MLMED

User Guide

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`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).

Contents

1 Scope of MLmed

Currently, `MLmed` is fairly limited in terms of available models relative to other macros available for mediation, moderation, and conditional process models, such as PROCESS (Hayes, 2013). `MLmed` is, in fact, a work in progress that will be expanded upon as time permits. Generally, these expansions will be made following research and user recommendations.

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.

2 System Requirements

`MLmed` is compatible with Windows and Mac Operating Systems for SPSS Version 21 and higher. For the most user-friendly output, it is recommended that SPSS Version 22 or higher is used.

2.1 Note for using SPSS Version 21

`MLmed` contains syntax to remove unnecessary additional output provided by the use of the MIXED function in SPSS. However, this syntax is not recognized by SPSS versions older than Version 22. As a result, the additional output will not be removed and the output will also contain the following error code in numerous places:

```
>Error # 1.  Command name:  OUTPUT
>The first word in the line is not recognized as an SPSS
Statistics command.
>Execution of this command stops.
```

This error is simply due to attempts to modify the output *display*, and is not an indication of error in the output *content*. Consequently, users should ignore the warnings and additional output that is presented and instead focus on the output discussed in this manual and subsequent publications and tutorials.

2.2 Output Language

Unfortunately, the use of `MLmed` when the SPSS *Output Language* is specified as anything other than English will result in errors. The output language can be changed to English using the Output Language drop-down menu under the *Language* header found through *Edit* → *Options...*.

3 Preparation for Use

Before using `MLmed`, the syntax file containing the code necessary to define the macro (*MLmed.sps*), must be opened and executed without modification. The file can then be closed, and `MLmed` can be operated using a new syntax file. Note that the macro will remain active only for the duration of the SPSS session (i.e., until SPSS is closed). The macro will need to be re-executed at the start of a new session.

4 Model Syntax

Once the macro is activated, it can be called by typing `MLmed` followed by the appropriate macro arguments. Each argument, except the first, should begin with a forward slash, and the final argument should be followed by a period. The minimum syntax necessary to run the most basic model is:

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

where the italicized words are replaced with the correct dataset name, variable names, and file location. The dataset name should be the name that appears in brackets on the opened dataset window, rather then the saved *.sav* file name. By default, the first dataset opened in a new SPSS session is named *DataSet1* and `MLmed` defaults to this name. To be safe, specify the correct dataset name, even if it is the default. The **`x`**, **`m1`**, and **`y`** arguments should be the names of the variables in the dataset corresponding to X, M, and Y. The **`cluster`** argument should be a variable that labels which level-2 unit each row in the dataset belongs to. Finally, the **`folder`** argument should be a file path on the user's computer. This does not have to be the location of the dataset, syntax file, or any other specific file, but must be a correct folder location on the computer. Note that file paths on a Windows OS will use a backslash between folders, while a Mac OS will use a forward slash (see Section 5 for examples). The macro arguments do not have to be in any specific order, other than the **`folder`** specification being last.

This minimum syntax will fit a model where ***`Xvar`*** is the independent variable, ***`Mvar`*** is the mediator, and ***`Yvar`*** is the dependent variable. The macro automatically group-mean centers X and uses the group means as a level-2 predictor of M. Further, group-mean centered X and M are used as level-1 predictors of Y and the group means of X and M are used as level-2 predictors. All intercept terms are random. By default, all slope terms (described in this section and later sections) are fixed and the random effect covariance matrix is diagonal, where variances are freely estimated and covariances are constrained to zero. These defaults are useful for increasing the likelihood of convergence. Macro arguments that can change these specifications are described in a later section.

4.1 Adding Fixed Effects

The basic syntax can be expanded to fit models that include additional fixed effects that result from adding mediators, covariates, and moderators.

4.1.1 Mediators

Up to two additional mediators can be specified by including the arguments **`m2`** and **`m3`** with the variable name following. Each mediator included will be group-mean centered prior to the analysis. The group means will also be included as predictors to estimate between-group effects.

4.1.2 Level-1 Covariates

Up to three level-1 covariates can be included by using the **`cov1`**, **`cov2`**, and **`cov3`** arguments, with the appropriate variable names following. As with other level-1 variables, the covariates are automatically group mean centered to disentangle between-group and within-group effects.

4.1.3 Level-2 Covariates

Up to three level-2 covariates can be included by using the **`L2cov1`**, **`L2cov2`**, and **`L2cov3`** arguments, with the name of the covariates following. The user should manually center level-2 covariates prior to using `MLmed` if desired.

4.1.4 Level-2 Moderators

One level-2 moderator can be specified for the a path, and one level-2 moderator can be specified for the b path. These are specified using the **`modM`** and **`modY`** arguments, respectively, where the letters **`M`** and **`Y`** correspond to the dependent variable for the equation in which the moderator is included in. The user should NOT include the level-2 moderator as a level-2 covariate, as `MLmed` will do this automatically. It should also be noted that the variable is included as a moderator only for the first mediator listed (the one specified by **`m1`**).

By default, the moderation of both the between-group and within-group effects are tested for each moderator included. The same moderator can be specified for both paths to allow for the testing of a quadratic moderation effect. The user can also specify a specific value to center each moderator around using the **`modMcent`** and **`modYcent`** arguments, respectively. Any effect that is moderated will be conditional on the value in which the moderator is centered around (by default, the value is 0).

4.2 Removing Fixed Effects

Some of the effects automatically included by `MLmed` may be omitted from the model. These include a number of between-group effects, and also the within-group effect of X.

4.2.1 Between-group Effects

The general format for removing a between group effect is by listing the argument to specify the original variable followed by a **`B`** and setting this new argument equal to zero. That is, it can be thought of as specifying that between-group effect to be omitted. For example, removing the between-group effect of **`x`** can be specified using the argument **`xB = 0`**. The between-group effect of **`cov1`** can be omitted using **`cov1B = 0`**. Similarly, the between-effects of the M and/or Y moderators can be specified using **`modMB = 0`** and **`ModYB = 0`**, respectively.

There is, however, a slight deviation from this format for removing the between-group effect(s) of the mediator(s). Rather than the between-group effect of each mediator being specified with its own argument, the between-group effect of all mediators can be specified using **`mB`**, which should be a list of zeros and ones equal in length to the number of mediators where a 1 denotes that the between-group effect of that particular mediator should be estimated and a 0 denotes it should be omitted. For example, a model including three mediators where the between-group effect of mediators 1 and 3 on Y is estimated, but the effect of mediator 2 on Y is omitted can be specified using **`mB = 101`**.

There are two main reasons one may wish to omit a between-group effect. The first occurs if there is no actual between-group variability on a given variable. In this scenario, the group-mean for the variable will be the same for each group, making the vector of group means redundant. Consequently, the model cannot be estimated without this effect omitted. The second reason is simply for parsimony, as the removal of the effect can simplify the model. This is particularly true with the removal of the between-group moderator, given that including the moderator makes the indirect effect conditional. It should be noted that if the between-group effect of X or one of the mediators is not estimated, the between-group indirect effect involving that parameter is also not calculated.

4.2.2 Within-group Effect of X

The within-group effect of X can also be omitted using the argument **`xW = 0`**. Of course, no within-group indirect effects will then be estimated. The ability to omit the within-group effect of X expands `MLmed` to be able to estimate 2-1-1 multilevel mediation models, as the 2-1-1 model can be seen as a special case of the 1-1-1 model with no within-group variability on X.

4.3 Specifying Random Effects

Any intercept and/or within-group slope included in the model can be specified as randomly varying across groups.

4.3.1 Random Intercepts

By default, all intercepts included in the model are specified as random. Because nonconvergence may be an issue if the variance of a random effect nears zero, the user can specify any intercept as fixed. For the Y intercept, this is accomplished using **`randYint = 0`**, indicating that a random term for the Y intercept should be omitted. For M, the argument to omit a random intercept is **`randMint`**, though the exact specification depends on the number of mediators in the model. A list of zeros and ones that is the length of the number of mediators should be included, where a zero omits the random effect and a one estimates it. For example, **`randMint = 011`** should be specified to omit the random intercept for the first mediator in a three mediator model.

4.3.2 Random Slopes

Random slopes can be specified using similar syntax as random intercepts. To specify the effect of X to be random, the argument **`randx`** is used, which should be a list of binaries of length $k+1$ where k is the number of mediators in the model. The first binary refers to the effect of X on Y (the c' path), the second refers to the effect of X on M_1, the third refers to the effect of X on M_2, and so forth. A 1 corresponds to a random effect, while a 0 corresponds to a fixed effect. Random effects of the mediator(s) on Y are specified using **`randm`** which should be a list of binaries of length k, where the first refers to the effect of the first mediator on Y, the second refers to the effect of the second mediator on Y and so forth. Random effects of level-1 covariates are specified using **`randc1`**, **`randc2`**, and **`randc3`**. The format of these arguments follow that of **`randx`**.

4.4 Covariance Matrices

The residual covariance matrix and the covariance matrix of the random effects can be modified.

4.4.1 Residual Covariance Matrix

The residual covaraince matrix is specified as diagonal (**`DIAG`**) by default, where the residual variance of each equation is freely estimated and the covariance between the residuals of each equation are constrained to zero. The residual covariance matrix can be specified as unconstrained (where all variances and covariances are freely estimated) using the argument **`rescovmat = UN`**.

4.4.2 Random Effect Covariance Matrix

By default, the random effect covariance matrix is specified as diagonal, where all variances are freely estimated and the covariances are constrained to zero. However, some or all of the random effects can be permitted to covary. If there is more than one random slope, their covaraince(s) can be freely estimated by including the command **`covmat = UN`**. To estimated the covariance between random slopes and the Y intercept, the command **`ycov = 1`** can be included (if **`covmat = UN`**). If more than one mediator is in the model, the covariance between the random intercepts for the mediators can be estimated using **`mcovmat = UN`**. The covariance between the M and Y intercepts can be included in the model using **`indint = 0`**. If there are random slopes in the model, **`covmat = UN`**, **`ycov = 1`**, and **`indint = 0`**, then the whole random effect covariance matrix is unstructured, where all variances and covariances are freely estimated.

4.5 Estimation

The default estimator for `MLmed` is Restricted Maximum Likelihood (**`REML`**). Users may instead estimate the model using Full Maximum Likelihood by including the argument **`est = ML`**. The user may also provide a number of specifications that influence the estimation. These specifications include **`iters`** (maximum number of iterations), **`mxstep`** (maximum step-halving), and **`scoring`** (number of iterations in which the Fisher scoring algorithm is used). Further details of these can be found in the SPSS users manual under the section for MIXED.

4.6 Other Specifications

The user may specify the confidence level used for inferences provided in the output using the **`conf`** argument, which should include a number between 0 and 100 which corresponds to the percentage of confidence. By default, this value is 95. The number of Monte Carlo samples used can be changed using **`samples`**, which defaults to 10,000. Lastly, when the model fails to converge the estimates of the parameters is omitted from the output. The user may override this by specifying **`eor = 1`**, which is short for Error Override. This command can be useful for assessing issues in convergence by identifying which parameters may be causing the difficulties.

5 Example Syntax

This section contains example models to demonstrate the use of some the syntax arguments described previously. The models presented here are not exhaustive. The arguments from each of the following example models can be mixed and matched to correspond to the user's desired model.

5.1 Random Slopes

```
MLmed data = DataSet1
   /x = Xvar
   /randx = 11
   /m1 = Mvar
   /randm = 1
   /y = Yvar
   /covmat = UN
   /cluster = group
   /folder = /Users/username/Desktop/.
```

Here, **randx = 11** specifies that the within-group effects of X on Y and M randomly vary across upper-level units. The **randm = 1** specifies that the within-group effect of M on Y is also random. The covariance between these random slopes is estimated using **covmat = UN**. Finally, the **folder** argument is an example of a correct folder on a Mac.

5.2 Parallel Mediators with Covariates

```
MLmed data = DataSet1
   /x = Xvar
   /randx = 010
   /cov1 = Covvar
   /L2cov1 = L2Covvar
   /m1 = Mvar1
   /m2 = Mvar2
   /randm = 10
   /mcovmat = UN
   /y = Yvar
```

```
    /cluster = group
    /folder = C:\Users\rockwood.19\Desktop\.
```

This model is a parallel mediator model with mediators ***Mvar1*** and ***Mvar2***, level-1 covariate ***Covvar***, and level-2 covariate ***L2Covvar***. The within-group effects of X on Y, M_1, and M_2 are fixed, random, and fixed, respectively, as defined by **randx = 010**. Further, the within-group effect of M_1 on Y is random, while the within-group effect of M_2 on Y is fixed, as specified by **randm = 10**. Estimation of the covariance between the random intercepts for the M_1 and M_2 equations is requested using **mcovmat = UN**.

5.3 Moderated Mediation

```
MLmed data = DataSet1
    /x = Xvar
    /randx = 01
    /m1 = Mvar
    /modM = Modvar
    /modMB = 0
    /modMcent = 2.3
    /y = Yvar
    /cluster = group
    /folder = /Users/username/Desktop/.
```

This is a moderated mediation model in which the a path is moderated by ***Modvar***. By default, the moderation of both the within-group and between-group effects is estimated. However, the inclusion of **modMB = 0** omits the between-group moderation. The moderator is also centered around 2.3 prior to the analysis using **modMcent = 2.3**. The residual variance of the within-group a path is estimated using **randx = 01**. That is, the within-group effect of X on M randomly varies after controlling for ***Modvar***.

5.4 2-1-1 Design

```
MLmed data = DataSet1
   /x = Xvar
   /xW = 0
   /m1 = Mvar
   /y = Yvar
   /cluster = group
   /folder = /Users/username/Desktop/.
```

This is a standard 2-1-1 design with only random intercepts. It follows the same sytnax as the basic 1-1-1 design with the exception that the argument **`xW = 0`** is included to omit the estimation of the within-group effect of X which, by definition, does not exist (since X has no within-group variability).

5.5 1-1-1 Design with No Between Effects

```
MLmed data = DataSet1
   /x = Xvar
   /xB = 0
   /m1 = Mvar
   /mB = 0
   /y = Yvar
   /cluster = group
   /folder = /Users/username/Desktop/.
```

This is the standard 1-1-1 design without the estimation of between-group effects. The between-group effects of X are omitted using **`xB = 0`**, and the between-group effect of M is omitted using **`mB = 0`**. Note that X and M are still within-group centered prior to the analysis.

6 Output

The `MLmed` macro provides a very detailed output including individual parameter estimates, and the estimated indirect effects. In addition, the index of moderated mediation is included if a moderator is specified. This section provides an overview on each of the output tables provided.

6.1 Errors

If there are any errors when estimating the model, the estimated parameters are disabled from the output (unless this is overridden). Instead, the user is provided with the number of fixed effect and random effect parameters that could not be estimated, as well as a code labeling the specific parameters, where a 1 indicates the parameter could not be estimated. The user can use this information to respecify the model.

6.2 Model Fit Statistics

If the model converges, various statistics are provided, such as the sample size and number of model parameters, as well as several model fit statistics, including -2 times the Log Likelihood (-2LL), Akaike's Information Criterion (AIC), Hurvich and Tsai's Criterion (AICC), Bozdogan's Criterion (CAIC), and Schwarz's Bayesian Criterion (BIC). The fit statistics can be useful when comparing models.

6.3 Fixed Effects

After the model fit statistics, the fixed effect estimates are provided. These estimates are grouped by each outcome variable, starting with the mediator(s) and ending with Y. Within each section containing each outcome variable, the effects are broken up by within-group and between-group effects. If no covariates are included in the model and the between-group effect of X is disabled, there will not be any between-group effects in each of the mediators' sections. If any moderators are included, the interaction terms are labeled using `int`, and the *Interaction Codes* section contains information on what each interaction term represents.

6.4 Random Effects

If the level-1 residual covariance matrix is specified as diagonal, the estimates are displayed in the *Level-1 Residual Estimates* section. If the matrix is specified as unstructured, the effects are labeled with a number system where the effect is a variance parameter if the two numbers in parentheses are the same, and a covariance parameter if the two numbers differ. The numbers correspond to the key provided below the table.

If the random effect covariance matrix is specified as diagonal (the default), the *Random Effects* section of the output will contain the estimated variance of each random effect, as well as the relevant test statistics for that effect. If the covariance matrix is specified as unstructured, the *Random Effect Estimates* table will contained each estimated variance and covariance parameter, as well as the relevant test statistics for each of these parameters. These effects use the same number system as the *Level-1 Residual Estimates* section. A table containing the number key for each effect is also included. Finally, the estimated covariance and correlation matrices are provided.

6.5 Index of Moderated Mediation

If any moderators are included in the model, an *Index of Moderated Mediation* section follows the *Random Effects* section. This section includes the index of moderated mediation for each interaction term as well as a Monte Carlo confidence interval. If the same variable is specified as a moderator for both a and b, the linear and quadratic terms are included. Further, this section is broken up by within-group and between-group effects.

6.6 Indirect Effect(s)

The final section included in the output contains the indirect effect(s). If there are any moderators in the model, a code is provided which states what value of the moderator(s) the indirect effect(s) are conditional on. These are the values specified using **`modMcent`** and **`modYcent`**, which default to **`0`**. If no moderators are specified, the indirect effects are unconditional. The first *Within- Indirect Effect(s)* section displays the estimated average within-group indirect effect(s), as well as the estimated variability of indirect effects across level-2 units. If neither a nor b are random, the variance of the indirect effect is 0. The next *Within- Indirect Effect(s)* section contains a normal-theory test on the average within-group indirect effect(s). A Monte Carlo confidence interval is also provided. Finally, the *Between-Indirect Effect(s)* section contains the normal-theory test and Monte Carlo confidence interval for the between-group indirect effect(s). If **`xB = 0`**, this section is omitted.

If multiple mediators are specified, a section containing indirect effect contrasts follows. Every pairwise combination of indirect effects is tested using a Monte Carlo confidence interval. This section is broken up by within-group and between-group effects.

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.

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