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 effects.

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 path (X → M1) and one level-2 moderator of the path (M2 → Y) can be included. The same variable may moderate both paths. In models containing more than one mediator, only the ω and φ 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.

Basic Model

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

\[ M_{ij} = d_{ij} + a_{ij}X_{ij} + \epsilon_{ij} \]

\[ Y_{ij} = d_{ij} + a_{ij}X_{ij} + b_{ij}(M_{ij} - \overline{M}_j) + \epsilon_{ij} \]

where \( \overline{M}_j \) and \( \overline{Y}_j \) represent the observed group means of \( X \) and \( M \), respectively. The upper level equations are:

\[ d_{ij} = d_{j} + a_{j}X_{ij} + \epsilon_{ij} \]

\[ d_{j} = d_{j} + a_{j}X_{j} + b_{j}(M_{j} - \overline{M}_j) + \epsilon_{j} \]

\[ a_{j} = a_{j} + a_{j}X_{j} + \epsilon_{j} \]

\[ b_{j} = b_{j} + b_{j}M_{j} + \epsilon_{j} \]

\[ c_{ij} = c_{ij} + c_{ij}X_{ij} + \epsilon_{ij} \]

\[ c_{j} = c_{j} + c_{j}X_{j} + b_{j}(M_{j} - \overline{M}_j) + \epsilon_{j} \]

for \( p = 1, \ldots, k \). With \( k \) mediators, there are 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 \( M_j \) is:

\[ E(a_{j}b_{j}X_{j}) = a_{j}b_{j} + \sigma_{a_{j}b_{j}} \]

and the corresponding specific between-group indirect effect is:

\[ E(a_{j}b_{j}M_{j}) = a_{j}b_{j} + \sigma_{a_{j}b_{j}} \]

Examples

Random Slopes

```
Example Data: Dataset1
X = Xvar
X1 = 01 random X \( \rightarrow \) M1
X2 = 01 random X \( \rightarrow \) M2
X3 = 01 random X \( \rightarrow \) M3

Y = Yvar
Y1 = 01 random Y \( \rightarrow \) X1
Y2 = 01 random Y \( \rightarrow \) X2
Y3 = 01 random Y \( \rightarrow \) X3

Control = 0 Sum estimate slope covariances
Cluster = group
```

Parallel Mediators with Covariates

```
Example Data: Dataset2
X = Xvar
X1 = 01 random X \( \rightarrow \) M1
X2 = 01 random X \( \rightarrow \) M2
X3 = 01 random X \( \rightarrow \) M3

Y = Yvar
Y1 = 01 random Y \( \rightarrow \) M1
Y2 = 01 random Y \( \rightarrow \) M2
Y3 = 01 random Y \( \rightarrow \) M3

Cluster = group
```

Moderated Mediation

```
Example Data: Dataset3
X = Xvar
X1 = 01 random X \( \rightarrow \) M1
X2 = 01 random X \( \rightarrow \) M2
X3 = 01 random X \( \rightarrow \) M3

Y = Yvar
Y1 = 01 random Y \( \rightarrow \) M1
Y2 = 01 random Y \( \rightarrow \) M2
Y3 = 01 random Y \( \rightarrow \) M3

Cluster = group
```

References


Syntax

```
MLmed data = Dataset1
Y = Yvar
Y1 = Y \( \rightarrow \) M1
Y2 = Y \( \rightarrow \) M2
Y3 = Y \( \rightarrow \) M3
Cluster = group
```

```
MLmed data = Dataset2
Y = Yvar
Y1 = Y \( \rightarrow \) M1
Y2 = Y \( \rightarrow \) M2
Y3 = Y \( \rightarrow \) M3
Cluster = group
```

```
MLmed data = Dataset3
Y = Yvar
Y1 = Y \( \rightarrow \) M1
Y2 = Y \( \rightarrow \) M2
Y3 = Y \( \rightarrow \) M3
Cluster = group
```

Example Output:

```
*********** MODERATED MEDIATION ***********

The within-group effect of X on M1 is a1 = a1 + \epsilon1, and the within-group effect of M1 on Y1 controlling for X is b1 = b1 + \epsilon1. For the average within-group indirect effect of X on Y1, we have:

E(a1b1X1) = a1b1 + \sigma_{a1b1}

The within-group index of moderated mediation is E(a1b1X1) = a1b1 + \sigma_{a1b1}, as this determines how the indirect effect changes systematically as a function of Q1.

```

```
2-1 Design

Example Data: Dataset4
X = Xvar
X1 = 01 random X \( \rightarrow \) M1
X2 = 01 random X \( \rightarrow \) M2
X3 = 01 random X \( \rightarrow \) M3

Y = Yvar
Y1 = Y \( \rightarrow \) X1
Y2 = Y \( \rightarrow \) X2
Y3 = Y \( \rightarrow \) X3

Cluster = group
```

```
1-1 Design with No Between Effects

Example Data: Dataset5
X = Xvar
X1 = 01 random X \( \rightarrow \) M1
X2 = 01 random X \( \rightarrow \) M2
X3 = 01 random X \( \rightarrow \) M3

Y = Yvar
Y1 = Y \( \rightarrow \) X1
Y2 = Y \( \rightarrow \) X2
Y3 = Y \( \rightarrow \) X3

Cluster = group
```

```
To download MLmed and its user guide, please visit rockwood.19@osu.edu
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or scan this QR code.
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