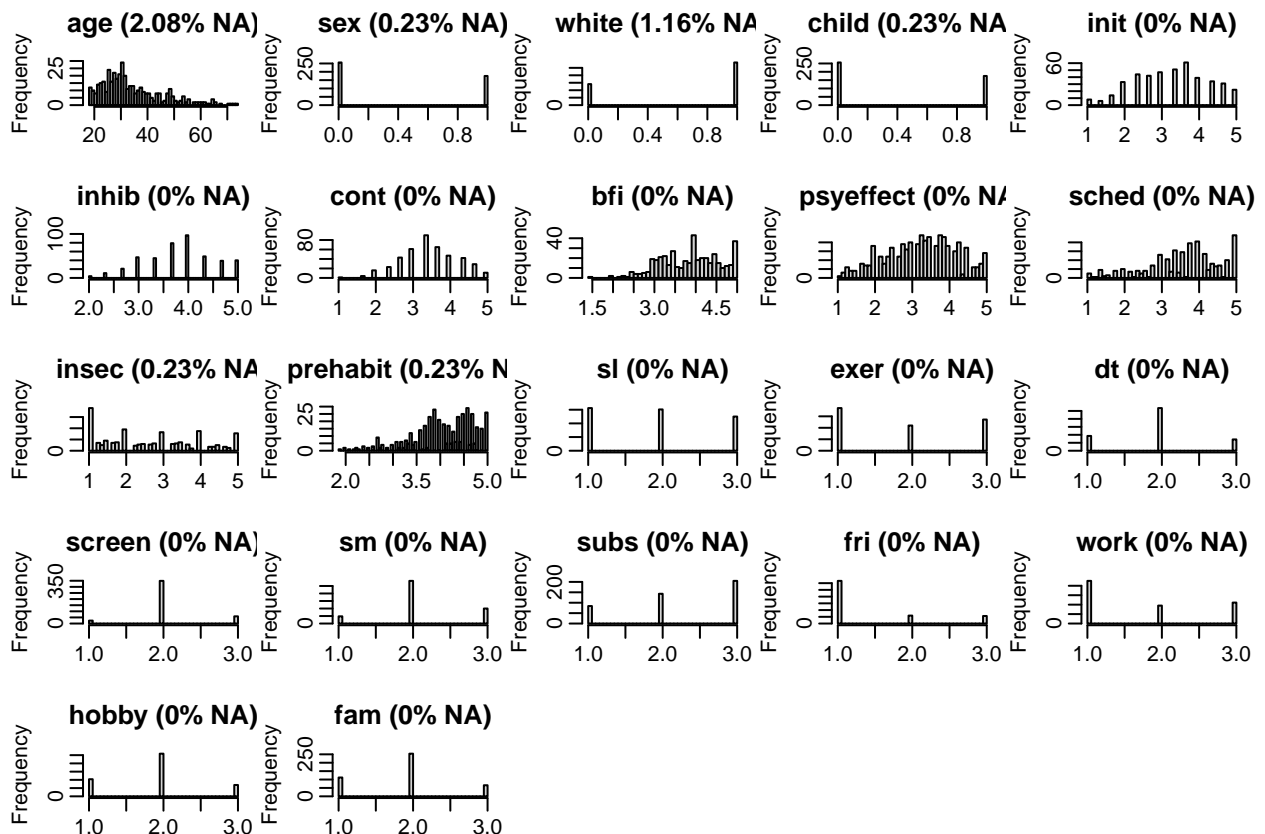
This is a longer dataset, so we'll add column names to the variables. Because we're using the same dataset as the one for Mplus, missing values are still “.” At last line of code in this chunk tells R to turn all variables into numeric, which means that the “.” (which are character) will be turned into NAs - and that's what we want.

```
colnames(habit) <- c("age", "sex", "white", "child", "init",  
  "inhib", "cont", "bfi", "psyeffect", "sched", "insec", "prehabit",  
  "sl", "exer", "dt", "screen", "sm", "subs", "fri", "work",  
  "hobby", "fam")  
  
habit <- data.frame(lapply(habit, function(x) as.numeric(as.character(x))))
```

```
## Warning in FUN(X[[i]], ...): NAs introduced by coercion  
## Warning in FUN(X[[i]], ...): NAs introduced by coercion  
## Warning in FUN(X[[i]], ...): NAs introduced by coercion  
## Warning in FUN(X[[i]], ...): NAs introduced by coercion  
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```

First, a quick overview of the data. If you use your own dataset, you'll need to replace "habit" in the code with your dataset.

```
nc <- max(5, ceiling(sqrt(ncol(habit))))
nr <- ceiling(ncol(habit)/nc)
par(mfrow = c(nr, nc), mgp = c(2, 0.6, 0), mar = c(2, 3, 3, 0.5))
for (i in 1:ncol(habit)) {
  if (is.numeric(habit[, i])) {
    hist(habit[, i], nclass = 50, xlab = "", main = paste0(names(habit[i]),
      " (", round(mean(is.na(habit[, i])) * 100, 2), "% NA)"))
  } else {
    barplot(table(habit[, i]), ylab = "Frequency", main = paste0(names(habit[i]),
      " (", round(mean(is.na(habit[, i])) * 100, 2), "% NA)"))
  }
}
```



You can first visualize missing data in R using packages like MICE. There are many others you can choose from but MICE has nice visualizations. As usual with R, if you haven't installed a package yet, make sure you do. Once you have installed it, you can just load the package library (you need to load the package library every time you use a package, otherwise you will get an error saying that R doesn't recognize the function).

```
# install.packages('mice')
library("mice")
```

```
##
```


## 4	1	1	1	1	1	1	0	1	1
## 1	1	1	1	1	1	1	0	0	2
## 1	1	1	1	1	1	0	1	1	1
## 1	1	1	1	1	0	1	1	1	1
## 1	1	1	1	0	1	1	1	0	2
## 1	1	1	0	1	1	1	1	1	1
##	0	0	1	1	1	1	5	9	18

This is a really cool output. Both windows show you the same information. On top, on the horizontal axis are the variables. On the left vertical axis are the sums of participants within a given missing data pattern across all variables. On the bottom horizontal axis are the sums of participants with missing data on each variable/column. A missing data pattern is basically each combination of missing data that we can find. That's represented on the right vertical axis. For example, you can see that there are 8 missing data patterns. The first is no missing data for 416 participants. The second is missing data on one 1 (right vertical axis) variable (age) for 7 participants (left vertical axis). The fourth missing data pattern is for 2 (right vertical axis) variables (age and race) for 1 participant (left vertical axis). And so on.

```
habit.sem <- "disrupt =~ psyeffect + sched + insec # Our latent variable 1 with 3 indicators
             sreg =~ init + inhib + cont + bfi # Our latent variable 2 with 4 indicators

             sl + exer + dt + subs ~ disrupt + sreg + prehabit + age + sex + white + child

             # Our regression with sl, exer, dt, and subs as endogenous variables and all else as exogenous
             # Note that we have a combination of latent and observed variables for exogenous variables
             # All endogenous are observed

             sreg ~~ disrupt + prehabit + age + sex + white + child # Covariances between exogenous variables
             disrupt ~~ prehabit + age + sex + white + child
             prehabit ~~ age + sex + white + child
             age ~~ sex + white + child
             sex ~~ white + child
             white ~~ child
             "
```

Then we estimate the model as we did before

```
cont.fit <- sem(
  model = habit.sem, # tell R the model you're using (we specified it above and gave it a name)
  data = habit, # Tell R the dataset you're using (we gave it a name above)
  missing = "fiml", # Listwise is the default, and we know there's a lot of missing data
  estimator = "mlr" # Tell R the estimator we're using
)

summary(cont.fit, # Tell R which model to output
  fit.measures = TRUE, # Tell R you want the fit measures (CFI, TLI etc.)
  standardized = TRUE) # Tell R you want the standardized solution
```

```
## lavaan 0.6-9 ended normally after 141 iterations
##
##      Estimator                      ML
##      Optimization method          NLMINB
##      Number of model parameters    94
##
```

```

##      Number of observations                432
##      Number of missing patterns           8
##
## Model Test User Model:
##
##              Standard      Robust
##      Test Statistic      164.661    166.366
##      Degrees of freedom         58         58
##      P-value (Chi-square)      0.000      0.000
##      Scaling correction factor              0.990
##      Yuan-Bentler correction (Mplus variant)
##
## Model Test Baseline Model:
##
##      Test statistic      1223.810    1182.152
##      Degrees of freedom      120         120
##      P-value              0.000      0.000
##      Scaling correction factor              1.035
##
## User Model versus Baseline Model:
##
##      Comparative Fit Index (CFI)      0.903      0.898
##      Tucker-Lewis Index (TLI)        0.800      0.789
##
##      Robust Comparative Fit Index (CFI)              0.902
##      Robust Tucker-Lewis Index (TLI)              0.798
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)      -8314.432    -8314.432
##      Scaling correction factor              0.984
##      for the MLR correction
##      Loglikelihood unrestricted model (H1)      -8232.102    -8232.102
##      Scaling correction factor              0.986
##      for the MLR correction
##
##      Akaike (AIC)      16816.865    16816.865
##      Bayesian (BIC)      17199.297    17199.297
##      Sample-size adjusted Bayesian (BIC)      16900.994    16900.994
##
## Root Mean Square Error of Approximation:
##
##      RMSEA      0.065      0.066
##      90 Percent confidence interval - lower      0.054      0.054
##      90 Percent confidence interval - upper      0.077      0.078
##      P-value RMSEA <= 0.05      0.016      0.014
##
##      Robust RMSEA              0.065
##      90 Percent confidence interval - lower      0.054
##      90 Percent confidence interval - upper      0.077
##
## Standardized Root Mean Square Residual:
##
##      SRMR      0.036      0.036
##

```

```

## Parameter Estimates:
##
## Standard errors                      Sandwich
## Information bread                    Observed
## Observed information based on        Hessian
##
## Latent Variables:
##      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##  disrupt =~
##    psyeffect      1.000
##    sched          1.070    0.184    5.811    0.000    0.680    0.724
##    insec          1.022    0.145    7.029    0.000    0.695    0.538
##  sreg =~
##    init           1.000
##    inhib          0.425    0.046    9.258    0.000    0.792    0.818
##    cont           0.616    0.047   13.146    0.000    0.336    0.483
##    bfi            0.616    0.047   13.146    0.000    0.488    0.654
##    bfi            0.781    0.043   18.342    0.000    0.619    0.879
##
## Regressions:
##      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##  sl ~
##    disrupt        -0.318    0.074   -4.271    0.000   -0.216   -0.269
##    sreg            -0.026    0.060   -0.433    0.665   -0.020   -0.025
##    prehabit        -0.028    0.061   -0.449    0.654   -0.028   -0.023
##    age             -0.001    0.004   -0.398    0.690   -0.001   -0.021
##    sex              -0.016    0.079   -0.209    0.834   -0.016   -0.010
##    white            -0.061    0.082   -0.745    0.456   -0.061   -0.036
##    child            0.136    0.083    1.646    0.100    0.136    0.083
##  exer ~
##    disrupt        -0.319    0.075   -4.235    0.000   -0.217   -0.254
##    sreg             0.028    0.061    0.464    0.643    0.022    0.026
##    prehabit         0.054    0.064    0.845    0.398    0.054    0.043
##    age             -0.001    0.004   -0.148    0.882   -0.001   -0.008
##    sex              -0.001    0.083   -0.016    0.987   -0.001   -0.001
##    white            -0.130    0.088   -1.474    0.141   -0.130   -0.071
##    child            0.093    0.089    1.051    0.293    0.093    0.054
##  dt ~
##    disrupt        -0.096    0.062   -1.562    0.118   -0.066   -0.107
##    sreg            -0.028    0.046   -0.604    0.546   -0.022   -0.036
##    prehabit         0.022    0.047    0.464    0.643    0.022    0.024
##    age             0.003    0.003    1.036    0.300    0.003    0.059
##    sex             -0.024    0.060   -0.395    0.693   -0.024   -0.019
##    white           -0.011    0.063   -0.167    0.868   -0.011   -0.008
##    child            0.096    0.065    1.472    0.141    0.096    0.077
##  subs ~
##    disrupt        -0.267    0.071   -3.781    0.000   -0.182   -0.236
##    sreg             0.019    0.058    0.332    0.740    0.015    0.020
##    prehabit         0.078    0.063    1.235    0.217    0.078    0.068
##    age             0.003    0.003    0.934    0.350    0.003    0.047
##    sex             -0.021    0.076   -0.276    0.783   -0.021   -0.013
##    white            0.162    0.081    2.008    0.045    0.162    0.099
##    child            0.028    0.082    0.344    0.731    0.028    0.018
##
## Covariances:

```

##		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
##	disrupt ~~						
##	sreg	-0.072	0.039	-1.837	0.066	-0.134	-0.134
##	sreg ~~						
##	prehabit	0.119	0.030	4.002	0.000	0.150	0.223
##	age	1.731	0.501	3.458	0.001	2.185	0.190
##	sex	-0.046	0.020	-2.305	0.021	-0.059	-0.119
##	white	0.024	0.019	1.251	0.211	0.030	0.064
##	child	0.057	0.021	2.777	0.005	0.072	0.147
##	disrupt ~~						
##	prehabit	0.074	0.028	2.653	0.008	0.108	0.161
##	age	-0.689	0.462	-1.490	0.136	-1.013	-0.088
##	sex	-0.021	0.022	-0.945	0.345	-0.030	-0.061
##	white	-0.028	0.019	-1.527	0.127	-0.042	-0.089
##	child	0.058	0.023	2.523	0.012	0.086	0.174
##	prehabit ~~						
##	age	1.003	0.371	2.703	0.007	1.003	0.130
##	sex	-0.024	0.016	-1.503	0.133	-0.024	-0.072
##	white	-0.020	0.015	-1.342	0.180	-0.020	-0.064
##	child	0.025	0.016	1.571	0.116	0.025	0.075
##	age ~~						
##	sex	-0.342	0.266	-1.287	0.198	-0.342	-0.061
##	white	0.746	0.244	3.054	0.002	0.746	0.138
##	child	1.072	0.260	4.123	0.000	1.072	0.190
##	sex ~~						
##	white	-0.018	0.011	-1.632	0.103	-0.018	-0.080
##	child	-0.000	0.012	-0.033	0.973	-0.000	-0.002
##	white ~~						
##	child	-0.011	0.011	-0.945	0.345	-0.011	-0.046
##	.sl ~~						
##	.exer	0.017	0.034	0.515	0.607	0.017	0.027
##	.dt	-0.010	0.023	-0.433	0.665	-0.010	-0.021
##	.subs	0.059	0.028	2.101	0.036	0.059	0.103
##	.exer ~~						
##	.dt	0.011	0.024	0.441	0.659	0.011	0.021
##	.subs	-0.033	0.030	-1.086	0.278	-0.033	-0.054
##	.dt ~~						
##	.subs	0.011	0.023	0.454	0.650	0.011	0.024
##							
##	Intercepts:						
##		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
##	.psyeffect	3.251	0.045	71.940	0.000	3.251	3.461
##	.sched	3.641	0.047	77.870	0.000	3.641	3.747
##	.insec	2.661	0.062	42.751	0.000	2.661	2.060
##	.init	3.270	0.047	70.144	0.000	3.270	3.375
##	.inhib	3.826	0.033	114.233	0.000	3.826	5.496
##	.cont	3.448	0.036	96.077	0.000	3.448	4.623
##	.bfi	3.861	0.034	113.981	0.000	3.861	5.484
##	.sl	2.083	0.275	7.570	0.000	2.083	2.593
##	.exer	1.734	0.286	6.065	0.000	1.734	2.027
##	.dt	1.730	0.229	7.561	0.000	1.730	2.817
##	.subs	1.746	0.287	6.086	0.000	1.746	2.273
##	prehabit	4.056	0.032	125.295	0.000	4.056	6.035
##	age	34.647	0.557	62.200	0.000	34.647	3.017

```
##      sex      0.406    0.024   17.163    0.000    0.406    0.827
##     white     0.669    0.023   29.394    0.000    0.669    1.423
##     child     0.406    0.024   17.159    0.000    0.406    0.826
##    disrupt     0.000                    0.000    0.000
##     sreg      0.000                    0.000    0.000
##
## Variances:
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##    .psyeffect     0.420   0.077   5.435   0.000   0.420   0.476
##    .sched         0.415   0.093   4.458   0.000   0.415   0.439
##    .insec         1.186   0.096  12.299   0.000   1.186   0.711
##    .init          0.311   0.034   9.053   0.000   0.311   0.331
##    .inhib         0.371   0.025  14.936   0.000   0.371   0.766
##    .cont          0.318   0.029  11.123   0.000   0.318   0.572
##    .bfi           0.113   0.020   5.710   0.000   0.113   0.227
##    .sl            0.599   0.027  21.976   0.000   0.599   0.929
##    .exer          0.683   0.030  22.816   0.000   0.683   0.934
##    .dt            0.370   0.023  16.029   0.000   0.370   0.981
##    .subs          0.545   0.029  18.762   0.000   0.545   0.923
##    prehabit       0.452   0.032  13.991   0.000   0.452   1.000
##    age            131.838  10.579  12.462   0.000  131.838   1.000
##    sex            0.241   0.004  54.251   0.000   0.241   1.000
##    white          0.221   0.008  28.625   0.000   0.221   1.000
##    child          0.241   0.004  54.240   0.000   0.241   1.000
##    disrupt        0.463   0.091   5.095   0.000   1.000   1.000
##    sreg           0.628   0.058  10.808   0.000   1.000   1.000
```

We'll show you two options for MI in R. On the first, you'll create the imputed dataset using a flexible MI package called mice, then you'll fit your lavaan model to your datasets using semTools package.

In the second method, we'll just use the semTools package to do MI and fit the models. In both cases you'll need to download semTools (if your first time using it) and then load the library (every time you use it within an R session).

We'll first do the two-part method in which we mice to do multiple imputation with Bayesian regression, as in Mplus. This is the Rubin (1987) and Schafer (1997) method. The function for this algorithm is called "norm".

```
# install.packages('semTools')
library(semTools)
```

```
##
```

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

```
## This is semTools 0.5-5
```

```
## All users of R (or SEM) are invited to submit functions or ideas for functions.
```

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



```
habit.imp <- mice(habit, # the dataframe name
                 maxit = 0, # A scalar giving the number of iterations, default is 5
                 m = 10, # Number of imputed datasets, default is 5
                 defaultMethod = "norm") # The method we're choosing, which is norm
```

Now we use semTools package to fit a lavaan model using the imputed values we obtained in mice. To do this, we need to clean the mice output a little to create the 5 datasets it generated during imputation. That's the two lines of code below.

```
mice.imp <- NULL
for (i in 1:10) mice.imp[[i]] <- complete(habit.imp, action = i,
    inc = FALSE) # On this line, you'll need to change the 1:5 (one through 5) if you have more than 5
```

We then fit the model.

```
impsem <- runMI(habit.sem, # Tell R the model we specified earlier
               data = mice.imp, # Tell R the imputed datasets that we created with mice
               fun = "sem" # tell MI the
               )
```

And we get our output

```
summary(impsem, # Tell R which model to output
       fit.measures = TRUE, # Tell R you want the fit measures (CFI, TLI etc.)
       standardized = TRUE) # Tell R you want the standardized solution
```

```
## lavaan.mi object based on 10 imputed data sets.
## See class?lavaan.mi help page for available methods.
##
## Convergence information:
## The model converged on 10 imputed data sets
##
## Rubin's (1987) rules were used to pool point and SE estimates across 10 imputed data sets, and to ca
##
## Model Test User Model:
##
##      Test statistic          162.218
##      Degrees of freedom           58
##      P-value                   0.000
##
## Model Test Baseline Model:
##
##      Test statistic          1214.224
##      Degrees of freedom           120
##      P-value                   0.000
##
## User Model versus Baseline Model:
##
##      Comparative Fit Index (CFI)          0.905
##      Tucker-Lewis Index (TLI)            0.803
##
## Root Mean Square Error of Approximation:
```

```
##
## RMSEA 0.064
## 90 Percent confidence interval - lower 0.053
## 90 Percent confidence interval - upper 0.076
## P-value RMSEA <= 0.05 0.021
##
```

```
## Standardized Root Mean Square Residual:
```

```
##
## SRMR 0.038
```

```
##
## Parameter Estimates:
```

```
## Standard errors Standard
## Information Expected
## Information saturated (h1) model Structured
##
```

```
## Latent Variables:
```

	Estimate	Std.Err	t-value	df	P(> t)	Std.lv
disrupt =~						
psyeffect	1.000					0.680
sched	1.071	0.103	10.367	Inf	0.000	0.728
insec	1.022	0.114	8.966	Inf	0.000	0.695
sreg =~						
init	1.000					0.793
inhib	0.425	0.044	9.752	Inf	0.000	0.336
cont	0.616	0.045	13.712	Inf	0.000	0.488
bfi	0.781	0.045	17.267	Inf	0.000	0.619
Std.all						
	0.724					
	0.749					
	0.538					
	0.818					
	0.483					
	0.655					
	0.879					

```
## Regressions:
```

	Estimate	Std.Err	t-value	df	P(> t)	Std.lv
sl ~						
disrupt	-0.317	0.073	-4.364	Inf	0.000	-0.216
sreg	-0.026	0.056	-0.469	Inf	0.639	-0.021
prehabit	-0.030	0.060	-0.496	Inf	0.620	-0.030
age	-0.001	0.003	-0.314	Inf	0.753	-0.001
sex	-0.016	0.079	-0.208	Inf	0.835	-0.016
white	-0.067	0.082	-0.815	Inf	0.415	-0.067
child	0.136	0.082	1.655	Inf	0.098	0.136
exer ~						
disrupt	-0.319	0.077	-4.132	Inf	0.000	-0.217
sreg	0.029	0.060	0.479	Inf	0.632	0.023
prehabit	0.053	0.064	0.832	Inf	0.406	0.053
age	-0.001	0.004	-0.244	Inf	0.808	-0.001

##	sex	-0.002	0.084	-0.023	Inf	0.981	-0.002
##	white	-0.126	0.088	-1.436	Inf	0.151	-0.126
##	child	0.095	0.087	1.088	Inf	0.277	0.095
##	dt ~						
##	disrupt	-0.096	0.055	-1.761	Inf	0.078	-0.066
##	sreg	-0.027	0.043	-0.622	Inf	0.534	-0.021
##	prehabit	0.022	0.047	0.461	Inf	0.645	0.022
##	age	0.003	0.003	1.121	Inf	0.262	0.003
##	sex	-0.025	0.061	-0.407	Inf	0.684	-0.025
##	white	-0.012	0.064	-0.181	Inf	0.857	-0.012
##	child	0.096	0.064	1.503	Inf	0.133	0.096
##	subs ~						
##	disrupt	-0.267	0.069	-3.892	Inf	0.000	-0.182
##	sreg	0.020	0.053	0.379	Inf	0.704	0.016
##	prehabit	0.075	0.057	1.319	Inf	0.187	0.075
##	age	0.003	0.003	0.932	Inf	0.351	0.003
##	sex	-0.022	0.075	-0.290	Inf	0.772	-0.022
##	white	0.158	0.078	2.024	Inf	0.043	0.158
##	child	0.029	0.078	0.367	Inf	0.714	0.029
##	Std.all						
##							
##	-0.269						
##	-0.026						
##	-0.025						
##	-0.016						
##	-0.010						
##	-0.039						
##	0.083						
##							
##	-0.254						
##	0.026						
##	0.042						
##	-0.012						
##	-0.001						
##	-0.069						
##	0.055						
##							
##	-0.107						
##	-0.035						
##	0.024						
##	0.057						
##	-0.020						
##	-0.009						
##	0.076						
##							
##	-0.236						
##	0.021						
##	0.066						
##	0.046						
##	-0.014						
##	0.097						
##	0.018						
##							
##	Covariances:						

	Estimate	Std.Err	t-value	df	P(> t)	Std.lv
##						
##	disrupt ~~					
##	sreg	-0.072	0.033	-2.183	Inf	0.029
##	sreg ~~					
##	prehabit	0.118	0.029	4.130	Inf	0.000
##	age	1.691	0.482	3.512	Inf	0.000
##	sex	-0.047	0.020	-2.283	Inf	0.022
##	white	0.023	0.019	1.172	Inf	0.241
##	child	0.057	0.020	2.788	Inf	0.005
##	disrupt ~~					
##	prehabit	0.072	0.026	2.761	Inf	0.006
##	age	-0.694	0.441	-1.574	Inf	0.116
##	sex	-0.020	0.019	-1.077	Inf	0.281
##	white	-0.027	0.018	-1.516	Inf	0.130
##	child	0.058	0.019	3.028	Inf	0.002
##	prehabit ~~					
##	age	0.965	0.374	2.577	4024.431	0.010
##	sex	-0.024	0.016	-1.473	Inf	0.141
##	white	-0.021	0.015	-1.374	Inf	0.170
##	child	0.025	0.016	1.562	Inf	0.118
##	age ~~					
##	sex	-0.331	0.272	-1.218	Inf	0.223
##	white	0.732	0.262	2.788	3885.525	0.005
##	child	1.048	0.276	3.796	Inf	0.000
##	sex ~~					
##	white	-0.018	0.011	-1.650	Inf	0.099
##	child	-0.000	0.012	-0.035	Inf	0.972
##	white ~~					
##	child	-0.010	0.011	-0.921	Inf	0.357
##	.sl ~~					
##	.exer	0.017	0.032	0.547	Inf	0.584
##	.dt	-0.010	0.023	-0.442	Inf	0.659
##	.subs	0.059	0.029	2.062	Inf	0.039
##	.exer ~~					
##	.dt	0.011	0.025	0.435	Inf	0.663
##	.subs	-0.033	0.030	-1.095	Inf	0.273
##	.dt ~~					
##	.subs	0.011	0.022	0.488	Inf	0.625
##	Std.all					
##						
##	-0.134					
##						
##	0.221					
##	0.186					
##	-0.120					
##	0.061					
##	0.147					
##						
##	0.158					
##	-0.089					
##	-0.061					
##	-0.086					
##	0.175					
##						

```
##      0.125
##     -0.071
##     -0.066
##      0.076
##
##     -0.059
##      0.136
##      0.186
##
##     -0.080
##     -0.002
##
##     -0.044
##
##      0.027
##     -0.022
##      0.103
##
##      0.021
##     -0.054
##
##      0.024
##
```

```
## Variances:
```

	Estimate	Std.Err	t-value	df	P(> t)	Std.lv
## .psyeffect	0.420	0.048	8.744	Inf	0.000	0.420
## .sched	0.415	0.052	7.945	Inf	0.000	0.415
## .insec	1.185	0.094	12.653	Inf	0.000	1.185
## .init	0.311	0.034	9.011	Inf	0.000	0.311
## .inhib	0.371	0.027	13.961	Inf	0.000	0.371
## .cont	0.318	0.025	12.876	Inf	0.000	0.318
## .bfi	0.113	0.018	6.256	Inf	0.000	0.113
## .sl	0.599	0.042	14.252	Inf	0.000	0.599
## .exer	0.683	0.048	14.297	Inf	0.000	0.683
## .dt	0.370	0.025	14.591	Inf	0.000	0.370
## .subs	0.545	0.038	14.340	Inf	0.000	0.545
## prehabit	0.452	0.031	14.655	Inf	0.000	0.452
## age	131.182	8.952	14.654	Inf	0.000	131.182
## sex	0.241	0.016	14.655	Inf	0.000	0.241
## white	0.221	0.015	14.655	Inf	0.000	0.221
## child	0.241	0.016	14.655	Inf	0.000	0.241
## disrupt	0.462	0.065	7.056	Inf	0.000	1.000
## sreg	0.628	0.066	9.476	Inf	0.000	1.000
## Std.all						
## 0.476						
## 0.439						
## 0.711						
## 0.331						
## 0.766						
## 0.572						
## 0.227						
## 0.929						
## 0.934						
## 0.981						

```
##      0.924
##      1.000
##      1.000
##      1.000
##      1.000
##      1.000
##      1.000
##      1.000
```

Now let's do the second method, in which we use semTools to do MI and fit the model in one go.

```
impsem2 <- runMI(habit.sem, # tell which model to estimate
  data = habit, # tell which data to use
  m = 5, # how many datasets we're creating
  miPackage = "mice", # which package we're using to do MI
  fun = "sem", # the sem function we're using to estimate the model
  meanstructure = TRUE) # whether we also want the mean structure to be estimated

summary(impsem2, # Tell R which model to output
  fit.measures = TRUE, # Tell R you want the fit measures (CFI, TLI etc.)
  standardized = TRUE) # Tell R you want the standardized solution
```

```
## lavaan.mi object based on 5 imputed data sets.
## See class?lavaan.mi help page for available methods.
##
## Convergence information:
## The model converged on 5 imputed data sets
##
## Rubin's (1987) rules were used to pool point and SE estimates across 5 imputed data sets, and to calculate
##
## Model Test User Model:
##
##      Test statistic                165.643
##      Degrees of freedom              58
##      P-value                        0.000
##
## Model Test Baseline Model:
##
##      Test statistic                1222.707
##      Degrees of freedom             120
##      P-value                        0.000
##
## User Model versus Baseline Model:
##
##      Comparative Fit Index (CFI)    0.902
##      Tucker-Lewis Index (TLI)      0.798
##
## Root Mean Square Error of Approximation:
##
##      RMSEA                        0.066
##      90 Percent confidence interval - lower    0.054
##      90 Percent confidence interval - upper    0.077
##      P-value RMSEA <= 0.05              0.015
```

```

##
## Standardized Root Mean Square Residual:
##
##    SRMR                                0.036

##
## Parameter Estimates:
##
##    Standard errors                    Standard
##    Information                      Expected
##    Information saturated (h1) model    Structured
##
## Latent Variables:
##      Estimate  Std.Err  t-value      df  P(>|t|)  Std.lv
##    disrupt =~
##      psyeffect      1.000
##      sched          1.071    0.103   10.414    Inf    0.000    0.728
##      insec          1.027    0.114    9.016    Inf    0.000    0.698
##    sreg =~
##      init           1.000
##      inhib          0.424    0.043    9.757    Inf    0.000    0.336
##      cont           0.616    0.045   13.719    Inf    0.000    0.488
##      bfi            0.781    0.045   17.287    Inf    0.000    0.619
##    Std.all
##
##      0.724
##      0.749
##      0.540
##
##      0.818
##      0.483
##      0.654
##      0.879
##
## Regressions:
##      Estimate  Std.Err  t-value      df  P(>|t|)  Std.lv
##    sl ~
##      disrupt      -0.318    0.073   -4.376    Inf    0.000   -0.216
##      sreg          -0.027    0.056   -0.475    Inf    0.635   -0.021
##      prehabit     -0.027    0.060   -0.449    Inf    0.654   -0.027
##      age          -0.001    0.003   -0.322  4596.669    0.747   -0.001
##      sex          -0.016    0.078   -0.209    Inf    0.834   -0.016
##      white        -0.062    0.082   -0.755  6207.121    0.450   -0.062
##      child         0.137    0.082    1.671    Inf    0.095    0.137
##    exer ~
##      disrupt      -0.319    0.077   -4.134    Inf    0.000   -0.217
##      sreg          0.027    0.060    0.460    Inf    0.646    0.022
##      prehabit     0.055    0.064    0.854    Inf    0.393    0.055
##      age          -0.000    0.004   -0.083    Inf    0.934   -0.000
##      sex          -0.001    0.084   -0.008    Inf    0.993   -0.001
##      white        -0.126    0.088   -1.435  6628.007    0.151   -0.126
##      child         0.092    0.087    1.051    Inf    0.293    0.092
##    dt ~
##      disrupt      -0.096    0.055   -1.757    Inf    0.079   -0.065

```

```

##      sreg      -0.027    0.043   -0.615     Inf    0.539   -0.021
##      prehabit    0.023    0.047    0.484     Inf    0.628    0.023
##      age         0.003    0.003    1.088     Inf    0.276    0.003
##      sex        -0.023    0.061   -0.382     Inf    0.703   -0.023
##      white      -0.009    0.064   -0.144     Inf    0.885   -0.009
##      child       0.094    0.064    1.474     Inf    0.140    0.094
##      subs ~
##      disrupt    -0.267    0.069   -3.891     Inf    0.000   -0.181
##      sreg       0.018    0.053    0.336     Inf    0.737    0.014
##      prehabit   0.079    0.057    1.378     Inf    0.168    0.079
##      age        0.004    0.003    1.066     Inf    0.287    0.004
##      sex       -0.019    0.075   -0.258     Inf    0.796   -0.019
##      white      0.164    0.078    2.105     Inf    0.035    0.164
##      child      0.029    0.078    0.373     Inf    0.710    0.029
##      Std.all
##
##      -0.269
##      -0.026
##      -0.023
##      -0.016
##      -0.010
##      -0.036
##      0.084
##
##      -0.254
##      0.025
##      0.043
##      -0.004
##      -0.000
##      -0.069
##      0.053
##
##      -0.107
##      -0.035
##      0.025
##      0.055
##      -0.019
##      -0.007
##      0.075
##
##      -0.236
##      0.018
##      0.069
##      0.053
##      -0.012
##      0.101
##      0.019
##
## Covariances:
##      Estimate  Std.Err  t-value    df  P(>|t|)  Std.lv
##      disrupt ~~
##      sreg      -0.072    0.033   -2.173    Inf    0.030   -0.133
##      sreg ~~
##      prehabit   0.120    0.029    4.191    Inf    0.000    0.151

```


##	age	1.703	0.483	3.530	Inf	0.000	2.149
##	sex	-0.046	0.020	-2.282	Inf	0.022	-0.059
##	white	0.024	0.019	1.242	Inf	0.214	0.030
##	child	0.057	0.020	2.777	Inf	0.005	0.072
##	disrupt ~~						
##	prehabit	0.075	0.026	2.846	Inf	0.004	0.110
##	age	-0.682	0.441	-1.545	Inf	0.122	-1.003
##	sex	-0.021	0.019	-1.096	Inf	0.273	-0.030
##	white	-0.029	0.018	-1.611	Inf	0.107	-0.043
##	child	0.058	0.019	3.009	Inf	0.003	0.085
##	prehabit ~~						
##	age	0.999	0.375	2.663	9896.618	0.008	0.999
##	sex	-0.024	0.016	-1.516	Inf	0.129	-0.024
##	white	-0.020	0.015	-1.338	Inf	0.181	-0.020
##	child	0.024	0.016	1.493	Inf	0.135	0.024
##	age ~~						
##	sex	-0.355	0.272	-1.301	Inf	0.193	-0.355
##	white	0.727	0.263	2.766	6906.285	0.006	0.727
##	child	1.061	0.277	3.835	Inf	0.000	1.061
##	sex ~~						
##	white	-0.019	0.011	-1.709	Inf	0.087	-0.019
##	child	-0.001	0.012	-0.059	Inf	0.953	-0.001
##	white ~~						
##	child	-0.012	0.011	-1.035	9084.367	0.301	-0.012
##	.sl ~~						
##	.exer	0.017	0.032	0.549	Inf	0.583	0.017
##	.dt	-0.010	0.023	-0.440	Inf	0.660	-0.010
##	.subs	0.059	0.028	2.061	Inf	0.039	0.059
##	.exer ~~						
##	.dt	0.011	0.025	0.430	Inf	0.667	0.011
##	.subs	-0.033	0.030	-1.108	Inf	0.268	-0.033
##	.dt ~~						
##	.subs	0.010	0.022	0.478	Inf	0.632	0.010
##	Std.all						
##							
##	-0.133						
##							
##	0.224						
##	0.187						
##	-0.119						
##	0.065						
##	0.146						
##							
##	0.163						
##	-0.087						
##	-0.062						
##	-0.091						
##	0.173						
##							
##	0.129						
##	-0.073						
##	-0.065						
##	0.072						
##							

```

##      -0.063
##      0.135
##      0.188
##
##      -0.083
##      -0.003
##
##      -0.050
##
##      0.027
##      -0.022
##      0.103
##
##      0.021
##      -0.055
##
##      0.023
##
## Intercepts:
##      Estimate Std.Err t-value df P(>|t|) Std.lv
##      .psyeffect      3.251   0.045  71.789 Inf  0.000   3.251
##      .sched          3.641   0.047  77.706 Inf  0.000   3.641
##      .insec          2.663   0.062  42.711 Inf  0.000   2.663
##      .init           3.270   0.047  69.996 Inf  0.000   3.270
##      .inhib          3.826   0.034 113.993 Inf  0.000   3.826
##      .cont           3.448   0.036  95.875 Inf  0.000   3.448
##      .bfi            3.861   0.034 113.742 Inf  0.000   3.861
##      .sl             2.069   0.273   7.570 Inf  0.000   2.069
##      .exer           1.719   0.291   5.898 Inf  0.000   1.719
##      .dt             1.732   0.212   8.165 Inf  0.000   1.732
##      .subs           1.723   0.260   6.637 Inf  0.000   1.723
##      prehabit        4.056   0.032 125.202 Inf  0.000   4.056
##      age            34.661   0.554  62.603 Inf  0.000  34.661
##      sex             0.406   0.024  17.148 Inf  0.000   0.406
##      white           0.669   0.023  29.455 Inf  0.000   0.669
##      child           0.406   0.024  17.165 Inf  0.000   0.406
##      disrupt         0.000
##      sreg            0.000
## Std.all
##      3.461
##      3.747
##      2.059
##      3.375
##      5.496
##      4.623
##      5.484
##      2.576
##      2.009
##      2.821
##      2.243
##      6.036
##      3.018
##      0.827
##      1.420

```

```

##      0.828
##      0.000
##      0.000
##
## Variances:
##      Estimate Std.Err t-value df P(>|t|) Std.lv
##      .psyeffect      0.420   0.048   8.772  Inf  0.000   0.420
##      .sched          0.414   0.052   7.966  Inf  0.000   0.414
##      .insec          1.185   0.094  12.647  Inf  0.000   1.185
##      .init           0.311   0.034   9.025  Inf  0.000   0.311
##      .inhib          0.371   0.027  13.973  Inf  0.000   0.371
##      .cont           0.318   0.025  12.889  Inf  0.000   0.318
##      .bfi            0.113   0.018   6.251  Inf  0.000   0.113
##      .sl             0.599   0.042  14.262  Inf  0.000   0.599
##      .exer           0.683   0.048  14.309  Inf  0.000   0.683
##      .dt             0.370   0.025  14.603  Inf  0.000   0.370
##      .subs           0.544   0.038  14.352  Inf  0.000   0.544
##      prehabit        0.452   0.031  14.666  Inf  0.000   0.452
##      age            131.870   8.992  14.666 8161.780 0.000 131.870
##      sex             0.241   0.016  14.666  Inf  0.000   0.241
##      white           0.222   0.015  14.666  Inf  0.000   0.222
##      child           0.241   0.016  14.666  Inf  0.000   0.241
##      disrupt         0.462   0.065   7.075  Inf  0.000   1.000
##      sreg            0.628   0.066   9.482  Inf  0.000   1.000
## Std.all
##      0.476
##      0.439
##      0.708
##      0.331
##      0.767
##      0.572
##      0.227
##      0.929
##      0.934
##      0.981
##      0.922
##      1.000
##      1.000
##      1.000
##      1.000
##      1.000
##      1.000
##      1.000

```