MLmed: An SPSS Macro for Multilevel Mediation and Conditional Process Analysis

Nicholas J. Rockwood & Andrew F. Hayes

The Ohio State University, Department of Psychology

rockwood.19@osu.edu   hayes.338@osu.edu

Abstract

MLmed is a computational macro for SPSS that simplifies the fitting of multilevel mediation and moderated mediation models, including models containing more than one mediator. After the model specification, the macro automatically performs all of the tedious data management necessary prior to fitting the model. This includes within-group centering of lower-level predictor variables, creating new variables containing the group means of lower-level predictor variables, and stacking the data as outlined in Bauer, Preacher, and Gil (2006) and their supplementary material to allow for the simultaneous estimation of all parameters in the model.

The output is conveniently separated by equation, which includes a further separation of between-group and within-group effects. Further, indirect effects, including Monte Carlo confidence intervals around these effects, are automatically provided. The index of moderated mediation (Hayes, 2015) is also provided for models involving level-2 moderators of the indirect effect(s).

Scope of MLmed

In its current form, MLmed can accommodate up to three continuous, parallel mediators and one continuous dependent variable. Up to three level-1 and three level-2 covariates can be included. Finally, one level-2 moderator of the a path ($X \rightarrow M$) and one level-2 moderator of the b path ($M \rightarrow Y$) can be included. The same variable may moderate both paths. In models containing more than one mediator, only the a and b paths for the first mediator may be moderated. Further, the direct effect for any model cannot be moderated. For those familiar with PROCESS (Hayes, 2013), MLmed can handle multilevel models similar to Models 4, 7, 14, 21, and 58. A special multilevel type of Model 74 can also be fit.

Within-group and between-group indirect effects can be estimated when X, M, and Y all have variability at the within-group and between-group levels. MLmed estimates within-group effects by within-group centering variables prior to the analysis, and between-group effects are estimated using group means. The details of this approach can be found in Zhang, Zyphur, and Preacher (2009).

In connection to the multilevel mediation literature, MLmed can handle 1-1-1 and 2-1-1 data designs, where the three numbers refer to the lowest level in which X, M, and Y vary.

Basic Model

The lower level equations for the 1-1-1 multilevel mediation model using within-group centering are:

$$M_{ij} = d_{Mj} + a_j(X_{ij} - \overline{X}_{.j}) + e_{ij}$$

$$Y_{ij} = d_{Yj} + c'_j(X_{ij} - \overline{X}_{.j}) + b_j(M_{ij} - \overline{M}_{.j}) + e_{ij}$$

where $\overline{X}_{.j}$ and $\overline{M}_{.j}$ represent the observed group means of X and M, respectively. The upper level equations are:

$$d_{Mj} = d_M + a_B\overline{X}_{.j} + u_{Mj}$$

$$d_{Yj} = d_Y + c'_B\overline{X}_{.j} + b_B\overline{M}_{.j} + u_{Yj}$$

$$a_j = a_W + u_{aj}$$

$$b_j = b_W + u_{bj}$$

$$c'_j = c'_W + u_{c'j}$$

which disentangles the within-group effects from the between-group effects, denoted with the subscripts W and B, respectively.

The average within-group indirect effect is (Kenny, Korchmaros, & Bolger, 2003; Bauer et al., 2006):

$$E(a_jb_j) = ab + \sigma_{a_j,b_j}$$

where σ_{a_j,b_j} is the covariance between a_j and b_j. The between-group indirect effect is (Tofighi, West, & MacKinnon, 2013):

$$E(a_Bb_B) = a_Bb_B$$

Multiple Mediators

The lower level equations for a 1-1-1 parallel mediation model with k mediators is:

$$M_{pij} = d_{Mpj} + a_{pj}(X_{ij} - \overline{X}_{.j}) + e_{ij}$$

for $p = 1, ..., k$.

$$Y_{ij} = d_{Yj} + c'_j(X_{ij} - \overline{X}_{.j}) + \sum_{p=1}^{k} b_{pj}(M_{pij} - \overline{M}_{p.j}) + e_{ij}$$

The upper level equations, with no level-2 predictors except observed group means are:

$$d_{Mpj} = d_{Mp} + a_{Bp}\overline{X}_{.j} + u_{Mpj}$$

for $p = 1, ..., k$.

$$d_{Yj} = d_Y + c'_B\overline{X}_{.j} + \sum_{p=1}^{k} b_{Bp}\overline{M}_{p.j} + u_{Yj}$$

$$a_{pj} = a_{Wp} + u_{apj}$$

$$b_{pj} = b_{Wp} + u_{bpj}$$

$$c'_j = c'_W + u_{c'j}$$

for $p = 1, ..., k$. With k mediators, there are k specific within-group and between-group indirect effects.

The average specific within-group indirect effect that quantifies the within-group indirect effect of X on Y through M_h is:

$$E(a_{Wh}b_{Wh}) = a_{Wh}b_{Wh} + \sigma_{a_{hj},b_{hj}} \tag{1}$$

and the corresponding specific between-group indirect effect is:

$$E(a_{Bh}b_{Bh}) = a_{Bh}b_{Bh} \tag{2}$$

Moderated Mediation

A level-2 variable can moderate both the within-group and between-group indirect effect. For example, consider a level-2 moderator, Q, of the b path. The equations from the basic model remain the same with the exception that:

$$b_j = b_W + g_{b1}Q_j + u_{bj}$$

$$d_{Yj} = d_Y + c'_B\overline{X}_{.j} + b_B\overline{M}_{.j} + g_{Y3}Q_j + g_{Y4}\overline{M}_{.j}Q_j + u_{Yj}$$

The within-group effect of X_{ij} on M_{ij} is $a_j = a_W + u_{aj}$, and the within-group effect of M_{ij} on Y_{ij} controlling for X_{ij} is $b_j = b_W + g_{b1}Q_j + u_{bj}$, so the average within-group indirect effect of X_{ij} on Y_{ij} is:

$$E(a_jb_j) = a_Wb_W + a_Wg_{b1}Q_j + \sigma_{a_j,b_j} \tag{3}$$

where σ_{a_j,b_j} is the residual covariance between a_j and b_j after removing the variance explained by Q_j.

The *within-group index of moderated mediation* is a_Wg_{b1}, as this determines how the indirect effect changes systematically as a function of Q_j.

The between-group effect of M_{ij} on Y_{ij} is $b_B + g_{Y4}Q_j$, so the between-group indirect effect of X_{ij} on Y_{ij} is $a_B(b_B + g_{Y4}Q_j) = a_Bb_B + a_Bg_{Y4}Q_j$ and the *between-group index of moderated mediation* is a_Bg_{Y4}.

Syntax

Basic Model

```
MLmed data = DataSet1
  /x = Xvar
  /m1 = Mvar
  /y = Yvar
  /cluster = group
  /folder = FilePath.
```

Examples

Random Slopes

```
MLmed data = DataSet1
  /x = Xvar
  /randx = 11 random X → Y and X → M1
  /m1 = Mvar
  /randm = 1 random M1 → Y
  /y = Yvar
  /covmat = UN estimate slope covariances
  /cluster = group
  /folder = /Users/username/Desktop/.
```

Parallel Mediators with Covariates

```
MLmed data = DataSet1
  /x = Xvar
  /randx = 010 random X → M1
  /cov1 = Covvar level-1 covariate
  /L2cov1 = L2Covvar level-2 covariate
  /m1 = Mvar1
  /m2 = Mvar2
  /randm = 10 random M1 → Y
  /mcovmat = UN covariance between M1, M2
  intercepts
  /y = Yvar
  /cluster = group
  /folder = C:\Users\username\Desktop\.
```

Moderated Mediation

```
MLmed data = DataSet1
  /x = Xvar
  /randx = 01 random X → M1
  /m1 = Mvar
  /modM = Modvar L2 moderator of X → M1
  /modMB = 0 Omit between-group moderation
  /modMcent = 2.3 Center Modvar around
  2.3
  /y = Yvar
  /cluster = group
  /folder = /Users/username/Desktop/.
```

2-1-1 Design

```
MLmed data = DataSet1
  /x = Xvar
  /xW = 0 Omit within-group effects of X
  /m1 = Mvar
  /y = Yvar
  /cluster = group
  /folder = /Users/username/Desktop/.
```

1-1-1 Design with No Between Effects

```
MLmed data = DataSet1
  /x = Xvar
  /xB = 0 Omit between-group effects of X
  /m1 = Mvar
  /mB = 0 Omit between-group effect of M
  /y = Yvar
  /cluster = group
  /folder = /Users/username/Desktop/.
```

Example Output*

```
**************************  FIXED EFFECTS  **************************

*********************************************************************
 Outcome: Mvar

Within- Effects
         Estimate     S.E.        df         t         p        LL        UL
constant  33.9232    .8899   43.6966   38.1217     .0000   32.1295   35.7170
Xvar       5.3563    .9906   47.7240    5.4072     .0000    3.3643    7.3483

Between- Effects
     Estimate     S.E.        df         t         p        LL        UL
Xvar   -.9908   8.0188   48.1332    -.1236     .9022  -17.1125   15.1308

*********************************************************************
 Outcome: Yvar

Within- Effects
         Estimate     S.E.        df         t         p        LL        UL
constant   5.3067   2.6001   45.1210    2.0409     .0471     .0702   10.5432
int_1      -.0148    .0057   41.2561   -2.5725     .0138    -.0264    -.0032
Xvar       -.0718    .3079  399.0726    -.2330     .8158    -.6772     .5336
Mvar        .3228    .0763   41.9474    4.2320     .0001     .1689     .4767

Between- Effects
       Estimate     S.E.        df         t         p        LL        UL
Modvar   -.1081    .0707   45.0212   -1.5294     .1332    -.2504     .0343
Xvar    -3.2389   3.7562   47.2601    -.8623     .3929  -10.7942    4.3165
Mvar      .0619    .0682   45.8908     .9083     .3685    -.0753     .1992

Interaction Codes
int_1 Within-  Modvar      x     Mvar        ->    Yvar

*********************************************************************

*************************  RANDOM EFFECTS  **************************

Level-1 Residual Estimates
     Estimate     S.E.   Wald Z        p        LL        UL
Yvar   7.8171    .5835  13.3980    .0000    6.7532    9.0485
Mvar  47.4493   3.5379  13.4117    .0000   40.9980   54.9158

Random Effect Estimates
      Estimate     S.E.   Wald Z        p        LL        UL
(1,1)  32.1432   8.0982   3.9692    .0001   19.6172   52.6673
(2,2)   7.2619   1.7480   4.1543    .0000    4.5306   11.6398
(3,3)  23.5030   8.9862   2.6154    .0089   11.1089   49.7250
(4,3)    .1545    .1951    .7918    .4285    -.2279     .5370
(4,4)    .0248    .0098   2.5257    .0115     .0114     .0539

Random Effect Key
1    Int        Mvar
2    Int        Yvar
3    Slope      Xvar          ->      Mvar
4    Slope      Mvar          ->      Yvar

*********************************************************************

******************  INDEX OF MODERATED MEDIATION  *******************

Within- Index of Moderated Mediation
            Est      MCLL     MCUL
Modvar   -.0791   -.1531   -.0184

*********************************************************************

**********************  INDIRECT EFFECT(S)  *************************

NOTE: First Within- Indirect Effect is Conditional on a Moderator Value of:
          value
Modvar  10.0000

Within- Indirect Effect(s)
        E(ab)  Var(ab)   SD(ab)
Mvar   1.8835   4.3029   2.0743

Within- Indirect Effect(s)
       Effect       SE         Z        p      MCLL      MCUL
Mvar   1.8835    .5673    3.3204    .0009     .8528    3.0982

Between- Indirect Effect(s)
       Effect       SE         Z        p      MCLL      MCUL
Mvar   -.0614    .7419    -.0827    .9341   -1.7720    1.5077
```

*Some sections of output were removed due to space constraints.

References

Bauer, D. J., Preacher, K. J., & Gil, K. M. (2006). Conceptualizing and testing random indirect effects and moderated mediation in multilevel models: new procedures and recommendations. *Psychological Methods*, *11*(2), 142–163.

Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford Press.

Hayes, A. F. (2015). An index and test of linear moderated mediation. *Multivariate Behavioral Research*, *50*(1), 1–22.

Kenny, D. A., Korchmaros, J. D., & Bolger, N. (2003). Lower level mediation in multilevel models. *Psychological Methods*, *8*(2), 115–128.

Tofighi, D., West, S. G., & MacKinnon, D. P. (2013). Multilevel mediation analysis: The effects of omitted variables in the 1–1–1 model. *British Journal of Mathematical and Statistical Psychology*, *66*(2), 290–307.

Zhang, Z., Zyphur, M. J., & Preacher, K. J. (2009). Testing multilevel mediation using hierarchical linear models problems and solutions. *Organizational Research Methods*, *12*(4), 695–719.

To download MLmed and its user guide, please visit njrockwood.com/mlmed or scan this QR code.