%MEMORE

Syntax Structure

```
%MEMORE (data=filename, Y = depA depB
        [,M = med1A med1B [med2A med2B...]]
        [,W = mod1 [mod2...]]
        [,MODEL = {mod}{1**}]
        [,MC = {mc}{0**}]
        [,BC = {bc}(0**)]
        [,NORMAL = {n}(0**)]
        [,CONF = {c}{95**}]
        [,SAMPLES = {sm}(5000**)]
        [,CONTRAST = {cn}(0**)]
        [,SAVE = filename]
        [,SEED = {sd}{0**}]
        [,SERIAL = {s}{0**}]
        [,XMINT = {xm}{1**}]
        [,DECIMALS = {dc}{10.4**}]
        [,JN = {jn}{0**}]
        [,QUANTILE = {q}{0**}]
        [,PLOT = {p}{0**}]
        [,CENTER = {ce}{0**}
        [,WMODVAL1 = {mm1}]
        [,WMODVAL2 = {mm2}]
        [,WMODVAL3 = {mm3}]);
```

Subcommands in brackets are optional
M subcommand is required for Model 1 (default) and 4 - 18
W subcommand is required for Models 2 - 18
** Default if subcommand is omitted

Overview

MEMORE (pronounced like "memory") is a macro for estimating mediation, moderation, and moderated mediation models in two-condition repeated measures designs. For all models in MEMOE the focal independent variable (X) is the repeated-measures factor.

Model 1 estimates the total, direct, and indirect effects of X on Y through one or more mediators M in the two- condition or two-occasion within-subjects/repeated measures design. X is not a variable in the data, rather what differentiates the two instances or occasions. In a path-analytic form using OLS regression as illustrated in Montoya and Hayes (2017), MEMORE implements the method described by Judd, Kenny, and McClelland (2001) for single mediators while extending it as described in Montoya and Hayes (2017) to multiple mediators operating in parallel or serial. Along with an estimate of the indirect effect(s), MEMORE generates confidence intervals for inference about the indirect effect(s) using bootstrapping, Monte Carlo, or normal theory approaches. MEMORE also provides an option that conducts pairwise contrasts between specific indirect effects in models with multiple mediators.

Models 2 and 3 estimate regression coefficients and conditional effects of X on Y when this relationship is moderated by at least one between-person variable, W, in two-condition or two-occasion within-subjects/repeated measures designs. A between-person variable is one which is not measured repeatedly, and is assumed to be constant across the measurement instances (e.g., height). X is not a variable in the data, rather what differentiates the two instances or occasions. MEMORE implements the methods described in Judd, McClelland, and Smith (1996) and Judd, Kenny, and McClelland (2001) for single moderator models. MEMORE includes generalizations of these methods to multiple moderator models as described in Montoya (2019). Multiple moderator models include additive moderation, where the effect of X on Y is a linear function of each of the moderators W1…Wk (Model 2) and multiplicative moderation, where the effect of X on Y is a a multiplicative function of each of the moderators W1…Wk (Model 3). Along with estimates of all regression coefficients, MEMORE probes the interaction in both directions (the effect of X on Y conditional on W and the effect of W on Y conditional on X), provides results of the Johnson-Neyman procedure, and provides syntax for plotting conditional effects.

Models 4 through 18 combine mediation and moderation to estimate conditional process models. These involve the conditional total, conditional direct, and conditional indirect effects of X on Y through one or more mediators M conditional on a between-person variable, W. X is not a variable in the data, rather the factor which differentiates the two instances or repeated-measures occasions. MEMORE implements the methods described in Montoya (2018); Montoya, Hayes, and Gomez (in prep); and Montoya (2025). MEMORE generates coefficient estimates and related inferential information (standard errors, t-values, p-values, confidence intervals), and similar information for conditional total, direct, and indirect effects. Additionally, MEMORE output provides the index of moderated mediation, a test of whether the mediation is linearly moderated, with standard error and confidence interval estimates. Most options for Model 1 can be combined with options from Models 2 and 3, to customize the output you your specific needs, including different inferential approaches, and moderation probing output. At this time only one moderator is allowed in Models 4 – 18 and serial mediation cannot be combined with moderated mediation.

Preparation for Use

The MEMORE.sas file should be opened as a program file in SAS. Once it has been opened, execute the entire file exactly as is. Do not modify the code at all. Once the program is executed, the MEMORE.sas program can be closed. Access to the MEMORE command is available after activation until quitting SAS. The MEMORE.sas file must be loaded and re-executed each time SAS is opened.

Model Specification

MEMORE expects data in wide-form rather than long-form. In this form, the data file for a within-subjects mediation analysis generally does not contain a column for the X variable. As a result, there is no specification of the X variable in the MEMORE code. Rather, the X variable is represented in the data by two repeated measurements of the mediator(s) and dependent variable in the data file in the case of mediation and repeated measurements of the dependent variable in the case of moderation. It is the repeated measurements that appear in the MEMORE code. Moderators for Models 2 and 3 are between-subjects variables and should not have repeated measurements.

Mediation Example: For instance, *X* might be a manipulation of content in a stimulus, with each participant in the study receiving stimulus version A and stimulus version B. Each participant's measurement of the mediator and outcome is collected following exposure to each of the two stimuli. If the data were stored in a SAS data file named "study," the mediator measurements are variables `med1A` and `med1B` following exposure to stimulus A and B, respectively, and the dependent variables measurements are variables `depA` and `depB` following exposure to stimulus A and B, then

```
%MEMORE (data=study,Y=depA depB,M=med1A med1B,model=1);
```

estimates the direct and total effects of independent variable *X* (the content manipulation) on dependent variable *Y* as well as the indirect effect of *X* on *Y* through mediator *M* and produces a bootstrap confidence interval for the indirect effect based on 5,000 bootstrap samples.

Various options are available in MEMORE to control the confidence level, number of samples used for inference, pairwise comparisons between specific indirect effects, and so forth. For example,

```
%MEMORE (data=study,Y=depA depB,M=med1A
         med1B,conf=99,mc=1,samples=10000, save=est);
```

estimates the effects of X, produces 99 percent confidence intervals for all model estimates (**`conf=99`**), generates a Monte Carlo confidence interval (**`mc=1`**)for the indirect effect based on 10,000 samples (**`samples=10000`**), and saves the Monte Carlo estimates to a data file named "est" (**`save=est`**).

MEMORE constructs the difference between the two mediator measurements and the difference between the two dependent variable measurements, and these are modeled in accordance with the procedure described in Montoya and Hayes (2017) and Judd et al. (2001). MEMORE constructs the difference score as $M_A – M_B$ and $Y_A – Y_B$, where M_A and M_B are the mediator measurements following `M=` and Y_A and Y_B are the dependent variable measurements following `Y=`. The order these are listed in following `M=` and `Y=` matters for the sake of the construction of the difference, and the order must be consistent between the `M=` and `Y=` lists. For instance, if the dependent variable in condition A is listed first following `Y=`, then the mediator in condition A should also be listed first following `M=`. The top of the output will denote how the difference scores were constructed based on the MEMORE code submitted. Check this section of the output for consistency with your intentions before interpreting the results.

Moderator Example: X might be a manipulation of content in a stimulus, with each participant in the study receiving stimulus version A and stimulus version B. Each participant's measurement of the outcome is collected following exposure to each of the two stimuli. Additionally, a single measurement of the moderator of interest will be collected. If in the data the moderator measurement is the variable `mod1` and the dependent variables measurements are variables `depA` and `depB` following exposure to stimulus A and B, then

```
%MEMORE (data=study,Y=depA depB,W=mod1,model=2);
```

estimates allow the effect of X to vary linearly by W and estimate the effect of X and W on Y. MEMORE provides regression coefficient estimates, standard errors, and test statistics. Additionally, MEMORE provides a variety of tables which probe the effect of X on Y and the effect of W on Y.

Some of the options which are available in MEMORE for mediation are also available in moderation. For example, controlling the confidence level and the number of decimal places printed. Additional, options for moderation allow the user to decide what values will be probed, if the moderator should be centered before analysis, and if syntax for a plot should be printed. For example,

```
MEMORE (data=study,Y=depA
        depB,W=mod1,conf=99,wmodval1=5,quantile=1,plot=1,
        center=1);
```

estimates the effects of X and M on Y, produces 99 percent confidence intervals for all model estimates (**`conf=99`**), conducts all analyses using a mean centered W (**`center=1`**), probes the effect of X on Y at $W = 5$ (**`wmodval1=5`**), probes the effect of X on Y at the 10th, 25th, 50th, 75th, and 90th quantiles of the observed distribution of W (**`quantile=1`**), and prints syntax for making plots of conditional effects (**`plot=1`**).

MEMORE constructs the difference between the outcome measurements and models this difference in accordance with the procedure described in Judd et al. (1996, 2001). MEMORE constructs the difference score $Y_A – Y_B$, where Y_A and Y_B are the dependent variable measurements following `Y=`. The order these are listed in following `Y=` matters for the sake of the construction of the difference. The top of the output will denote how the difference score was constructed based on the MEMORE code submitted. Check this section of the output for consistency with your intentions before interpreting the results.

Moderated Mediation Example: For instance, X might be a manipulation of content in a stimulus, with each participant in the study receiving stimulus version A and stimulus version B. Each participant's measurement of the mediator and outcome is collected following exposure to each of the two stimuli. If the data were stored in a SAS data file named "study," the mediator measurements are variables `med1A` and `med1B` following exposure to stimulus A and B, respectively, and the dependent variables measurements are variables `depA` and `depB` following exposure to stimulus A and B. Additionally, a single measurement of the moderator of interest will be collected, and represented in the data as `mod1`. If it is hypothesized that the moderator moderates all possible paths in the mediation model, then the corresponding MEMORE command would be,

```
%MEMORE (data=study,Y=depA depB,M=med1A med1B,W=mod1,model=4);
```

This command estimates the condition total, direct, and indirect effects of independent variable X (the content manipulation) on dependent variable Y. Bootstrap confidence intervals for the conditional indirect effects and the index of moderated mediation will be generated based on 5,000 bootstrap samples. Additionally, MEMORE provides a variety of tables which probe the effect moderated effects in the model.

Most of the additional options available for mediation or moderation can be used with the moderated mediation models. For example,

```
%MEMORE (data=study,Y=depA depB,M=med1A
med1B,W=mod1,model=4,conf=99,mc=1,
samples=10000,save=est,wmodval1=5,quantile=1,plot=1,center=1);
```

produces 99% confidence intervals for all model estimates (**`conf=99`**), generates a Monte Carlo confidence interval (**`mc=1`**)for the conditional indirect effects and index of moderated mediation based on 10,000 samples (**`samples=10000`**), and saves the Monte Carlo estimates to a data file named "est" (**`save=est`**). Additionally, all models are estimated using a mean centered W (**`center=1`**), probes the effect of conditional effects at $W = 5$ (**`wmodval1=5`**), probes the conditional effects at the 10th, 25th, 50th, 75th, and 90th quantiles of the observed distribution of W (**`quantile=1`**), and prints syntax for making plots of conditional effects (**`plot=1`**).

Options which are not available in the moderated mediation models are…
1) **`serial = 1`**: no serial moderated mediation models are currently available.
2) **`contrast = 1`**: No contrasts are available among conditional indirect effects.
3) More than one moderator: Currently MEMORE only handles one moderator for moderated mediation models.

Multiple Mediators

MEMORE can estimate specific indirect effects of X on Y in models with up to ten mediators operating in parallel (mediation or moderated mediation models), or up to five in serial (mediation only, no moderated mediation), as well as the total indirect effect of X on Y aggregated across all mediators. As mediators must come in pairs of measurements, in a model with k parallel mediators, there should be $2k$ variablesprovided in the `M=` list. The pairs should come in sequence of the mediators, with the occasion of measurement within each pair also preserved across pairs in the `M=` list. For instance, suppose three mediators M_1, M_2, and M_3 were each measured following stimulus A and stimulus B. In that case the MEMORE command for a parallel multiple mediator model would be

```
%MEMORE (data=study,Y=depA depB/M=med1A med1B med2A med2B med3A
med3B);
```

where depA and depB are the measurement of the dependent variable following stimulus A and B, med1A and med1B are the measurements of mediator 1 following stimulus A and B, med2A and med2B are the measurements of mediator 2 following stimulus A and B, and med3A and med3B are the measurements of mediator 3 following stimulus A and B. Check the top of the output carefully to make sure MEMORE is constructing the difference scores as expected given the order in which the variables in M= are listed.

For a discussion of the parallel multiple mediator model, see Montoya and Hayes (2017), Preacher and Hayes (2008), or Hayes (2018, Chapter 5).

For the serial mediator model, the order of the pairs (MEMORE allows up to five pairs for a serial model) in the M= list dictates the presumed direction of causal flow. The serial mediation model is specified by setting the s argument in the serial option to 1 (i.e., serial=1) in the MEMORE command. Thus, the MEMORE command below estimates a serial multiple mediator model with mediator 1 (med1A and med1B) causally prior to mediator 2 (med2A and med2B):

```
%MEMORE (data=study,Y=depA depB/M=med1A med1B med2A med2B/serial=1);
```

In the parallel and serial multiple mediator models, all direct and indirect effects are freely estimated. It is not possible to constrain a direct effect to zero using MEMORE.

Multiple Moderators

MEMORE can allow the effect of X on Y to depend on up to five moderators. The effect of X on Y can be either a linear function of each of the moderators (Model 2) or a linear function of the products of all of the moderators (Model 3). For instance, suppose there were two moderators W_1 and W_2, the MEMORE command for an additive moderator model would be

```
%MEMORE (data=study,Y=depA depB,W=mod1 mod2,model=2);
```

where **depA** and **depB** are the measurement of the dependent variable following stimulus A and B, mod1 is the measurement of moderator 1, and mod2 is the measurement of moderator 2. In this case, the model of the difference of the dependent variables would only include mod1 and mod2. If however, we had specified model = 3 instead, then the product of mod1 and mod2 would also be included in the model of the differences in the outcome variables. Currently moderated mediation models only allow one moderator.

Inference for Indirect Effects

By default, MEMORE generates percentile bootstrap confidence intervals for inference about indirect effects, conditional indirect effects, or indices of moderated mediation based on 5,000 bootstrap samples. Bias-corrected bootstrap and Monte Carlo confidence intervals are also available. To generate a Monte Carlo confidence interval instead of a percentile bootstrap confidence interval, use the MC option, setting its argument to 1 (i.e., MC=1). To generate a bias-corrected bootstrap confidence interval, use the BC option, setting its argument to 1 (i.e., BC = 1). The use of bias-corrected bootstrap confidence intervals is **heavily discouraged** as this method has been shown to have unacceptably high Type I Error rates (Yzerbyt, Muller, Batailler, and Judd, 2018). The lower and upper bounds of bootstrap confidence intervalsare listed in the output under BootLLCI and BootULCI, respectively, whereas Monte Carlo confidence interval estimates are denoted MCLCCI and MCULCI. In a single run of MEMORE, a confidence interval is generated using only one method. The Monte Carlo confidence interval takes precedence when both the bias corrected confidence interval and Monte Carlo method are specified in a

MEMORE command.

The standard error of the indirect effect is not required for confidence interval construction for the indirect effectwhen using bootstrapping or Monte Carlo methods. However, MEMORE does produce an estimate of the standard error of the indirect effect. This standard error is the standard deviation of the distribution of the bootstrap or Monte Carlo estimates. It appears in the output as BootSE (when using bootstrapping) or MCSE (when using the Monte Carlo method).

The `NORMAL` option generates a test of significance for the indirect effect, conditional indirect effect, or indices of moderated mediation using the Sobel test (Sobel, 1982). The Sobel test assumes that the sampling distribution of the indirect effect is normal, an assumption which has been shown to be inaccurate. To produce the Sobel test, set the `n` argument in the `NORMAL` option to 1 (i.e., `NORMAL=1`). By default, MEMORE does not produce this test in the output.

Confidence Interval Width

The `c` argument in the `CONF` option specifies the desired confidence for confidence interval-based inference. The default is 95%. Confidence can be specified anywhere between 50 and 99.99% (e.g., `CONF=99` generates 99% confidence intervals). Note that the closer the confidence level requested gets to one, the more bootstrap or Monte Carlo samples are required in order to generate trustworthy confidence intervals for inference about indirect effects. If the number of bootstrap or Monte Carlo samples requested is too small to construct a confidence interval of the desired confidence, the program will not run and an error will appear in the "Analysis Notes and Warnings" section of the output.

Number of Samples for Bootstrap and Monte Carlo Inference

The `SAMPLES` option sets the number of samples used in the generation of bootstrap or Monte Carlo confidence intervals for inference about indirect effects. The `sm` argument defaults to 5000 and can be set to any integer between 1000 and infinity. Any number less than 1000, except zero, is ignored, and the default is implemented. If zero is specified, MEMORE generates a Monte Carlo confidence interval for indirect effects based on 5000 samples.

Covariates

For the purposes of this documentation a "covariate" is considered a between-person (or Level-2) variable, which does not change across repeated-measurements and does not interact with either the repeated-measures factor or other variables in the model. There are no options available in MEMORE for the inclusion of covariates in the model. When a covariate unaffected by measurement instance (such as gender or some other stable individual difference) and it is assumed that the covariate's effect on each outcome and mediator variable is the same, then the effect of the covariate on the mediator and covariate differences becomes ignorable and thus the covariate can be excluded from the model (see Montoya, 2019). If a covariates effect differs across measurement instances, it should be included as a moderator.

Pairwise Contrasts Between Specific Indirect Effects

In models with more than one mediator, setting the `cn` argument in the `CONTRAST` option to one (i.e., `CONTRAST=1`) generates pairwise contrasts between all specific indirect effects, including bootstrap or Monte Carlo confidence intervals for inference. Each contrast corresponds to a test of the difference between two specific indirect effects. When there are only two repeated mediator variables in the model, the contrast between specific indirect effects is listed in the output as `(C1)`. With k repeated mediators, the $0.5k(k-1)$ possible pairwise contrasts are listed as `(C1)`, `(C2)`, `(C3)`, and so forth, and a key for interpreting which code corresponds to which contrast is provided. There are no corrections for multiple comparisons included in the computation of confidence intervals for these contrasts. To correct for multiple comparisons, change the `conf` argument to correspond with the level of confidence desired for each contrast.

Pairwise contrasts of specific indirect effects are not available for moderated mediation models (Models 4 – 18).

Saving Bootstrap and Monte Carlo estimates

The `SAVE` subcommand generates a temporary SAS work data file containing regression coefficients produced through bootstrap or Monte Carlo sampling. All model regression coefficients are saved and labelled in line with the model template document. This file can be used for visualizing sampling distributions or the construction of custom hypothesis tests involving functions of regression coefficients. By default, this file is not created. To activate this option, specify `SAVE=name` in the MEMORE command, where `name` is a valid SAS data file name. The file is not permanently saved to a storage device, so this file should be saved for future use if desired. Subsequent runs of MEMORE without first permanently saving the file produced by a prior run will erase the old file in favor of the new file.

Removing X-M interaction

As described in Montoya & Hayes (2017) for mediation models, MEMORE automatically allows the relationship between *M* and *Y* to vary across instances. Setting the `xm` argument in the `xmint` option to zero (i.e., `xmint = 0`) fixes the estimated relationship between *M* and *Y* to be equal across instances, and the model output no longer includes terms which involve the average of the repeated measurements of the mediator. This option can also be used for any of the moderated mediation models (Model 4 – 18).

Seeding the Random Number Generator

Bootstrap and Monte Carlo confidence intervals require random resampling of the data or from theoretical distributions and thus will differ from run to run of MEMORE even when the data and model are the same. The `SEED` option can be used to seed the random number generator, thereby allowing for the replication of the output from run to run when analyzing the same data. By default MEMORE sets the seed randomly. The `sd` argument in the `SEED` command can be set to any positive integer that is less than or equal to 2,000,000. When this option is used, the random number seed specified is printed in the output for later reference.

Decimal Precision in Output

Output precision, in the form of number of decimal places of resolution, can be set with the `dc` argument in the `DECIMALS` command. The default for `dc` is 10.4, meaning 10 characters and four points to the right of the decimals place. Changing this to, for example, 8.2 will allocate eight characters with two to the right of the decimal point. See the *SAS Syntax Reference Manual* for additional format options.

Johnson-Neyman Procedure

For moderation and moderated mediation models with a continuous moderator, the Johnson-Neyman procedure will find the points along the observed range of the moderator (if they exist) for which the effect of *X* on *Y* is exactly statistically significant, based on a $\alpha =$ 1-`c`/100 level test. By setting the `jn` argument in the `JN` command to 1, the Johnson-Neyman procedure will be implemented and the points of interested printed along with a table of conditional effects which are useful for interpreting the Johnson-Neyman solutions. See Montoya (2019) for technical details.

Probing Conditional Effects

For moderation models, the default is to probe the effect of *X* on *Y* at three values of the moderator: the mean minus one standard deviation, the mean, and the mean plus one standard deviation. When the `q` argument in the `QUANTILE` command is set to 1 (i.e. `quantile = 1`), the probed values will instead be the 10th, 25th, 50th, 75th, and 90th quantile of the observed distribution of *W*.
The three `WMODVAL` commands can be used to specify sets of values of the moderators to probe at. The arguments for these commands must be numeric, and if there are multiple moderators, each number should be separated by spaces. The arguments for the `WMODVAL` commands should be the same length as the list of *W* variables. For example, if the model has two moderators, then each of the `WMODVAL` arguments should be two numbers (the first number specifies a value for the first moderator, and the second number specifies a value for the second moderator).

```
%MEMORE (data=study,Y=depA depB,W=mod1 mod2,model=2,wmodval1=3 1,
         wmodval2=2.3 4);
```

MEMORE will output the conditional effect of *X* on *Y* when `mod1`=3 and `mod2` = 1 as well as the conditional effect of *X* on *Y* when `mod1` = 2.3 and `mod2` = 4. MEMORE will check each of the subsequent `WMODVAL` commands. If there is no point specified for `WMODVAL1` then any information input in `WMODVAL2` will not be used. The first point of interest for probing should be specified as `WMODVAL1` and the second point should be specified as `MMODVAL2` etc. A maximum of three `WMODVAL` arguments can be used.

Plot of Conditional Effects

When the `p` argument of the `PLOT` command is set to 1 (i.e. `plot = 1`), MEMORE will print a table of values which may be used for plotting the conditional effects of '*X*' on the outcome at different values of the moderator. When run this syntax will generate multiple plots. Each plot has the moderator *W* on the *X* axis, and different outcomes on the *Y* axis. Plots will either have the difference between the two observations of the outcome or mediator variables, or the other plots will have each of the outcome/mediator variables separately. See the notes printed with the plots for the specific cases in each model.

Additionally, some plots require conditioning on other levels of variables in the models. Unless otherwise noted, other variables are conditioned at their average in order to calculate the generated predicted outcomes. For these variables, conditioning at the average (compared to some other value) only changes the vertical axis, but not the shape of the graph. However, in some cases when other variables interact with variables involved in the graph, the shape of the graph depends on the conditioned value. In these cases, the moderator is used to predict the additional variables, and a predicted value for those variables is used to calculate the predicted outcome. This is clear in the tables of conditional effects, but not as clear in the plotting output. See the tables of conditional effects for additional information about the conditioning of additional variables. Most frequently this applies to the Mavg variable interacting with a moderator in the conditional direct effect, but this can occur in other parts of MEMORE models.

Centering Moderator Variables

When the `ce` argument of the `CENTER` command is set to 1 (i.e., `center = 1`), MEMORE will mean center all moderator variables before conducting the regression analyses. When the `ce` argument of the `CENTER` command is set to 2 (i.e., `center = 1`), MEMORE will mean center only non-dichotomous moderator variables before conducting the regression analyses. The default for the `CENTER` command is 0, which does not center any moderator variables. When centering, all conditional effects will be estimated using the new mean centered moderators, and the Johnson-Neyman procedure will be conducted on the mean centered version of the moderators. The `center` argument is used for moderation (Model 2 & 3) or moderated mediation models (Models 4 – 18), but is not used for mediation models (Model 1).

Notes

- A case will be deleted from the analysis if missing on any of the variables in the model.
- All variable names must be 8 characters or fewer in length.
- Exactly two variables containing measurements of *Y* must be listed following `Y=`.
- For Model 1 and Models 4 - 18, mediator measurements must be listed in sets of 2. Listing an odd number of variables in the `M=` list will produce an error.
- Do not use STRING formatted variables in any of your models. Doing so will produce errors. All variables should be in NUMERIC format.
- A data file must be specified in the MEMORE command following `data=`.

References

Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis* (2nd ed.). NewYork: The Guilford Press.

Judd, C. M., Kenny, D. A., & McClelland, G. H. (2001). Estimating and testing mediation and moderation inwithin-subjects designs. *Psychological Methods, 6*, 115-134.

Judd, C. M., McClelland, G. H., and Smith, E. R. (1996). Testing treatment by covariate interactions when treatment varies within subjects. *Psychological Methods, 1*(4), 366-378.

Montoya, A. K. (2018). Conditional process analysis in two-instance repeated-measures designs (Dissertation). The Ohio State University.

Montoya (2019). Moderation Analysis in Two-Instance Repeated Measures Designs: Probing Methods andMultiple Moderator Models. *Behavior Research Methods*, *51*(1), 61-82.

Montoya, A. K., & Hayes, A. F. (2017). Two-condition within-participant statistical mediation analysis: A path-analytic framework. Psychological Methods, 22(1), 6-27.

Montoya, A. K., Hayes, A. F., & Gomez, N. (in prep). Mediation Analysis in the Two Condition Pretest-Posttest Design: A Treatment-as-Moderator Conditional Process Approach.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40*, 879-891.

Yzerbyt, V., Muller, D., Batailler, C., and Judd, C. M. (2018). New recommendations for testing indirect effects in mediational models: The need to report and test component paths. *Journal of Personality and Social Psychology: Attitudes and Social Cognition*, *115*(6), 929-943.