

## FSEM Real Data Analysis

### Load Libraries

```
# requires blimp installation: www.appliedmissingdata.com/blimp
# install.packages('remotes')
# install.packages('ggplot2')
# install.packages('GGally')
# remotes::install_github("bkeller2/fdir")
# remotes::install_github('blimp-stats/rblimp')

library(fdir)
library(rblimp)
library(ggplot2)
library(GGally)
```

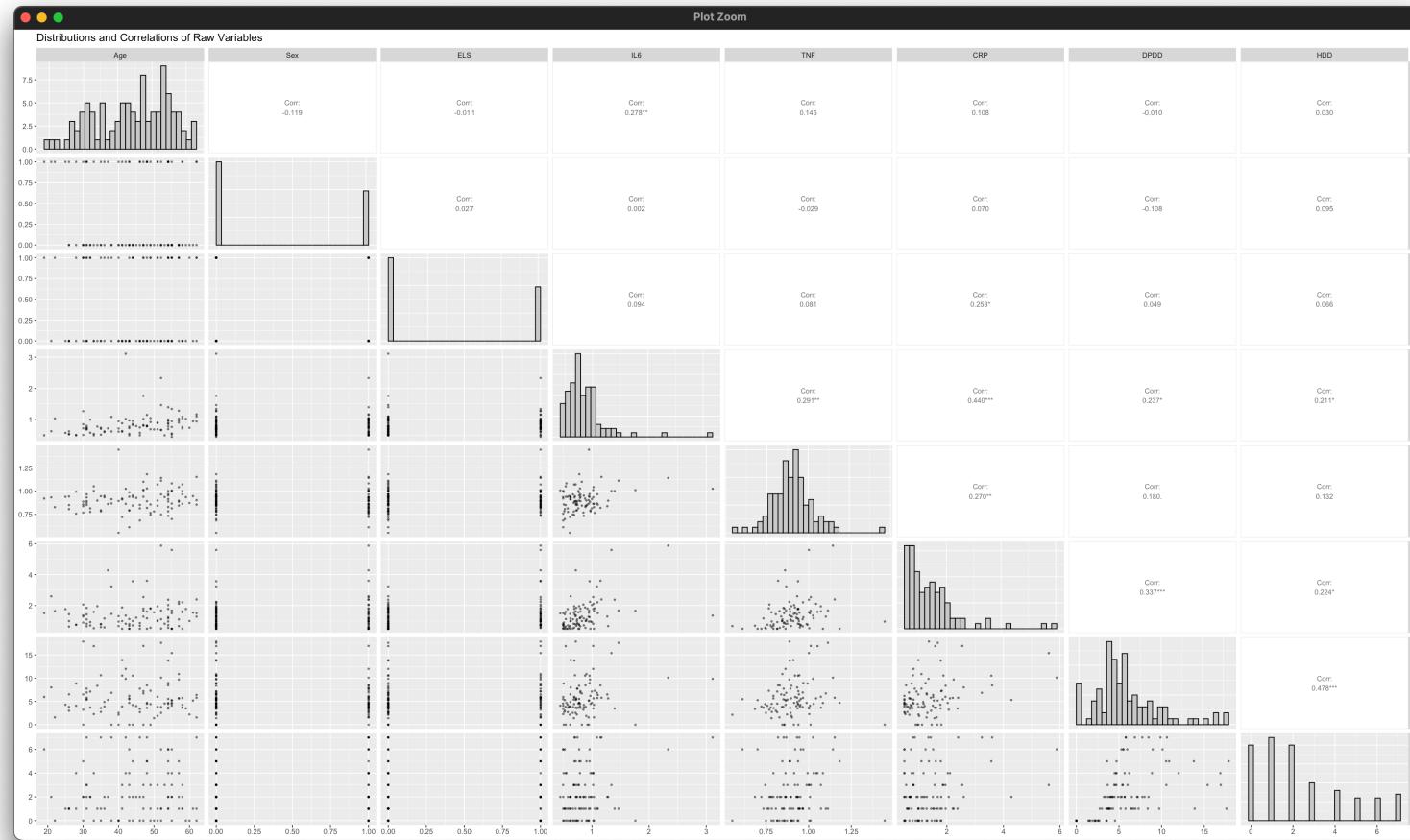
### Read Data

```
# Set working directory to the folder that contains the R script
set()
load('fsem.rda')
```

### Inspect Distributions

Histograms of the raw data show that two of the three inflammation indicators (IL6 and CRP) and the drinks per drinking day outcome (DPDD) have positively skewed distributions. These variables will be normalized in the analysis models using the Yeo–Johnson transformation.

```
# Distributions and correlations for raw variables
ggpairs(
  fsem[, c('Age','Sex','ELS','IL6','TNF','CRP','DPDD','HDD')],
  upper = list(continuous = wrap("cor", size = 3)),
  lower = list(continuous = wrap("points", alpha = 0.5, size = 0.7)),
  diag = list(continuous = wrap("barDiag", colour= "black", fill = "grey80"))
) + ggtitle("Distributions and Correlations of Raw Variables")
```



## Confirmatory Factor Analysis for the Inflammation Mediator

The confirmatory factor analysis (CFA) model for the inflammation mediator is identified by setting the latent variable's mean to zero (the default, no syntax required) and its variance to one. A positive-valued prior is assigned to the first loading to ensure that all loadings are positive.

```
# Inflammation CFA with Yeo-Johnson indicators
cfa <- rblimp(
  data = fsem,
  latent = 'Inflammation', # Define latent variable
  model = '
    Inflammation ~ Inflammation@1; # Fix factor variance to 1
    Inflammation -> yjt(CRPz)@lo1prior yjt(IL6z) TNFz;', # Measurement model
  parameters = 'lo1prior ~ truncate(0, Inf);', # Positive prior distribution
  seed = 90291,
  burn = 10000,
  iter = 20000
)
# Print output
output(cfa)

## -----
##          Blimp
##          3.2.20
##
##          Blimp was developed with funding from Institute of
##          Education Sciences awards R305D150056 and R305D190002.
##
##          Craig K. Enders, P.I. Email: cenders@psych.ucla.edu
##          Brian T. Keller, Co-P.I. Email: btkeller@missouri.edu
##          Han Du, Co-P.I. Email: hdu@psych.ucla.edu
```

```
## Roy Levy, Co-P.I. Email: roy.levy@asu.edu
##
## Programming and Blimp Studio by Brian T. Keller
##
## There is no expressed license given.
##
## -----
##
##
## ALGORITHMIC OPTIONS SPECIFIED:
##
## Imputation method: Fully Bayesian model-based
## MCMC algorithm: Full conditional Metropolis sampler with
##                   Auto-Derived Conditional Distributions
## Between-cluster imputation model: Not applicable, single-level imputation
## Prior for random effect variances: Not applicable, single-level imputation
## Prior for residual variances: Zero sum of squares, df = -2 (PRIOR2)
## Prior for predictor variances: Unit sum of squares, df = 2 (XPRIOR1)
## Chain Starting Values: Random starting values
##
##
```

The maximum potential scale reduction factor diagnostic (Gelman & Rubin, 1992) should be less than approximately 1.05 at the final iteration of the burn-in period, which was set to 10,000 iterations.

```

##          501 to 1000      1.080      15
##          751 to 1500      1.045       9
##          1001 to 2000     1.090       9
##          1251 to 2500     1.088       4
##          1501 to 3000     1.089       9
##          1751 to 3500     1.032       9
##          2001 to 4000     1.143      10
##          2251 to 4500     1.039       9
##          2501 to 5000     1.032      10
##          2751 to 5500     1.066      10
##          3001 to 6000     1.048      10
##          3251 to 6500     1.037      10
##          3501 to 7000     1.008      10
##          3751 to 7500     1.011       9
##          4001 to 8000     1.015      17
##          4251 to 8500     1.020      16
##          4501 to 9000     1.026      17
##          4751 to 9500     1.057      16
##          5001 to 10000    1.013      17
##
##
## METROPOLIS-HASTINGS ACCEPTANCE RATES:
##
##   Chain 1:
##
##   Variable           Type   Probability   Target Value
##   yjt(CRPz)         parameter    0.504      0.500
##   yjt(IL6z)         parameter    0.405      0.500
##
##   NOTE: Suppressing printing of 1 chains.
##         Use keyword 'tuneinfo' in options to override.
##
##

```

```
## DATA INFORMATION:  
##  
##   Sample Size:          99  
##   Missing Data Info:  
##  
##           miss %      1  
##  
##           CRPz =  0.0      -  
##           IL6z =  0.0      -  
##           TNFz =  0.0      -  
##  
##           % 100.0  
##  
##  
## MODEL INFORMATION:  
##  
##   NUMBER OF PARAMETERS  
##   Outcome Models:      11  
##   Predictor Models:    0  
##  
##   FACTORS  
##   Level-1:             Inflammation  
##  
##   MODELS  
##   [1] Inflammation ~ Intercept@0  
##   [2] yjt(CRPz) ~ Intercept Inflammation@lo1prior  
##   [3] yjt(IL6z) ~ Intercept Inflammation  
##   [4] TNFz ~ Intercept Inflammation  
##  
##   PRIORS SPECIFIED  
##   [1] lo1prior ~ truncate(0, inf)  
##  
##  
##   WARNING MESSAGES:  
##  
##   No warning messages.
```

```

## 
## MODEL FIT:
## 
## 
## INFORMATION CRITERIA
## 
## Conditional Likelihood
##   DIC2           906.402
##   WAIC          943.679
## 
## 
##
```

The CORRELATIONS AMONG RESIDUALS table shows the estimated correlations for every pair of residuals in the model. The correlations are quite small and none are significant. The factor model appears to provide adequate fit.

```

## CORRELATIONS AMONG RESIDUALS:
## 
## Summaries based on 20000 iterations using 2 chains.
## NOTE: Estimate column based on posterior median.
## 
## 
## Correlations             Estimate   StdDev    2.5%   97.5%   ChiSq   PValue   N_Eff
## ----- 
## 
## Inflammation, yjt(CRPz)  0.003    0.145   -0.285   0.283   0.000   0.995   19651.416
## Inflammation, yjt(IL6z)  -0.001   0.145   -0.281   0.280   0.000   0.996   20083.986
## Inflammation, TNFz       -0.000   0.146   -0.280   0.285   0.000   0.998   19612.147
## yjt(CRPz), yjt(IL6z)    0.026    0.145   -0.260   0.306   0.031   0.860   5741.725
## yjt(CRPz), TNFz          0.028    0.142   -0.253   0.299   0.036   0.849   2154.687
## yjt(IL6z), TNFz          0.010    0.136   -0.263   0.267   0.004   0.949   2254.710
## 
## -----
```

Each variable in the model has its own summary table. The values in the Estimate column are posterior medians, the StdDev column contains “Bayesian standard errors”, and the 2.5% and 97.5% columns give the 95% credible interval limits. The ChiSq and PValue columns contain frequentist significance tests (Asparouhov & Muthén, 2021). The rightmost column of the tables—the effective number of MCMC samples—is essentially the number of independent estimates on which the parameter summaries are based after removing autocorrelations from the MCMC process. Gelman et al. (2014, p. 287) recommend that these values should exceed 100. If any of the values fall below this threshold, increase the number of iterations after the burn-in period (specified as 20,000 for this analysis).

```
## OUTCOME MODEL ESTIMATES:
##
##    Summaries based on 20000 iterations using 2 chains.
##    NOTE: Estimate column based on posterior median.
##
##
## Latent Variable: Inflammation
##
## Parameters           Estimate   StdDev    2.5%   97.5%   ChiSq   PValue   N_Eff
## -----
## Variances:
## Residual Var.      @ 1.000     ---     ---     ---     ---     ---     ---
## 
## Proportion Variance Explained
## by Coefficients       0.000     0.000     0.000     0.000     ---     ---     nan
## by Residual Variation 1.000     0.000     1.000     1.000     ---     ---     nan
## 
## -----
```

## Outcome Variable: yjt(CRPz)								
## Parameters	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff	
<hr/>								
## Variances:								
## Residual Var.	0.316	0.118	0.068	0.543	---	---	327.862	
<hr/>								
## Coefficients:								
## Intercept	-0.281	0.089	-0.456	-0.109	10.109	0.001	3184.857	
## Inflammation	0.553	0.119	0.324	0.791	21.577	0.000	425.090	
<hr/>								
## Transformation:								
## Yeo-Johnson (lambda)	-0.081	0.169	-0.442	0.215	---	---	1793.861	
<hr/>								
## Standardized Coefficients:								
## Inflammation	0.692	0.132	0.421	0.941	27.248	0.000	346.783	
<hr/>								
## Proportion Variance Explained								
## by Coefficients	0.479	0.181	0.177	0.886	---	---	285.368	
## by Residual Variation	0.521	0.181	0.114	0.823	---	---	285.368	
<hr/>								
##								
##								
##								
##								
## Outcome Variable: yjt(IL6z)								
## Parameters	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff	
<hr/>								
## Variances:								
## Residual Var.	0.336	0.102	0.101	0.522	---	---	416.683	
<hr/>								
## Coefficients:								
## Intercept	-0.246	0.082	-0.410	-0.084	8.919	0.003	3835.312	
## Inflammation	0.472	0.111	0.272	0.710	18.559	0.000	519.623	

```

## Transformation:
## Yeo-Johnson (lambda) -0.036 0.153 -0.368 0.228 --- --- 2165.283
##
## Standardized Coefficients:
## Inflammation 0.622 0.129 0.376 0.903 23.268 0.000 387.788
##
## Proportion Variance Explained
## by Coefficients 0.387 0.165 0.141 0.815 --- --- 360.686
## by Residual Variation 0.613 0.165 0.185 0.859 --- --- 360.686
##
## -----
## 
## 
## 
## Outcome Variable: TNFz
##
## Parameters Estimate StdDev 2.5% 97.5% ChiSq PValue N_Eff
## -----
## Variances:
## Residual Var. 0.855 0.149 0.605 1.191 --- --- 5162.535
##
## Coefficients:
## Intercept -0.001 0.103 -0.201 0.203 0.000 0.995 9459.928
## Inflammation 0.421 0.131 0.170 0.690 10.344 0.001 2980.859
##
## Standardized Coefficients:
## Inflammation 0.406 0.115 0.170 0.618 12.314 0.000 2457.462
##
## Proportion Variance Explained
## by Coefficients 0.165 0.093 0.029 0.382 --- --- 2490.811
## by Residual Variation 0.835 0.093 0.618 0.971 --- --- 2490.811
##
## -----
## 
## 
```

```

## 
## 
## Additional Parameters:
## 
## Parameters           Estimate   StdDev    2.5%   97.5%   ChiSq   PValue   N_Eff
## -----
## lo1prior            0.553     0.119    0.324    0.791    21.577   0.000    425.090
## -----

```

## Mediation Model

The syntax in this section specifies a mediation model where early life stress (ELS) influences the inflammation latent variable which, in turn, predicts two indicators of alcohol use: drinks per drinking day (DPDD) and the count of number of heavy drinking days (HDD). Age and sex are covariates in the equations, and both are centered at their grand means. The regression equations are as follows.

$$INFLAMMATION_i = a_0 + a_1(ELS_i) + a_2(SEX_i) + a_3(AGE_i) + \varepsilon_i$$

$$yjt(DPDD_i) = b_{0,DPDD} + b_{1,DPDD}(INFLAMMATION_i) + b_{2,DPDD}(ELS_i) + b_{3,DPDD}(SEX_i) + b_{4,DPDD}(AGE_i) + \epsilon_i$$

$$\ln(HDD_i) = b_{0,HDD} + b_{1,HDD}(INFLAMMATION_i) + b_{2,HDD}(ELS_i) + b_{3,HDD}(SEX_i) + b_{4,HDD}(AGE_i)$$

Histograms of the raw data showed that two of the three inflammation indicators (IL6 and CRP) and the drinks per drinking day outcome (DPDD) have positively skewed distributions. It is typical log transform these variables prior to analysis. Instead, they are normalized using the Yeo-Johnson transformation. As before, the CFA model for the inflammation mediator is

identified by setting the latent variable's mean to zero (the default, no syntax required) and its residual variance to one. A positive-valued prior is assigned to the first loading to ensure that all loadings are positive. Finally, the indirect effect for the drinks per drinking day outcome is computed using the usual product of coefficients estimator, as follows.

$$(ab_{DPDD}) = a_1 \times b_{1,DPDD}$$

For the count outcome (HDD), indirect effects are conditional on the value of early life stress (ELS). The conditional indirect effects are computed following procedures described in Hayes and Preacher (2010) and Geldhof et al. (2018, Table 2), as follows. Note that  $b_{3,HDD}$  and  $b_{4,HDD}$  vanish because the covariates are centered at their grand means.

$$(ab_{HDD}|ELS = 0) = a_1 \times b_{1,HDD} \times e(b_0 + b_{1,HDD}(\widehat{INFLAMMATION}|ELS = 0) + b_{2,HDD}(0) + b_{3,HDD}(0) + b_{4,HDD}(0))$$

$$(ab_{HDD}|ELS = 1) = a_1 \times b_{1,HDD} \times e(b_0 + b_{1,HDD}(\widehat{INFLAMMATION}|ELS = 1) + b_{2,HDD}(1) + b_{3,HDD}(0) + b_{4,HDD}(0))$$

The indirect effect equations require specific values for the mediator, which are computed as follows (recall that  $a_0$  is fixed at zero for identification).

$$(\widehat{INFLAMMATION}|ELS = 0) = a_0 + a_1(ELS_i) = 0$$

$$(INFLAMMATION|ELS = 1) = a_0 + a_1(ELS_i) = a_1$$

```

# Fit mediation model
med <- rblimp(
  data = fsem,
  ordinal = 'ELS Sex', # Identify binary variables
  count = 'HDD', # Identify count variable
  latent = 'Inflammation', # Define latent variable
  center = 'Sex Age', # Center covariates
  model = '
    mediator: # Arbitrary label to group summary tables in output
    Inflammation ~ 1@0 ELS@a1 Sex Age; # @ labels coefficients
    Inflammation ~~ Inflammation@1; # Fix factor residual variance to 1
    outcomes: # Arbitrary label to group summary tables in output
    yjt(DPDDz) ~ Inflammation@b1_DPDD ELS Sex Age; # @ labels coefficients
    HDD ~ 1@b0_HDD Inflammation@b1_HDD ELS@b2_HDD Sex Age; # @ labels coefficients
    measurement: # Arbitrary label to group summary tables in output
    Inflammation -> yjt(CRPz)@lo1prior yjt(IL6z) TNFz;', # Measurement model
    parameters = '
      indirect_DPDD = a1 * b1_DPDD; # Indirect effect for DPDD
      # Expected values of mediator
      M_ELS0 = 0;
      M_ELS1 = a1;
      # Conditional indirect effects for HDD
      indirect_HDD_ELS0 = a1 * (b1_HDD * exp(b0_HDD + b1_HDD*M_ELS0 + b2_HDD*0));
      indirect_HDD_ELS1 = a1 * (b1_HDD * exp(b0_HDD + b1_HDD*M_ELS1 + b2_HDD*1));
      lo1prior ~ truncate(0, Inf);', # Positive prior distribution
    seed = 90291,
    burn = 10000,
    iter = 20000
)

```

```
# Print output
output(med)

##
## -----
##
##                               Blimp
##                               3.2.20
##
##           Blimp was developed with funding from Institute of
##           Education Sciences awards R305D150056 and R305D190002.
##
##           Craig K. Enders, P.I. Email: cenders@psych.ucla.edu
##           Brian T. Keller, Co-P.I. Email: btkeller@missouri.edu
##           Han Du, Co-P.I. Email: hdu@psych.ucla.edu
##           Roy Levy, Co-P.I. Email: roy.levy@asu.edu
##
##           Programming and Blimp Studio by Brian T. Keller
##
##           There is no expressed license given.
##
## -----
##
##           ALGORITHMIC OPTIONS SPECIFIED:
##
##           Imputation method:          Fully Bayesian model-based
##           MCMC algorithm:             Full conditional Metropolis sampler with
##                                         Auto-Derived Conditional Distributions
##           Between-cluster imputation model: Not applicable, single-level imputation
##           Prior for random effect variances: Not applicable, single-level imputation
##           Prior for residual variances:    Zero sum of squares, df = -2 (PRIOR2)
##           Prior for predictor variances:   Unit sum of squares, df = 2 (XPRIOR1)
##           Chain Starting Values:        Random starting values
##
```

```

##  

##   NOTE: The default prior for regression coefficients  

##          in categorical models is 'normal( 0.0, 5.0)'  

##
```

The maximum potential scale reduction factor diagnostic (Gelman & Rubin, 1992) should be less than approximately 1.05 at the final iteration of the burn-in period, which was set to 10,000 iterations.

```

## BURN-IN POTENTIAL SCALE REDUCTION (PSR) OUTPUT:  

##  

##   NOTE: Split chain PSR is being used. This splits each chain's  

##         iterations to create twice as many chains.  

##  

##   Comparing iterations across 2 chains      Highest PSR  Parameter #  

##  

##           251 to 500           1.206        42  

##           501 to 1000          1.145        41  

##           751 to 1500          1.122        41  

##           1001 to 2000          1.080        46  

##           1251 to 2500          1.109        47  

##           1501 to 3000          1.025        23  

##           1751 to 3500          1.048        47  

##           2001 to 4000          1.018        47  

##           2251 to 4500          1.021        42  

##           2501 to 5000          1.029         5  

##           2751 to 5500          1.020         4  

##           3001 to 6000          1.013        17  

##           3251 to 6500          1.012        43  

##           3501 to 7000          1.020        47  

##           3751 to 7500          1.008        41  

##           4001 to 8000          1.008        41  

##           4251 to 8500          1.019        43  

##           4501 to 9000          1.011        65  

##           4751 to 9500          1.008        47  

##           5001 to 10000         1.009        23

```

```

##  

##  

## METROPOLIS-HASTINGS ACCEPTANCE RATES:  

##  

##    Chain 1:  

##  

##      Variable           Type   Probability  Target Value  

##      Inflammation     latent imp      0.518    0.500  

##      yjt(DPDDz)       parameter      0.492    0.500  

##      yjt(CRPz)        parameter      0.529    0.500  

##      yjt(IL6z)        parameter      0.464    0.500  

##      Sex              parameter      0.516    0.500  

##      Age              parameter      0.460    0.500  

##  

##      NOTE: Suppressing printing of 1 chains.  

##             Use keyword 'tuneinfo' in options to override.  

##  

##  

##  

## DATA INFORMATION:  

##  

##      Sample Size:          99  

##      Missing Data Info:  

##                  miss %      1  

##                               -----  

##      CRPz =  0.0      -  

##      IL6z =  0.0      -  

##      TNFz =  0.0      -  

##      DPDDz = 0.0      -  

##      HDD =  0.0      -  

##      Sex =  0.0      -  

##      Age =  0.0      -  

##      ELS =  0.0      -  

##                               -----  

##                               % 100.0  

##
```

```
##  
## MODEL INFORMATION:  
##  
## NUMBER OF PARAMETERS  
## Outcome Models: 26  
## Generated Parameters: 5  
## Predictor Models: 10  
##  
## PREDICTORS  
## Complete continuous: Age  
## Complete ordinal: Sex ELS  
##  
## FACTORS  
## Level-1: Inflammation  
##  
## CENTERED PREDICTORS  
## Grand Mean Centered: Sex Age  
##  
## MODELS  
##  
## mediator:  
## [1] Inflammation ~ ELS@a1 Sex Age  
##  
## outcomes:  
## [2] yjt(DPDDz) ~ Intercept Inflammation@b1_dpdd ELS Sex Age  
## [3] HDD ~ Intercept@b0_hdd Inflammation@b1_hdd ELS@b2_hdd Sex Age  
##  
## measurement:  
## [4] yjt(CRPz) ~ Intercept Inflammation@lo1prior  
## [5] yjt(IL6z) ~ Intercept Inflammation  
## [6] TNFz ~ Intercept Inflammation  
##  
## PRIORS SPECIFIED  
## [1] lo1prior ~ truncate(0, inf)  
##
```

```

## GENERATED PARAMETERS
## [1] indirect_DPDD = a1*b1_dpdd
## [2] M_ELS0 = 0
## [3] M_ELS1 = a1
## [4] indirect_HDD_ELS0 = a1*(b1_hdd*exp(b0_hdd+b1_hdd*m_els0+b2_hdd*0))
## [5] indirect_HDD_ELS1 = a1*(b1_hdd*exp(b0_hdd+b1_hdd*m_els1+b2_hdd*1))
##
##
## WARNING MESSAGES:
##
## No warning messages.
##
##
## MODEL FIT:
##
##
## INFORMATION CRITERIA
##
## Conditional Likelihood
## DIC2           1138.649
## WAIC          1180.679
##
##
## CORRELATIONS AMONG RESIDUALS:
##
## Summaries based on 20000 iterations using 2 chains.
## NOTE: Estimate column based on posterior median.
##
##
## Correlations             Estimate   StdDev    2.5%   97.5%   ChiSq   PValue   N_Eff
## -----
## Inflammation, yjt(DPDDz)  0.000    0.144   -0.282   0.283   0.000   0.996  20244.396
## Inflammation, yjt(CRPz)   0.076    0.142   -0.207   0.349   0.273   0.601  9186.954
## Inflammation, yjt(IL6z)   -0.032   0.144   -0.312   0.249   0.048   0.827  8134.708

```

```

##   Inflammation, TNFz          0.021    0.139   -0.250    0.289    0.024    0.877 14642.336 006
##   yjt(DPDDz), yjt(CRPz)      0.054    0.130   -0.209    0.299    0.159    0.691 2616.949
##   yjt(DPDDz), yjt(IL6z)      -0.024    0.137   -0.292    0.242    0.031    0.861 4324.287
##   yjt(DPDDz), TNFz           -0.003    0.119   -0.238    0.229    0.001    0.975 4713.107
##   yjt(CRPz), yjt(IL6z)       0.035    0.144   -0.246    0.315    0.059    0.809 1920.949
##   yjt(CRPz), TNFz            0.127    0.122   -0.126    0.350    1.014    0.314 2764.683
##   yjt(IL6z), TNFz            -0.027    0.135   -0.289    0.232    0.045    0.833 4266.559
##
## -----
##
```

Each variable in the model has its own summary table. The values in the Estimate column are posterior medians, the StdDev column contains “Bayesian standard errors”, and the 2.5% and 97.5% columns give the 95% credible interval limits. The ChiSq and PValue columns contain frequentist significance tests (Asparouhov & Muthén, 2021). The rightmost column of the tables—the effective number of MCMC samples—is essentially the number of independent estimates on which the parameter summaries are based after removing autocorrelations from the MCMC process. Gelman et al. (2014, p. 287) recommend that these values should exceed 100. If any of the values fall below this threshold, increase the number of iterations after the burn-in period (specified as 20,000 for this analysis).

```

## OUTCOME MODEL ESTIMATES:
##
##   Summaries based on 20000 iterations using 2 chains.
##   NOTE: Estimate column based on posterior median.
##
##   mediator block:
##
```

```

## Latent Variable: Inflammation
##
## Grand Mean Centered: Age Sex
##
##
## Parameters           Estimate   StdDev    2.5%   97.5%   ChiSq   PValue   N_Eff
## -----
## Variances:
##   Residual Var.      @ 1.000    ---     ---     ---     ---     ---     ---
## 
## Coefficients:
##   ELS                 0.608    0.286    0.074    1.200    4.660    0.031    539.010
##   Sex                  0.147    0.269   -0.373    0.679    0.306    0.580    3408.679
##   Age                  0.046    0.014    0.020    0.076   10.889    0.001    958.234
## 
## Standardized Coefficients:
##   ELS                 0.256    0.108    0.032    0.457    5.453    0.020    585.515
##   Sex                  0.062    0.110   -0.156    0.273    0.308    0.579    3502.268
##   Age                  0.431    0.105    0.201    0.612   16.445    0.000   1136.633
## 
## Proportion Variance Explained
##   by Coefficients        0.270    0.096    0.102    0.474    ---     ---    599.471
##   by Residual Variation  0.730    0.096    0.526    0.898    ---     ---    599.471
## 
## -----
## 
## outcomes block:
## 
## Outcome Variable: yjt(DPDDz)
## 
## Grand Mean Centered: Age Sex
## 
## Parameters           Estimate   StdDev    2.5%   97.5%   ChiSq   PValue   N_Eff

```

```

## Variances:
## Residual Var.          0.748    0.134    0.519    1.046    ---    --- 2663.691
##
## Coefficients:
## Intercept             -0.202    0.129   -0.457    0.057    2.435    0.119 3965.916
## Inflammation          0.364    0.126    0.127    0.622    8.530    0.003 1711.314
## ELS                   -0.180    0.213   -0.613    0.227    0.752    0.386 2576.381
## Sex                  -0.189    0.196   -0.577    0.190    0.938    0.333 7883.268
## Age                  -0.017    0.011   -0.040    0.003    2.622    0.105 2302.383
##
## Transformation:
## Yeo-Johnson (lambda)  0.392    0.137    0.112    0.652    ---    --- 3075.142
##
## Standardized Coefficients:
## Inflammation          0.438    0.146    0.156    0.734    9.006    0.003 1200.696
## ELS                   -0.093    0.108   -0.307    0.115    0.767    0.381 2470.628
## Sex                  -0.098    0.099   -0.287    0.097    0.962    0.327 7662.988
## Age                  -0.199    0.121   -0.441    0.032    2.710    0.100 2147.601
##
## Proportion Variance Explained
## by Coefficients          0.171    0.089    0.043    0.385    ---    --- 1316.725
## by Residual Variation    0.829    0.089    0.615    0.957    ---    --- 1316.725
##
## Outcome Variable: HDD
##
## Grand Mean Centered: Age Sex
##
## Parameters              Estimate   StdDev   2.5%   97.5%   ChiSq   PValue   N_Eff

```

```

## Variances:
## Dispersion Parameter          0.511      0.155      0.276      0.879      ---      ---    701.559
##
## Coefficients:
## Intercept                     0.819      0.133      0.556      1.082      37.828     0.000   11151.986
## Inflammation                  0.179      0.124     -0.048      0.442      2.216      0.137   2814.868
## ELS                           -0.003      0.222     -0.449      0.427      0.001      0.981   5511.640
## Sex                           0.153      0.208     -0.257      0.562      0.536      0.464   15153.335
## Age                          -0.005      0.011     -0.028      0.016      0.203      0.652   5170.939
##
## Exponentiated Coefficients:
## Intercept                     2.268      0.306      1.744      2.950      ---      ---   10917.575
## Inflammation                  1.196      0.153      0.953      1.555      ---      ---   2730.490
## ELS                           0.997      0.229      0.638      1.533      ---      ---   5956.684
## Sex                           1.165      0.251      0.773      1.754      ---      ---   15317.628
## Age                          0.995      0.011      0.973      1.017      ---      ---   5199.152
##
## -----
## 
## 
## measurement block:
## 
## Outcome Variable: yjt(CRPz)
## 
## Parameters           Estimate   StdDev   2.5%   97.5%   ChiSq   PValue   N_Eff
## -----
## 
## Variances:
## Residual Var.        0.421      0.082      0.280      0.603      ---      ---   1637.598
## 
## Coefficients:
## Intercept             -0.358      0.099     -0.558     -0.170     13.170     0.000   1255.969
## Inflammation          0.379      0.087      0.218      0.560     19.309     0.000   1001.460
## 
## Transformation:
## Yeo-Johnson (lambda) -0.042      0.172     -0.407      0.248      ---      ---   2571.342

```

```

##  

## Standardized Coefficients:  

##   Inflammation          0.557    0.096    0.349    0.727    33.081    0.000    1299.118  

##  

## Proportion Variance Explained  

##   by Coefficients       0.311    0.104    0.122    0.528    ---      ---      1223.140  

##   by Residual Variation 0.689    0.104    0.472    0.878    ---      ---      1223.140  

##  

##  

##  

##  

##  

## Outcome Variable: yjt(IL6z)  

##  

## Parameters           Estimate StdDev 2.5% 97.5% ChiSq PValue N_Eff  

##  

## Variances:  

##   Residual Var.        0.229    0.080    0.082    0.394    ---      ---      394.381  

##  

## Coefficients:  

##   Intercept            -0.365    0.098   -0.564   -0.178    14.208   0.000    680.432  

##   Inflammation         0.493    0.083    0.330    0.653    35.009   0.000    447.238  

##  

## Transformation:  

##   Yeo-Johnson (lambda) -0.084    0.152   -0.407    0.172    ---      ---      1638.866  

##  

## Standardized Coefficients:  

##   Inflammation         0.762    0.093    0.559    0.921    66.517   0.000    407.851  

##  

## Proportion Variance Explained  

##   by Coefficients       0.581    0.138    0.312    0.849    ---      ---      373.523  

##   by Residual Variation 0.419    0.138    0.151    0.688    ---      ---      373.523  

##  

##  

##
```

```

##  

##  

## Outcome Variable: TNFz  

##  

## Parameters  

##  

## Variances:  

## Residual Var.  

##  

## Coefficients:  

## Intercept  

## Inflammation  

##  

## Standardized Coefficients:  

## Inflammation  

##  

## Proportion Variance Explained  

## by Coefficients  

## by Residual Variation  

##  

##  

## Additional Parameters:  

##  

## Parameters  

##  

##  

## lo1prior  

##  

##  

##
```

	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
## Residual Var.	0.890	0.144	0.659	1.222	---	---	6306.814
## Intercept	-0.074	0.111	-0.292	0.140	0.455	0.500	2133.798
## Inflammation	0.324	0.108	0.120	0.547	9.163	0.002	1918.602
## Inflammation	0.368	0.106	0.142	0.557	11.798	0.001	2582.800
## by Coefficients	0.135	0.075	0.020	0.311	---	---	2467.640
## by Residual Variation	0.865	0.075	0.689	0.980	---	---	2467.640
## lo1prior	0.379	0.087	0.218	0.560	19.309	0.000	1001.460

Indirect effect estimates are in a table labeled GENERATED PARAMETERS. The indirect effect of ELS on DPDD is significant because the 95% credible interval does not contain zero. The conditional indirect effects of ELS on HDD are not significant because zero is inside the 95% interval, albeit just barely.

```
## GENERATED PARAMETERS:
##
##   Summaries based on 20000 iterations using 2 chains.
##   NOTE: Estimate column based on posterior median.
##
##
## Parameters           Estimate   StdDev    2.5%   97.5%   ChiSq   PValue   N_Eff
## -----
##   indirect_DPDD      0.207     0.138    0.018   0.553   2.727   0.099   743.287
##   M_ELS0              0.000     0.000    0.000   0.000   nan     nan     nan
##   M_ELS1              0.608     0.286    0.074   1.200   4.660   0.031   539.010
##   indirect_HDD_ELS0   0.107     0.131   -0.037   0.470   1.062   0.303   1483.642
##   indirect_HDD_ELS1   0.117     0.158   -0.041   0.556   0.951   0.330   1592.151
##
## -----
##   Predictor Model Estimates:
##
##   Summaries based on 20000 iterations using 2 chains.
##   NOTE: Estimate column based on posterior median.
##
##
## Complete predictor: Sex
##
## Parameters           Estimate   StdDev    2.5%   97.5%   ChiSq   PValue   N_Eff
## -----
```

## Grand Mean	-0.263	0.131	-0.535	-0.018	4.147	0.042	2330.797
##							
## Level 1:							
## Age	-0.014	0.012	-0.037	0.009	1.344	0.246	8638.893
## ELS	0.042	0.157	-0.262	0.353	0.074	0.785	4942.220
## Residual Var.	1.000	0.000	1.000	1.000	---	---	nan
## Thresholds:							
## Tau 1	0.000	0.000	0.000	0.000	---	---	nan
##							
##							
##							
##							
## Complete predictor: Age							
##							
## Parameters	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
##							
##							
## Grand Mean	44.299	1.130	42.045	46.539	1538.488	0.000	2427.743
##							
## Level 1:							
## Sex	-1.591	1.360	-4.264	1.094	1.370	0.242	14184.533
## ELS	-0.073	1.401	-2.854	2.644	0.003	0.954	13574.489
## Residual Var.	116.253	17.513	88.715	157.278	---	---	17714.625
##							
##							
##							
##							
## Complete predictor: ELS							
##							
## Parameters	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
##							
##							
## Grand Mean	-0.271	0.130	-0.528	-0.018	4.319	0.038	7883.380

```

## 
## Level 1:
##   Sex           0.041    0.158   -0.267    0.352    0.073    0.787  4627.783
##   Age          -0.001    0.012   -0.025    0.023    0.003    0.954  8474.414
##   Residual Var. 1.000    0.000    1.000    1.000    ---     ---      nan
## Thresholds:
##   Tau 1        0.000    0.000    0.000    0.000    ---     ---      nan
## 
## -----

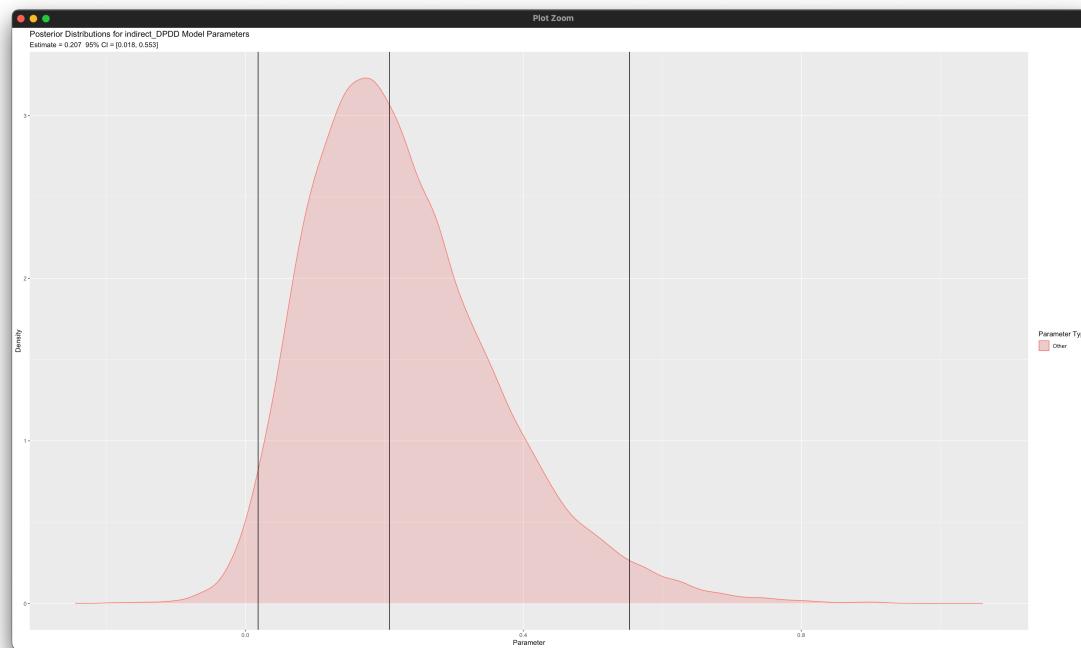
```

The `posterior_plot` functions generate kernel density plots of the distribution of indirect effects.

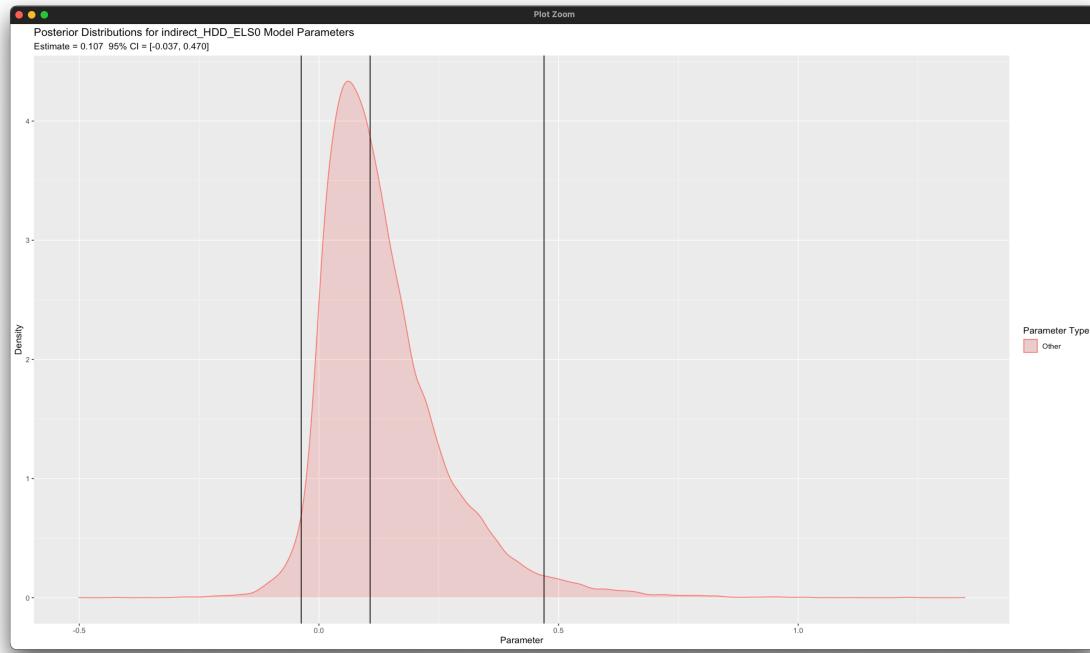
```

# Plot distributions of indirect effects
posterior_plot(med, 'indirect_DPDD')

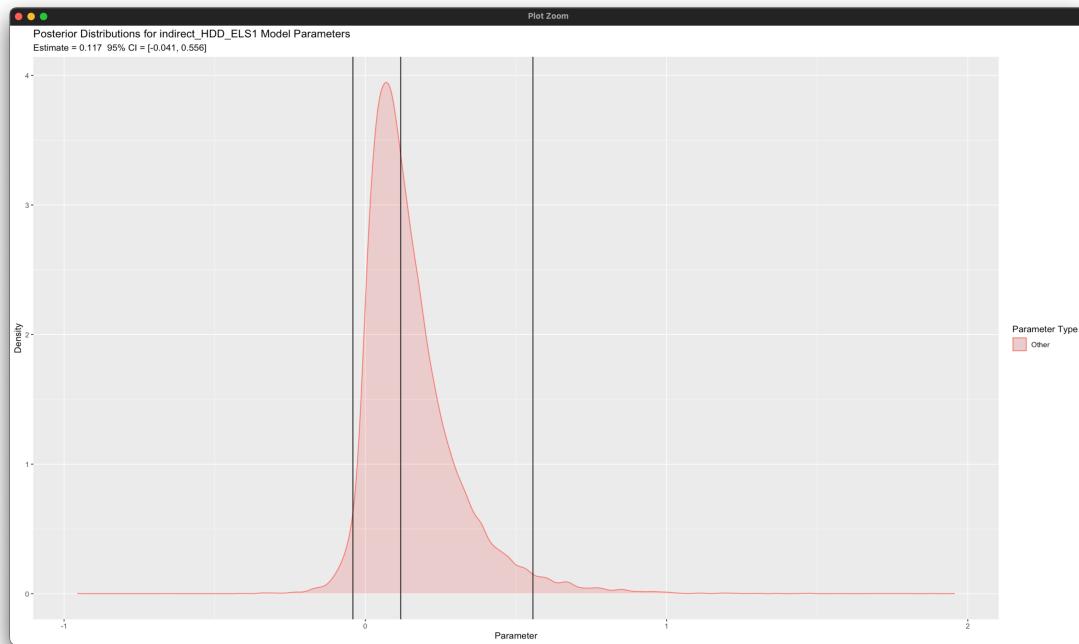
```



```
posterior_plot(med, 'indirect_HDD_ELS0')
```



```
posterior_plot(med, 'indirect_HDD_ELS1')
```



## Moderated Mediation Model

The syntax in this section specifies a moderated mediation model where early life stress (ELS) influences the inflammation latent variable which, in turn, predicts two indicators of alcohol use: drinks per drinking day (DPDD) and the count of number of heavy drinking days (HDD). The path from early life stress (ELS) to inflammation is moderated by sex. Age is a covariate in the equations and is centered at its grand mean. The regression equations are as follows.

$$INFLAMMATION_i = a_0 + a_1(ELS_i) + a_2(SEX_i) + a_3(ELS_i)(SEX_i) + a_4(AGE_i) + \varepsilon_i$$

$$yjt(DPDD_i) = b_{0,DPDD} + b_{1,DPDD}(INFLAMMATION_i) + b_{2,DPDD}(ELS_i) + b_{3,DPDD}(SEX_i) + b_{4,DPDD}(AGE_i) + \epsilon_i$$

$$\ln(HDD_i) = b_{0,HDD} + b_{1,HDD}(INFLAMMATION_i) + b_{2,HDD}(ELS_i) + b_{3,HDD}(SEX_i) + b_{4,HDD}(AGE_i)$$

Histograms of the raw data showed that two of the three inflammation indicators (IL6 and CRP) and the drinks per drinking day outcome (DPDD) have positively skewed distributions. It is typical log transform these variables prior to analysis. Instead, they are normalized using the Yeo–Johnson transformation. As before, the CFA model for the inflammation mediator is identified by setting the latent variable's mean to zero (the default, no syntax required) and its residual variance to one. A positive-valued prior is assigned to the first loading to ensure that all loadings are positive. Finally, the conditional indirect effect for the drinks per drinking day outcome is computed using the usual product of coefficients estimator within each gender group, as follows.

$$(ab_{DPDD}|SEX = 0) = a_1 \times b_{1,DPDD}$$

$$(ab_{DPDD}|SEX = 1) = (a_1 + a_3) \times b_{1,DPDD}$$

For the count outcome (HDD), indirect effects are conditional on the value of early life stress (ELS). The conditional indirect effects are computed following procedures described in Hayes and Preacher (2010) and Geldhof et al. (2018, Table 2), as follows. Note that  $b_{3,HDD}$  and  $b_{4,HDD}$  vanish because the covariates are centered at their grand means.

$$(ab_{HDD}|ELS = 0, SEX = 0) = \\ a_1 \times b_{1,HDD} \times e(b_0 + b_{1,HDD}(INFLAMMATION|ELS = 0, SEX = 0) + b_{2,HDD}(0) + b_{3,HDD}(0) + b_{4,HDD}(0))$$

$$(ab_{HDD}|ELS = 0, SEX = 1) = \\ (a_1 + a_3) \times b_{1,HDD} \times e(b_0 + b_{1,HDD}(INFLAMMATION|ELS = 0, SEX = 1) + b_{2,HDD}(0) + b_{3,HDD}(1) + b_{4,HDD}(0))$$

$$(ab_{HDD}|ELS = 1, SEX = 0) = \\ a_1 \times b_{1,HDD} \times e(b_0 + b_{1,HDD}(INFLAMMATION|ELS = 1, SEX = 0) + b_{2,HDD}(1) + b_{3,HDD}(0) + b_{4,HDD}(0))$$

$$(ab_{HDD}|ELS = 1, SEX = 1) = \\ (a_1 + a_3) \times b_{1,HDD} \times e(b_0 + b_{1,HDD}(INFLAMMATION|ELS = 1, SEX = 1) + b_{2,HDD}(1) + b_{3,HDD}(1) + b_{4,HDD}(0))$$

The indirect effect equations require specific values for the mediator, which are computed as follows (recall that  $a_0$  is fixed at zero for identification).

$$(INFLAMMATION|ELS = 0, SEX = 0) = a_0 + a_1(ELS_i) + a_2(SEX_i) + a_3(ELS_i)(SEX_i) = 0$$

$$(INFLAMMATION|ELS = 0, SEX = 1) = a_0 + a_1(ELS_i) + a_2(SEX_i) + a_3(ELS_i)(SEX_i) = a_2$$

$$(INFLAMMATION|ELS = 1, SEX = 0) = a_0 + a_1(ELS_i) + a_2(SEX_i) + a_3(ELS_i)(SEX_i) = a_1$$

$$(INFLAMMATION|ELS = 1, SEX = 1) = a_0 + a_1(ELS_i) + a_2(SEX_i) + a_3(ELS_i)(SEX_i) = a_1 + a_2 + a_3$$

```

modmed <- rblimp(
  data = fsem,
  ordinal = 'ELS Sex', # Identify binary variables
  count = 'HDD', # Identify count variable
  latent = 'Inflammation', # Define latent variable
  center = 'Age', # Center covariate
  model = '
    mediator: # Arbitrary label to group summary tables in output
    Inflammation ~ 1@0 ELS@a1 Sex@a2 ELS*Sex@a3 Age; # Product of ELS and Sex
    Inflammation ~~ Inflammation@1; # Fix factor residual variance to 1
    outcomes: # Arbitrary label to group summary tables in output
    yjt(DPDDz) ~ Inflammation@b1_DPDD ELS Sex Age; # @ labels coefficients
    HDD ~ 1@b0_HDD Inflammation@b1_HDD ELS@b2_HDD Sex@b3_HDD Age; # @ labels coefficients
    measurement: # Arbitrary label to group summary tables in output
    Inflammation -> yjt(CRPz)@lo1prior yjt(IL6z) TNFz;', # Measurement model
    simple = 'ELS | Sex', # Conditional effects of ELS by Sex
    parameters = '
      # Conditional indirect effects for DPDD
      indirect_DPDD_Sex0 = a1 * b1_DPDD;
      indirect_DPDD_Sex1 = (a1 + a3) * b1_DPDD;
      # Expected values of mediator
      M_ELS0_Sex0 = 0;
      M_ELS0_Sex1 = 0 + a2;
      M_ELS1_Sex0 = 0 + a1;
      M_ELS1_Sex1 = 0 + a1 + a2 + a3;
      # Conditional indirect effects for DPDD
      indirect_HDD_ELS0_Sex0 = a1 * (b1_HDD * exp(b0_HDD + b1_HDD*M_ELS0_Sex0));
      indirect_HDD_ELS0_Sex1 = (a1 + a3) * (b1_HDD * exp(b0_HDD + b1_HDD*M_ELS0_Sex1 + b3_HDD));
      indirect_HDD_ELS1_Sex0 = a1 * (b1_HDD * exp(b0_HDD + b1_HDD*M_ELS1_Sex0 + b2_HDD));
      indirect_HDD_ELS1_Sex1 = (a1 + a3) * (b1_HDD * exp(b0_HDD + b1_HDD*M_ELS1_Sex1 + b2_HDD + b3_HDD));
      lo1prior ~ truncate(0, Inf);', # Positive prior distribution
    seed = 90291,
    burn = 10000,
    iter = 20000
)

```

```
# Print output
output(modmed)

##
## -----
##                               Blimp
##                               3.2.20
##
##           Blimp was developed with funding from Institute of
##           Education Sciences awards R305D150056 and R305D190002.
##
##           Craig K. Enders, P.I. Email: cenders@psych.ucla.edu
##           Brian T. Keller, Co-P.I. Email: btkeller@missouri.edu
##           Han Du, Co-P.I. Email: hdu@psych.ucla.edu
##           Roy Levy, Co-P.I. Email: roy.levy@asu.edu
##
##           Programming and Blimp Studio by Brian T. Keller
##
##           There is no expressed license given.
## -----
##           ALGORITHMIC OPTIONS SPECIFIED:
##
##           Imputation method:          Fully Bayesian model-based
##           MCMC algorithm:             Full conditional Metropolis sampler with
##                                         Auto-Derived Conditional Distributions
##           Between-cluster imputation model: Not applicable, single-level imputation
##           Prior for random effect variances: Not applicable, single-level imputation
##           Prior for residual variances:    Zero sum of squares, df = -2 (PRIOR2)
##           Prior for predictor variances:   Unit sum of squares, df = 2 (XPRIOR1)
##           Chain Starting Values:        Random starting values
```

```
##  
##  
##   NOTE: The default prior for regression coefficients  
##          in categorical models is 'normal( 0.0, 5.0)'  
##
```

The maximum potential scale reduction factor diagnostic (Gelman & Rubin, 1992) should be less than approximately 1.05 at the final iteration of the burn-in period, which was set to 10,000 iterations.

```
## BURN-IN POTENTIAL SCALE REDUCTION (PSR) OUTPUT:  
##  
##   NOTE: Split chain PSR is being used. This splits each chain's  
##          iterations to create twice as many chains.  
##  
##   Comparing iterations across 2 chains      Highest PSR  Parameter #  
##           251 to 500           1.235        42  
##           501 to 1000          1.055        37  
##           751 to 1500          1.034        52  
##           1001 to 2000         1.034        10  
##           1251 to 2500         1.050        62  
##           1501 to 3000         1.015        62  
##           1751 to 3500         1.023        62  
##           2001 to 4000         1.039        44  
##           2251 to 4500         1.043        44  
##           2501 to 5000         1.028        44  
##           2751 to 5500         1.016        44  
##           3001 to 6000         1.046        44  
##           3251 to 6500         1.048        44  
##           3501 to 7000         1.026        44  
##           3751 to 7500         1.017        48  
##           4001 to 8000         1.020        48  
##           4251 to 8500         1.009        45  
##           4501 to 9000         1.009        45  
##           4751 to 9500         1.019        49
```

```

##                               5001 to 10000      1.010      44
##
##
## METROPOLIS-HASTINGS ACCEPTANCE RATES:
##
##   Chain 1:
##
##   Variable           Type   Probability  Target Value
##   Inflammation      latent imp     0.509    0.500
##   yjt(DPDDz)        parameter     0.509    0.500
##   yjt(CRPz)         parameter     0.437    0.500
##   yjt(IL6z)         parameter     0.481    0.500
##   Age               parameter     0.487    0.500
##
##   NOTE: Suppressing printing of 1 chains.
##          Use keyword 'tuneinfo' in options to override.
##
##
## DATA INFORMATION:
##
##   Sample Size:          99
##   Missing Data Info:
##                         miss %      1
##                         -----
##                         CRPz =  0.0      -
##                         IL6z =  0.0      -
##                         TNFz =  0.0      -
##                         DPDDz = 0.0      -
##                         HDD =  0.0      -
##                         Sex =  0.0      -
##                         Age =  0.0      -
##                         ELS =  0.0      -
##                         -----
##                         % 100.0
##

```

```
##  
## MODEL INFORMATION:  
##  
## NUMBER OF PARAMETERS  
## Outcome Models: 27  
## Generated Parameters: 10  
## Predictor Models: 10  
##  
## PREDICTORS  
## Complete continuous: Age  
## Complete ordinal: Sex ELS  
##  
## FACTORS  
## Level-1: Inflammation  
##  
## CENTERED PREDICTORS  
## Grand Mean Centered: Age  
##  
## MODELS  
##  
## mediator:  
## [1] Inflammation ~ ELS@a1 Sex@a2 Age ELS*Sex@a3  
##  
## outcomes:  
## [2] yjt(DPDDz) ~ Intercept Inflammation@b1_dpdd ELS Sex Age  
## [3] HDD ~ Intercept@b0_hdd Inflammation@b1_hdd ELS@b2_hdd Sex@b3_hdd Age  
##  
## measurement:  
## [4] yjt(CRPz) ~ Intercept Inflammation@lo1prior  
## [5] yjt(IL6z) ~ Intercept Inflammation  
## [6] TNFz ~ Intercept Inflammation  
##  
## PRIORS SPECIFIED  
## [1] lo1prior ~ truncate(0, inf)  
##
```

```

## GENERATED PARAMETERS
## [1] indirect_DPDD_Sex0 = a1*b1_dpdd
## [2] indirect_DPDD_Sex1 = (a1+a3)*b1_dpdd
## [3] M_ELS0_Sex0 = 0
## [4] M_ELS0_Sex1 = 0+a2
## [5] M_ELS1_Sex0 = 0+a1
## [6] M_ELS1_Sex1 = 0+a1+a2+a3
## [7] indirect_HDD_ELS0_Sex0 = a1*(b1_hdd*exp(b0_hdd+b1_hdd*m_els0_sex0))
## [8] indirect_HDD_ELS0_Sex1 = (a1+a3)*(b1_hdd*exp(b0_hdd+b1_hdd*m_els0_sex1+b3_hdd))
## [9] indirect_HDD_ELS1_Sex0 = a1*(b1_hdd*exp(b0_hdd+b1_hdd*m_els1_sex0+b2_hdd))
## [10] indirect_HDD_ELS1_Sex1 = (a1+a3)*(b1_hdd*exp(b0_hdd+b1_hdd*m_els1_sex1+b2_hdd+b3_hdd))
##
##
## WARNING MESSAGES:
##
## WARNING: The focal predictor "ELS" is not centered.
##           Simple intercepts in the conditional effects table are
##           evaluated at a score of zero on the focal predictor.
##
##
## MODEL FIT:
##
##
## INFORMATION CRITERIA
##
## Conditional Likelihood
## DIC2          1147.578
## WAIC          1190.328
##
##
## CORRELATIONS AMONG RESIDUALS:
##
## Summaries based on 20000 iterations using 2 chains.
## NOTE: Estimate column based on posterior median.

```

##		Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
<hr/>								
## Correlations								
<hr/>								
##	Inflammation, yjt(DPDDz)	0.025	0.145	-0.262	0.304	0.027	0.868	16630.254 506
##	Inflammation, yjt(CRPz)	0.058	0.142	-0.222	0.333	0.163	0.687	8707.231
##	Inflammation, yjt(IL6z)	-0.022	0.144	-0.306	0.254	0.025	0.874	7987.313
##	Inflammation, TNFz	0.008	0.139	-0.264	0.280	0.003	0.956	11842.707
##	yjt(DPDDz), yjt(CRPz)	0.050	0.130	-0.212	0.298	0.132	0.716	3817.167
##	yjt(DPDDz), yjt(IL6z)	0.002	0.136	-0.269	0.263	0.000	0.995	3840.709
##	yjt(DPDDz), TNFz	-0.006	0.118	-0.240	0.220	0.005	0.944	7288.231
##	yjt(CRPz), yjt(IL6z)	0.039	0.143	-0.250	0.307	0.063	0.801	1920.327
##	yjt(CRPz), TNFz	0.106	0.125	-0.153	0.335	0.651	0.420	2569.900
##	yjt(IL6z), TNFz	-0.030	0.132	-0.289	0.222	0.052	0.820	5043.330
##								
##								
##								
##								

Each variable in the model has its own summary table. The values in the Estimate column are posterior medians, the StdDev column contains “Bayesian standard errors”, and the 2.5% and 97.5% columns give the 95% credible interval limits. The ChiSq and PValue columns contain frequentist significance tests (Asparouhov & Muthén, 2021). The rightmost column of the tables—the effective number of MCMC samples—is essentially the number of independent estimates on which the parameter summaries are based after removing autocorrelations from the MCMC process. Gelman et al. (2014, p. 287) recommend that these values should exceed 100. If any of the values fall below this threshold, increase the number of iterations after the burn-in period (specified as 20,000 for this analysis).

```

## OUTCOME MODEL ESTIMATES:
##
## Summaries based on 20000 iterations using 2 chains.
## NOTE: Estimate column based on posterior median.
##
## mediator block:
##
## Latent Variable: Inflammation
##
## Grand Mean Centered: Age
##
##
## Parameters           Estimate   StdDev    2.5%   97.5%   ChiSq   PValue   N_Eff
## -----
## Variances:
## Residual Var.      @ 1.000    ---     ---     ---     ---     ---     ---
## 
## Coefficients:
## ELS                 0.199    0.360   -0.483   0.927   0.327   0.567   507.159
## Sex                -0.312    0.357   -1.042   0.366   0.792   0.374   558.155
## Age                 0.047    0.015    0.018   0.078   9.510   0.002   743.616
## ELS*Sex             1.074    0.581   -0.024   2.268   3.519   0.061   1115.316
## 
## Standardized Coefficients:
## ELS                 0.081    0.141   -0.196   0.358   0.330   0.566   536.452
## Sex                -0.126    0.141   -0.405   0.148   0.809   0.368   523.162
## Age                 0.423    0.111    0.178   0.612  14.093   0.000   910.813
## ELS*Sex             0.328    0.165   -0.008   0.640   3.896   0.048   1053.674
## 
## Proportion Variance Explained
## by Coefficients          0.318    0.101    0.134   0.523     ---     ---   665.617
## by Residual Variation    0.682    0.101    0.477   0.866     ---     ---   665.617
## 
## -----
## 
```

##							
## Conditional Effects	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
<hr/>							
## ELS   Sex @ 0							
## Intercept	0.000	0.000	0.000	0.000	nan	nan	nan
## Slope	0.199	0.360	-0.483	0.927	0.327	0.567	507.159
##							
## ELS   Sex @ 1							
## Intercept	-0.312	0.357	-1.042	0.366	0.792	0.374	558.155
## Slope	1.281	0.483	0.406	2.298	7.182	0.007	1243.701
##							
##							
##	NOTE: Intercepts are computed by setting all predictors not involved in the conditional effect to zero.						
##							
##							
## outcomes block:							
##							
## Outcome Variable: yjt(DPDDz)							
##							
## Grand Mean Centered: Age							
##							
##							
## Parameters	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
##							
## Variances:							
## Residual Var.	0.751	0.132	0.532	1.049	---	---	3758.070
##							
## Coefficients:							
## Intercept	-0.091	0.156	-0.395	0.220	0.332	0.565	2654.127
## Inflammation	0.346	0.121	0.120	0.594	8.307	0.004	2083.764
## ELS	-0.179	0.212	-0.607	0.231	0.746	0.388	3292.117
## Sex	-0.180	0.195	-0.568	0.197	0.874	0.350	6284.059

```

## Age -0.017 0.011 -0.039 0.004 2.376 0.123 2178.015
##
## Transformation:
## Yeo-Johnson (lambda) 0.392 0.138 0.108 0.654 --- --- 3222.029
##
## Standardized Coefficients:
## Inflammation 0.430 0.142 0.152 0.705 9.117 0.003 1398.821
## ELS -0.092 0.107 -0.304 0.116 0.762 0.383 3172.329
## Sex -0.093 0.098 -0.285 0.100 0.891 0.345 6052.796
## Age -0.189 0.122 -0.432 0.044 2.454 0.117 2020.414
##
## Proportion Variance Explained
## by Coefficients 0.167 0.084 0.041 0.364 --- --- 1771.752
## by Residual Variation 0.833 0.084 0.636 0.959 --- --- 1771.752
##
## -----
## Conditional Effects
## Estimate StdDev 2.5% 97.5% ChiSq PValue N_Eff
## ELS | Sex @ 0
## Intercept -0.091 0.156 -0.395 0.220 0.332 0.565 2654.127
## Slope -0.179 0.212 -0.607 0.231 0.746 0.388 3292.117
## ELS | Sex @ 1
## Intercept -0.273 0.187 -0.640 0.092 2.109 0.146 1450.592
## Slope -0.179 0.212 -0.607 0.231 0.746 0.388 3292.117
##
## -----
## NOTE: Intercepts are computed by setting all predictors
##       not involved in the conditional effect to zero.

```

##							
## Outcome Variable: HDD							
##							
## Grand Mean Centered: Age							
##							
##							
## Parameters	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
##							
## Variances:							
## Dispersion Parameter	0.508	0.151	0.274	0.862	---	---	891.627
##							
## Coefficients:							
## Intercept	0.779	0.156	0.476	1.087	24.979	0.000	9406.942
## Inflammation	0.176	0.116	-0.041	0.414	2.343	0.126	4292.701
## ELS	-0.007	0.224	-0.455	0.429	0.001	0.972	7266.892
## Sex	0.155	0.205	-0.253	0.557	0.579	0.447	12421.567
## Age	-0.005	0.011	-0.026	0.016	0.192	0.661	5656.531
##							
## Exponentiated Coefficients:							
## Intercept	2.179	0.348	1.609	2.966	---	---	9244.148
## Inflammation	1.192	0.141	0.959	1.513	---	---	4137.292
## ELS	0.993	0.229	0.634	1.535	---	---	7906.208
## Sex	1.168	0.248	0.776	1.745	---	---	12326.303
## Age	0.995	0.011	0.974	1.016	---	---	5685.069
##							
##							
##							
##							
## Conditional Effects	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
##							
## ELS   Sex @ 0							
## Intercept	0.095	0.332	-0.575	0.738	0.076	0.783	965.512
## Slope	-0.007	0.224	-0.455	0.429	0.001	0.972	7266.892
##							

```

## ELS | Sex @ 1
## Intercept           0.251    0.348   -0.447    0.932    0.505    0.477    982.844
## Slope              -0.007   0.224   -0.455    0.429    0.001    0.972    7266.892
##
## -----
## NOTE: Intercepts are computed by setting all predictors
##       not involved in the conditional effect to zero.
##
## measurement block:
##
## Outcome Variable: yjt(CRPz)
##
## Parameters          Estimate StdDev 2.5% 97.5% ChiSq PValue N_Eff
## -----
## Variances:
## Residual Var.      0.404    0.085  0.249  0.585   ---   --- 1364.370
##
## Coefficients:
## Intercept          -0.315   0.109  -0.534  -0.103   8.375  0.004  592.593
## Inflammation        0.382    0.089  0.221  0.569  18.942  0.000  780.222
##
## Transformation:
## Yeo-Johnson (lambda) -0.037   0.166  -0.397  0.243   ---   --- 2316.667
##
## Standardized Coefficients:
## Inflammation        0.579    0.099  0.367  0.762  33.756  0.000  951.717
##
## Proportion Variance Explained
## by Coefficients        0.336    0.113  0.135  0.581   ---   --- 909.384
## by Residual Variation  0.664    0.113  0.419  0.865   ---   --- 909.384
##
## -----
## 
```

```

##  

##  

## Outcome Variable: yjt(IL6z)  

##  

## Parameters  

##  

## Variances:  

## Residual Var.  

##  

## Coefficients:  

## Intercept  

## Inflammation  

##  

## Transformation:  

## Yeo-Johnson (lambda)  

##  

## Standardized Coefficients:  

## Inflammation  

##  

## Proportion Variance Explained  

## by Coefficients  

## by Residual Variation  

##  

##  

##  

##  

##  

##  

## Outcome Variable: TNFz  

##  

## Parameters  

##  

## Variances:  

## Residual Var.  

##  

## Coefficients:

```

	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
## Residual Var.	0.255	0.077	0.113	0.417	---	---	543.589
## Intercept	-0.308	0.113	-0.535	-0.091	7.420	0.006	337.952
## Inflammation	0.457	0.082	0.306	0.629	31.227	0.000	553.578
## Yeo-Johnson (lambda)	-0.085	0.155	-0.417	0.184	---	---	1901.052
## Inflammation	0.731	0.091	0.531	0.890	63.013	0.000	523.527
## by Coefficients	0.534	0.130	0.282	0.792	---	---	490.310
## by Residual Variation	0.466	0.130	0.208	0.718	---	---	490.310

##	Intercept	-0.035	0.119	-0.278	0.191	0.102	0.750	939.997
##	Inflammation	0.328	0.105	0.130	0.541	9.974	0.002	1859.268
##								
##	Standardized Coefficients:							
##	Inflammation	0.385	0.105	0.160	0.569	13.020	0.000	2500.698
##								
##	Proportion Variance Explained							
##	by Coefficients	0.148	0.078	0.025	0.324	---	---	2396.867
##	by Residual Variation	0.852	0.078	0.676	0.975	---	---	2396.867
##								
##								
##								
##								
##	Additional Parameters:							
##								
##	Parameters	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
##								
##								
##	lo1prior	0.382	0.089	0.221	0.569	18.942	0.000	780.222
##								
##								
##								
##								

Indirect effect estimates are in a table labeled GENERATED PARAMETERS. The indirect effect of ELS on DPDD is significant because the 95% credible interval does not contain zero. The conditional indirect effects of ELS on HDD are not significant because zero is inside the 95% interval, albeit just barely.

```
## GENERATED PARAMETERS:
##
## Summaries based on 20000 iterations using 2 chains.
## NOTE: Estimate column based on posterior median.
##
```

##							
## Parameters	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
##							
##							
## indirect_DPDD_Sex0	0.060	0.137	-0.168	0.385	0.301	0.583	558.502
## indirect_DPDD_Sex1	0.419	0.220	0.092	0.939	4.088	0.043	1707.740
## M_ELS0_Sex0	0.000	0.000	0.000	0.000	nan	nan	nan
## M_ELS0_Sex1	-0.312	0.357	-1.042	0.366	0.792	0.374	558.155
## M_ELS1_Sex0	0.199	0.360	-0.483	0.927	0.327	0.567	507.159
## M_ELS1_Sex1	0.957	0.437	0.182	1.884	5.008	0.025	486.969
## indirect_HDD_ELS0_Sex0	0.023	0.100	-0.120	0.282	0.183	0.669	1028.981
## indirect_HDD_ELS0_Sex1	0.239	0.243	-0.072	0.874	1.339	0.247	2504.438
## indirect_HDD_ELS1_Sex0	0.024	0.106	-0.112	0.310	0.199	0.655	992.646
## indirect_HDD_ELS1_Sex1	0.295	0.370	-0.078	1.320	1.049	0.306	2832.783
##							
##							
##							
## PREDICTOR MODEL ESTIMATES:							
##							
## Summaries based on 20000 iterations using 2 chains.							
## NOTE: Estimate column based on posterior median.							
##							
##							
##							
## Complete predictor: Sex							
##							
## Parameters	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
##							
##							
## Grand Mean	-0.275	0.132	-0.536	-0.020	4.357	0.037	8349.127
##							
## Level 1:							
## Age	-0.014	0.012	-0.038	0.009	1.432	0.231	7897.572
## ELS	0.044	0.156	-0.261	0.352	0.079	0.779	5097.508

## Residual Var.	1.000	0.000	1.000	1.000	---	---	nan
## Thresholds:							
## Tau 1							
##							
-----							
##							
##							
##							
## Complete predictor: Age							
##							
## Parameters	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
-----							
##							
##							
## Grand Mean	44.347	1.118	42.177	46.556	1572.209	0.000	2620.552
##							
## Level 1:							
## Sex	-1.609	1.364	-4.254	1.106	1.387	0.239	12790.998
## ELS	-0.060	1.388	-2.772	2.673	0.002	0.963	13332.423
## Residual Var.	116.380	17.406	88.620	156.634	---	---	17147.879
##							
-----							
##							
##							
##							
## Complete predictor: ELS							
##							
## Parameters	Estimate	StdDev	2.5%	97.5%	ChiSq	PValue	N_Eff
-----							
##							
##							
## Grand Mean	-0.273	0.130	-0.531	-0.023	4.444	0.035	8459.826
##							
## Level 1:							
## Sex	0.043	0.158	-0.267	0.352	0.075	0.784	4970.805
## Age	-0.001	0.012	-0.024	0.023	0.003	0.955	8576.428
## Residual Var.	1.000	0.000	1.000	1.000	---	---	nan

```

## Thresholds:
##   Tau 1          0.000    0.000    0.000    0.000    ---    ---    nan
##                                         -----

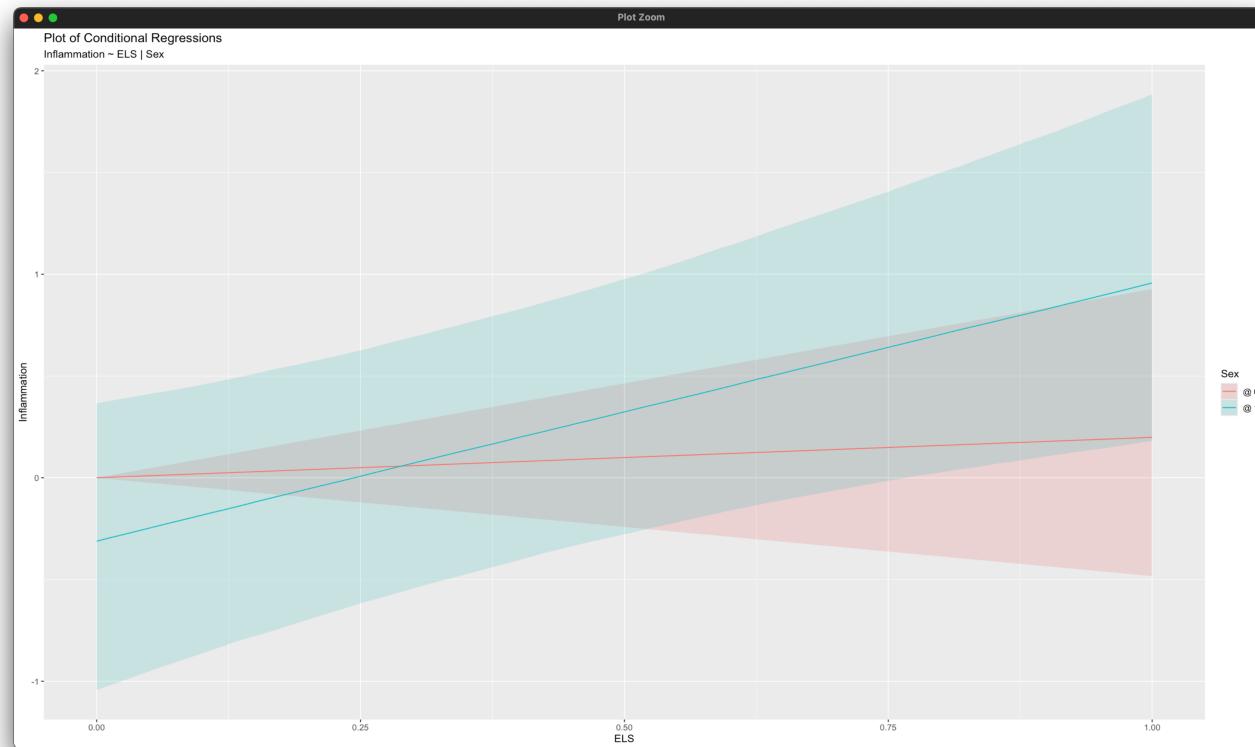
```

The `simple_plot` function generates a graph of the simple intercepts and slopes for the influence of early life stress (ELS) on the inflammation latent variable.

```

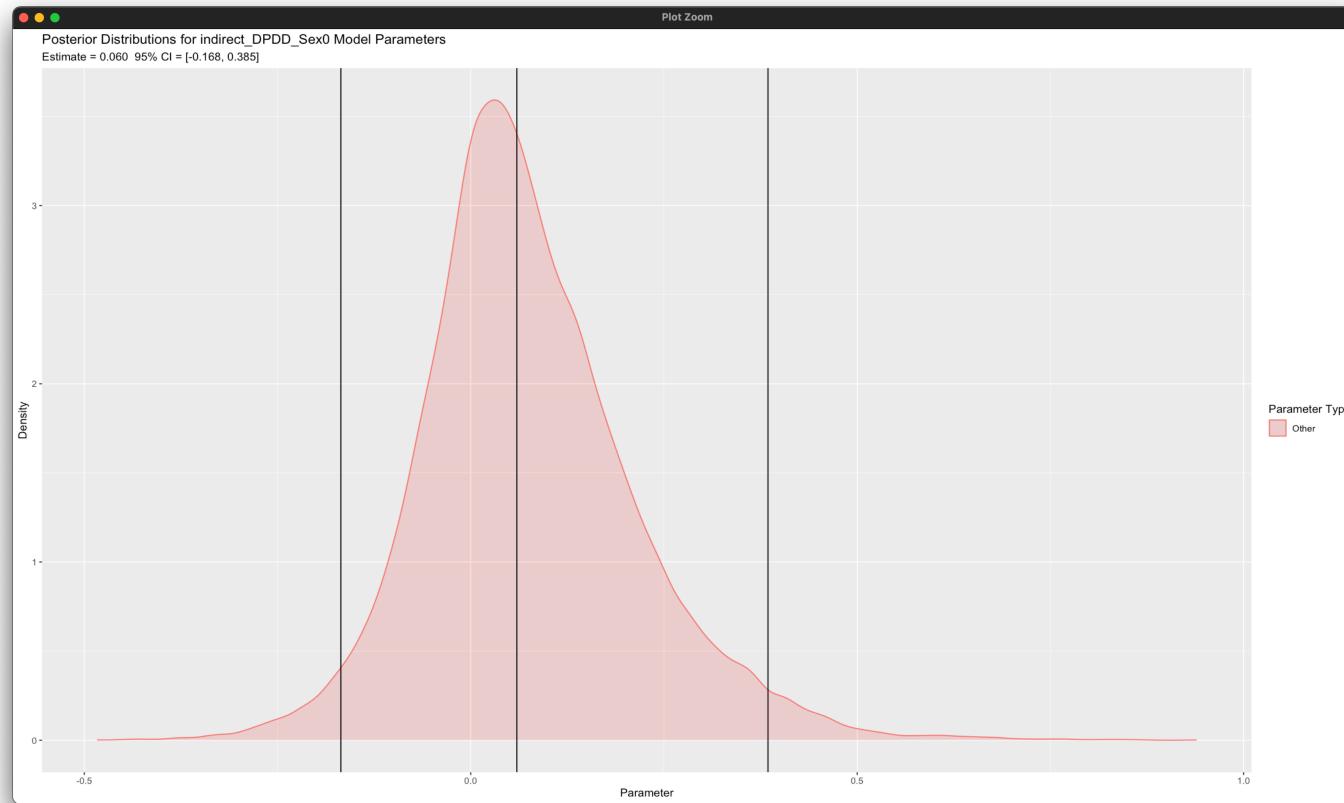
# Plot conditional effect of ELS by Sex
simple_plot(Inflammation ~ ELS | Sex, modmed)

```

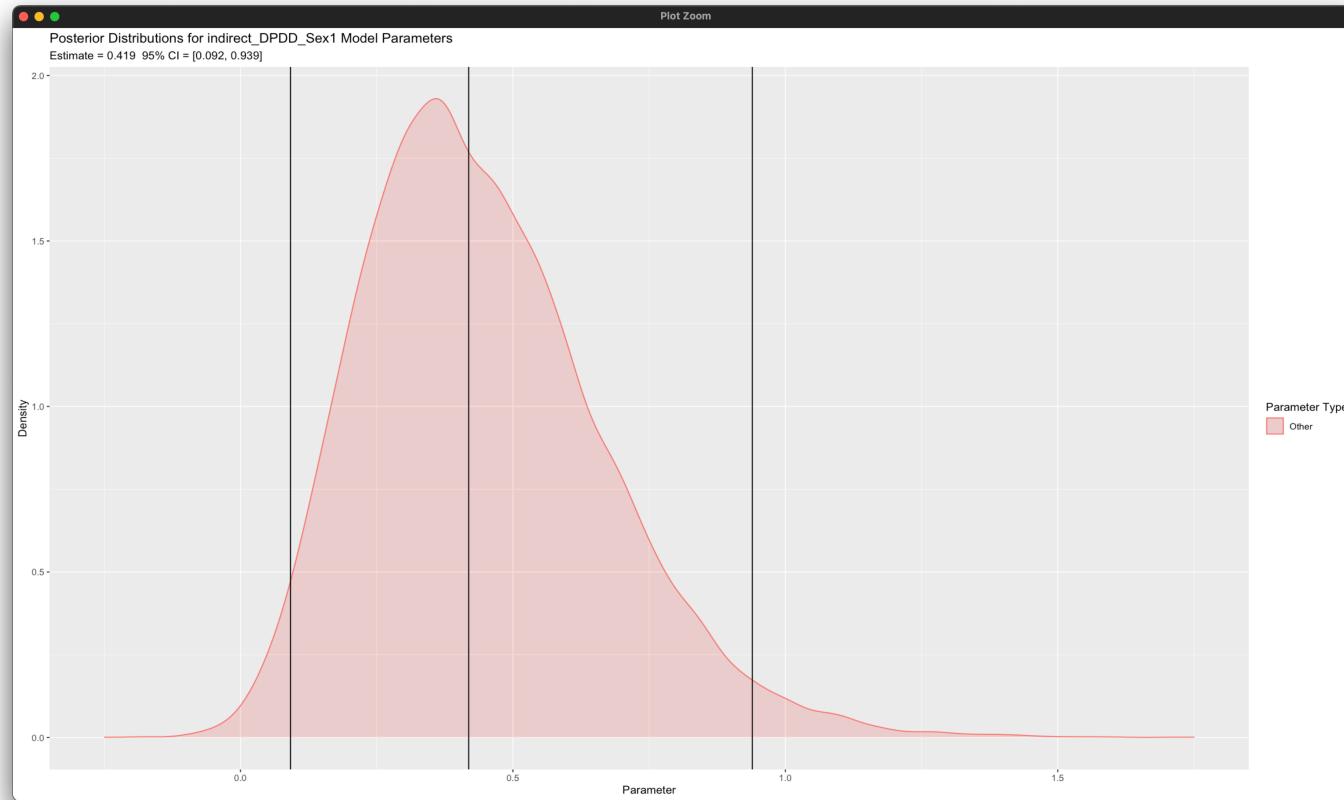


The `posterior_plot` functions generate kernel density plots of the distribution of indirect effects.

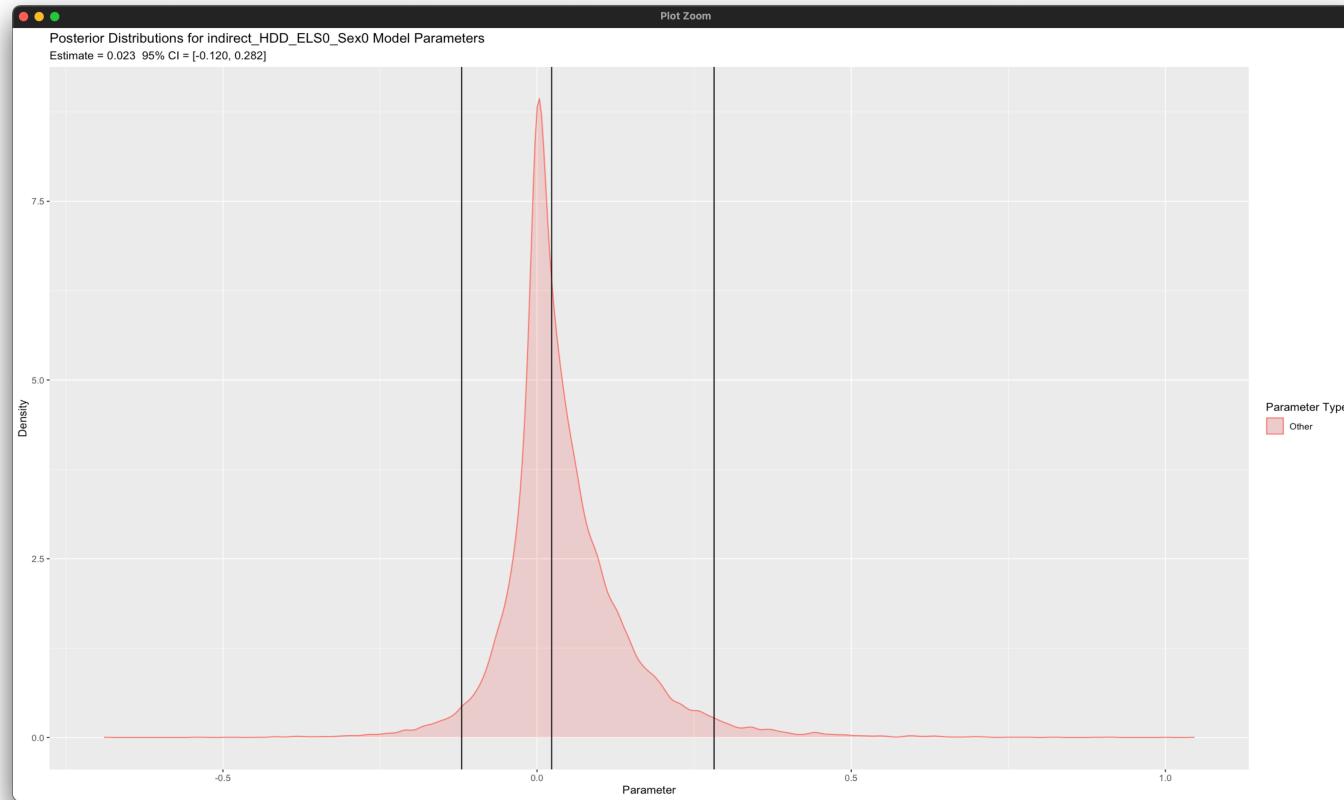
```
# Plot distributions of indirect effects
posterior_plot(modmed, 'indirect_DPDD_Sex0')
```



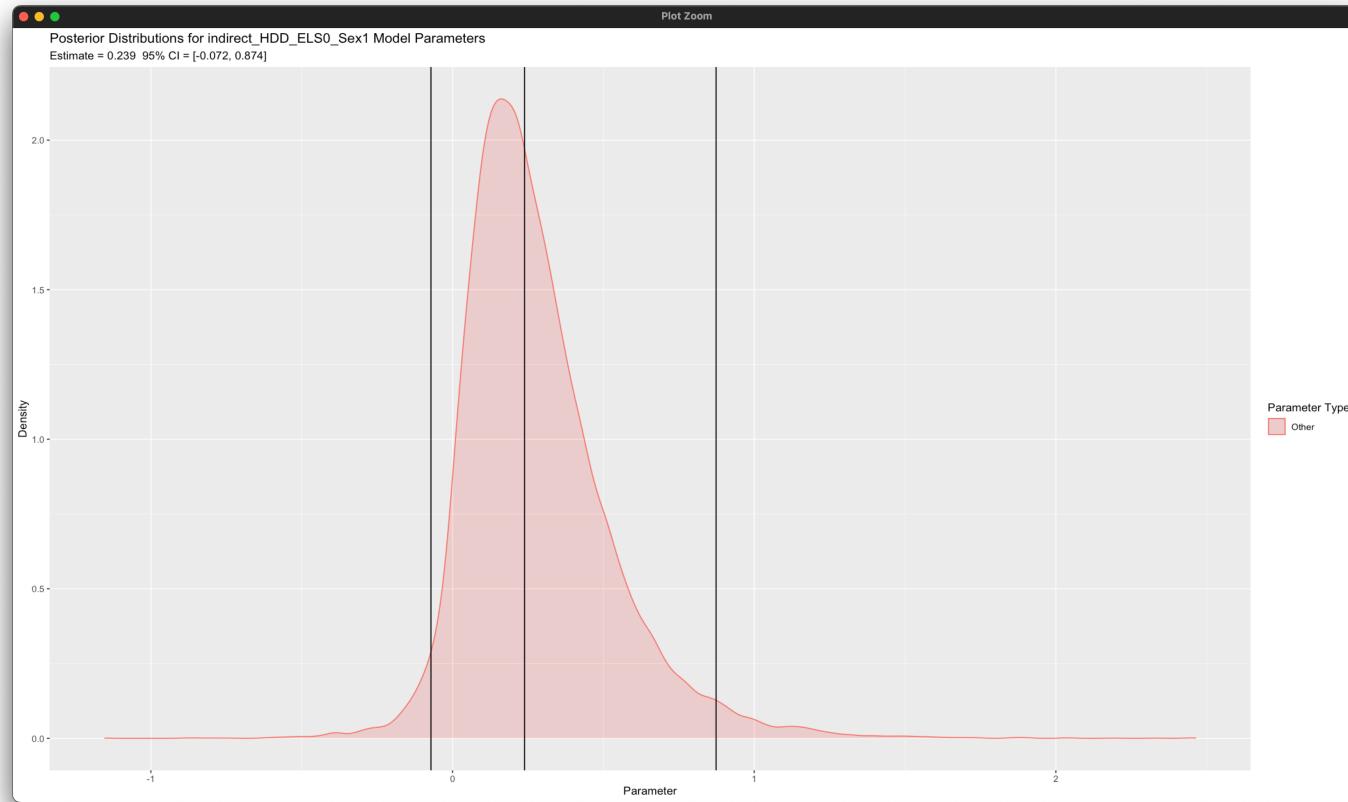
```
posterior_plot(modmed, 'indirect_DPDD_Sex1')
```



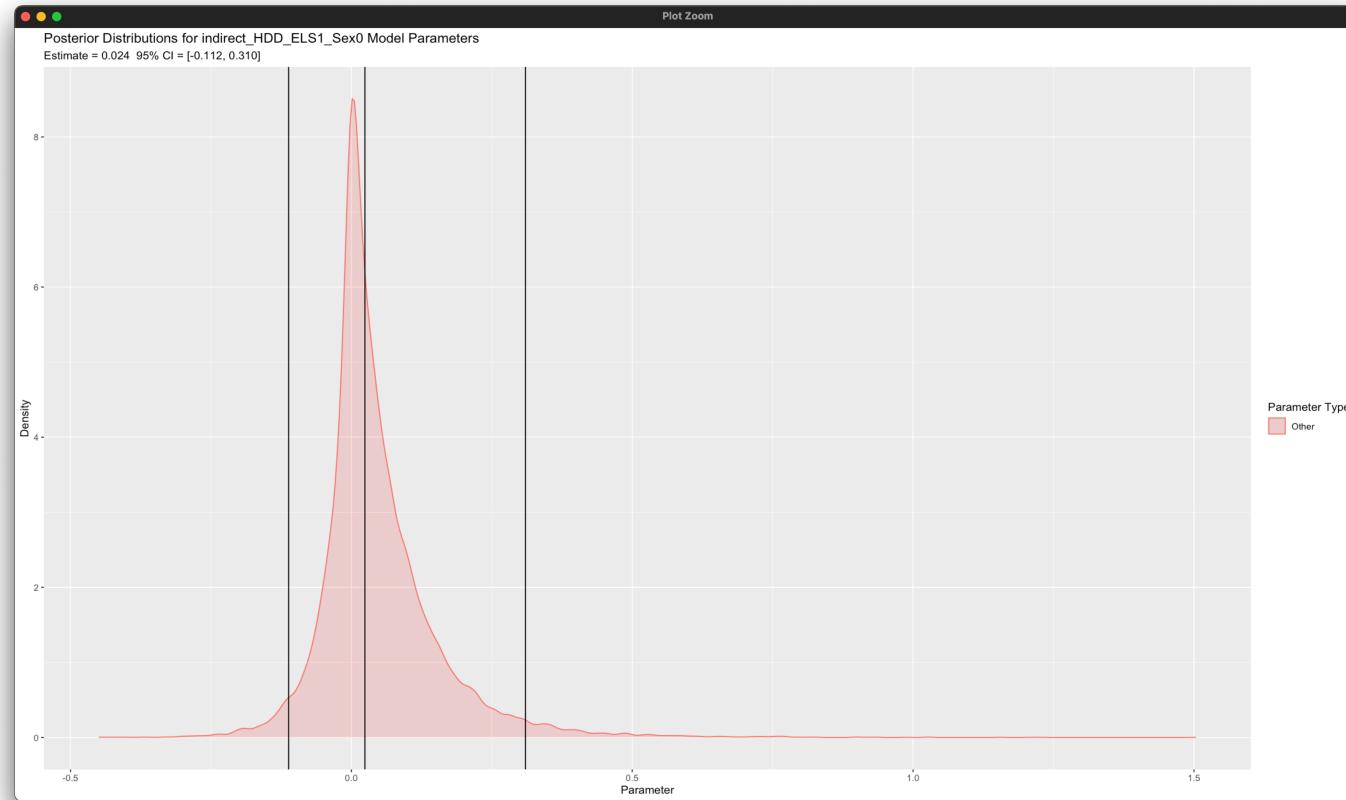
```
posterior_plot(modmed, 'indirect_HDD_ELS0_Sex0')
```



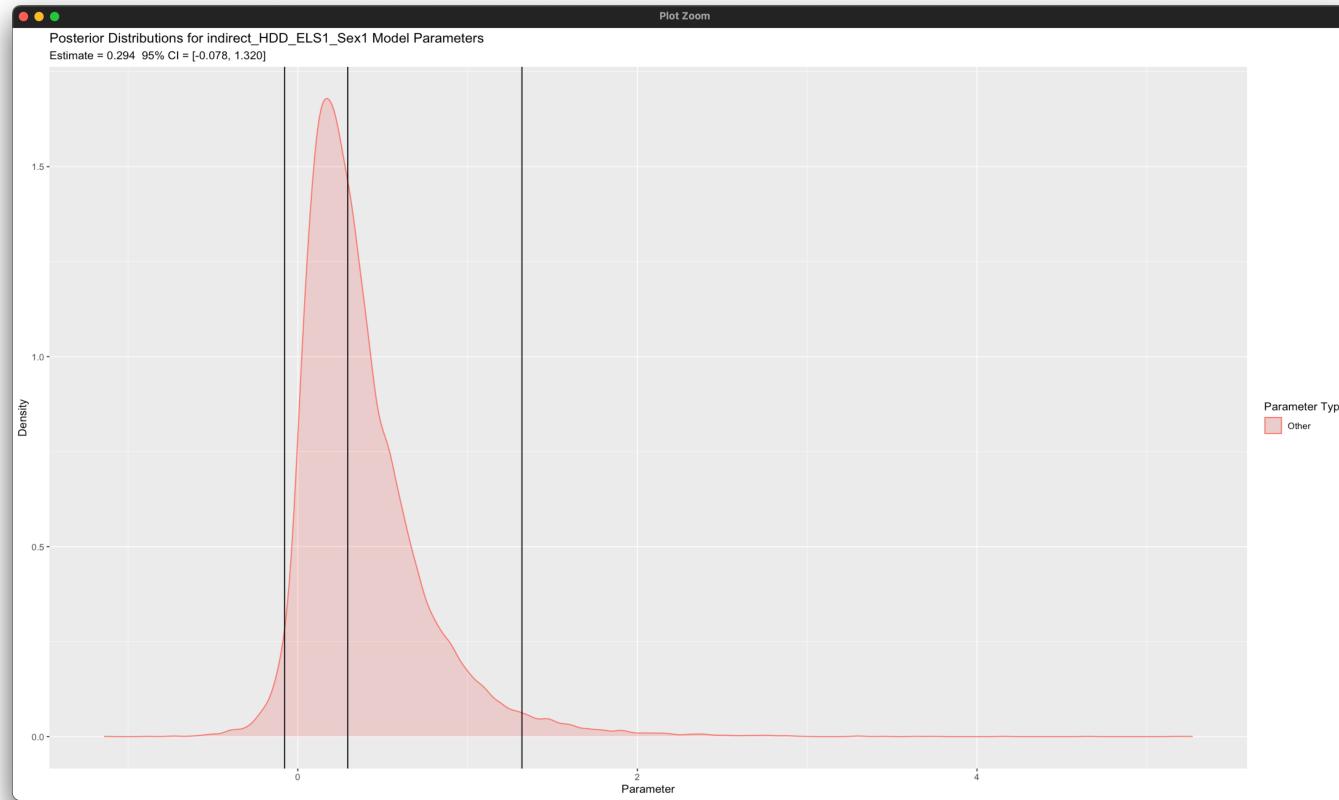
```
posterior_plot(modmed, 'indirect_HDD_ELS0_Sex1')
```



```
posterior_plot(modmed, 'indirect_HDD_ELS1_Sex0')
```



```
posterior_plot(modmed, 'indirect_HDD_ELS1_Sex1')
```



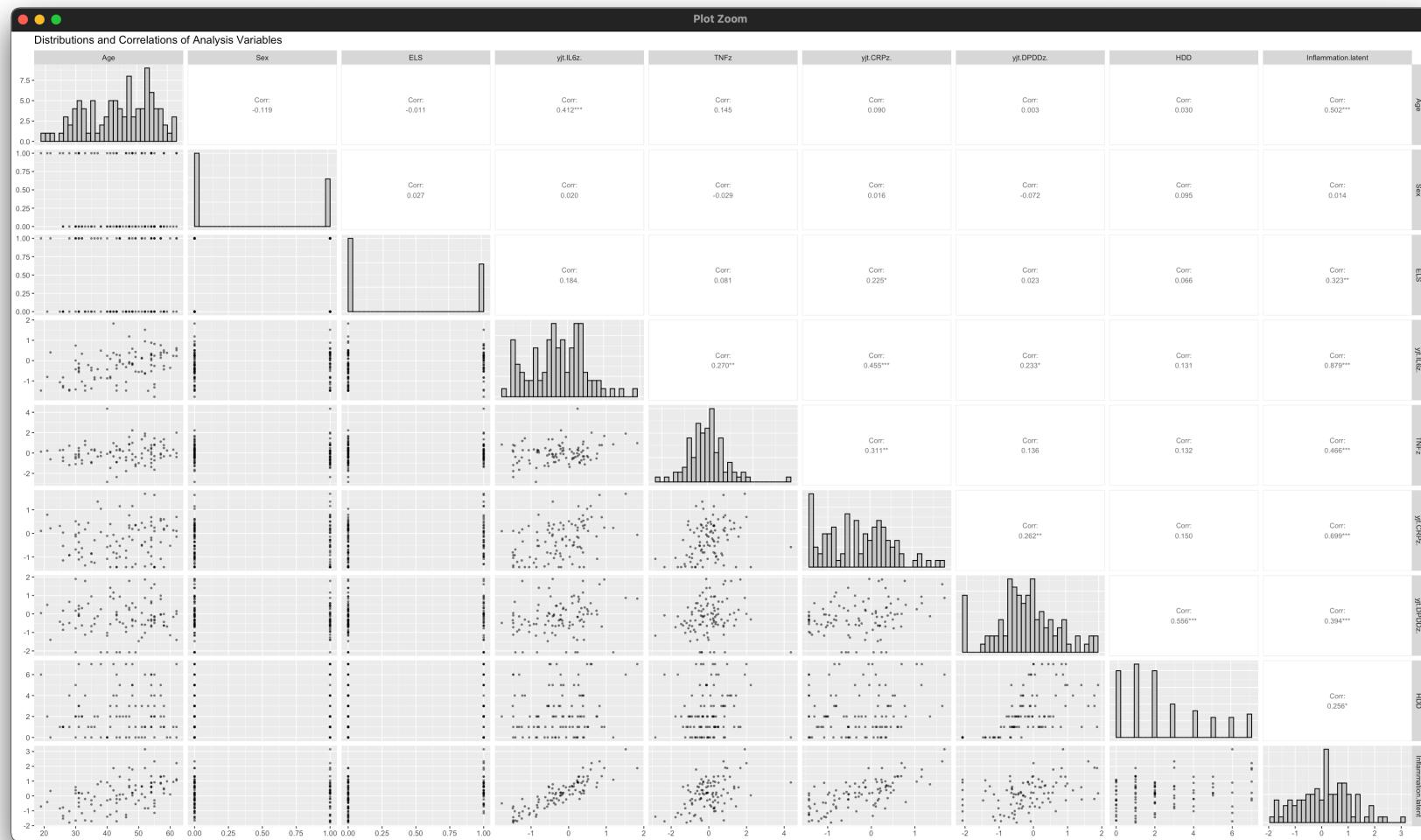
## Inspect Distributions

Histograms of the raw data showed that two of the three inflammation indicators (IL6 and CRP) and the drinks per drinking day outcome (DPDD) have positively skewed distributions. These variables were normalized in the analysis models using the Yeo–Johnson transformation. The normalized scores are saved at every MCMC iteration, and Blimp stores the average values of the normalized scores across iterations (along with any missing data imputations) in an object named @average\_imp. The code below extracts the variable names from this file and graphs the normalized variables for inspection. Relative to the raw data, the transformed variables are more symmetric.

```
# Get variable names from object containing average imputations
names(modmed@average_imp)

## [1] "Sex"                      "Age"                      "ELS"                      "
## [4] "CRP"                      "IL6"                      "TNF"                      "
## [7] "CRPz"                     "IL6z"                     "TNFz"                     "
## [10] "DPDD"                     "DPDDz"                    "HDD"                      "
## [13] "Inflammation.latent"     "yjt.DPDDz."              "yjt.CRPz."                "
## [16] "yjt.IL6z."                "Sex.latent"               "ELS.latent"               "
## [19] "Inflammation.residual"   "yjt.DPDDz..residual"    "HDD.residual"              "
## [22] "yjt.CRPz..residual"     "yjt.IL6z..residual"     "TNFz.residual"              "
## [25] "Inflammation.predicted"  "yjt.DPDDz..predicted"   "HDD.predicted"              "
## [28] "yjt.CRPz..predicted"     "yjt.IL6z..predicted"    "TNFz.predicted"              "

# Distributions and correlations of analysis variables
ggpairs(
  modmed@average_imp[, c('Age', 'Sex', 'ELS', 'yjt.IL6z.', 'TNFz', 'yjt.CRPz.', 'yjt.DPDDz.', 'HDD', 'Inflammation.latent')],
  upper = list(continuous = wrap("cor", size = 3)),
  lower = list(continuous = wrap("points", alpha = 0.5, size = 0.7)),
  diag = list(continuous = wrap("barDiag", colour= "black", fill = "grey80"))
) + ggtitle("Distributions and Correlations of Analysis Variables")
```



## References

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<https://doi.org/10.1177/0165025417727876>
- Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2014). *Bayesian data analysis* (3rd ed.). CRC Press.
- Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science*, 7, 457–472. <https://doi.org/10.1214/ss/1177011136>
- Hayes, A. F., & Preacher, K. J. (2010). Quantifying and testing indirect effects in simple mediation models when the constituent paths are nonlinear. *Multivariate Behavioral Research*, 45(4), 627–660.  
<https://doi.org/doi.org/10.1080/00273171.2010.498290>