

Example 6a: Path Analysis for Mediation among Conditionally Multivariate Normal Outcomes
(complete syntax and output available for STATA, Mplus, R, and SAS electronically)

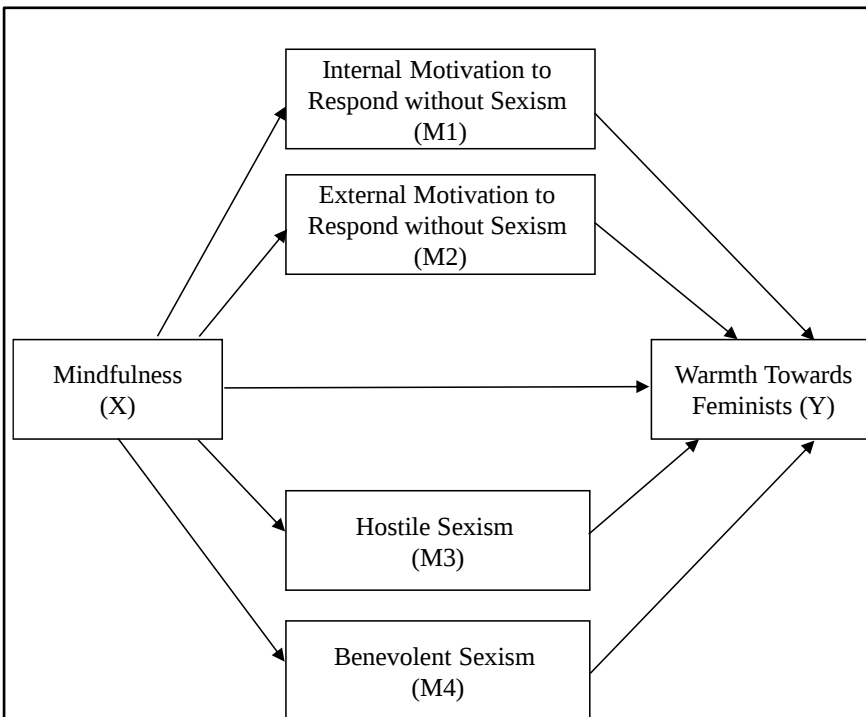


Figure 1 from: Gervais, S. J. & Hoffman, L. (2013). [Just think about it: Mindfulness, sexism, and prejudice towards feminists](#). *Sex Roles*, 68(5), 283–295.

A sample of 653 undergraduates completed the six measures depicted in Figure 1 (residual covariances among the four mediators are not shown for diagram clarity). Table 3 shows the correlations of the six variables by gender. (The published article is also included in the online materials for this example.)

The research questions were as follows:
 (1) To what extent do these four mediators account for the relationship between mindfulness and warmth towards feminists?
 (2) How do these direct and indirect effects differ by binary gender?

Table 3 Inter-correlations of all factors by participant gender for main study

	1.	2.	3.	4.	5.	6.
1. Mindfulness	–	.20	.10	–.17	–.08	.15
2. Internal motivation	.04	–	.39	.06	–.40	.45
3. External motivation	–.04	.38	–	.14	.05	.11
4. Benevolent sexism	.08	–.01	.17	–	.07	–.06
5. Hostile sexism	–.11	–.21	.03	.20	–	–.44
6. Warmth toward feminists	–.00	.30	.14	–.08	–.24	–

Bold font denotes significant correlation coefficients. Correlations for men ($N=272-273$) are reported above the diagonal and correlations for women ($N=378-380$) are reported below the diagonal. Mindfulness (1 = *rarely*, 4 = *almost always*), Warmth Toward Feminists (0° = *very coolly*, 100° = *very warmly*), and Internal Motivation, External Motivation, Hostile Sexism, Benevolent Sexism (1 = *disagree strongly*, 7 = *agree strongly*)

This example demonstrates how to bring predictors into the likelihood by estimating their mean and variance in any empty model—this turns them into endogenous variables instead of exogenous variables, even if they aren't being predicted by anything. This strategy then allows those predictors to have missing data (assuming missing at random, just like for the outcomes already in the likelihood), but doing so also assumes a multivariate normal distribution (for the marginal distribution for any variables not predicted in the model). The choice of whether to bring predictors into the likelihood is available in Mplus and in R lavaan (0.6-15 used here), but not in SAS PROC CALIS or STATA SEM, which forces all variables into the likelihood when full-information maximum likelihood is selected for any missing outcomes. Likewise, a robust version of full-information maximum likelihood (MLR) is available in Mplus and R lavaan that corrects fit statistics and parameter standard errors for multivariate normality. Robust standard errors are also available in STATA SEM, but not in SAS PROC CALIS in the presence of missing data (so the SAS standard errors differ slightly).

We will begin with a single-group model, and then examine a multiple-group model in which all parameters are estimated separately for (binary) men and women. In a multiple-group model, we will request Wald tests for the difference in each direct and indirect effect (which allows for faster, simultaneous testing of all differences). Alternatively, one could constrain specific direct and indirect effects to be equal across gender groups and track the decrease in model fit (best approach in theory, but it's more time-consuming)—this alternative strategy will be demonstrated in the last model.

STATA SEM Syntax for Single-Group Path Model using Regular FIML and Robust Standard Errors:

```
display "STATA Single-Group Path Model with Indirect Effects using Regular FIML and Robust SEs"
sem
    (intern extern hostile benev warmth <- _cons)    /// All intercepts estimated (by default)
    (warmth <- mindc)                                /// Regression X to Y
    (intern extern hostile benev <- mindc)           /// Regressions X to M1,M2,M3,M4
    (warmth <- intern extern hostile benev),         /// Regressions M1,M2,M3,M4 to Y
/// Note that fitting an empty model to the predictor causes problems with the R2 output, so the
/// next line is how to bring a predictor into the likelihood for its missing data (MAR)
means(mindc) var(mindc)                            /// Print X mean and variance (not default)
var(e.intern e.extern e.hostile e.benev e.warmth)    /// All residual variances (by default)
covstruct(e.intern e.extern e.hostile e.benev, unstructured) /// All possible residual covars
method(mlmv) vce(robust)                            // Full-information ML and robust SEs (fit is same)
estat teffects                                       // Direct, indirect, and total effects (combined)
nlcom _b[intern:mindc] *_b[warmth:intern]           // Indirect effect XtoM1toY
nlcom _b[extern:mindc] *_b[warmth:extern]           // Indirect effect XtoM2toY
nlcom _b[hostile:mindc] *_b[warmth:hostile]         // Indirect effect XtoM3toY
nlcom _b[benev:mindc] *_b[warmth:benev]            // Indirect effect XtoM4toY
nlcom _b[intern:mindc] *_b[warmth:intern] + _b[extern:mindc] *_b[warmth:extern] + ///
    _b[hostile:mindc] *_b[warmth:hostile] + _b[benev:mindc] *_b[warmth:benev] + ///
    _b[warmth:mindc]                               // Total indirect+direct effects
nlcom _b[intern:mindc] *_b[warmth:intern] + _b[extern:mindc] *_b[warmth:extern] + ///
    _b[hostile:mindc] *_b[warmth:hostile] + _b[benev:mindc] *_b[warmth:benev]      ///
    // Total indirect effects
sem, coeflegend                                     // Print parameter labels (to use in lincom)
sem, standardized                                   // Print standardized solution
estat gof, stats(all)                              // Print model fit statistics
estat eggof                                         // Print R2 per variable
```

R Syntax and Output for Single-Group Path Model using Robust FIML and Standard Errors:

```
print("R Single-Group Path Model with Indirect Effects using Robust FIML and Standard Errors")
# Create model syntax as separate text object
SyntaxSingle = "
```

```
# Means/Intercepts and Variances/Residual Variances (labels)
MindC ~ (Xint)*1; MindC ~~ (Xvar)*MindC;
Intern ~ (M1int)*1; Intern ~~ (M1var)*Intern;
Extern ~ (M2int)*1; Extern ~~ (M2var)*Extern;
Hostile ~ (M3int)*1; Hostile ~~ (M3var)*Hostile;
Benev ~ (M4int)*1; Benev ~~ (M4var)*Benev;
Warmth ~ (Yint)*1; Warmth ~~ (Yvar)*Warmth;
# Direct MindC --> Warmth
Warmth ~ (XtoY)*MindC
# Left side of model
Intern ~ (XtoM1)*MindC
Extern ~ (XtoM2)*MindC
Hostile ~ (XtoM3)*MindC
Benev ~ (XtoM4)*MindC
# Right side of model
Warmth ~ (M1toY)*Intern + (M2toY)*Extern + (M3toY)*Hostile + (M4toY)*Benev
# Residual Covariances
Intern ~~ (Cov1)*Extern + (Cov2)*Hostile + (Cov3)*Benev
Extern ~~ (Cov4)*Hostile + (Cov5)*Benev
Hostile ~~ (Cov6)*Benev
# Indirect effects, total indirect+direct, and total indirect effects
XtoM1toY := XtoM1*M1toY; XtoM2toY := XtoM2*M2toY
XtoM3toY := XtoM3*M3toY; XtoM4toY := XtoM4*M4toY
totXtoY := XtoM1*M1toY + XtoM2*M2toY + XtoM3*M3toY + XtoM4*M4toY + XtoY
totInd := XtoM1*M1toY + XtoM2*M2toY + XtoM3*M3toY + XtoM4*M4toY
" # Now estimate model and get output
```

Here I am fitting an empty model to the mindC predictor (requesting its mean and variance), which lavaan is fine with (and so is Mplus), in contrast to the STATA sem results

```
ModelSingle = lavaan(data=Mindful, model=SyntaxSingle, estimator="MLR", mimic="mplus")
summary(ModelSingle, fit.measures=TRUE, rsquare=TRUE, standardized=TRUE)
Estimator ML
Optimization method NLMINB
Number of model parameters 27
Number of observations 653
Number of missing patterns 3
```

Model Test User Model:

	Standard	Robust
Test Statistic	0.000	0.000
Degrees of freedom	0	0

Model Test Baseline Model:

Test statistic	439.601	396.087
Degrees of freedom	15	15
P-value	0.000	0.000
Scaling correction factor		1.110

User Model versus Baseline Model:

Comparative Fit Index (CFI)	1.000	1.000
Tucker-Lewis Index (TLI)	1.000	1.000
Robust Comparative Fit Index (CFI)		NA
Robust Tucker-Lewis Index (TLI)		NA

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-5410.773	-5410.773
Loglikelihood unrestricted model (H1)	-5410.773	-5410.773
Akaike (AIC)	10875.545	10875.545
Bayesian (BIC)	10996.548	10996.548
Sample-size adjusted Bayesian (BIC)	10910.823	10910.823

Root Mean Square Error of Approximation:

RMSEA	0.000	0.000
90 Percent confidence interval - lower	0.000	0.000
90 Percent confidence interval - upper	0.000	0.000
P-value RMSEA <= 0.05	NA	NA
Robust RMSEA		0.000
90 Percent confidence interval - lower		0.000
90 Percent confidence interval - upper		0.000

Standardized Root Mean Square Residual:

SRMR	0.000	0.000
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Parameter Estimates:

Standard errors	Sandwich
Information bread	Observed
Observed information based on	Hessian

Regressions:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Warmth ~							
MindC	(XtoY)	-0.012	0.213	-0.056	0.955	-0.012	-0.002
Intern ~							
MindC	(XtM1)	0.335	0.120	2.785	0.005	0.335	0.112
Extern ~							
MindC	(XtM2)	0.041	0.105	0.392	0.695	0.041	0.015
Hostile ~							
MindC	(XtM3)	-0.196	0.071	-2.750	0.006	-0.196	-0.103
Benev ~							
MindC	(XtM4)	-0.052	0.065	-0.801	0.423	-0.052	-0.029
Warmth ~							
Intern	(M1tY)	0.563	0.075	7.478	0.000	0.563	0.307
Extern	(M2tY)	0.058	0.074	0.777	0.437	0.058	0.029
Hostile	(M3tY)	-0.813	0.111	-7.343	0.000	-0.813	-0.282
Benev	(M4tY)	-0.212	0.110	-1.928	0.054	-0.212	-0.069

Covariances:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.Intern ~~							
.Extern	(Cov1)	0.602	0.077	7.850	0.000	0.602	0.377
.Hostile	(Cov2)	-0.374	0.052	-7.128	0.000	-0.374	-0.339
.Benev	(Cov3)	-0.007	0.045	-0.149	0.881	-0.007	-0.006
.Extern ~~							
.Hostile	(Cov4)	0.036	0.045	0.815	0.415	0.036	0.036
.Benev	(Cov5)	0.147	0.043	3.394	0.001	0.147	0.153
.Hostile ~~							
.Benev	(Cov6)	0.112	0.031	3.654	0.000	0.112	0.169

Intercepts:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
MindC	(Xint)	0.835	0.017	48.266	0.000	0.835	1.889

When you request MLR, those fit statistics appear in the right column (whereas the regular ML statistics are in the left column).

The LL, AIC, and BIC values all match SAS CALIS and STATA SEM because all variables are in the likelihood (after telling Mplus to estimate the mean and variance of the otherwise exogenous predictor X=Mindfulness by predicting it in an empty model).

Fit is perfect because the model is saturated (i.e., just-identified), such that there are direct relations (direct paths or covariances) between every pair of variables.

Under Covariances, Intercepts, and Variances, the dot in front of the term differentiates "residual" (conditional because the variable is being predicted as an outcome) from unconditional (unpredicted, but part of the likelihood)

.Intern	(M1nt)	4.971	0.115	43.276	0.000	4.971	3.757
.Extern	(M2nt)	4.063	0.100	40.820	0.000	4.063	3.342
.Hostile	(M3nt)	4.069	0.067	60.988	0.000	4.069	4.826
.Benev	(M4nt)	4.109	0.059	69.488	0.000	4.109	5.204
.Warmth	(Yint)	7.456	0.845	8.821	0.000	7.456	3.074

Variances:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
MindC	(Xvar)	0.195	0.012	16.398	0.000	0.195	1.000
.Intern	(M1vr)	1.729	0.087	19.890	0.000	1.729	0.987
.Extern	(M2vr)	1.478	0.081	18.154	0.000	1.478	1.000
.Hostile	(M3vr)	0.704	0.047	15.003	0.000	0.704	0.989
.Benev	(M4vr)	0.623	0.038	16.396	0.000	0.623	0.999
.Warmth	(Yvar)	4.401	0.247	17.822	0.000	4.401	0.748

R-Square:

	Estimate
Intern	0.013
Extern	0.000
Hostile	0.011
Benev	0.001
Warmth	0.252

Defined Parameters:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
XtoM1toY	0.189	0.072	2.609	0.009	0.189	0.034
XtoM2toY	0.002	0.007	0.346	0.730	0.002	0.000
XtoM3toY	0.159	0.062	2.579	0.010	0.159	0.029
XtoM4toY	0.011	0.015	0.717	0.474	0.011	0.002
totXtoY	0.349	0.235	1.484	0.138	0.349	0.064
totInd	0.361	0.109	3.328	0.001	0.361	0.066

Mplus Syntax and Partial Output for Single-Group Path Model using Robust FIML and Standard Errors:

TITLE: Mplus Example 6a Single-Group Path Model with Indirect Effects

DATA: FILE = Mindful.csv; ! Can just list file name if input is in same folder
 FORMAT = free; ! FREE (default) or FIXED format
 TYPE = individual; ! Individual (default) or matrix data as input

VARIABLE:

! Names of all variables in data set
 NAMES = ID SexMW MindC Intern Extern Hostile Benev Warmth;
 ! Names of all variables in model
 USEVARIABLES = MindC Intern Extern Hostile Benev Warmth;
 ! Missing data indicator
 MISSING = ALL(-999);

ANALYSIS: TYPE = GENERAL; ! For path models
 ESTIMATOR = MLR; ! Robust ML (cannot use with bootstrapping)
 !BOOTSTRAP = 1000; ! Bootstrapping for indirect effects
OUTPUT: STDYX; ! Standardized solution
 !MODINDICES (3.84); ! Cheat codes to improve model fit (not used with CONSTRAINT)
 CINTERVAL; ! Confidence interval for indirect effects
 !CINTERVAL(BCBOOTSTRAP); ! Bootstrap CI for indirect effects (not used with MLR)

! Model code: ON = Y ON X, WITH = covariance (labels to do math on parameters)

MODEL:

! Bring X into the likelihood by estimating its mean and variance in an empty model
 [MindC] (Xint); MindC (Xvar);
 ! Intercepts and residual variances for other variables
 [Intern Extern Hostile Benev Warmth] (M1int M2int M3int M4int Yint);
 Intern Extern Hostile Benev Warmth (M1var M2var M3var M4var Yvar);
 ! Direct MindC --> Warmth
 Warmth ON MindC (XtoY);
 ! Left side of model
 Intern Extern Hostile Benev ON MindC (XtoM1 XtoM2 XtoM3 XtoM4);
 ! Right side of model
 Warmth ON Intern Extern Hostile Benev (M1toY M2toY M3toY M4toY);
 ! All possible residual covariances among mediator variables (not labeled)
 Intern Extern Hostile Benev WITH Intern Extern Hostile Benev;

```

! First list newly created parameters to be defined below
MODEL CONSTRAINT:
  NEW (XtoM1toY XtoM2toY XtoM3toY XtoM4toY totXtoY totInd);
! Then define indirect effects, total indirect+direct, and total indirect effects
! (as done for you here using MODEL INDIRECT below, which is not always possible to use)
XtoM1toY = XtoM1*M1toY; XtoM2toY = XtoM2*M2toY;
XtoM3toY = XtoM3*M3toY; XtoM4toY = XtoM4*M4toY;
totXtoY = XtoM1toY + XtoM2toY + XtoM3toY + XtoM4toY + XtoY;
totInd = XtoM1toY + XtoM2toY + XtoM3toY + XtoM4toY;

! Get all indirect and total effects between Y IND X
MODEL INDIRECT: ! Only available for MVN outcomes
  Warmth IND MindC;

```

```

MODEL FIT INFORMATION
Number of Free Parameters          27
Loglikelihood
  H0 Value                        -5410.773
  H0 Scaling Correction Factor    1.0785
  for MLR
  H1 Value                        -5410.773
  H1 Scaling Correction Factor    1.0785
  for MLR
Information Criteria
  Akaike (AIC)                    10875.545
  Bayesian (BIC)                  10996.548
  Sample-Size Adjusted BIC        10910.823
  (n* = (n + 2) / 24)
Chi-Square Test of Model Fit
  Value                           0.000
  Degrees of Freedom              0
  P-Value                         0.0000
RMSEA (Root Mean Square Error Of Approximation)
  Estimate                        0.000
  90 Percent C.I.                 0.000 0.000
  Probability RMSEA <= .05        0.000
CFI/TLI
  CFI                            1.000
  TLI                            1.000
Chi-Square Test of Model Fit for the Baseline Model
  Value                           439.601
  Degrees of Freedom              15
  P-Value                         0.0000
SRMR (Standardized Root Mean Square Residual)
  Value                           0.000

```

The LL, AIC, and BIC values all match SAS CALIS and STATA SEM because all variables are in the likelihood (after requesting Mplus estimate the mean and variance of the otherwise exogenous predictor X=Mindfulness).

Fit is perfect because the model is saturated (i.e., just-identified), such that there are direct relations (direct paths or covariances) between every pair of variables.

```

MODEL RESULTS

```

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
WARMTH ON				
MINDC	-0.012	0.213	-0.056	0.955
INTERN	0.563	0.075	7.477	0.000
EXTERN	0.058	0.074	0.777	0.437
HOSTILE	-0.813	0.111	-7.343	0.000
BENEV	-0.212	0.110	-1.928	0.054
INTERN ON				
MINDC	0.335	0.120	2.785	0.005
EXTERN ON				
MINDC	0.041	0.105	0.393	0.695
HOSTILE ON				
MINDC	-0.196	0.071	-2.750	0.006
BENEV ON				
MINDC	-0.052	0.065	-0.801	0.423
INTERN WITH				
EXTERN	0.602	0.077	7.851	0.000
HOSTILE	-0.374	0.052	-7.127	0.000
BENEV	-0.007	0.045	-0.148	0.882
EXTERN WITH				
HOSTILE	0.036	0.045	0.816	0.415
BENEV	0.147	0.043	3.395	0.001
HOSTILE WITH				
BENEV	0.112	0.031	3.654	0.000

Means				
MINDC	0.835	0.017	48.266	0.000
Intercepts				
INTERN	4.971	0.115	43.275	0.000
EXTERN	4.063	0.100	40.820	0.000
HOSTILE	4.069	0.067	60.988	0.000
BENEV	4.109	0.059	69.488	0.000
WARMTH	7.457	0.845	8.822	0.000
Variances				
MINDC	0.195	0.012	16.398	0.000
Residual Variances				
INTERN	1.729	0.087	19.891	0.000
EXTERN	1.478	0.081	18.155	0.000
HOSTILE	0.704	0.047	15.003	0.000
BENEV	0.623	0.038	16.396	0.000
WARMTH	4.400	0.247	17.823	0.000
New/Additional Parameters				
XTOM1TOY	0.189	0.072	2.610	0.009
XTOM2TOY	0.002	0.007	0.346	0.729
XTOM3TOY	0.159	0.062	2.579	0.010
XTOM4TOY	0.011	0.015	0.716	0.474
TOTXTOY	0.349	0.235	1.484	0.138
TOTIND	0.361	0.109	3.328	0.001

“Means” are for unpredicted variables in the likelihood, whereas “intercepts” are for predicted variables (conditional)

“Variances” are for unpredicted variables forced into the likelihood, whereas “residual variances” are for predicted variables (leftover outcomes)

Indirect and total effects are also provided by MODEL INDIRECT below (but only for MVN outcomes), so this way is more generally useful

TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS				
	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Effects from MINDC to WARMTH				
Total	0.349	0.235	1.484	0.138
Total indirect	0.361	0.109	3.328	0.001
Specific indirect 1				
WARMTH				
INTERN				
MINDC	0.189	0.072	2.610	0.009
Specific indirect 2				
WARMTH				
EXTERN				
MINDC	0.002	0.007	0.346	0.729
Specific indirect 3				
WARMTH				
HOSTILE				
MINDC	0.159	0.062	2.579	0.010
Specific indirect 4				
WARMTH				
BENEV				
MINDC	0.011	0.015	0.716	0.474
Direct				
WARMTH				
MINDC	-0.012	0.213	-0.056	0.955

Total effects and total indirect effects given from X to Y (sum of all direct + indirect effects, or just sum or indirect effects, respectively)

Next, we will estimate the same path model separately but simultaneously for men and women in order to test “Moderated Mediation”—whether the model parameters (and direct/indirect effects specifically) differ by group. This model estimates all parameters separately by gender and uses Wald tests to examine gender differences.

STATA SEM Syntax for Multiple-Group Path Model using Regular FIML and Robust Standard Errors:

```
display "STATA Multiple-Group Path Model with Indirect Effects using Regular FIML and Robust SEs"
sem
    (intern extern hostile benev warmth <- _cons)          /// All intercepts estimated (by default)
    (warmth <- mindc)                                     /// Regression X to Y
    (intern extern hostile benev <- mindc)                 /// Regressions X to M1,M2,M3,M4
    (warmth <- intern extern hostile benev),              /// Regressions M1,M2,M3,M4 to Y
/// Note that fitting an empty model to the predictor causes problems with the R2 output, so the
/// next line is how to bring a predictor into the likelihood for its missing data (MAR)
means(mindc) var(mindc)                                  /// Print X mean and variance (not default)
var(e.intern e.extern e.hostile e.benev e.warmth)        /// All residual variances (by default)
covstruct(e.intern e.extern e.hostile e.benev, unstructured) /// All possible residual covars
method(mlmv) vce(robust)                                  /// Full-information ML and robust SEs (fit is same)
group(sexmw) ginvariant(none)                            /// none= full non-invariance
estat teffects                                           /// Direct, indirect (not correct), and total effects
```

```
// Men and women indirect effect XtoM1toY and difference
nlcom _b[intern:0bn.sexmw#c.mindc]*_b[warmth:0bn.sexmw#c.intern]
nlcom _b[intern:1.sexmw#c.mindc] *_b[warmth:1.sexmw#c.intern]
nlcom _b[intern:0bn.sexmw#c.mindc]*_b[warmth:0bn.sexmw#c.intern] - ///
      _b[intern:1.sexmw#c.mindc] *_b[warmth:1.sexmw#c.intern]
// Men and women indirect effect XtoM2toY and difference
nlcom _b[extern:0bn.sexmw#c.mindc]*_b[warmth:0bn.sexmw#c.extern]
nlcom _b[extern:1.sexmw#c.mindc] *_b[warmth:1.sexmw#c.extern]
nlcom _b[extern:0bn.sexmw#c.mindc]*_b[warmth:0bn.sexmw#c.extern] - ///
      _b[extern:1.sexmw#c.mindc] *_b[warmth:1.sexmw#c.extern]
// Men and women indirect effect XtoM3toY and difference
nlcom _b[hostile:0bn.sexmw#c.mindc]*_b[warmth:0bn.sexmw#c.hostile]
nlcom _b[hostile:1.sexmw#c.mindc] *_b[warmth:1.sexmw#c.hostile]
nlcom _b[hostile:0bn.sexmw#c.mindc]*_b[warmth:0bn.sexmw#c.hostile] - ///
      _b[hostile:1.sexmw#c.mindc] *_b[warmth:1.sexmw#c.hostile]
// Men and women indirect effect XtoM4toY and difference
nlcom _b[benev:0bn.sexmw#c.mindc]*_b[warmth:0bn.sexmw#c.benev]
nlcom _b[benev:1.sexmw#c.mindc] *_b[warmth:1.sexmw#c.benev]
nlcom _b[benev:0bn.sexmw#c.mindc]*_b[warmth:0bn.sexmw#c.benev] - ///
      _b[benev:1.sexmw#c.mindc] *_b[warmth:1.sexmw#c.benev]
// Total and total indirect per group would be computed as for single-group model
sem, coeflegend // Print parameter labels (to use in lincom)
sem, standardized // Print standardized solution
estat gof, stats(all) // Print model fit statistics
estat eqgof // Print R2 per variable
estat ginvariant // Wald or Score test for each parm's invariance
// Wald = test of constraining equal if unequal
// Score = test of allowing unequal if equal
```

R Syntax and Output for Multiple-Group Path Model using Robust FIML and Standard Errors:

```
print("R Multiple-Group Path Model with Indirect Effects using Robust FIML and Standard Errors")
# Create model syntax as separate text object
SyntaxMultiple = "
# Means/Intercepts and Variances/Residual Variances (labels)
MindC ~ c(mXint, wXint)*1; MindC ~~ c(mXvar, wXvar)*MindC;
Intern ~ c(mM1int, wM1int)*1; Intern ~~ c(mM1var, wM1var)*Intern;
Extern ~ c(mM2int, wM2int)*1; Extern ~~ c(mM2var, wM2var)*Extern;
Hostile ~ c(mM3int, wM3int)*1; Hostile ~~ c(mM3var, wM3var)*Hostile;
Benev ~ c(mM4int, wM4int)*1; Benev ~~ c(mM4var, wM4var)*Benev;
Warmth ~ c(mYint, wYint)*1; Warmth ~~ c(mYvar, wYvar)*Warmth;
# Direct MindC --> Warmth
Warmth ~ c(mXtoY, wXtoY)*MindC
# Left side of model
Intern ~ c(mXtoM1, wXtoM1)*MindC
Extern ~ c(mXtoM2, wXtoM2)*MindC
Hostile ~ c(mXtoM3, wXtoM3)*MindC
Benev ~ c(mXtoM4, wXtoM4)*MindC
# Right side of model
Warmth ~ c(mM1toY, wM1toY)*Intern + c(mM2toY, wM2toY)*Extern
      + c(mM3toY, wM3toY)*Hostile + c(mM4toY, wM4toY)*Benev
# Residual Covariances
Intern ~~ c(mCov1, wCov1)*Extern + c(mCov2, wCov2)*Hostile + c(mCov3, wCov3)*Benev
Extern ~~ c(mCov4, wCov4)*Hostile + c(mCov5, wCov5)*Benev
Hostile ~~ c(mCov6, wCov6)*Benev
# Indirect effects for both groups
mXtoM1Y := mXtoM1*mM1toY; wXtoM1Y := wXtoM1*wM1toY
mXtoM2Y := mXtoM2*mM2toY; wXtoM2Y := wXtoM2*wM2toY
mXtoM3Y := mXtoM3*mM3toY; wXtoM3Y := wXtoM3*wM3toY
mXtoM4Y := mXtoM4*mM4toY; wXtoM4Y := wXtoM4*wM4toY
# Total indirect+direct and total indirect effects for both groups
mtotXtoY := mXtoM1*mM1toY + mXtoM2*mM2toY + mXtoM3*mM3toY + mXtoM4*mM4toY + mXtoY
mtotInd := mXtoM1*mM1toY + mXtoM2*mM2toY + mXtoM3*mM3toY + mXtoM4*mM4toY
wtotXtoY := wXtoM1*wM1toY + wXtoM2*wM2toY + wXtoM3*wM3toY + wXtoM4*wM4toY + wXtoY
wtotInd := wXtoM1*wM1toY + wXtoM2*wM2toY + wXtoM3*wM3toY + wXtoM4*wM4toY
# Differences in direct effects across groups
```

I am still fitting an empty model to the mindC predictor (requesting its mean and variance), which lavaan is fine with (and so is Mplus), in contrast to the STATA sem results

Two labels are given per parameter to request different parameters by group

```

dXtoM1 := mXtoM1-wXtoM1; dXtoM2 := mXtoM2-wXtoM2;
dXtoM3 := mXtoM3-wXtoM3; dXtoM4 := mXtoM4-wXtoM4;
dM1toY := mM1toY-wM1toY; dM2toY := mM2toY-wM2toY;
dM3toY := mM3toY-wM3toY; dM4toY := mM4toY-wM4toY;
# Differences in indirect effects across groups
dXtoM1Y := mXtoM1Y-wXtoM1Y; dXtoM2Y := mXtoM2Y-wXtoM2Y
dXtoM3Y := mXtoM3Y-wXtoM3Y; dXtoM4Y := mXtoM4Y-wXtoM4Y
# Differences in total indirect+direct and total indirect effects across groups
dtotXtoY := mtotXtoY-wtotXtoY; dtotInd := mtotInd-wtotInd
" # Now estimate model and get output
ModelMultiple = lavaan(data=Mindful, model=SyntaxMultiple, estimator="MLR", mimic="mplus",
                        group="SexMW") # group lists variable to define separate groups
summary(ModelMultiple, fit.measures=TRUE, rsquare=TRUE, standardized=TRUE)

```

Estimator	ML
Optimization method	NLMINB
Number of model parameters	54
Number of observations per group:	
0	273
1	380
Number of missing patterns per group:	
0	3
1	3

Model Test User Model:

	Standard	Robust
Test Statistic	0.000	0.000
Degrees of freedom	0	0
Test statistic for each group:		
0	0.000	0.000
1	0.000	0.000

Fit is perfect because the model is still just-identified (all model parameters are separately estimated across groups).

Model Test Baseline Model:

Test statistic	399.257	363.321
Degrees of freedom	30	30
P-value	0.000	0.000
Scaling correction factor		1.099

User Model versus Baseline Model:

Comparative Fit Index (CFI)	1.000	1.000
Tucker-Lewis Index (TLI)	1.000	1.000
Robust Comparative Fit Index (CFI)		NA
Robust Tucker-Lewis Index (TLI)		NA

Loglikelihood and Information Criteria

Loglikelihood user model (H0)	-5332.207	-5332.207
Loglikelihood unrestricted model (H1)	-5332.207	-5332.207
Akaike (AIC)	10772.414	10772.414
Bayesian (BIC)	11014.420	11014.420
Sample-size adjusted Bayesian (BIC)	10842.970	10842.970

Root Mean Square Error of Approximation:

RMSEA	0.000	0.000
90 Percent confidence interval - lower	0.000	0.000
90 Percent confidence interval - upper	0.000	0.000
P-value RMSEA <= 0.05	NA	NA

Robust RMSEA	0.000
90 Percent confidence interval - lower	0.000
90 Percent confidence interval - upper	0.000

Standardized Root Mean Square Residual:

SRMR	0.000	0.000
------	-------	-------

Parameter Estimates:

Standard errors	Sandwich
Information bread	Observed
Observed information based on	Hessian

Group 1 [0]: → Model for Men

Regressions:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Warmth ~							
MindC	(mXtY)	0.213	0.364	0.585	0.558	0.213	0.038
Intern ~							
MindC	(mXM1)	0.633	0.199	3.179	0.001	0.633	0.197
Extern ~							
MindC	(mXM2)	0.273	0.166	1.648	0.099	0.273	0.095
Hostile ~							
MindC	(mXM3)	-0.171	0.126	-1.357	0.175	-0.171	-0.084
Benev ~							
MindC	(mXM4)	-0.314	0.111	-2.829	0.005	-0.314	-0.170
Warmth ~							
Intern	(mM1Y)	0.548	0.107	5.127	0.000	0.548	0.316
Extern	(mM2Y)	0.047	0.109	0.433	0.665	0.047	0.024
Hostile	(mM3Y)	-0.845	0.155	-5.454	0.000	-0.845	-0.311
Benev	(mM4Y)	-0.158	0.168	-0.937	0.349	-0.158	-0.052

Covariances:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.Intern ~~							
.Extern	(mCv1)	0.640	0.132	4.857	0.000	0.640	0.380
.Hostile	(mCv2)	-0.475	0.088	-5.406	0.000	-0.475	-0.393
.Benev	(mCv3)	0.107	0.074	1.445	0.148	0.107	0.099
.Extern ~~							
.Hostile	(mCv4)	0.058	0.077	0.750	0.453	0.058	0.053
.Benev	(mCv5)	0.154	0.067	2.299	0.021	0.154	0.158
.Hostile ~~							
.Benev	(mCv6)	0.036	0.048	0.742	0.458	0.036	0.051

Intercepts:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
MindC	(mXnt)	0.817	0.026	31.181	0.000	0.817	1.887
.Intern	(mM1n)	4.391	0.185	23.735	0.000	4.391	3.159
.Extern	(mM2n)	3.871	0.158	24.499	0.000	3.871	3.123
.Hostile	(mM3n)	4.334	0.113	38.332	0.000	4.334	4.877
.Benev	(mM4n)	4.460	0.093	48.212	0.000	4.460	5.567
.Warmth	(mYnt)	6.815	1.258	5.418	0.000	6.815	2.823

Variances:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
MindC	(mXvr)	0.187	0.019	10.023	0.000	0.187	1.000
.Intern	(mM1v)	1.857	0.147	12.667	0.000	1.857	0.961
.Extern	(mM2v)	1.522	0.126	12.056	0.000	1.522	0.991
.Hostile	(mM3v)	0.784	0.076	10.385	0.000	0.784	0.993
.Benev	(mM4v)	0.623	0.059	10.504	0.000	0.623	0.971
.Warmth	(mYvr)	4.124	0.394	10.465	0.000	4.124	0.708

R-Square:

	Estimate
Intern	0.039
Extern	0.009
Hostile	0.007
Benev	0.029
Warmth	0.292

Group 2 [1]: → Model for Women

Regressions:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
Warmth ~							
MindC	(wXtY)	-0.126	0.254	-0.498	0.618	-0.126	-0.026
Intern ~							
MindC	(wXM1)	0.099	0.146	0.676	0.499	0.099	0.036
Extern ~							
MindC	(wXM2)	-0.117	0.133	-0.874	0.382	-0.117	-0.044
Hostile ~							
MindC	(wXM3)	-0.181	0.081	-2.250	0.024	-0.181	-0.109
Benev ~							
MindC	(wXM4)	0.138	0.079	1.762	0.078	0.138	0.081
Warmth ~							
Intern	(wM1Y)	0.449	0.105	4.264	0.000	0.449	0.247
Extern	(wM2Y)	0.084	0.099	0.841	0.401	0.084	0.045
Hostile	(wM3Y)	-0.535	0.161	-3.328	0.001	-0.535	-0.180
Benev	(wM4Y)	-0.159	0.151	-1.054	0.292	-0.159	-0.055

Covariances:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
.Intern ~~							
.Extern (wCv1)		0.556	0.085	6.556	0.000	0.556	0.383
.Hostile (wCv2)		-0.184	0.047	-3.900	0.000	-0.184	-0.205
.Benev (wCv3)		-0.012	0.050	-0.233	0.816	-0.012	-0.013
.Extern ~~							
.Hostile (wCv4)		0.023	0.044	0.522	0.602	0.023	0.026
.Benev (wCv5)		0.157	0.052	3.000	0.003	0.157	0.171
.Hostile ~~							
.Benev (wCv6)		0.118	0.032	3.656	0.000	0.118	0.210

Intercepts:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
MindC (wXnt)		0.847	0.023	36.886	0.000	0.847	1.892
.Intern (wM1n)		5.414	0.138	39.269	0.000	5.414	4.457
.Extern (wM2n)		4.200	0.125	33.482	0.000	4.200	3.504
.Hostile (wM3n)		3.853	0.077	50.063	0.000	3.853	5.185
.Benev (wM4n)		3.848	0.074	51.657	0.000	3.848	5.025
.Warmth (wYnt)		7.172	1.081	6.633	0.000	7.172	3.256

Variances:

		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
MindC (wXvr)		0.200	0.015	13.042	0.000	0.200	1.000
.Intern (wM1v)		1.473	0.089	16.634	0.000	1.473	0.999
.Extern (wM2v)		1.433	0.105	13.603	0.000	1.433	0.998
.Hostile (wM3v)		0.545	0.043	12.743	0.000	0.545	0.988
.Benev (wM4v)		0.583	0.046	12.659	0.000	0.583	0.993
.Warmth (wYvr)		4.230	0.303	13.972	0.000	4.230	0.872

R-Square:

	Estimate
Intern	0.001
Extern	0.002
Hostile	0.012
Benev	0.007
Warmth	0.128

Defined Parameters:

	Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
mXtoM1Y	0.347	0.126	2.750	0.006	0.347	0.062
wXtoM1Y	0.044	0.066	0.671	0.502	0.044	0.009
mXtoM2Y	0.013	0.030	0.434	0.665	0.013	0.002
wXtoM2Y	-0.010	0.015	-0.644	0.520	-0.010	-0.002
mXtoM3Y	0.145	0.111	1.300	0.194	0.145	0.026
wXtoM3Y	0.097	0.053	1.846	0.065	0.097	0.020
mXtoM4Y	0.050	0.058	0.855	0.393	0.050	0.009
wXtoM4Y	-0.022	0.024	-0.937	0.349	-0.022	-0.004
mtotXtoY	0.768	0.402	1.910	0.056	0.768	0.138
mtotInd	0.554	0.204	2.717	0.007	0.554	0.099
wtotXtoY	-0.017	0.257	-0.066	0.948	-0.017	-0.003
wtotInd	0.109	0.097	1.127	0.260	0.109	0.022
dXtoM1	0.535	0.247	2.166	0.030	0.535	0.161
dXtoM2	0.389	0.213	1.831	0.067	0.389	0.139
dXtoM3	0.010	0.150	0.066	0.948	0.010	0.026
dXtoM4	-0.452	0.136	-3.327	0.001	-0.452	-0.250
dM1toY	0.099	0.150	0.661	0.509	0.099	0.068
dM2toY	-0.036	0.148	-0.245	0.806	-0.036	-0.021
dM3toY	-0.310	0.223	-1.390	0.164	-0.310	-0.131
dM4toY	0.001	0.226	0.006	0.995	0.001	0.003
dXtoM1Y	0.303	0.142	2.126	0.034	0.303	0.053
dXtoM2Y	0.023	0.033	0.678	0.498	0.023	0.004
dXtoM3Y	0.048	0.123	0.389	0.697	0.048	0.006
dXtoM4Y	0.072	0.063	1.144	0.253	0.072	0.013
dtotXtoY	0.784	0.477	1.644	0.100	0.784	0.141
dtotInd	0.445	0.226	1.969	0.049	0.445	0.077

Indirect effects by group

Total indirect+direct and total indirect effects by group

Differences in direct effects by group

Differences in indirect, total indirect + direct, and total indirect effects by group

Mplus Syntax and Partial Output for Multiple-Group Path Model using Robust FIML and Standard Errors:

DATA: FILE IS Mindful.csv; ! Can just list file name if input is in same folder
 FORMAT = free; ! FREE (default) or FIXED format
 TYPE = individual; ! Individual (default) or matrix data as input

VARIABLE:

! Names of all variables in data set
 NAMES = ID SexMW MindC Intern Extern Hostile Benev Warmth;

SexMW is now in USEVARIABLES

```

! Names of all variables in model
USEVARIABLES = SexMW MindC Intern Extern Hostile Benev Warmth;
! Missing data indicator
MISSING = ALL(-999);
! Grouping variable for multiple group analysis
GROUPING = SexMW (0=Men, 1=Women);
ANALYSIS: TYPE = GENERAL;           ! For path models
          ESTIMATOR = MLR;           ! Robust ML (cannot use with bootstrapping)
          !BOOTSTRAP = 1000;         ! Bootstrapping for indirect effects
OUTPUT: STDYX;                      ! Standardized solution
          !MODINDICES (3.84);        ! Cheat codes to improve model fit (not with CONSTRAINT)
          CINTERVAL;                ! Confidence interval for indirect effects
          !CINTERVAL(BCBOOTSTRAP); ! Bootstrap CI for indirect effects (not with MLR)

! Model code: ON = Y ON X, WITH = correlation
! Labels in parentheses (can be used to name constraints between groups)
MODEL:
! Bring X into the likelihood by estimating its mean and variance
[MindC] (mXint); MindC (mXvar);
! Intercepts and residual variances for other variables
[Intern Extern Hostile Benev Warmth] (mM1int mM2int mM3int mM4int mYint);
Intern Extern Hostile Benev Warmth (mM1var mM2var mM3var mM4var mYvar);
! Direct MindC --> Warmth
Warmth ON MindC (mXtoY);
! Left side of model
Intern Extern Hostile Benev ON MindC (mXtoM1 mXtoM2 mXtoM3 mXtoM4);
! Right side of model
Warmth ON Intern Extern Hostile Benev (mM1toY mM2toY mM3toY mM4toY);
! All possible residual covariances among mediator variables (not labeled)
Intern Extern Hostile Benev WITH Intern Extern Hostile Benev;

MODEL Women:
! Bring X into the likelihood by estimating its mean and variance
[MindC] (wXint); MindC (wXvar);
! Intercepts and residual variances for other variables
[Intern Extern Hostile Benev Warmth] (wM1int wM2int wM3int wM4int wYint);
Intern Extern Hostile Benev Warmth (wM1var wM2var wM3var wM4var wYvar);
! Direct MindC --> Warmth
Warmth ON MindC (wXtoY);
! Left side of model
Intern Extern Hostile Benev ON MindC (wXtoM1 wXtoM2 wXtoM3 wXtoM4);
! Right side of model
Warmth ON Intern Extern Hostile Benev (wM1toY wM2toY wM3toY wM4toY);
! All possible residual covariances among mediator variables (not labeled)
Intern Extern Hostile Benev WITH Intern Extern Hostile Benev;

! First list newly created parameters to be defined below
MODEL CONSTRAINT:
NEW (mXtoM1Y mXtoM2Y mXtoM3Y mXtoM4Y wXtoM1Y wXtoM2Y wXtoM3Y wXtoM4Y
mtotXtoY mtotInd wtotXtoY wtotInd
dXtoM1 dXtoM2 dXtoM3 dXtoM4 dM1toY dM2toY dM3toY dM4toY
dXtoM1Y dXtoM2Y dXtoM3Y dXtoM4Y dtotXtoY dtotInd);
! Indirect effects for both groups
mXtoM1Y = mXtoM1*mM1toY; wXtoM1Y = wXtoM1*wM1toY;
mXtoM2Y = mXtoM2*mM2toY; wXtoM2Y = wXtoM2*wM2toY;
mXtoM3Y = mXtoM3*mM3toY; wXtoM3Y = wXtoM3*wM3toY;
mXtoM4Y = mXtoM4*mM4toY; wXtoM4Y = wXtoM4*wM4toY;
! Total indirect+direct and total indirect effects for both groups
mtotXtoY = mXtoM1Y + mXtoM2Y + mXtoM3Y + mXtoM4Y + mXtoY;
mtotInd = mXtoM1Y + mXtoM2Y + mXtoM3Y + mXtoM4Y;
wtotXtoY = wXtoM1Y + wXtoM2Y + wXtoM3Y + wXtoM4Y + wXtoY;
wtotInd = wXtoM1Y + wXtoM2Y + wXtoM3Y + wXtoM4Y;
! Differences in direct effects across groups
dXtoM1 = mXtoM1-wXtoM1; dXtoM2 = mXtoM2-wXtoM2;
dXtoM3 = mXtoM3-wXtoM3; dXtoM4 = mXtoM4-wXtoM4;
dM1toY = mM1toY-wM1toY; dM2toY = mM2toY-wM2toY;
dM3toY = mM3toY-wM3toY; dM4toY = mM4toY-wM4toY;
! Differences in indirect effects across groups

```

GROUPING defines groups for multiple-group model for MVN outcomes.

```

dXtoM1Y = mXtoM1Y-wXtoM1Y; dXtoM2Y = mXtoM2Y-wXtoM2Y;
dXtoM3Y = mXtoM3Y-wXtoM3Y; dXtoM4Y = mXtoM4Y-wXtoM4Y;
! Differences in total indirect+direct and total indirect effects across groups
dtotXtoY = mtotXtoY-wtotXtoY; dtotInd = mtotInd-wtotInd;

```

! Get all indirect and total effects between Y IND X

MODEL INDIRECT: ! Only available for MVN outcomes

Warmth IND MindC;

MODEL FIT INFORMATION

Number of Free Parameters 54
Loglikelihood

H0 Value -5332.207
H0 Scaling Correction Factor 1.0648
for MLR

H1 Value -5332.207
H1 Scaling Correction Factor 1.0648
for MLR

Information Criteria

Akaike (AIC) 10772.414
Bayesian (BIC) 11014.420
Sample-Size Adjusted BIC 10842.970
(n* = (n + 2) / 24)

Chi-Square Test of Model Fit

Value 0.000
Degrees of Freedom 0
P-Value 0.0000

Chi-Square Contribution From Each Group

MEN 0.000
WOMEN 0.000

Fit is perfect because the model is still just-identified (all model parameters are separately estimated across groups).

RMSEA (Root Mean Square Error Of Approximation)

Estimate 0.000
90 Percent C.I. 0.000 0.000
Probability RMSEA <= .05 0.000

CFI/TLI

CFI 1.000
TLI 1.000

Chi-Square Test of Model Fit for the Baseline Model

Value 399.257
Degrees of Freedom 30
P-Value 0.0000

SRMR (Standardized Root Mean Square Residual)

Value 0.000

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Group MEN				
WARMTH ON				
MINDC	0.213	0.364	0.585	0.558
INTERN	0.548	0.107	5.127	0.000
EXTERN	0.047	0.109	0.433	0.665
HOSTILE	-0.845	0.155	-5.454	0.000
BENEV	-0.158	0.168	-0.937	0.349
INTERN ON				
MINDC	0.633	0.199	3.179	0.001
EXTERN ON				
MINDC	0.273	0.166	1.648	0.099
HOSTILE ON				
MINDC	-0.171	0.126	-1.357	0.175
BENEV ON				
MINDC	-0.314	0.111	-2.829	0.005
INTERN WITH				
EXTERN	0.640	0.132	4.857	0.000
HOSTILE	-0.475	0.088	-5.406	0.000
BENEV	0.107	0.074	1.445	0.148
EXTERN WITH				
HOSTILE	0.058	0.077	0.750	0.453
BENEV	0.154	0.067	2.299	0.021
HOSTILE WITH				
BENEV	0.036	0.048	0.742	0.458
Means				
MINDC	0.817	0.026	31.181	0.000

Intercepts				
INTERN	4.391	0.185	23.735	0.000
EXTERN	3.871	0.158	24.499	0.000
HOSTILE	4.334	0.113	38.332	0.000
BENEV	4.460	0.093	48.212	0.000
WARMTH	6.814	1.258	5.418	0.000
Variances				
MINDC	0.187	0.019	10.023	0.000
Residual Variances				
INTERN	1.857	0.147	12.667	0.000
EXTERN	1.522	0.126	12.056	0.000
HOSTILE	0.784	0.076	10.385	0.000
BENEV	0.623	0.059	10.504	0.000
WARMTH	4.124	0.394	10.465	0.000

Group WOMEN

WARMTH ON				
MINDC	-0.126	0.254	-0.498	0.618
INTERN	0.449	0.105	4.264	0.000
EXTERN	0.084	0.099	0.841	0.401
HOSTILE	-0.535	0.161	-3.328	0.001
BENEV	-0.159	0.151	-1.054	0.292
INTERN ON				
MINDC	0.099	0.146	0.676	0.499
EXTERN ON				
MINDC	-0.117	0.133	-0.874	0.382
HOSTILE ON				
MINDC	-0.181	0.081	-2.250	0.024
BENEV ON				
MINDC	0.138	0.079	1.762	0.078
INTERN WITH				
EXTERN	0.556	0.085	6.556	0.000
HOSTILE	-0.184	0.047	-3.900	0.000
BENEV	-0.012	0.050	-0.233	0.816
EXTERN WITH				
HOSTILE	0.023	0.044	0.522	0.602
BENEV	0.157	0.052	3.000	0.003
HOSTILE WITH				
BENEV	0.118	0.032	3.656	0.000
Means				
MINDC	0.847	0.023	36.886	0.000
Intercepts				
INTERN	5.414	0.138	39.269	0.000
EXTERN	4.200	0.125	33.482	0.000
HOSTILE	3.853	0.077	50.063	0.000
BENEV	3.848	0.074	51.657	0.000
WARMTH	7.172	1.081	6.633	0.000
Variances				
MINDC	0.200	0.015	13.042	0.000
Residual Variances				
INTERN	1.473	0.089	16.634	0.000
EXTERN	1.433	0.105	13.603	0.000
HOSTILE	0.545	0.043	12.743	0.000
BENEV	0.583	0.046	12.659	0.000
WARMTH	4.230	0.303	13.972	0.000
New/Additional Parameters				
MX TOM1Y	0.347	0.126	2.750	0.006
MX TOM2Y	0.013	0.030	0.434	0.665
MX TOM3Y	0.145	0.111	1.300	0.194
MX TOM4Y	0.050	0.058	0.855	0.393
WX TOM1Y	0.044	0.066	0.671	0.502
WX TOM2Y	-0.010	0.015	-0.644	0.520
WX TOM3Y	0.097	0.053	1.846	0.065
WX TOM4Y	-0.022	0.024	-0.937	0.349
MT OTX TOY	0.768	0.402	1.910	0.056
MT OT IND	0.554	0.204	2.717	0.007
WT OTX TOY	-0.017	0.257	-0.066	0.948
WT OT IND	0.109	0.097	1.127	0.260
DX TOM1	0.535	0.247	2.166	0.030
DX TOM2	0.389	0.213	1.831	0.067
DX TOM3	0.010	0.150	0.066	0.948
DX TOM4	-0.452	0.136	-3.327	0.001
DM1 TOY	0.099	0.150	0.661	0.509
DM2 TOY	-0.036	0.148	-0.245	0.806
DM3 TOY	-0.310	0.223	-1.390	0.164
DM4 TOY	0.001	0.226	0.006	0.995

“Means” are for unpredicted variables in the likelihood, whereas “intercepts” are for predicted variables (conditional)

“Variances” are for unpredicted variables forced into the likelihood, whereas “residual variances” are for predicted variables (leftover outcomes)

Indirect effects by group

Total indirect+direct and total indirect effects by group

Differences in direct effects by group

DXTOM1Y	0.303	0.142	2.126	0.034
DXTOM2Y	0.023	0.033	0.678	0.498
DXTOM3Y	0.048	0.123	0.389	0.697
DXTOM4Y	0.072	0.063	1.144	0.253
DTOTXTOY	0.784	0.477	1.644	0.100
DTOTIND	0.445	0.226	1.969	0.049

Differences in indirect, total
indirect + direct, and total
indirect effects by group

New Syntax by Program for holding the XtoM1 path equal across genders—Model χ^2 then provides significance test of 1 new constraint (against null hypothesis of 0 difference across groups)

```
display "STATA Testing Equality of Direct effect XtoM1 by Holding it Equal by Sex with @a"
sem
    (intern extern hostile benev warmth <- _cons)
    (warmth <- mindc)
    (0: intern@a extern hostile benev <- mindc)
    (1: intern@a extern hostile benev <- mindc)
    (warmth <- intern extern hostile benev)

print("R Testing Equality of Direct effect XtoM1 by Holding it Equal by Sex")
# Create model syntax as separate text object
SyntaxMultipleXtoM1 = "
# Left side of model
    Intern ~ (XtoM1)*MindC
" # Now estimate model and get output
```

Single label is used instead of two labels—the rest
of syntax is as for previous multiple group model

Mplus New Syntax and Partial Output for XtoM1 path now equal across genders

MODEL:

```
    Intern ON MindC (XtoM1);
MODEL Women:
    Intern ON MindC (XtoM1);
```

```
MODEL FIT INFORMATION
Number of Free Parameters          53
Loglikelihood
    H0 Value                      -5334.764
    H0 Scaling Correction Factor   1.0641
    for MLR
    H1 Value                      -5332.207
    H1 Scaling Correction Factor   1.0648
    for MLR

Information Criteria
    Akaike (AIC)                  10775.527
    Bayesian (BIC)                11013.051
    Sample-Size Adjusted BIC      10844.776
    (n* = (n + 2) / 24)

Chi-Square Test of Model Fit
    Value                         4.626*
    Degrees of Freedom            1
    P-Value                       0.0315
    Scaling Correction Factor     1.1052
    for MLR

Chi-Square Contribution From Each Group
    MEN                           3.031
    WOMEN                         1.595
```

In the manuscript, indirect effects were tested individually by constraining both involved direct paths to be equal (misabeled in the manuscript as DF=1 when it should be DF=2), although this is a conservative approach (i.e., one could also make an argument for testing the difference in the indirect effect specifically). Given that there are infinitely many ways two different sets of direct effects could yield the same indirect effect, it seems testing the direct effects specifically would be more informative as to what extent the pattern implied by the indirect effect differs across groups.

For a sample results section, please see the manuscript.

The test of the model is actually the test of whether the XtoM1 direct path differs across groups (as was given by a Wald test instead in the previous model).