# Understanding PROCESS v3.0

## New Features, Building, and Editing Models

Github.com/akmontoya/USC18

www.akmontoya.com
www.afhayes.com
www.processmacro.org

## Overview of Today

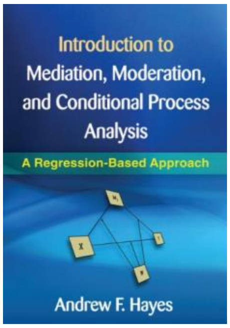
- PROCESS: what it can and cannot do
- Overview of Mediation, Moderation, and Conditional Process Analysis
- How to conduct Mediation, Moderation, and Conditional Process Analysis using PROCESS
- What's new in Version 3.0/3.1 of PROCESS?

Github.com/akmontoya/USC18

What we will not cover:
- Logistic Regression functions
- In-depth Mediation, Moderation, and Conditional Process Analysis
- Repeated-Measures or Multilevel Designs
- Latent variable models

Please do:
- Ask questions!
- Work along with me on your computer
- Work with your neighbors on activities

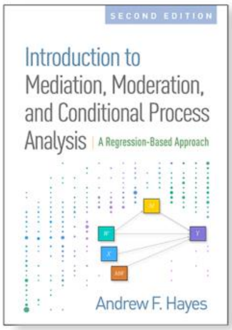
## What is PROCESS?




www.guilford.com

- An observed variable OLS-based (or logistic) regression modeling tool for moderation, mediation, and conditional process analysis.
- Available for both SPSS (in macro and "custom dialog" form) and SAS. Freely available at www.processmacro.org
- An integration of features found in earlier macros (SOBEL, INDIRECT, MODMED, MODPROBE, MEDIATE) into a single easy-to-use macro, with many features not available in any of these earlier macros.
- First released in beta form in March of 2012 and then as version 2 with the release of the 1st edition of *Introduction to Mediation, Moderation, and Conditional Process Analysis* (published by the Guilford Press) in May 2013.

## What is PROCESS?

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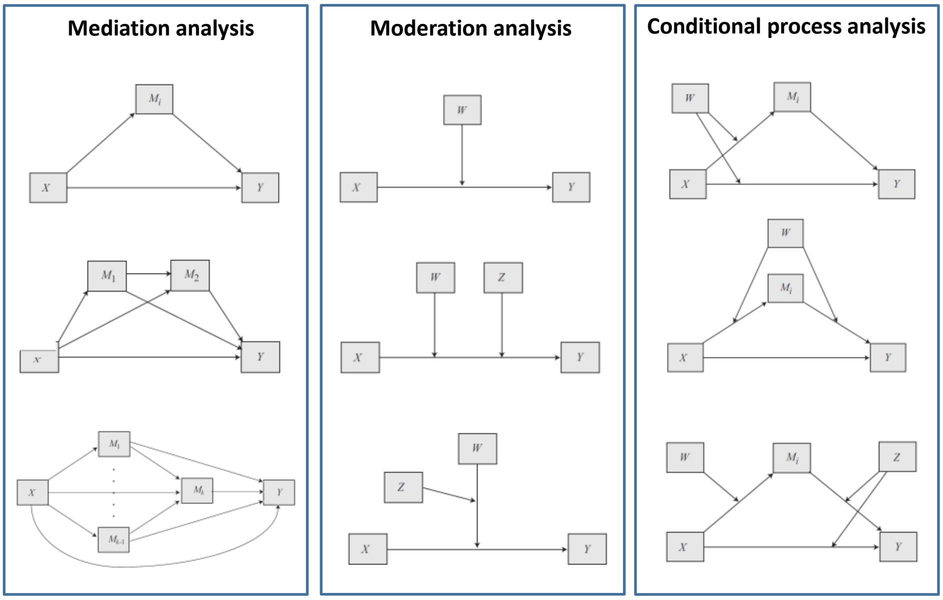
- Many patchwork updates over the years to deal with limitations and user requests.
- Version 3 released in December 2017 with the second edition of *Introduction to Mediation, Moderation, and Conditional Process Analysis.*
- A complete rewriting of the original code to add frequently requested features and allow for greater flexibility in expansion and addition of features later.
- Documented in the 2nd edition, Appendix A, which also includes information about the 55 preprogrammed models PROCESS can estimate.
- A new Appendix B added to the documentation describing how to create your own models and edit preprogrammed models.
- Freely available at www.processmacro.org. The current release is v3. 1

## Three main applications of PROCESS




## processmacro.org

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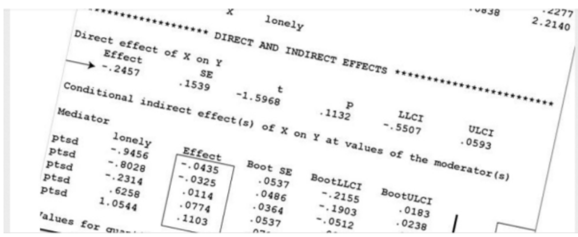
### The PROCESS macro for SPSS and SAS



**PROCESS** is an easy to use add-on for SPSS and SAS for statistical mediation, moderation, and conditional process analysis. The use of **PROCESS** is described and documented in *Introduction to Mediation, Moderation, and Conditional Process Analysis*, published by The Guilford Press.

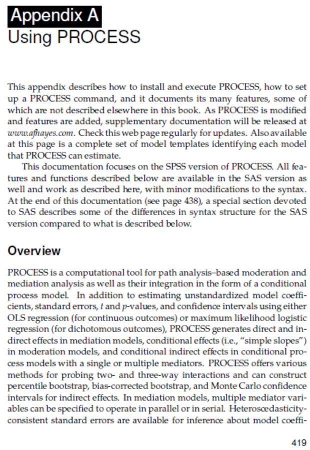
**PROCESS** uses an ordinary least squares or logistic regression-based path analytic framework for estimating direct and indirect effects in simple and multiple mediator models, two and three way interactions in moderation models along with simple slopes and regions of significance for probing interactions, conditional indirect effects in moderated mediation models with a single or multiple mediators and moderators, and indirect effects of interactions in mediated moderation models also with a single or multiple mediators. Bootstrap and Monte Carlo confidence intervals are implemented for inference about indirect effects. **PROCESS** can estimate moderated mediation models with multiple mediators, multiple moderators of individual paths, interactive effects of moderators on individual paths, and models with dichotomous outcomes.

**PROCESS** was written by Andrew F. Hayes, Professor of Quantitative Psychology at The Ohio State University.

Facebook users can stay appraised of latest developments in **PROCESS** by liking here. Tweeters about **PROCESS** can use the hashtag #processmacro

## Read the documentation (eventually)

The PROCESS documentation is an eventual must-read. It describes how to use PROCESS, as well as its various options, capabilities, and limitations. It is available as Appendix A in Hayes (2017). *Introduction to Mediation, Moderation, and Conditional Process Analysis (2nd Ed)*. At a minimum, you must have the model templates handy, as PROCESS expects you to tell it which model number you are estimating and which variables play what role. You have a mini version of the templates PDF.



Appendix A
Using PROCESS

This appendix describes how to install and execute PROCESS, how to set up a PROCESS command, and it documents its many features, some of which are not described elsewhere in this book. As PROCESS is modified and features are added, supplementary documentation will be released at *www.afhayes.com*. Check this web page regularly for updates. Also available at this page is a complete set of model templates identifying each model that PROCESS can estimate.

This documentation focuses on the SPSS version of PROCESS. All features and functions described below are available in the SAS version as well and work as described here, with minor modifications to the syntax. At the end of this documentation (see page 438), a special section devoted to SAS describes some of the differences in syntax structure for the SAS version compared to what is described below.

Overview

PROCESS is a computational tool for path analysis–based moderation and mediation analysis as well as their integration in the form of a conditional process model. In addition to estimating unstandardized model coefficients, standard errors, *t* and *p*-values, and confidence intervals using either OLS regression (for continuous outcomes) or maximum likelihood logistic regression (for dichotomous outcomes), PROCESS generates direct and indirect effects in mediation models, conditional effects (i.e., "simple slopes") in moderation models, and conditional indirect effects in conditional process models with a single or multiple mediators. PROCESS offers various methods for probing two- and three-way interactions and can construct percentile bootstrap, bias-corrected bootstrap, and Monte Carlo confidence intervals for indirect effects. In mediation models, multiple mediator variables can be specified to operate in parallel or in serial. Heteroscedasticity-consistent standard errors are available for inference about model coeffi-

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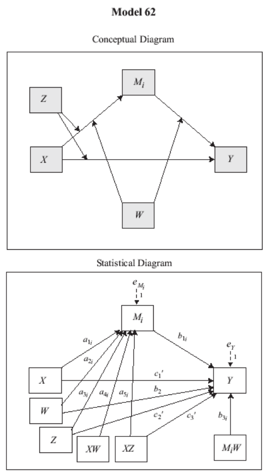
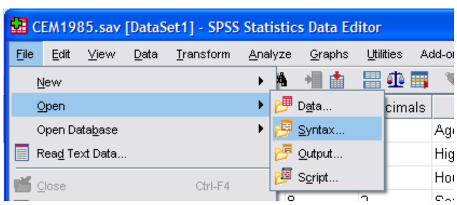
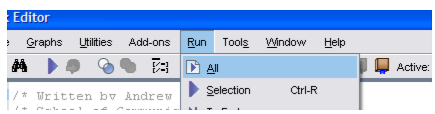



## PROCESS as a syntax-driven macro

Open process.sps as a syntax file and run the entire program **exactly as is.** This produces a new SPSS command called PROCESS. See the documentation for details on the syntax structure. PROCESS goes away when you close SPSS.



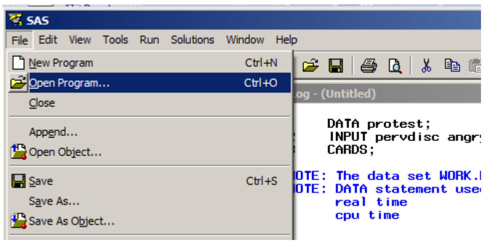



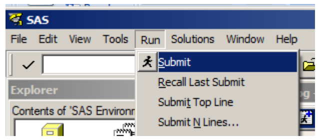

Once PROCESS is defined, you can run a properly-formatted PROCESS command in a new syntax window. Such a command might look something like below. Not all of the arguments below are required.

```
process y=liking/x=protest/m=respappr/total=1/normal=1
        /model=4/boot=10000.
```

## PROCESS for SAS

In SAS, open process.sas and submit the entire program **exactly as is.** This produces a new SAS command called %PROCESS. The syntax structure is described in the documentation.



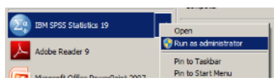

Once PROCESS is defined, you can run a properly-formatted PROCESS command in a new syntax window. Such a command might look something like below. Not all of the arguments below are required.

```
%process (data=protest,y=liking,x=protest,m=respappr,total=1,
          normal=1,boot=10000,model=4);
```

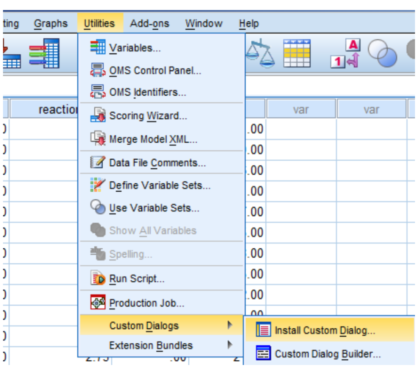
## PROCESS "Custom Dialog"

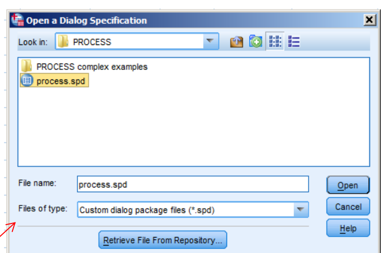
The PROCESS macro must be run at least once in your SPSS session to activate the PROCESS command. Custom Dialog files are permanently installed in SPSS, integrating the procedure into SPSS menus. Use the procedure below. In Windows, installation requires administrative access to your machine. You **probably** have to open SPSS as an administrator as well. You may not have access to do so.

In SPSS 23 and earlier:




Right click SPSS to select

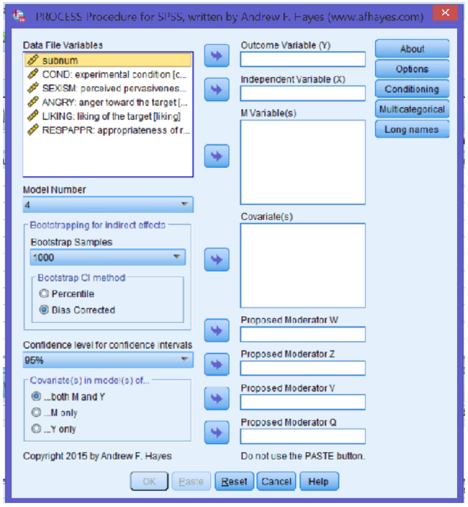



In SPSS24, look under "Extensions" for the Utilities option

When installed, PROCESS can be found under "Analyze"→"Regression"

## PROCESS “Custom Dialog”

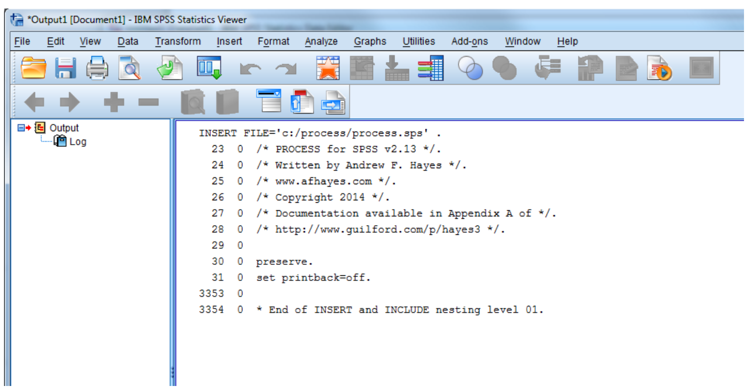



Installing the dialog box does not eliminate the need to run the PROCESS code if you plan on executing with syntax. And don’t use the PASTE button.

## Autoexecution

It is possible to get SPSS to execute the PROCESS code on its own when SAS/SPSS executes. A document is provided to you with the course files that provides instructions for SPSS for Windows and Mac.

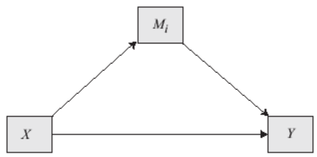
When successful, SPSS for Windows users typically see something like the following in the output window when SPSS is opened:



## Model template system

PROCESS has 55 model templates, referred to by number in PROCESS, which specify the form of the model (moderation, mediation, moderated mediation, and so forth) and which variables play what roles.

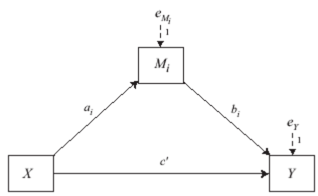
Conceptual diagram




Example #1:

Model 4 is a simple or parallel multiple mediator model, which estimates the direct and indirect effect(s) of *X* on *Y* through one or more mediators (*M*) (up to 10 mediators at once)

Statistical diagram



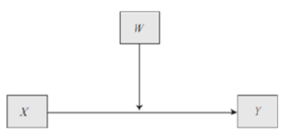


## Model template system

PROCESS has 55 model templates, referred to by number in PROCESS, which specify the form of the model (moderation, mediation, moderated mediation, and so forth) and which variables play what roles.


Conceptual diagram

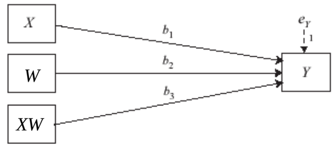
Example #2:




Model 1 is a simple moderation model, with *W* moderating the effect of *X* on *Y*.

Statistical diagram

The statistical diagram shows the model in the form of a path diagram. This is the form in which the model is estimated.



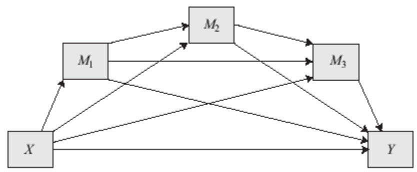
## Model template system

PROCESS has 55 model templates, referred to by number in PROCESS, which specify the form of the model (moderation, mediation, moderated mediation, and so forth) and which variables play what roles.

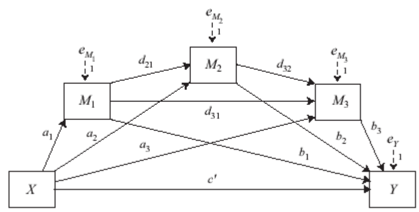
Example #3:

Model 6 is a serial multiple mediator model, which estimates the direct and indirect effect(s) of *X* on *Y* through up to 4 mediators (*M*) chained together in serial. An example with **three** mediators is depicted to the right.

Conceptual diagram




Statistical diagram



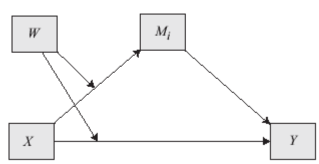

## Model template system

PROCESS has 55 model templates, referred to by number in PROCESS, which specify the form of the model (moderation, mediation, moderated mediation, and so forth) and which variables play what roles.

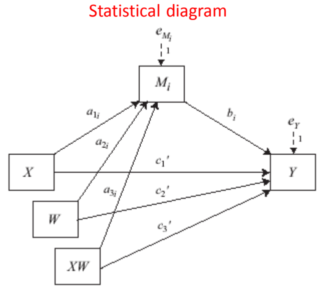
Example #4:

Model 8 is a conditional process model which estimates the conditional direct and indirect effects of *X* on *Y* through *M*, with direct effect and "first stage" moderation by *W*.

Conceptual diagram



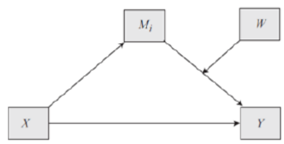

Statistical diagram



## Model template system

PROCESS has 55 model templates, referred to by number in PROCESS, which specify the form of the model (moderation, mediation, moderated mediation, and so forth) and which variables play what roles.

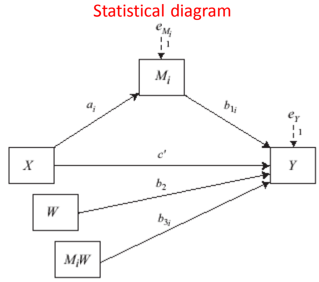
Conceptual diagram




Example #5:

Model 14 is a conditional process model which estimates the direct effect of *X* on *Y* and conditional indirect effects of *X* on *Y* through *M*, with "second stage" moderation by *W*.

Statistical diagram



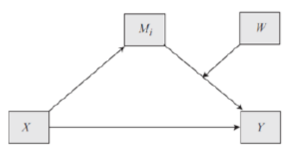

## Model template system

PROCESS has 55 model templates, referred to by number in PROCESS, which specify the form of the model (moderation, mediation, moderated mediation, and so forth) and which variables play what roles.

Minimum required specifications

- Which variables play which role in the model (**y=** **x=** **m=** **w =** and so forth)
- Model number (**model=**)
- SAS only: Data file (**data=**)

Conceptual diagram




SPSS

```
PROCESS y=yvar/x=xvar/m=mvlist/w=vvar/model=14.
```

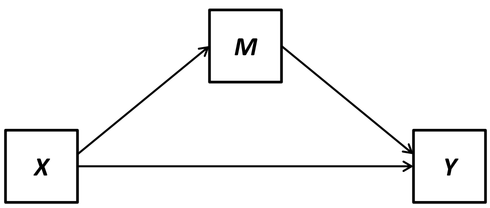
SAS

```
%process (data=filename,y=yvar,x=xvar,m=mvlist,w=vvar,model=14);
```

## Limitations and constraints

- Only one *X* and one *Y* allowed in a model.
- PROCESS is an OLS or logistic regression modeling tool. Categorical mediators are not allowed.
- Up to 10 mediators in numbered models, 6 in custom models.
- No more than two moderators can be used in any model.
- A variable can play only one role in the model. For example a variable can't be both a moderator and a covariate, or both a mediator and a moderator.
- PROCESS is a single-level observed variable modeling system. No multilevel problems can be analyzed with PROCESS.
- PROCESS requires complete data. Listwise deletion is used for cases missing on any variable in the model.
- Although PROCESS will accept them, it is safer to restrict variable names to eight characters or fewer.

## Mediation




A simple mediation model connects an assumed causal variable (*X*) to an assumed outcome variable (*Y*), through some mechanism (*M*). The effect of *X* on *Y* can move completely through *M* or only partially through *M*.

*M* is frequently referred to as a *mediator* or *intermediary variable*.

Many different kind of variables may act as mediators. Emotional variables, situational, individual level variables, cognitive variables, environmental variables, etc.

Mediation can be found throughout the psychology and business literature

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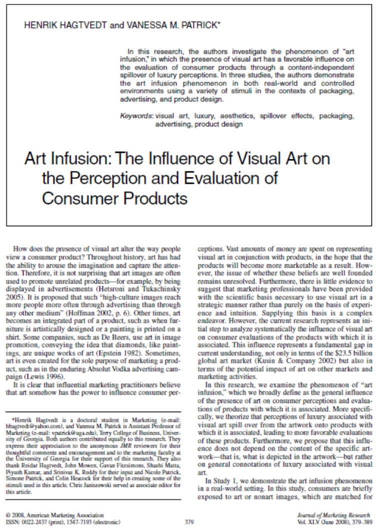
A quick example: Name some possible mediators!

## Understanding causal effects

Hagtvedt, H., & Patrick, V. M. (2008). Art infusion: The influence of visual art on the perception and evaluation of consumer products. *Journal of Marketing Research, 45*, 379-389.



HENRIK HAGTVEDT and VANESSA M. PATRICK*

In this research, the authors investigate the phenomenon of "art infusion," in which the presence of visual art has a favorable influence on the evaluation of consumer products through a content-independent spillover of luxury perceptions. In three studies, the authors demonstrate the art infusion phenomenon in both real-world and controlled environments using a variety of stimuli in the contexts of packaging, advertising, and product design.

*Keywords:* visual art, luxury, aesthetics, spillover effects, packaging, advertising, product design

Art Infusion: The Influence of Visual Art on the Perception and Evaluation of Consumer Products

How does the presence of visual art alter the way people view a consumer product? Throughout history, art has had the ability to arouse the imagination and capture the attention. Therefore, it is not surprising that art images are often used to promote unrelated products—for example, by being displayed in advertisements (Hetsroni and Tukachinsky 2005). It is proposed that such "high-culture images reach more people more often through advertising than through any other medium" (Hoffman 2002, p. 6). Other times, art becomes an integrated part of a product, such as when furniture is artistically designed or a painting is printed on a shirt. Some companies, such as De Beers, use art in image promotion, conveying the idea that diamonds, like paintings, are unique works of art (Epstein 1982). Sometimes, art is even created for the sole purpose of marketing a product, such as in the enduring Absolut Vodka advertising campaign (Lewis 1996).

It is clear that influential marketing practitioners believe that art somehow has the power to influence consumer perceptions. Vast amounts of money are spent on representing visual art in conjunction with products, in the hope that the products will become more marketable as a result. However, the issue of whether these beliefs are well founded remains unresolved. Furthermore, there is little evidence to suggest that marketing professionals have been provided with the scientific basis necessary to use visual art in a strategic manner rather than purely on the basis of experience and intuition. Supplying this basis is a complex endeavor. However, the current research represents an initial step to analyze systematically the influence of visual art on consumer evaluations of the products with which it is associated. This influence represents a fundamental gap in current understanding, not only in terms of the $23.5 billion global art market (Kusin & Company 2002) but also in terms of the potential impact of art on other markets and marketing activities.

In this research, we examine the phenomenon of "art infusion," which we broadly define as the general influence of the presence of art on consumer perceptions and evaluations of products with which it is associated. More specifically, we theorize that perceptions of luxury associated with visual art spill over from the artwork onto products with which it is associated, leading to more favorable evaluations of these products. Furthermore, we propose that this influence does not depend on the content of the specific artwork—that is, what is depicted in the artwork—but rather on general connotations of luxury associated with visual art.

In Study 1, we demonstrate the art infusion phenomenon in a real-world setting. In this study, consumers are briefly exposed to art or nonart images, which are matched for

*Henrik Hagtvedt is a doctoral student in Marketing (e-mail: hhagtvedt@yahoo.com), and Vanessa M. Patrick is Assistant Professor of Marketing (e-mail: vpatrick@uga.edu), Terry College of Business, University of Georgia. Both authors contributed equally to this research. They express their appreciation to the anonymous *JMR* reviewers for their thoughtful comments and encouragement and to the marketing faculty at the University of Georgia for their support of this research. They also thank Reidar Hagtvedt, John Mowen, Gavan Fitzsimons, Shashi Matta, Piyush Kumar, and Srinivas K. Reddy for their input and Nicole Patrick, Simone Patrick, and Colin Heacock for their help in creating some of the stimuli used in this article. Chris Janiszewski served as associate editor for this article.

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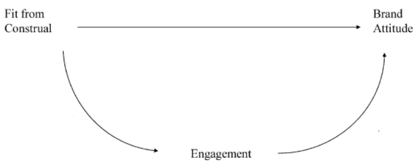
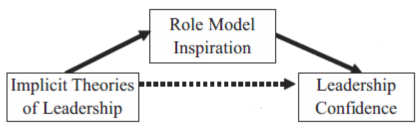
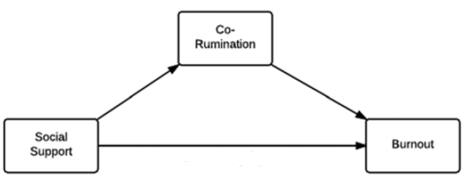
## Some examples in the literature



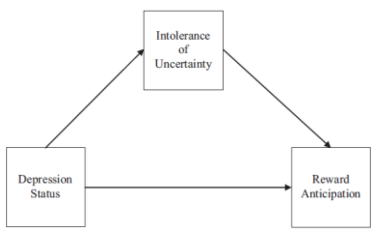

Lee, A. Y., Keller, P. A., & Sternthal, B. (2010). Value from regulatory construal fit: Persuasive impact of fit between consumer goals and message concreteness. ***Journal of Consumer Research**, 36*, 735-747.




Hoyt, C. L., Burnette, J. L., & Innella, A. N. (2012). I can do that: The impact of implicit theories on leadership model effectiveness. ***Personality and Social Psychology Bulletin**, 38*, 257-268.




Boren, J. P. (2014). The relationship between co-rumination, social support, stress, and burnout among working adults. ***Management Communication Quarterly**, 28*, 3-25.




Nelson, B. D., Shankman, S. A., & Proudfit, G. H. (2014). Intolerance of uncertainty mediates reduced reward anticipation in major depressive disorder. ***Journal of Affective Disorders**, 158*, 108-113.

## Mediation: Path Analysis

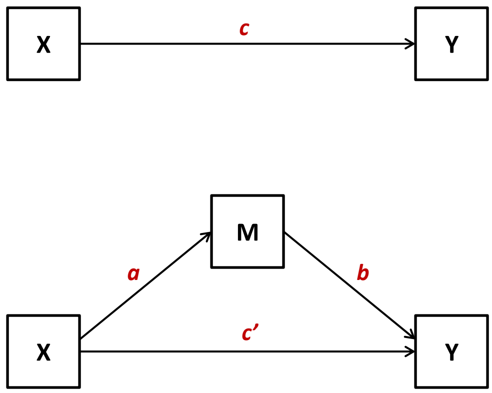
Consider *a*, *b*, *c*, and *c′* to be measures of the causal effect of the variables in the mediation model.

These could be measured using regression coefficients from OLS or path estimates in a structural equation model using maximum likelihood estimation.

$$Y_i = i_{Y^*} + cX_i + e_{Y_i^*}$$

$$M_i = i_M + aX_i + e_{M_i}$$

$$Y_i = i_Y + c'X_i + bM_i + e_{Y_i}$$




Direct effect of *X* on *Y* (not through *M*) = *c′*

Indirect effect of *X* on *Y* (through *M*) = *a* × *b*

Total effect = direct effect + indirect effect
*c* = *c′* + *a* × *b*

Indirect effect = total effect - direct effect
*a* × *b* = *c* - *c′*



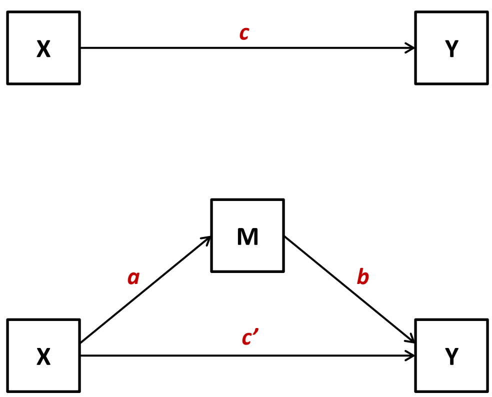
## Interpreting the Coefficients

**Total Effect (*c*):** The effect of our presumed cause (*X*) on our outcome (*Y*), without controlling for any other variables.

***a*-path:** The effect of our presumed cause (*X*) on our mediator *(M)*.

***b*-path:** The effect of our mediator (*M*) on the outcome (*Y*) while controlling for *X*. (i.e. predicted difference in *Y* for two people with the same score on X but who differ on *M* by one unit).

**Direct effect (*c′*):** The effect of our presumed cause (*X*) on *Y* while controlling for *M*. (i.e. predicted difference in *Y* for two people who differ by one unit on *X* but with the same score on *M*)




**Indirect Effect (*ab*):** Product of effect of *X* on *M*, and effect of *M* on *Y* controlling for *X*. The effect of *X* on *Y* through *M*.

## Protest Example

Garcia, D. M., Schmitt, M. T., Branscombe, N. R., & Ellemers, N. (2010). Women's reactions to ingroup members who protest discriminatory treatment: The importance of beliefs about inequality and response appropriateness. ***European Journal of Social Psychology, 49***, 733-745.


European Journal of Social Psychology
Eur. J. Soc. Psychol. 40, 733–745 (2010)
Published online 6 July 2009 in Wiley InterScience
(www.interscience.wiley.com) DOI: 10.1002/ejsp.644

Research article

Women's reactions to ingroup members who protest discriminatory treatment: The importance of beliefs about inequality and response appropriateness

DONNA M. GARCIA[1]*, MICHAEL T. SCHMITT[2], NYLA R. BRANSCOMBE[3] AND NAOMI ELLEMERS[4]
[1] University of Guelph, Canada
[2] Simon Fraser University, Canada
[3] University of Kansas, USA
[4] Leiden University, The Netherlands

Abstract

Our goal was to identify factors that shape women's responses to ingroup members who protest gender discrimination. We predicted and found that women who perceived gender discrimination as pervasive regarded a protest response as being more appropriate than a no protest response and expressed greater liking and less anger towards a female lawyer who protested rather than did not protest an unfair promotion decision. Further, beliefs about the appropriateness of the response to discrimination contributed to evaluations of the protesting lawyer. Perceptions that the complaint was an appropriate response to the promotion decision led to more positive evaluations of an ingroup discrimination protester. Copyright © 2009 John Wiley & Sons, Ltd.

SOCIAL CONSEQUENCES OF CLAIMING DISCRIMINATION

Copyright © 2009 John Wiley & Sons, Ltd.

Participants (all female) read a narrative about a female attorney who lost a promotion at her firm to a much less qualified male through unequivocally discriminatory actions of the senior partners.

Participants assigned to the 'protest' condition were then told she protested the decision by presenting an argument to the partners about how unfair the decision was.

Participants assigned to the 'no protest' condition were told that although she was disappointed, she accepted the decision and continued working at the firm.

After reading the narrative, the participants evaluated **how appropriate they perceived her response to be**, and also evaluated the characteristics of the attorney, the responses of which were aggregated to produce a measure of **"liking."** Prior to the study, the participants filled out the Modern Sexism Scale.

## The data: PROTEST

*protest.sav [DataSet1] - IBM SPSS Statistics Data Editor

| | subnum | cond | sexism | angry | liking | respappr | protest |
|---|---|---|---|---|---|---|---|
| 1 | 209 | 2 | 4.87 | 2 | 4.83 | 4.25 | 1.00 |
| 2 | 44 | 0 | 4.25 | 1 | 4.50 | 5.75 | .00 |
| 3 | 124 | 2 | 5.00 | 3 | 5.50 | 4.75 | 1.00 |
| 4 | 232 | 2 | 5.50 | 1 | 5.66 | 7.00 | 1.00 |
| 5 | 30 | 2 | 5.62 | 1 | 6.16 | 6.75 | 1.00 |
| 6 | 140 | 1 | 5.75 | 1 | 6.00 | 5.50 | 1.00 |
| 7 | 27 | 2 | 5.12 | 2 | 4.66 | 5.00 | 1.00 |
| 8 | 64 | 0 | 6.62 | 1 | 6.50 | 6.25 | .00 |
| 9 | 67 | 0 | 5.75 | 6 | 1.00 | 3.00 | .00 |
| 10 | 182 | 0 | 4.62 | 1 | 6.83 | 5.75 | .00 |
| 11 | 85 | 2 | 4.75 | 2 | 5.00 | 5.25 | 1.00 |
| 12 | 109 | 2 | 6.12 | 5 | 5.66 | 7.00 | 1.00 |
| 13 | 122 | 0 | 4.87 | 2 | 5.83 | 4.50 | .00 |
| 14 | 69 | 1 | 5.87 | 1 | 6.50 | 6.25 | 1.00 |

SAS users, run this program to make a temporary or "work" data file named PROTEST.

protest

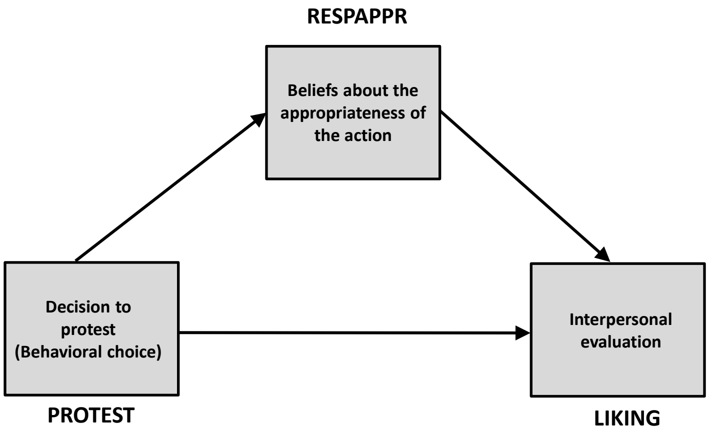
```
data protest;
input subnum cond sexism angry liking respappr protest;
cards;
209 2   4.87    2   4.83    4.25    1.00
44  0   4.25    1   4.50    5.75    .00
124 2   5.00    3   5.50    4.75    1.00
232 2   5.50    1   5.66    7.00    1.00
30  2   5.62    1   6.16    6.75    1.00
140 1   5.75    1   6.00    5.50    1.00
27  2   5.12    2   4.66    5.00    1.00
64  0   6.62    1   6.50    6.25    .00
67  0   5.75    6   1.00    3.00    .00
182 0   4.62    1   6.83    5.75    .00
85  2   4.75    2   5.00    5.25    1.00
109 2   6.12    5   5.66    7.00    1.00
122 0   4.87    2   5.83    4.50    .00
69  1   5.87    1   6.50    6.25    1.00
```

**PROTEST**: Experimental condition (1 = protest, 0 = no protest)

**LIKING** : Evaluation (liking) of the lawyer (higher = more positive evaluation, i.e. like more)

**RESPAPPR**: A measure of how appropriate the lawyer's behavior in response to the action of the partners was perceived to be for the situation (higher = more appropriate)

## Our question

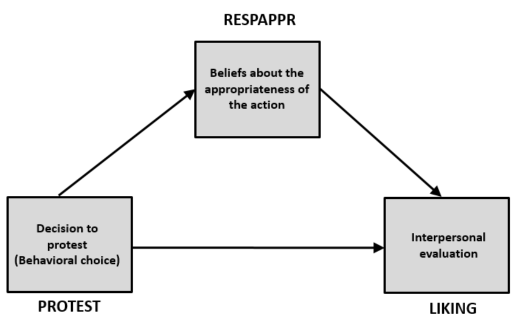


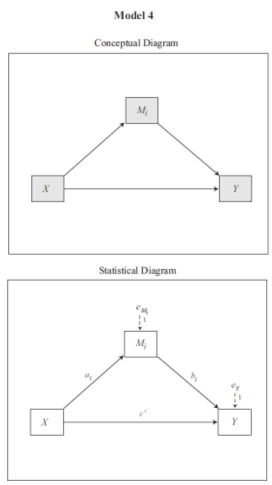

Do perceptions of the appropriateness of the response act as the mechanism through which that choice influences interpersonal evaluation?

Notice that this question is not asked contingent on evidence of simple association between the choice and the evaluation.

## Estimation of the PROTEST model in PROCESS

**PROCESS Model 4**




What should the PROCESS command look like?

```
process y=liking/x=protest/m=respappr/model=4/boot=10000/normal=1/total=1.
```

not required

```
%process (data=protest, y=liking,x=protest,m=respappr,model=4,boot=10000,normal=1,total=1);
```

## PROCESS output

```
*************** PROCESS Procedure for SPSS Version 3.00 ****************

         Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : liking
    X  : protest
    M  : respappr

Sample
Size:  129
```

Make sure your model number is correct

Make sure each variable is assigned the correct role

PROCESS uses listwise deletion, so your same size  may be different than your total sample. Assess whether this is appropriate.

## PROCESS output

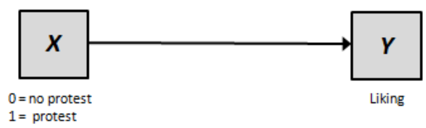
```
**************************************************************************
OUTCOME VARIABLE:
 respappr

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4992      .2492     1.3753    42.1550     1.0000   127.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.8841      .1831    21.2078      .0000     3.5217     4.2466
protest      1.4397      .2217     6.4927      .0000     1.0009     1.8785
```

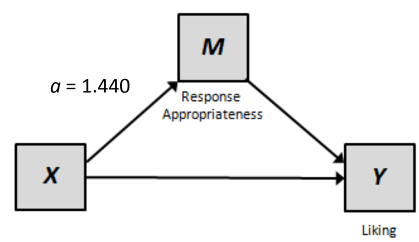
path *a*

```
*********************************************
```

Because the two groups differ by one unit on X, this is the difference between the group means.  Protesting was seen as more appropriate for the situation than doing nothing.

$$\hat{M} = 3.884 + 1.440X$$



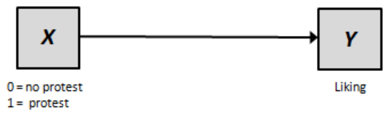



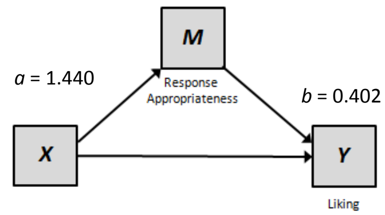
## PROCESS output

```
******************************************************************************
Outcome: liking

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4959      .2459      .8441    20.5483     2.0000   126.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.7473      .3058    12.2553      .0000     3.1422     4.3524
respappr      .4024      .0695     5.7884      .0000      .2648      .5400
protest      -.1007      .2005     -.5023      .6163     -.4975      .2960
```

path *b*

Holding constant what the attorney did, she was liked more by those who saw her behavior as more appropriate for the situation.



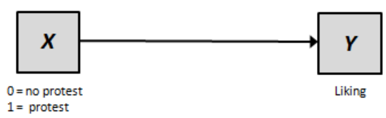

$$\hat{Y} = 3.751 - 0.100X + 0.402M$$

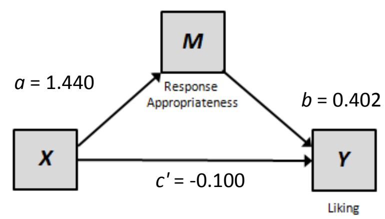
## PROCESS output

```
******************************************************************************
Outcome: liking

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4959      .2459      .8441    20.5483     2.0000   126.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.7473      .3058    12.2553      .0000     3.1422     4.3524
respappr      .4024      .0695     5.7884      .0000      .2648      .5400
protest      -.1007      .2005     -.5023      .6163     -.4975      .2960
```

path *c′*

Because the two groups differ by one unit on *X*, this is the difference between the group means adjusted for differences between the groups in how appropriate her behavior was perceived as being for the situation (i.e., holding it constant)



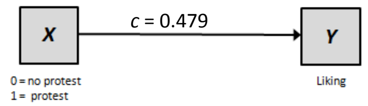

$$\hat{Y} = 3.751 - 0.100X + 0.402M$$

## PROCESS output

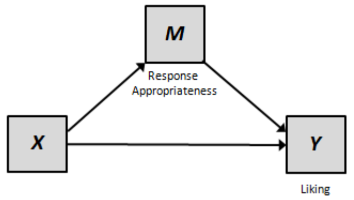
```
************************* TOTAL EFFECT MODEL ****************************
Outcome: liking

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2131      .0454     1.0601     6.0439     1.0000   127.0000      .0153

Model
              coeff         se          t          p       LLCI       ULCI
constant     5.3102      .1608    33.0244      .0000     4.9921     5.6284
protest       .4786      .1947     2.4584      .0153      .0934      .8639
*************************************************************************
```

path *c*

Because the two groups differ by one unit on *X*, this is the difference between the group means. The attorney was liked more when she protested than when she did not.




$$\hat{Y} = 5.310 + 0.479X$$




## Inference about the Indirect Effect

- How to make proper inference about the indirect effect may be the most active area of research in mediation analysis
- Some methods you may have heard of
  - Causal Steps / Baron and Kenny Method / Baron and Kenny Steps
  - Test of Joint Significance
  - Sobel Test / Multivariate Delta Method
  - Monte Carlo Confidence Intervals
  - Distribution of the Product Method
  - Bootstrap Confidence Intervals
    - Percentile Bootstrap
    - Bias-Corrected Bootstrap
    - Bias Corrected and Accelerated Bootstrap

- Why is this so hard?

  The product of two normal distributions is not necessarily normal. There are many instances where the indirect effect could be zero (either *a* or *b* could be zero, or both could be zero).

## Causal Steps Method

**Method**

1. Test if there is a significant total effect ($c \neq 0$).
2. Test if there is a significant effect of $X$ on $M$ ($a \neq 0$).
3. Test if there is a significant effect of $M$ on $Y$ controlling for $X$ ($b \neq 0$).
4. If all three steps are confirmed, test for partial vs. complete mediation.
    1. If $X$ still has an effect on $Y$ controlling for $M$ ($c' \neq 0$), this is partial mediation
    2. If $X$ does not have a significant effect on $Y$ controlling for $M$, complete mediation

**Appeal**

- Easy to do, just need regression
- Intuitive

**What's wrong with it?**

- No estimate of the indirect effect
- No quantification of uncertainty about conclusion
    - $p$-value
    - Confidence Interval
- Requirement that the total effect is significant before looking for indirect effect
- Multiple testing problem
- Issues with *complete* and *partial* mediation

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## Statistical inference: The indirect effect

The indirect effect estimates the influence of $X$ on $Y$ through the mechanism represented by $M$ (i.e., the $X \rightarrow M \rightarrow Y$ sequence). 21st-century mediation analysis bases claims of mediation on evidence that the indirect effect is different from zero.

**A popular "20th-century" approach to inference: The Sobel test**

Indirect effect

"Second order" estimator of the standard error of *ab*

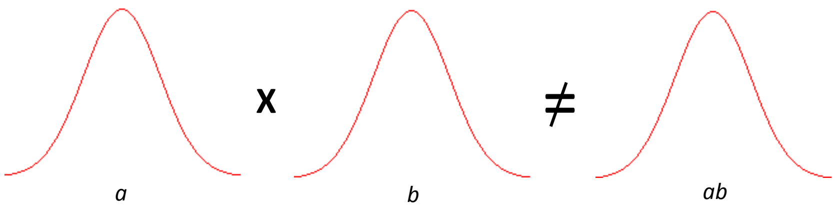
$$Z = \frac{ab}{\sqrt{b^2 s_a^2 + a^2 s_b^2 + s_a^2 s_b^2}}$$

One version eliminates this term ("first order" estimator) ,

A $p$-value is derived by assuming normality of the sampling distribution of the indirect effect and using the standard normal distribution for derivation of $p$. A $p$-value no greater than $\alpha$ leads to the claim that the indirect effect is statistically different from zero at the $\alpha$ level of significance.

## What's wrong with the Sobel test?

For the Sobel test, the *p*-value is derived by assuming normality of the sampling distribution of the indirect effect and using the standard normal distribution. **Although this assumption is fairly sensible in large samples, it is not in smaller ones. What is a sufficiently large sample is situationally-specific, and typically you won't know going into the analysis whether or not to trust <u>large sample theory</u>.**




This assumption, which typically will not hold, yields a test that is lower in power than alternatives. **Experts in mediation analysis don't recommend the use of this test, though it remains popular.** Eventually, researchers will get the message.

## Bootstrap Confidence Intervals (Percentile)

Empirically estimate sampling distribution of the indirect effect. From this distribution compute confidence intervals which can be used for estimation and hypothesis testing.

**Bootstrapping the Indirect Effect**

1. Randomly sample *n* cases from your dataset with replacement.
2. Estimate the indirect effect using resampled dataset, call this $ab^{(1)}$
3. Repeat steps 1 and 2 a total of *K* times where *K* is many (10,000 recommended), each time calculated $ab^{(k)}$.
4. The sampling distribution of the $ab^{(i)}$'s can be used as an estimate of the sampling distribution of the indirect effect.
5. For a 95% confidence interval the lower and upper bounds will be the $2.5^{th}$ and $97.5^{th}$ percentiles of the *K* estimates of the indirect effect.

**Appeal**

- No assumptions about the sampling distribution of the indirect effect
- Provides point estimate of indirect effect
- Can calculate confidence intervals
- Most simulation work suggests this is a very good method which balances Type I Error and Power

**What's wrong with it?**

- Most software does not have this functionality built in
- Requires original data

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## Bootstrapping

Your data

| $X$ | $M$ | $Y$ |
|---|---|---|
| 4.3 | 1.4 | 9.1 |
| 1.4 | 5.4 | 6.4 |
| 4.9 | 4.3 | 1.3 |
| 5.9 | 2.3 | 5.4 |
| 6.1 | 3.3 | 3.9 |
| 3.8 | 3.1 | 6.3 |
| 2.8 | 3.2 | 1.5 |
| 9.4 | 4.1 | 2.3 |
| 4.3 | 1.3 | 4.4 |
| 4.9 | 3.7 | 2.1 |

$a$ = -0.051  $b$ = -0.844

$ab$ = 0.043

A resampling of your data

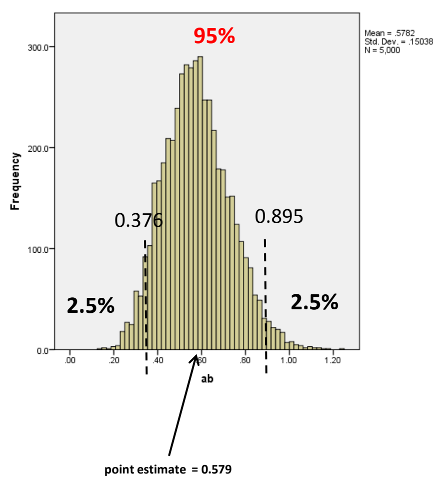
| $X$ | $M$ | $Y$ |
|---|---|---|
| 5.9 | 2.3 | 5.4 |
| 4.9 | 4.3 | 1.3 |
| 9.4 | 4.1 | 2.3 |
| 4.9 | 4.3 | 1.3 |
| 4.3 | 1.4 | 9.1 |
| 1.4 | 5.4 | 6.4 |
| 3.8 | 3.1 | 6.3 |
| 9.4 | 4.1 | 2.3 |
| 6.1 | 3.3 | 3.9 |
| 4.3 | 1.3 | 4.4 |

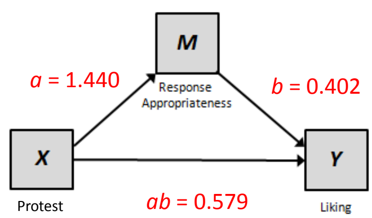
$a$ = 0.020  $b$ = -0.921

$ab$ = -0.018

## 5,000 bootstrap estimates of the indirect effect

95% of the 5,000 bootstrap estimates of the indirect effect were between 0.376 and 0.895. This is our 95% confidence interval.




Zero is not in the confidence interval, so we **can** claim an indirect effect different from zero with 95% confidence. This is akin to (though not exactly the same as) rejecting the null hypothesis of no indirect effect at the $\alpha$ = 0.05 level of significance.

## PROCESS output

```
***************** TOTAL, DIRECT, AND INDIRECT EFFECTS ********************

Total effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      .4786      .1947     2.4584      .0153      .0934      .8639

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
     -.1007      .2005     -.5023      .6163     -.4975      .2960

Indirect effect of X on Y
             Effect    Boot SE   BootLLCI   BootULCI
respappr      .5793      .1519      .3113      .9067

Normal theory tests for indirect effect
     Effect         se          Z          p
      .5793      .1350     4.2924      .0000
```

path *c*

path *c'*

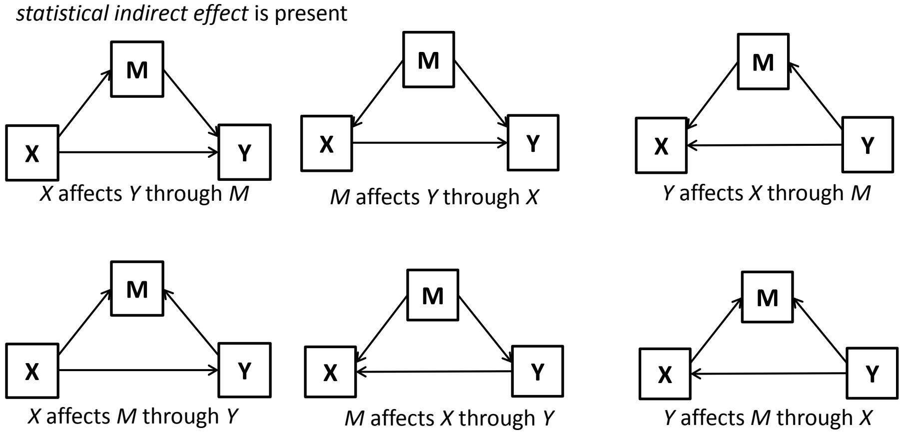
*ab* with 95% bootstrap confidence interval

Sobel test

Her behavior was perceived as more appropriate if she protested relative to when she did not ($a$ = 1.440), and the more appropriate her behavior, the more positively she was perceived ($b$ = 0.402). Her choice to protest had a positive effect on how favorably she was perceived indirectly through perceived appropriateness of the response (point estimate: 0.579, 95% CI = 0.311 to 0.907). After accounting for this mechanism, there was no effect of her choice to protest on how she was evaluated (direct effect = -0.101, $p$ = 0.62)

## A Brief Caution on Causality

There are a number of alternative causal processes that may be occurring when a *statistical indirect effect* is present

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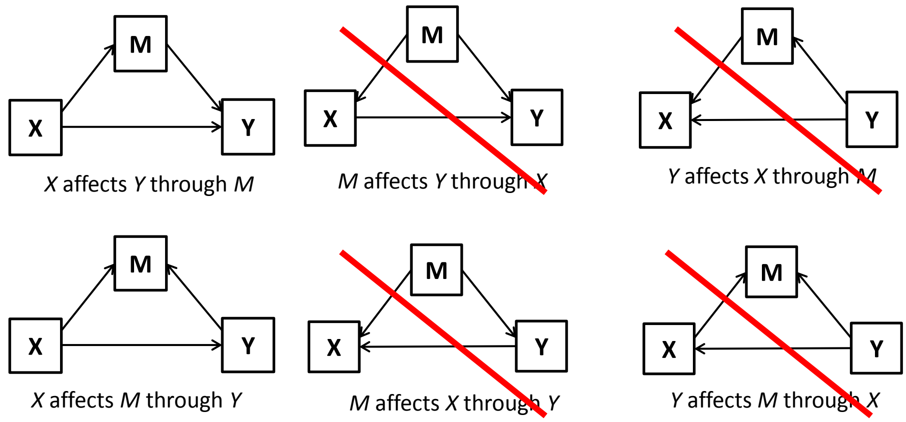
## A Brief Caution on Causality

**What you get by manipulating *X*.**




Even when *X* is manipulated, we can not provide evidence for the causal order between *M* and *Y*. This can only be supported using other experiments or previous research. *A statistically significant indirect effect does not lend credence to one model over another.*

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## Mediation Wrap Up Activity

**The following slides have examples of mediation from the literature. Try to draw the path diagram for these models and write out the PROCESS code to analyze the data.**

Gong, Y. Huang, J.C., & Farh, J. L. (2009) *Employee Learning Orientation, Tranformational Leadership, and Employee Creativity: The Mediating Role of Employee Creative Self-Efficacy*

"Hypothesis 2. Employee learning orientation is positively related to employee creativity."

"Hypothesis 4. Employee creative self-efficacy mediates the positive relationship between employee learning orientation and employee creativity predicted by Hypothesis 2."

**Activity:**

- Draw a path diagram and label *X*, *M*, and *Y* with variable names
- If Employee Learning Orientation is saved as a variable called `ELO`, Employee Creative Self-Efficacy is saved as `ECSE`, and Employee Creativity is saved as `ECrea`, what would the PROCESS command be to run this analysis? What if you want to print the total effect results, percentile bootstrap, and use 90% confidence?
- Is the total effect positive or negative?

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## Mediation Wrap Up Activity

**The following slides have examples of mediation from the literature. Try to draw the path diagram for these models and write out the PROCESS code to analyze the data.**

Barnes, C. M., Schaubroeck, J., Huth, M., & Ghumann, S. (2011) Lack of sleep and unethical conduct, *Organizational Behavior and Human Decision Processes*

"Lack of sleep will be negatively related to cognitive self-control."

"Cognitive self-control will be negatively related to unethical behavior."

"Lack of sleep will be positively related to unethical behavior."

"Lack of cognitive self-control will mediate the relationship between lack of sleep and unethical behavior."

**Activity:**

- Draw a path diagram and label *X*, *M*, and *Y* with variable names
- Variable Names: Lack of Sleep (`LOS`), Unethical Behavior (`UnethB`), and Cognitive Self Control (`CogSC`). What would the PROCESS command be to run this analysis? What if you want to print the Sobel test results and include 10,000 bootstrap samples?
- What are the hypothesized signs of the total effect, indirect effect, *a*-path, *b*-path?

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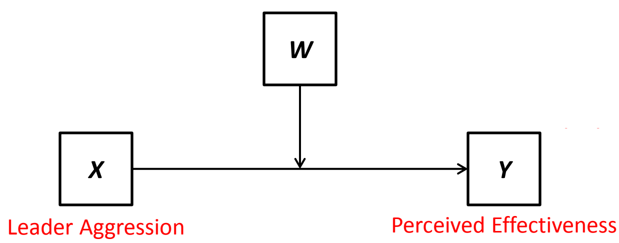
## Moderation




Moderation is the idea that the relationship between a focal predictor (*X*) and an outcome (*Y*) may depend on some other variable (*W*).

This can be described as a *contingent relationship* or an *interaction*.

The idea being that the magnitude or the sign (or both) of the relationship between *X* and *Y* depends on *W*.

Many different kinds of variables may act as moderators: experimental condition, individual differences, demographics, physiological variables, company level variables, environmental variables, etc.

A quick example: Name some possible moderators!

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## Modeling Non-Contingent Relationships

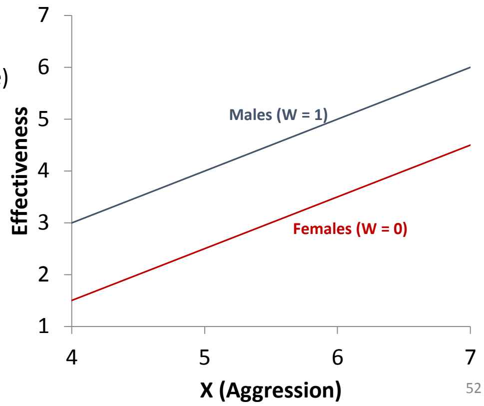
A multiple regression model without interaction terms, fixes the relationship between the predictors and the outcomes to be the same regardless of the level of other predictors.

$$Y_i = b_0 + b_1X_i + b_2W_i$$

A one unit increase in aggressiveness results in a .5 unit increase in perceived effectiveness, regardless of gender.

Example:
Y: Perceived Effectiveness ( 1- 7)
X: Aggression(1 - 7)
W: Gender of Leader (0 female, 1 male)

| Y | X | W |
|---|---|---|
| 1.5 | 4 | 0 |
| 2.0 | 4.5 | 0 |
| 2.5 | 5 | 0 |
| 3.0 | 4 | 1 |
| 3.5 | 4.5 | 1 |
| 4.0 | 5 | 1 |






## Modeling Contingent Relationships

What if instead we felt that the relationship between Aggression and Effectiveness depends on Gender? Thus the relationship between aggression and effectiveness is a *function* of gender

$$Y_i = b_0 + f(W_i)X_i + b_2W_i$$

One popular model for $f(W_i)$ is a linear model:

$$f(W_i) = b_1 + b_3W_i = \theta_{X \rightarrow Y|W}$$

This way we can rewrite the model:

$$Y_i = b_0 + \theta_{X \rightarrow Y|W}X_i + b_2W_i$$

$$Y_i = b_0 + (b_1 + b_3W_i)X_i + b_2W_i$$

$$Y_i = b_0 + b_1X_i + b_2W_i + b_3W_iX_i$$

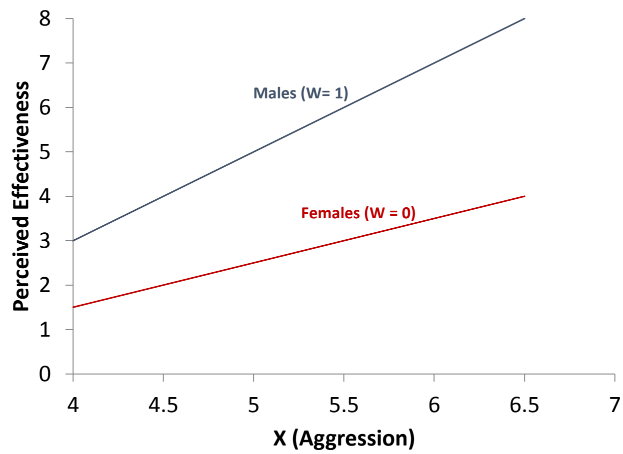
This is a regression model which can be estimated, where the significance of $b_3$ reflects whether the relationship between *X* and *Y* is linearly dependent on *w.*

## Modeling Contingent Relationships

What if instead we felt that the relationship between aggression and effectiveness depends on Gender?

$$Y_i = b_0 + (b_1 + b_3 W_i) X_i + b_2 W_i$$

| Y | X | W |
|---|---|---|
| 1.5 | 4 | 0 |
| 2 | 4.5 | 0 |
| 2.5 | 5 | 0 |
| 3 | 4 | 1 |
| 4 | 4.5 | 1 |
| 5 | 5 | 1 |

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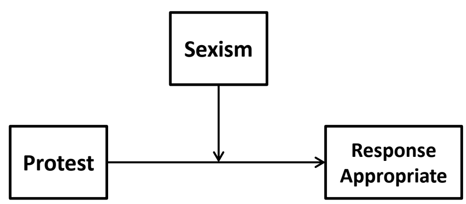
## Estimation with Protest Data

Consider the question: **Does the effect of protesting on perceptions of response appropriateness depend on someone's beliefs about the pervasiveness of sexism?**




$$Y_i = b_0 + b_1 X_i + b_2 W_i + b_3 W_i X_i$$

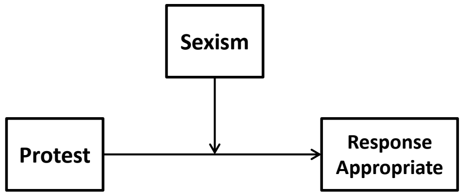
```
process y=respappr/x=protest/w=sexism/model=1/jn=1/plot=1/moments=1.
```

56

## Estimation with Protest Data

Consider the question **Does the effect of protesting on perceptions of response appropriateness depend on someone's beliefs about the pervasiveness of sexism?**

$$Y_i = b_0 + b_1X_i + b_2W_i + b_3W_iX_i$$




```
process y=respappr/x=protest/w=sexism/model=1/jn=1/plot=1/moments=1.
```

```
Outcome: respappr

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5442      .2962     1.3098    17.5340     3.0000   125.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     6.5667     1.2095     5.4295      .0000     4.1730     8.9604
sexism       -.5290      .2359    -2.2426      .0267     -.9959     -.0622
protest     -2.6866     1.4515    -1.8509      .0665    -5.5594      .1861
int_1         .8100      .2819     2.8732      .0048      .2520     1.3679

Product terms key:

 int_1    protest     X     sexism

R-square increase due to interaction(s):
         R2-chng          F        df1        df2          p
int_1      .0465     8.2551     1.0000   125.0000      .0048
```

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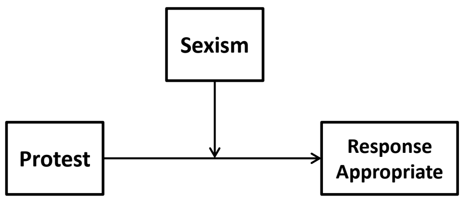
$b_1 = -2.687$: When participants score 0 on sexism pervasiveness, Catherine's response is seen as 2.687 units less appropriate when she protests

$b_2 = -.529$: When Catherine doesn't protest, a one unit increase in sexism beliefs results in a .5 unit **decrease** in response appropriateness.

## Estimation with Protest Data

Consider the question **Does the effect of protesting on perceptions of response appropriateness depend on someone's beliefs about the pervasiveness of sexism?**

$$Y_i = b_0 + b_1X_i + b_2W_i + b_3W_iX_i$$




```
process y=respappr/x=protest/w=sexism/model=1/jn=1/plot=1/moments=1.
```

```
Outcome: respappr

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5442      .2962     1.3098    17.5340     3.0000   125.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     6.5667     1.2095     5.4295      .0000     4.1730     8.9604
sexism       -.5290      .2359    -2.2426      .0267     -.9959     -.0622
protest     -2.6866     1.4515    -1.8509      .0665    -5.5594      .1861
int_1         .8100      .2819     2.8732      .0048      .2520     1.3679

Product terms key:

 int_1    protest     X     sexism

R-square increase due to interaction(s):
         R2-chng          F        df1        df2          p
int_1      .0465     8.2551     1.0000   125.0000      .0048
```

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$b_3 = .810$: For each one unit increase in protest (i.e. no protest to protest), the effect of perceived sexism on response appropriateness increases by .810 units. Influence of perceived sexism is more positive in protest condition.

## Probing an Interaction: The "Pick-a-Point" Approach

$$Y_i = b_0 + b_1 X_i + b_2 W_i + b_3 W_i X_i$$

Select a value of the moderator (*W*) at which you'd like to have an estimate of the focal predictor variable's (*X*) effect on *Y*. Then derive its standard error. The ratio of the effect to its standard error is distributed as $t(df_{residual})$ under the null hypothesis that the effect of the focal predictor is zero at that moderator value.

We already know that

$$\theta_{X \to Y|W} = (b_1 + b_3 W_i)$$

The estimated standard error of θ is

$$s_{\theta_{X \to Y|W}} = \sqrt{(s_{b_1}^2 + 2W s_{b_1 b_3} + W^2 s_{b_3}^2)}$$

Squared standard error of $b_1$

Covariance of $b_1$ and $b_3$

Squared standard error of $b_3$

## Probing an Interaction: The "Pick-a-Point" Approach

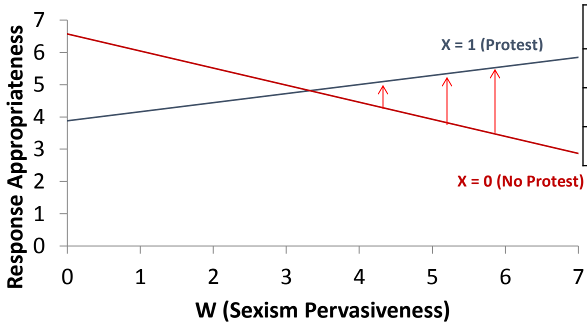
You must choose the points along the moderator to "probe" the effect of *X* on *Y*. There are some conventions for choosing to do so:

If *W* is dichotomous, choose the two coded values of *W*

If *W* is continuous, choose the Mean ± 1 SD or specific percentiles

Let's look at an example with our protest data:

$$Y_i = 6.567 + (-2.687 + .810 W_i) X_i - .529 W_i$$




| W | $\theta_{X \to Y\|W}$ | $s_{\theta_{X \to Y\|W}}$ | *p* |
|---|---|---|---|
| 4.33 | .823 | .304 | .008 |
| 5.11 | 1.46 | .217 | <.001 |
| 5.90 | 2.09 | .315 | <.001 |

Participants felt Catherine's response was more appropriate in the protest condition, at relatively low (1SD below mean), relatively moderate (mean), and relatively high values (1SD above mean) of perceived sexism.

## Pick-a-point output

PROCESS sees that the moderator is quantitative (because it has more than 2 values) so it implements the pick-a-point procedure with moderator values equal to the mean of the moderator as well as ± one SD from the mean.

Conditional effect of X on Y at values of the moderator(s):

| sexism | Effect | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| 4.3332 | .8232 | .3043 | 2.7056 | .0078 | .2210 | 1.4253 |
| 5.1170 | 1.4580 | .2167 | 6.7282 | .0000 | 1.0291 | 1.8869 |
| 5.9007 | 2.0929 | .3146 | 6.6518 | .0000 | 1.4702 | 2.7156 |

Values for quantitative moderators are the mean and plus/minus one SD from mean.
Values for dichotomous moderators are the two values of the moderator.

$\theta_{X\rightarrow Y|M} = -2.687 + .810M$

Catherine's choice to protest (compared to not protest) was perceived as more appropriate among those "relatively low" in perceived sexism ($\theta_{X\rightarrow Y|M=4.33} = .823$, $p < .01$), among those "relatively moderate" in perceived sexism ($\theta_{X\rightarrow Y|M=5.11} = 1.46$, $p < .001$), and among Those "relatively high" in perceived sexism ($\theta_{X\rightarrow Y|M=5.90} = 2.09$, $p < .001$).

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## Additional probing options

Setting `moments = 0` or leaving it out, produces estimates of the conditional effect of *X* at the 16th, 50th, and 84th percentiles of the moderator rather than the mean and plus/minus one standard deviation. Or use the **wmodval** option to request a specific value of the moderator at which you'd like the conditional effect of *X*.

```
process y = ... /moments = 0.
```

```
%process (data = ... , moments = 0);
```

Conditional effects of the focal predictor at values of the moderator(s):

| bdi0 | Effect | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| .9020 | -.2683 | .1850 | -1.4500 | .1490 | -.6336 | .0971 |
| 1.1900 | -.5414 | .1375 | -3.9384 | .0001 | -.8129 | -.2699 |
| 1.5180 | -.8525 | .1941 | -4.3923 | .0000 | -1.2358 | -.4692 |

W values in conditional tables are the 16th, 50th, and 84th percentiles.

```
process y = ... /wmodval = 1.5.
```

```
%process (data = ... , wmodval = 1.5);
```

Conditional effect of X on Y at values of the moderators(s)

| bdi0 | Effect | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| 1.5000 | -.8354 | .1888 | -4.4253 | .0000 | -1.2082 | -.4626 |

## The Johnson-Neyman Technique

The Johnson-Neyman technique seeks to find the value or values of the moderator (*W*) within the data, if they exist, such that the *p*-value for the conditional effect of the focal predictor at that value or those values of *W* is exactly equal to some chosen level of significance $\alpha$. Thus, no need to select values of *W* in advance.

To do so, we ask what value of *W* produces a ratio of $\theta_{X \rightarrow Y|W}$ to its standard error exactly equal to the critical *t* value ($t_{crit}$) required to reject the null hypothesis that $\theta_{X \rightarrow Y|W}$ is equal to zero at that value of *W*?

$$t_{crit} = \frac{b_1 + b_3 W}{\sqrt{\left\{s_{b_1}^2 + 2W s_{b_1 b_3}^2 + W^2 s_{b_3}^2\right\}}}$$

Isolating *W* yields to the solution in the form of a quadratic equation which always has two roots, though not always two that are interpretable.



## Johnson-Neyman technique

```
Moderator value(s) defining Johnson-Neyman significance region(s)
     Value    % below    % above
    4.1525     9.3023    90.6977
```

Conditional effect of X on Y at values of the moderator (M)

*W*

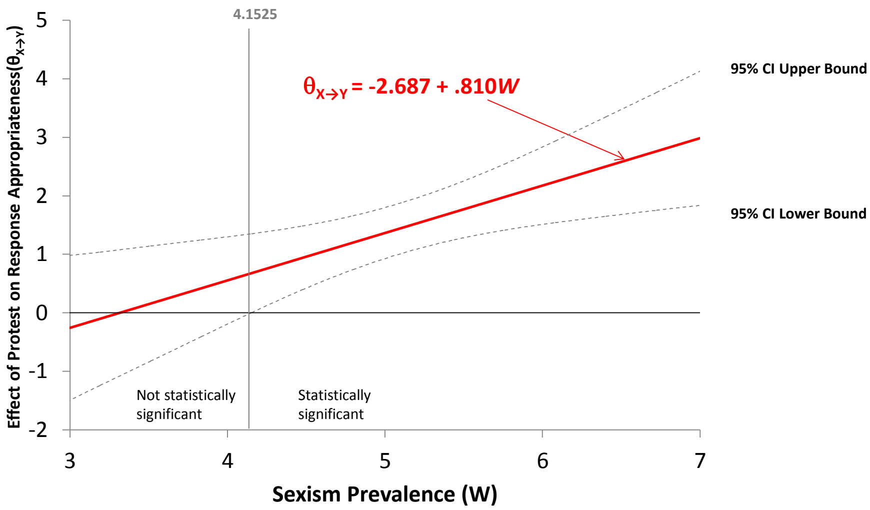
$\theta_{X \rightarrow Y}|W$

| sexism | Effect | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| 2.8700 | -.3620 | .6626 | -.5463 | .5858 | -1.6733 | .9493 |
| 3.0765 | -.1947 | .6079 | -.3203 | .7492 | -1.3978 | 1.0083 |
| 3.2830 | -.0275 | .5539 | -.0496 | .9605 | -1.1236 | 1.0687 |
| 3.4895 | .1398 | .5008 | .2792 | .7806 | -.8513 | 1.1309 |
| 3.6960 | .3071 | .4490 | .6839 | .4953 | -.5816 | 1.1957 |
| 3.9025 | .4743 | .3990 | 1.1888 | .2368 | -.3154 | 1.2640 |
| 4.1090 | .6416 | .3515 | 1.8251 | .0704 | -.0542 | 1.3373 |
| 4.1525 | .6768 | .3420 | 1.9791 | .0500 | .0000 | 1.3536 |
| 4.3155 | .8088 | .3078 | 2.6280 | .0097 | .1997 | 1.4180 |
| 4.5220 | .9761 | .2695 | 3.6213 | .0004 | .4426 | 1.5096 |
| 4.7285 | 1.1434 | .2395 | 4.7739 | .0000 | .6694 | 1.6174 |
| 4.9350 | 1.3106 | .2210 | 5.9301 | .0000 | .8732 | 1.7480 |
| 5.1415 | 1.4779 | .2170 | 6.8091 | .0000 | 1.0483 | 1.9075 |
| 5.3480 | 1.6452 | .2284 | 7.2042 | .0000 | 1.1932 | 2.0971 |
| 5.5545 | 1.8124 | .2529 | 7.1660 | .0000 | 1.3119 | 2.3130 |
| 5.7610 | 1.9797 | .2873 | 6.8897 | .0000 | 1.4110 | 2.5484 |
| 5.9675 | 2.1469 | .3285 | 6.5348 | .0000 | 1.4967 | 2.7972 |
| 6.1740 | 2.3142 | .3743 | 6.1830 | .0000 | 1.5734 | 3.0550 |
| 6.3805 | 2.4815 | .4231 | 5.8649 | .0000 | 1.6441 | 3.3188 |
| 6.5870 | 2.6487 | .4741 | 5.5874 | .0000 | 1.7105 | 3.5869 |
| 6.7935 | 2.8160 | .5265 | 5.3484 | .0000 | 1.7740 | 3.8580 |
| 7.0000 | 2.9832 | .5801 | 5.1429 | .0000 | 1.8352 | 4.1313 |

Region of significance

Among those with perceived sexism greater than 4.1524, Catherine's choice to protest results in higher perceived appropriateness. Below that value, protesting had no effect.

## A Plot of the "Region of Significance"

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## Writing up a Moderation Analysis

**Does the effect of protesting on response appropriateness depend on beliefs about the prevalence of sexism today?**

Overall, Catherine's protesting behavior is seen as differentially appropriate depending on beliefs in the prevalence of sexism ($b_3$ = .81, $p$ = .0048). The positive sign of the interaction coefficient reflects that as beliefs about the prevalence of sexism increase, the effect of protesting increases (i.e. protesting is seen as more appropriate as beliefs about sexism increase). Indeed we found that Catherine's choice to protest (compared to not protest) was perceived as more appropriate among those "relatively low" in perceived sexism ($\theta_{X\to Y|M=4.33}$ = .823, $p$ < .01), among those "relatively moderate" in perceived sexism ($\theta_{X\to Y|M=5.11}$ = 1.46, $p$ < .001), and among those "relatively high" in perceived sexism ($\theta_{X\to Y|M=5.90}$ = 2.09, $p$ < .001). The Johnson-Neyman procedure revealed that among those whose perceived sexism was greater than 4.15, the protest condition was seen as significantly more appropriate than the no protest condition. Participants with perceived sexism less than 4.15 showed no significant differences based on condition.

Tips:

- Interpret the sign and the magnitude of the interaction coefficient with respect to *X*'s effect on *Y*
- Provide probing results with interpretations
- Read the write ups of other's moderation analyses
- Provide a graphical representation of the effect of interest (like the ones we've done)

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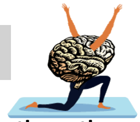
## Moderation Wrap Up Activity



**The following slides have examples of moderation from the literature. Try to draw the path diagram for these models and write out the PROCESS code to analyze the data.**

Porath, C. L. & Erez, A. (2009) Overlooked but not untouched: How rudeness reduces onlookers' performance on routine and creative tasks, *Organizational Behavior and Human Decision Processes*

"Witnesses of incivility may experience negative affect."

"Competition for resources with victims would moderate the relationship between witnesses of rudeness and … negative affect. Specifically, the effects of witnessing rudeness on these dependent variables will be weaker under a competitive condition than under a cooperative condition."

**Activity:**

- Draw a path diagram and label *X*, *M*, and *Y* with variable names
- Variable Names: Witness Rudeness (`Rude`; 1 = Yes, 0 = No), Competition (`Comp` ; 1 = Yes, 0 = No), and Negative Affect (`NegAff`). What would the PROCESS command be to run this analysis?
- What are the hypothesized signs of the $b_1$ and $b_3$?
- Draw a graphical representation which fits your expectations for these results.

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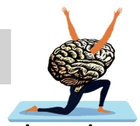
## Moderation Wrap Up Activity



**The following slides have examples of moderation from the literature. Try to draw the path diagram for these models and write out the PROCESS code to analyze the data.**

Grant, A., Gino, F., Hofmann, D. (2011) Reversing the extraverted leadership advantage: The role of employee proactivity, *Academy of Management Journal*

"Hypothesis 1. Employee proactivity moderates the association between leader extraversion and group performance. When employees are passive, leader extraversion is positively related to group performance, but when employees are proactive, leader extraversion is negatively related to group performance."

**Activity:**

- Draw a path diagram and label *X*, *M*, and *Y* with variable names
- Variable Names: Leader Extroversion (`LExt;` Continuous), Employee Proactivity (`EPro` ; Continuous), and Group Performance (`GPerf`). What would the PROCESS command be to run this analysis? What if I would like a table for plotting and to use the Johnson-Neyman procedure?
- What is the hypothesized sign of $b_3$?
- Draw a graphical representation which fits your expectations for these results.

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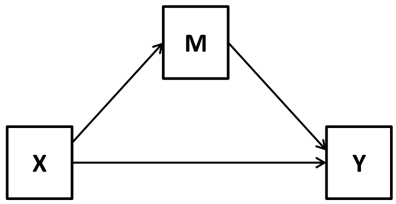
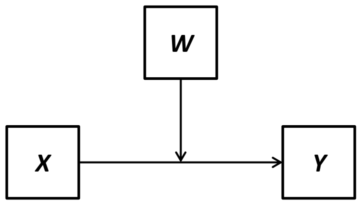
## Conditional Process Analysis

Conditional process analysis combines the ideas of **mediation** and **moderation**. All conditional process models have a mediation model where one or more paths in this model is moderated.




Conditional process analysis is useful for identifying the "when" or "for whom" certain mechanisms operate between *X* and *Y*.

When one or more paths of the indirect effect is moderated, the indirect effect can be defined as a *function of the moderator*, allowing for tests of moderation and probing.




Conditional process analysis is not a new concept, really just a new name. You may know it by *moderated mediation* or *mediated moderation*.

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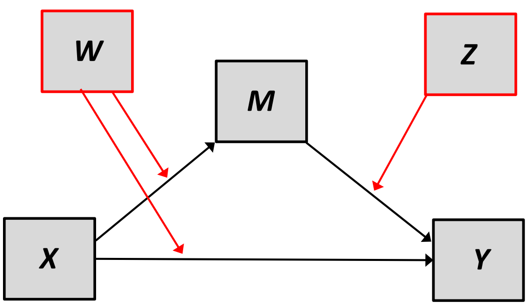
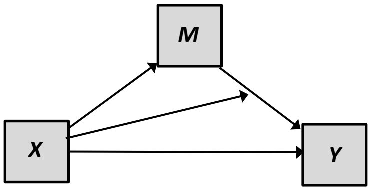
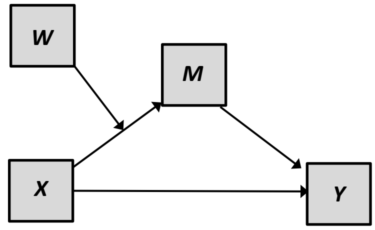
## Conditional Process Modeling

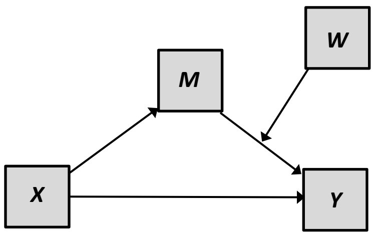


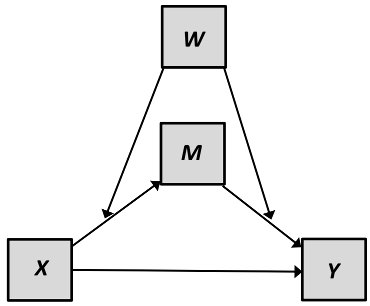

- The indirect effect of *X* on *Y* through *M* is estimated as the product of two paths
- But what if size of *the X* → *M* path or *M* → *Y path* (or both) depends on another variable (i.e., is moderated)?
- If so, then the magnitude of the indirect effect therefore depends on a third variable— "moderated mediation"
- When *either* path is moderated, it is sensible then to estimate "conditional indirect effects"— values of indirect effect conditioned on values of the moderator variable that moderates one of the paths.
- Direct effects can also be conditional. For instance, in the above, *W* could moderate *X*'s direct effect on *Y*.

## A Few of the Many Possibilities

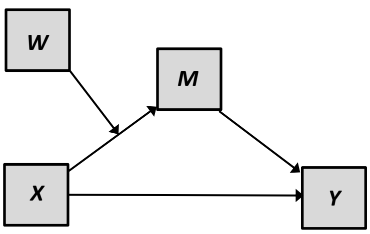


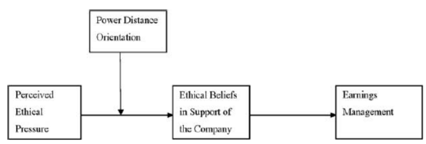



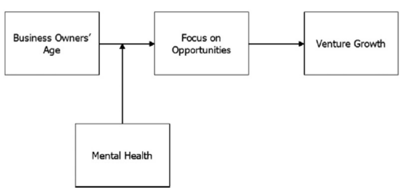




## Examples: *X* to *M* Path Moderated by *W*

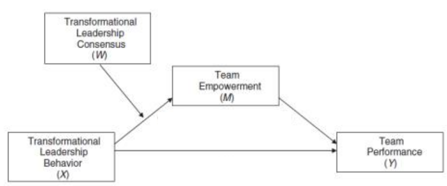



Tian, Q., & Peterson, D. K. (2016). The effects of ethical pressure and power distance orientation on unethical pro-organizational behavior: the case of earnings management. ***Business Ethics: A European Review,*** *25*(2), 159-171.

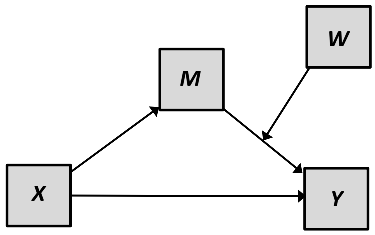



Gielnik, M. M., Zacher, H., & Frese, M. (2012). Focus on opportunities as a mediator of the relationship between business owners' age and venture growth. ***Journal of Business Venturing,*** *27*, 127-142.

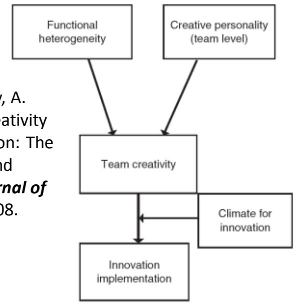


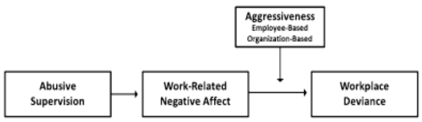

Cole, M. S., Bedeian, A. G., & Bruch, H. (2011). Linking leader behavior and leadership consensus to team performance: Integrating direct consensus and dispersion models to group composition. ***The Leadership Quarterly,*** *22*, 383-398.

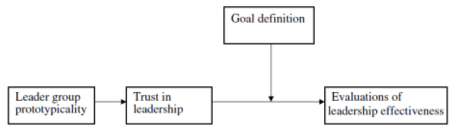
## Examples: *M* to *Y* Path Moderated by *W*




Somech, A., & Drach-Zahavy, A. (2013). Translating team creativity to innovation implementation: The role of team composition and climate for innovation. ***Journal of Management***, 39(3), 684-708.



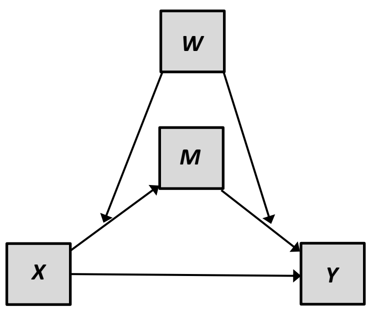



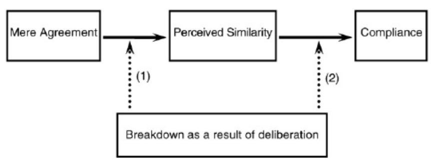

Michel, J. S., Newness, K., & Duniewicz, K. (2015). How abusive supervision affects workplace deviance: A moderated-mediation examination of aggresiveness and work-related negative affect. ***Journal of Business Psychology***, 31(1), 1-22.

Giessner, S., van Knippenberg, D., & Sleebos, E. (2008). "License to fail": Goal definition, leader group prototypicality, and perceptions of leadership effectiveness after leader failure. ***Organizational Behavior and Human Decision Processes***, *105*, 14-35



## Examples: *X* to *M* and *M* to *Y* Path Moderated by *W*

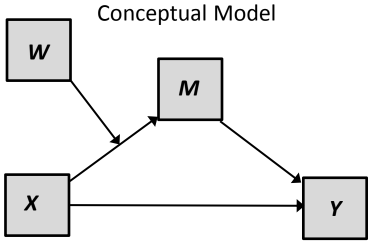


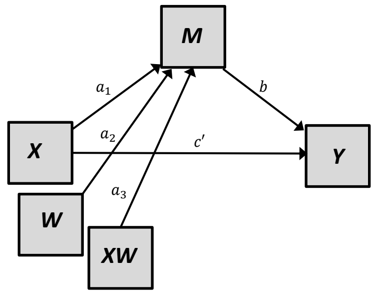

Pandelaere, M., Briers, B., Dewitte, S., & Warlop, L. (2010). Better think before agreeing twice. Mere agreement: A similarity-based persuasion mechanism. ***International Journal of Research in Marketing***, *27*, 133-141.

## *X* to *M* Path Moderated by *W*

Conceptual Model




Statistical Model




*X* is proposed to influence *Y* indirectly through *M*, but the effect of *X* on *M* is moderated by *W*. Therefore the degree to which *M* operates as a mediator of the effect of *X* on *Y* depends on *W*.

In order to describe this relationship it will be worthwhile to construct an estimate of the indirect effect at different values of *W*.

$$M_i = i_M + a_1X_i + a_2W_i + a_3X_iW_i + \epsilon_{Mi}$$

equivalently

$$M_i = i_M + (a_1 + a_3W_i)X_i + a_2W_i + \epsilon_{Mi}$$

$$M_i = i_M + \theta_{X\to M|W}X_i + a_2W_i + \epsilon_{Mi}$$

Where $\theta_{X\to M|W} = a_1 + a_3W_i$

$$Y_i = i_Y + c'X_i + bM_i + \epsilon_{Yi}$$

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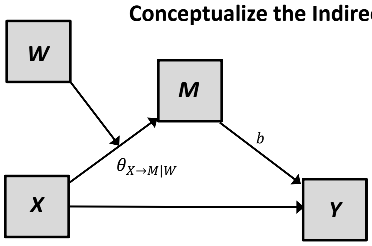
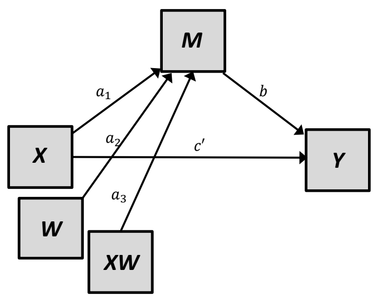
## *X* to *M* Path Moderated by *W*

**Conceptualize the Indirect Effect as the Product of Two Paths**




$\theta_{X\to M|W}$ is a quantification of the effect of *X* on *M* conditional on *W*. The estimate of the effect of *M* on *Y* is *b*.

An estimate of the conditional indirect effect of *X* on *Y* through *M* conditional on *W*

$$\theta_{X\to M|W}b = (a_1 + a_3W)b$$ ← The indirect effect is now a function of W

Now we have an estimate of the indirect effect at any value of *W*.

$$M_i = i_M + \theta_{X\to M|W}X_i + a_2W_i + \epsilon_{Mi}$$

Where $\theta_{X\to M|W} = a_1 + a_3W_i$

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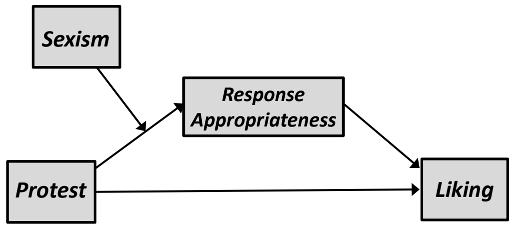
## Conceptual Model with Protest Data




We have set up the mediation model that we examined before: where Catherine's protesting behavior influences liking through response appropriateness. But remember we found that the relationship between protesting and response appropriateness depended on perceived sexism.

Now we can ask **Does the degree to which response appropriateness acts as a mediator between protesting and liking depend on beliefs about the prevalence of sexism?**

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## Implementation Using PROCESS

Model templates for PROCESS for SPSS and SAS
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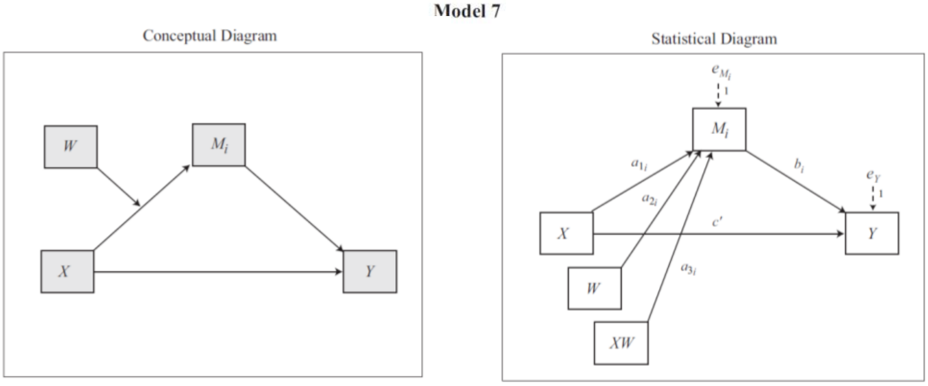
**Model 7**




Conditional indirect effect of $X$ on $Y$ through $M_i = (a_{1i} + a_{3i}W)b_i$

Direct effect of $X$ on $Y = c'$

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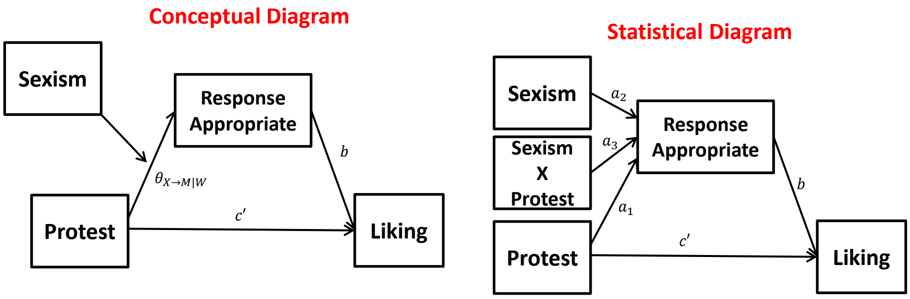
## Conceptual and Statistical Diagram




$$M_i = i_M + a_1X_i + a_2W_i + a_3X_iW_i + \epsilon_{Mi}$$

$$Y_i = i_Y + c'X_i + bM_i + \epsilon_{Yi}$$

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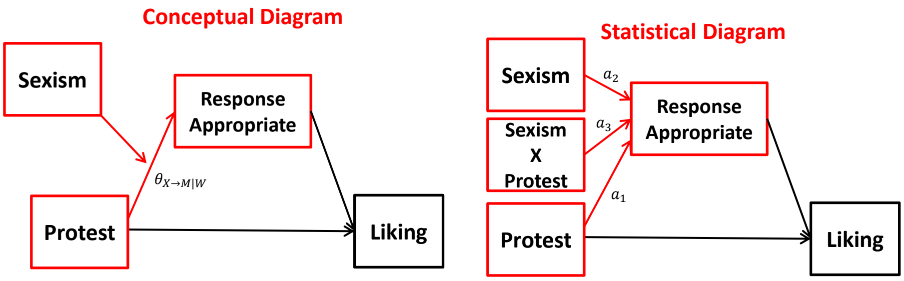
## The Model of *M*




The effect of protesting on response appropriateness can be modeled as a function of perceived prevalence of sexism

$$\boxed{M_i = i_M + a_1X_i + a_2W_i + a_3X_iW_i + \epsilon_{Mi}}$$

$$M_i = i_M + (a_1 + a_3W_i)X_i + a_2W_i + \epsilon_{Mi}$$

$$\theta_{X\to M|W} = a_1 + a_3W_i$$

$$Y_i = i_Y + c'X_i + bM_i + \epsilon_{Yi}$$

A quantification of the effect of *X* on *M*: $\theta_{X\to M|W} = (a_1 + a_3W)$

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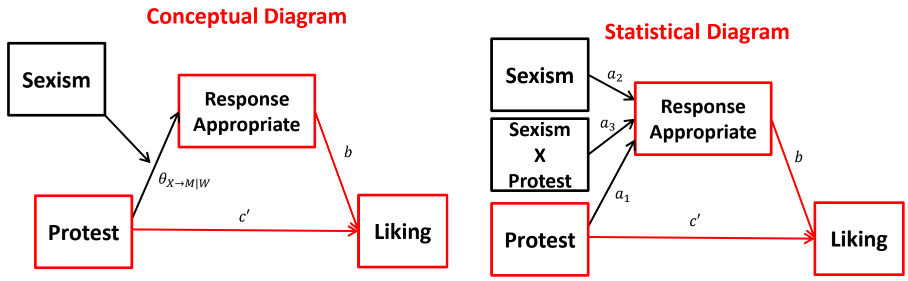
## The Model of *Y*




$$M_i = i_M + a_1X_i + a_2W_i + a_3X_iW_i + \epsilon_{Mi}$$

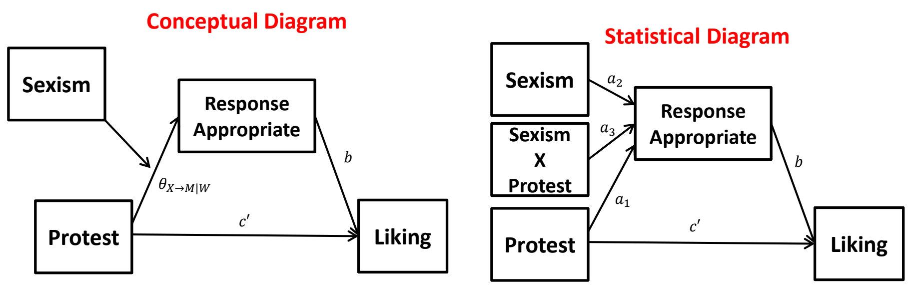
The effect of response appropriateness on liking is constant. This is a modeling choice!

$$\boxed{Y_i = i_Y + c'X_i + bM_i + \epsilon_{Yi}}$$

A quantification of the effect of *M* on *Y*: $b$



## The Conditional Indirect Effect



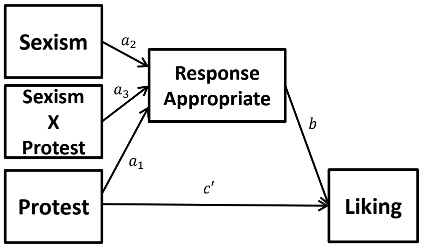

$$M_i = i_M + a_1X_i + a_2W_i + a_3X_iW_i + \epsilon_{Mi}$$
$$Y_i = i_Y + c'X_i + bM_i + \epsilon_{Yi}$$

The indirect effect of *X* on *Y* through *M* is **not** $a_1b$. It is $\theta_{X\to M|W}b$ where $\theta_{X\to M|W} = a_1 + a_3W$, so the indirect effect of *X* is $(a_1+a_3W)b$. It is conditional because it *depends on W*.

A quantification of the conditional indirect effect: $\theta_{X\to Y|W}b = (a_1 + a_3W)b$

# Implementation Using PROCESS

```
process y=liking/x=protest/m=respappr/w=sexism/model=7/boot=10000/moments=1.
```




```
Model = 7
    Y = liking
    X = protest
    M = respappr
    W = sexism

Sample size
        129
```

Always double check that your model information is correct!

```
**************************************************************************
Outcome: respappr

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5442      .2962     1.3098    17.5340     3.0000   125.0000      .0000
```

This is the moderation model that we just estimated, but now it's part of a larger moderated mediation model.

Model

| | coeff | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| constant | 6.5667 | 1.2095 | 5.4295 | .0000 | 4.1730 | 8.9604 |
| protest | -2.6866 | 1.4515 | -1.8509 | .0665 | -5.5594 | .1861 |
| sexism | -.5290 | .2359 | -2.2426 | .0267 | -.9959 | -.0622 |
| int_1 | .8100 | .2819 | 2.8732 | .0048 | .2520 | 1.3679 |

$a_1$ and $a_3$

Product terms key:

```
 int_1     protest      X      sexism
```

$$\theta_{X\rightarrow Y|W} = (a_1 + a_3W) = -2.687 + .810W$$

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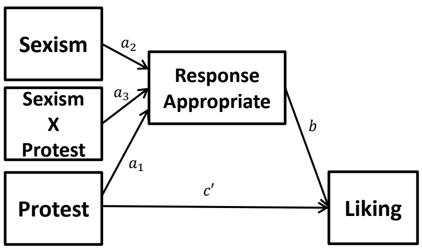
# Implementation Using PROCESS

```
process y=liking/x=protest/m=respappr/w=sexism/model=7/boot=10000/moments=1.
```




```
Outcome: liking

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4959      .2459      .8441    20.5483     2.0000   126.0000      .0000
```

Model

| | coeff | se | t | p | LLCI | ULCI | |
|---|---|---|---|---|---|---|---|
| constant | 3.7473 | .3058 | 12.2553 | .0000 | 3.1422 | 4.3524 | |
| respappr | .4024 | .0695 | 5.7884 | .0000 | .2648 | .5400 | $b$ |
| protest | -.1007 | .2005 | -.5023 | .6163 | -.4975 | .2960 | $c'$ |

This is the same model for liking as from the mediation model, so all interpretations stay the same.

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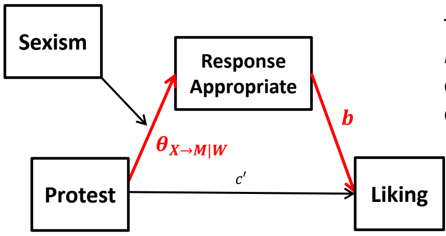
## The Conditional Indirect Effect




The conditional indirect effect of *X* on *Y* through *M* is the product of the conditional effect of *X* on *M* ($\theta_{X\to M|W} = a_1 + a_3W$) and the effect of *M* on *Y* (*b*).

$\theta_{X\to M}b = (a_1 + a_3W)b_1 = (-2.687 + 0.810W)0.402$

| Sexism (*W*) | $\theta_{X\to M|W}$ | *b* | $\theta_{X\to M}b$ |
|---|---|---|---|
| 3.000 | -0.257 | 0.402 | -0.103 |
| 4.000 | 0.553 | 0.402 | 0.222 |
| 5.000 | 1.363 | 0.402 | 0.547 |
| 6.000 | 2.173 | 0,402 | 0.873 |
| 7.000 | 2.983 | 0.402 | 1.199 |

The **indirect effect** of protesting on liking through response appropriateness is positively related to *perceived sexism*. It appears to be larger and positive among those who believe sexism is more prevalent, and smaller and sometimes negative among those who believe sexism is not as prevalent. Bootstrap CIs can be used for inference about conditional indirect effects.



## Implementation Using PROCESS

```
process y=liking/x=protest/m=respappr/w=sexism/model=7/boot=10000/moments=1.
```

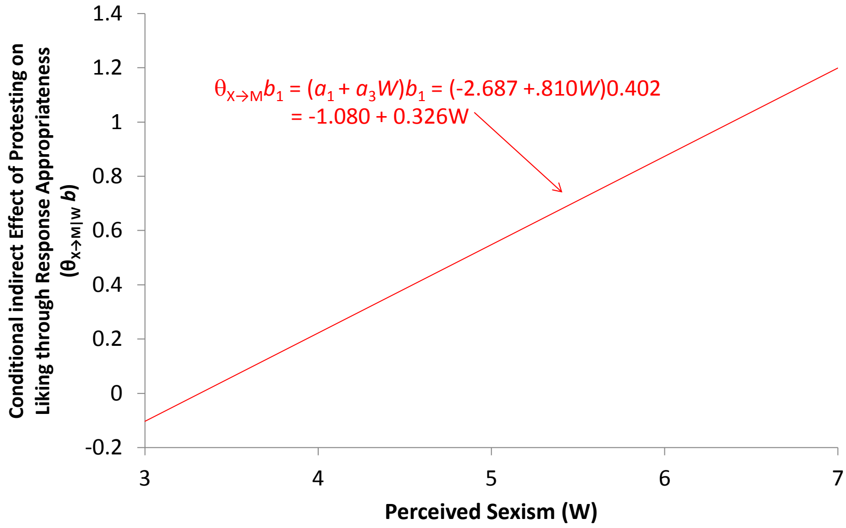
```
******************** DIRECT AND INDIRECT EFFECTS *************************

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
     -.1007      .2005     -.5023      .6163     -.4975      .2960

Conditional indirect effect(s) of X on Y at values of the moderator(s):

Mediator
            sexism     Effect    Boot SE   BootLLCI   BootULCI
respappr    4.3332      .3312      .1376      .0756      .6214
respappr    5.1170      .5867      .1485      .3219      .9031
respappr    5.9007      .8422      .2417      .4138     1.3578

Values for quantitative moderators are the mean and plus/minus one SD from mean.
Values for dichotomous moderators are the two values of the moderator.

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

Mediator
             Index   SE(Boot)   BootLLCI   BootULCI
respappr     .3259      .1645      .0353      .6804
```

*c′*

Conditional Indirect Effects. For continuous moderators, PROCESS estimates at mean ± 1 SD. For dichotomous, estimated at two coded values

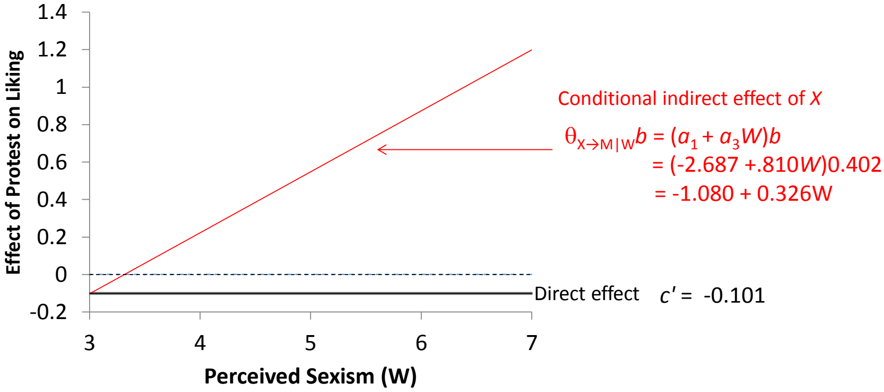
The index of moderated mediation with a bootstrap confidence interval. CI does not include zero, so we conclude moderation of the indirect effect.

## A visual depiction






## A visual summary




The indirect effect of protesting on liking through response appropriateness is negative only among those *very* low in perceived sexism, for all others it is positive, and increasing with beliefs in the prevalence of sexism. Independent of this mechanism, there is no effect of protesting on liking.

## An Attempt at Inference for Moderated Mediation

**These results are consistent with a claim of moderation mediation---the indirect effect is contingent on a moderator, i.e., the size of the indirect effect depends on a moderator.**

**The approach just outlined and illustrated has become the standard approach to "testing" a moderated mediation hypothesis *(until very recently):***

(1) Evidence of moderation of one of the paths of the indirect effect?

**and/or**

(2) Evidence of differences in significance for various values of the conditional indirect effect, with the conditioning choice usually determined arbitrarily.

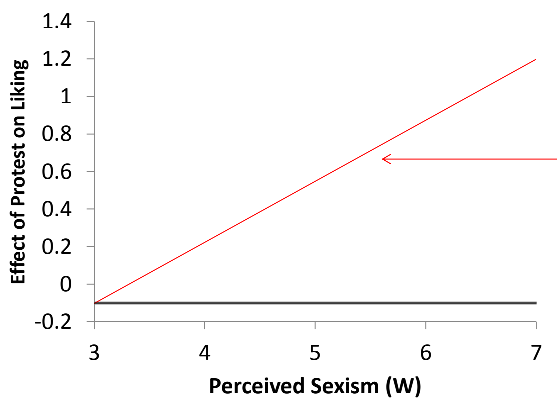
**But…**

(1) Evidence of moderation of a single path does not necessarily imply moderation of the *product* of paths, which is what the indirect effect is.
What if the other path is zero?

(2) Difference in significance does not imply significance of difference.



## A Formal Test of Moderated Mediation




**What would the line for the conditional indirect effect look like if it did not depend on W?**

Conditional indirect effect of *X*
$\theta_{X\rightarrow M|W}b = (a_1 + a_3W)b$
$= (-2.687 + .810W)0.402$

The **slope of the line** reflects the degree to which the indirect effect depends on W.

What is the slope of the line?

$$\theta_{X\rightarrow M|W}b = a_1b + \boxed{a_3b}W$$

If $a_3b$ is different from zero, this is evidence that the indirect effect depends on $W$. We call this term the **Index of Moderated Mediation**. A formal test on $a_3b$ can provide a formal test for if the mediation is moderated.

We can do this formal test using bootstrapping.

## IMM as Test of Difference in Indirect Effects

We may wonder if the indirect effect of *X* on *Y* through *M* at some value of the moderator *W* (call this $w_1$) is different from the indirect effect of *X* on *Y* through *M* at some **other** value of the moderator *W* (call this $w_2$)

$H_0: \theta_{X\to M|W=w_1} b = \theta_{X\to M|W=w_2} b$ or equivalently $H_0: \theta_{X\to M|W=w_1} b - \theta_{X\to M|W=w_2} b = 0$

$H_A: \theta_{X\to M|W=w_1} b - \theta_{X\to M|W=w_2} b \neq 0$

**We can test this!**

$$\theta_{X\to M|W=w_1} b = a_1 b + a_3 b w_1$$

$$\theta_{X\to M|W=w_2} b = a_1 b + a_3 b w_2$$

$$\begin{aligned}\theta_{X\to M|W=w_1} b - \theta_{X\to M|W=w_2} b &= (a_1 b + a_3 b w_1) - (a_1 b + a_3 b w_2)\\ &= a_3 b w_1 - a_3 b w_2\\ &= a_3 b (w_1 - w_2)\end{aligned}$$

So long as $w_1$ does not equal $w_2$, this means that the difference between the indirect effects is zero **only if $a_3$b is non zero**. Thus the *index of moderated mediation* is a test for if any two indirect effects differ from each other.



## Writing up a Conditional Process Analysis

**Is the indirect effect of protesting on liking through perceptions of response appropriateness moderated by perceived sexism?**

We estimated a first stage moderated mediation model, where the effect of protesting on response appropriateness was moderated by perceived prevalence of sexism, and the effect of response appropriateness on liking was not moderated by any variables. The effect of protesting on response appropriateness was significantly moderated by perceived prevalence of sexism ($a_3$= .810, *p* < .01). The conditional effect of protesting on response appropriateness was $\theta_{X\to M|W} = (a_1 + a_3 W) = -2.687 + .810W$. This means that as perceived sexism increases, the effect of protesting on response appropriateness increases. A one unit increase in response appropriateness resulted in a *b* = .402 unit increase in liking, controlling for whether or not Catherine protested (*p* < .001). The conditional indirect effect ($\theta_{X\to M|W} b$) can be quantified as $a_1 b + a_3 bW = -1.08 + .326W$. The conditional indirect effect was positive for those relatively low on perceived sexism ($\theta_{X\to M|W=4.33} = .33$, 95% bootstrap CI [.076,.621]), relatively moderate on perceived sexism ($\theta_{X\to M|W=5.11} = .59$, 95% bootstrap CI [.322,.903]), and among those relatively high on perceived sexism ($\theta_{X\to M|W=5.90} = .84$, 95% bootstrap CI [.413, 1.358]. The index of moderated mediation (Hayes & Preacher, 2015) was positive, suggesting as perceived sexism increases so does the indirect effect. The index of moderated mediation was significant as the bootstrap confidence interval did not include zero (IMM = .326, 95% bootstrap CI [.035, .680]. This suggests that the indirect effect of protesting on liking through response appropriateness depends on perceived prevalence of sexism. There was no significant direct effect between protesting and liking (*c'* = -.101, *p* = .616).

## Writing up a Conditional Process Analysis

Tips:

- Explain the model that you are using ("PROCESS Model 7" isn't good enough)
- Provide a diagram with the model and path labels
- Walk the reader through the steps of the mediation in a way that is intuitive.
  - Include interpretations of the results
  - Always break down the moderation analyses
  - Use equations and numbers *where helpful*.
  - Avoid using computational variable names (e.g. RESPAPPR)
- Order or presentation (that I like)
  - Paths
  - Conditional indirect effects
  - Index of moderated mediation
- Read the write ups of other's conditional process analyses
- Try estimating multiple models, interpreting them, and then putting them together.

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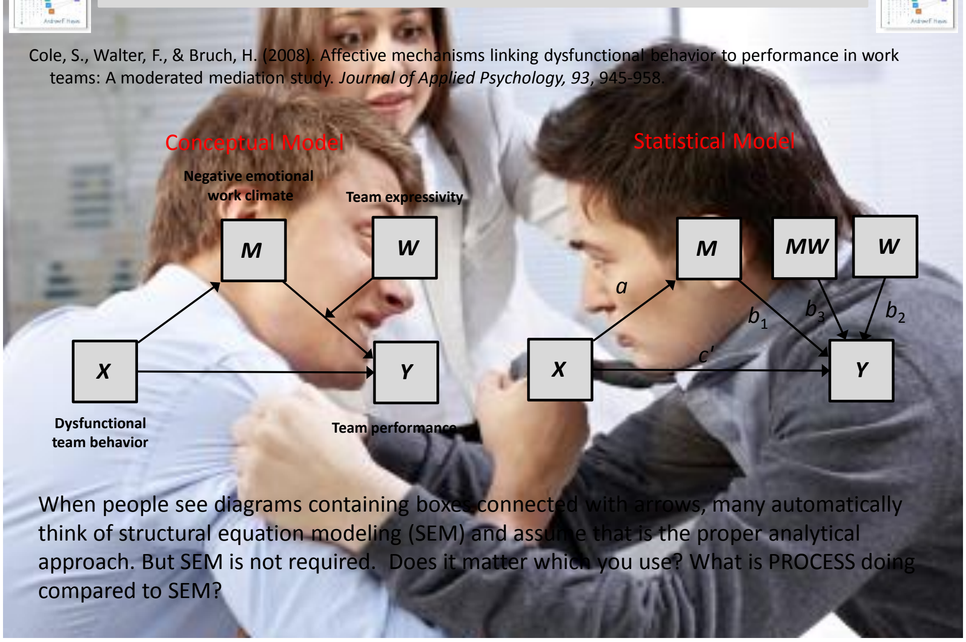
# PART II

# What's new with PROCESS?

I highly recommend asking lots of questions.

Many of these will start with "What if…?"

## PROCESS versus SEM



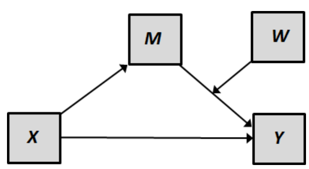

Cole, S., Walter, F., & Bruch, H. (2008). Affective mechanisms linking dysfunctional behavior to performance in work teams: A moderated mediation study. *Journal of Applied Psychology, 93*, 945-958.

When people see diagrams containing boxes connected with arrows, many automatically think of structural equation modeling (SEM) and assume that is the proper analytical approach. But SEM is not required. Does it matter which you use? What is PROCESS doing compared to SEM?

## What is an SEM program doing?

$$\hat{M} = i_M + aX$$

$$\hat{Y} = i_Y + c'X + b_1M + b_2W + b_3MW$$



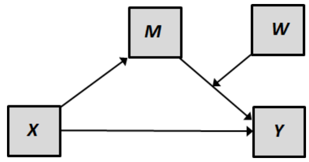

In an SEM program:

- The weights for the variables in the equations are estimated *simultaneously.*
- The model coefficients are estimated *iteratively*, tweaking the weights at each iteration until the correspondence between the model and the data is at its best.
- Changing the weights in one equation can influence the weights in the other.
- Correspondence is quantified by the likelihood of the data given the model using the method of *maximum likelihood* (or some other method if you choose).
- No guarantee you will get a solution (estimation may not "converge").
- No guarantee the solution is best. Your solution may be a "local" but not a "global" maximization of the likelihood.

## What is PROCESS doing?

$$\widehat{M} = i_M + aX$$

$$\hat{Y} = i_Y + c'X + b_1 M + b_2 W + b_3 MW$$



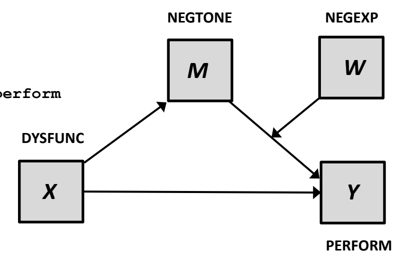

In PROCESS:

- The weights for the variables are estimated *independently between equations.*
- The estimation of the weights in one equation has no influence on the resulting weights in the other equation(s).
- Weights are estimated by the method of *ordinary least squares*, minimizing the residual sum of squares in each equation (and therefore minimizing the sum across equations). Any regression program can do this.
- There is always one best solution. A solution is guaranteed so long as a solution is mathematically possible.
- Many output options available you'd have to hard code in an SEM program, and many SEM programs wouldn't even allow you to do so.

## A comparison

In Mplus

```
DATA:
  file is 'c:\mplus\teams.txt';
VARIABLE:
  names are dysfunc negtone negexp perform;
  usevariables are dysfunc negexp negtone perform
                   toneexp;
DEFINE:
  toneexp = negtone*negexp;
ANALYSIS:
  !bootstrap=5000;
MODEL:
  perform ON dysfunc (cp)
             negtone (b1)
             negexp (b2)
             toneexp (b3);
  negtone ON dysfunc (a);
  negexp;
  dysfunc;
  toneexp;
  negtone with negexp;
  negtone with toneexp;
MODEL CONSTRAINT:
  new (athetaL athetaM athetaH ab3);
  athetaL=a*(b1+b3*(-0.530));
  athetaM=a*(b1+b3*(-0.060));
  athetaH=a*(b1+b3*(+0.600));
  ab3=a*b3;
OUTPUT:
  !cinterval(bootstrap);
```

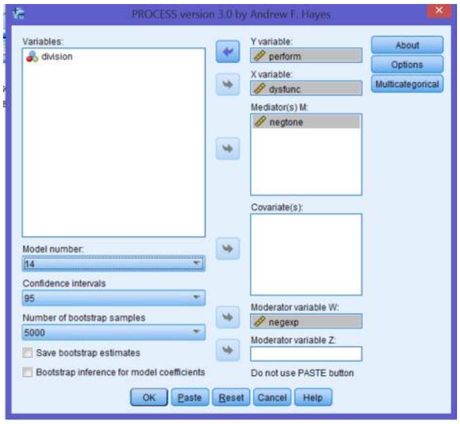


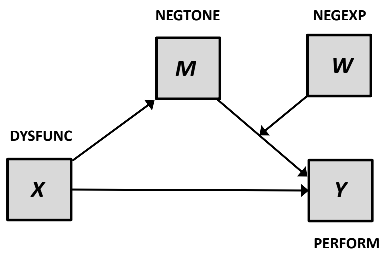

In PROCESS

```
process x=dysfunc/m=negtone/y=perform
  /w=negexp/model=14.
```

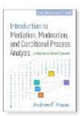
PROCESS has many features that can't be coded in any SEM programming environment.

## Or using the dialogue box

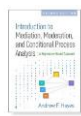


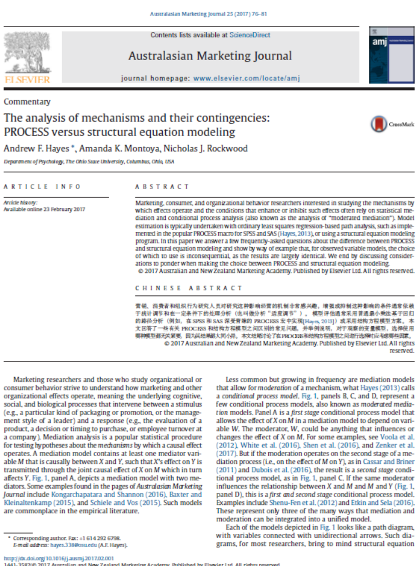




SPSS users have the option of installing a PROCESS dialog box in the Analyze menu for setting up the model and choosing options point-and-click style.



## PROCESS versus Structural Equation Modeling





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Commentary

The analysis of mechanisms and their contingencies: PROCESS versus structural equation modeling

Andrew F. Hayes *, Amanda K. Montoya, Nicholas J. Rockwood

Department of Psychology, The Ohio State University, Columbus, Ohio, USA

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ABSTRACT

Marketing, consumer, and organizational behavior researchers interested in studying the mechanisms by which effects operate and the conditions that enhance or inhibit such effects often rely on statistical mediation and conditional process analysis (also known as the analysis of "moderated mediation"). Model estimation is typically undertaken with ordinary least squares regression-based path analysis, such as implemented in the popular PROCESS macro for SPSS and SAS (Hayes, 2013), or using a structural equation modeling program. In this paper we answer a few frequently-asked questions about the difference between PROCESS and structural equation modeling and show by way of example that, for observed variable models, the choice of which to use is inconsequential, as the results are largely identical. We end by discussing considerations to ponder when making the choice between PROCESS and structural equation modeling.



CHINESE ABSTRACT



Marketing researchers and those who study organizational or consumer behavior strive to understand how marketing and other organizational effects operate, meaning the underlying cognitive, social, and biological processes that intervene between a stimulus (e.g., a particular kind of packaging or promotion, or the management style of a leader) and a response (e.g., the evaluation of a product, a decision or timing to purchase, or employee turnover at a company). Mediation analysis is a popular statistical procedure for testing hypotheses about the *mechanisms* by which a causal effect operates. A mediation model contains at least one mediator variable $M$ that is causally between $X$ and $Y$, such that $X$'s effect on $Y$ is transmitted through the joint causal effect of $X$ on $M$ which in turn affects $Y$. Fig. 1, panel A, depicts a mediation model with two mediators. Some examples found in the pages of *Australasian Marketing Journal* include Kongarchapatara and Shannon (2016), Baxter and Kleinaltenkamp (2015), and Schiele and Vos (2015). Such models are commonplace in the empirical literature.

Less common but growing in frequency are mediation models that allow for *moderation* of a mechanism, what Hayes (2013) calls a *conditional process model*. Fig. 1, panels B, C, and D, represent a few conditional process models, also known as *moderated mediation* models. Panel A is a *first stage* conditional process model that allows the effect of $X$ on $M$ in a mediation model to depend on variable $W$. The moderator, $W$, could be anything that influences or changes the effect of $X$ on $M$. For some examples, see Voola et al. (2012), White et al. (2016), Shen et al. (2016), and Zenker et al. (2017). But if the moderation operates on the second stage of a mediation process (i.e., on the effect of $M$ on $Y$), as in Cassar and Briner (2011) and Dubois et al. (2016), the result is a *second stage* conditional process model, as in Fig. 1, panel C. If the same moderator influences the relationship between $X$ and $M$ and $M$ and $Y$ (Fig. 1, panel D), this is a *first and second stage* conditional process model. Examples include Shenu-Fen et al. (2012) and Etkin and Sela (2016). These represent only three of the many ways that mediation and moderation can be integrated into a unified model.

Each of the models depicted in Fig. 1 looks like a path diagram, with variables connected with unidirectional arrows. Such diagrams, for most researchers, bring to mind structural equation

* Corresponding author. Fax: +1 614 292 6798.
E-mail address: hayes.338@osu.edu (A.F. Hayes).

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**Hayes, A. F., Montoya, A. K., & Rockwood, N. J. (2017). The analysis of mechanisms and their contingencies: PROCESS versus structural equation modeling. *Australasian Marketing Journal, 25,* 76-81.**

- For observed variable models, it makes no difference whether you use SEM or PROCESS. You get the same results and with a lot less effort.

**Some reasons to choose SEM:**

- More options for dealing with missing data.
- More sophisticated means of managing the effects of measurement error.
- Latent variables and blends of latent and observed variables.
- Measures of fit of the model to the data.
- Greater flexibility for model specification (though PROCESS v3 allows you to create your own model, unlike in v2).

## Differences between V2 & V3

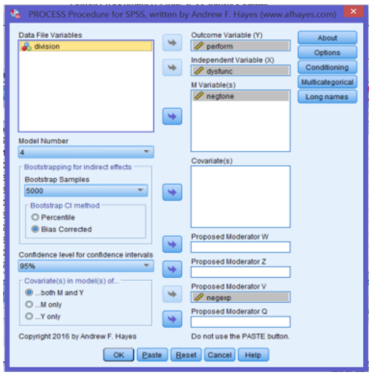
- No longer need the `vars` list
- Covariates now listed in `cov` list
- Moderators are always `W` and `Z`, no more `V`, `M` or `Q` moderators
- Dichotomous Y available for some models (starting with V3.1)
- A variety of models have been cut, but new ability to create and edit models
- New models for serial moderated mediation and serial and parallel mediation
- Probing option now defaults to what used to be `quantiles`, can use `moments` argument for legacy output
- Probing and plotting for models with any moderation
- Default is now percentile bootstrap, no more BC or ABC
- Multicategorical X or Moderators
- `wmodval` and `zmodval` allow for multiple values
- Covariate assignment
- Bootstrap CIs for regression coefficients
- Model construction
- `cluster`, `ws`, `varorder`, and `percent` are no longer options

## PROCESS v2 versus v3

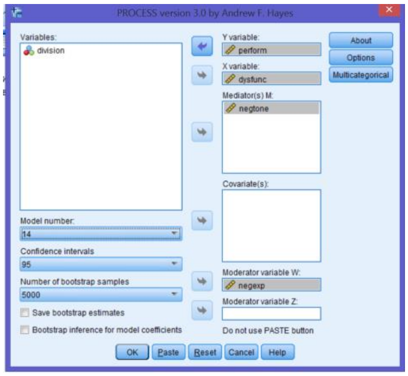
| | Version 2 | Version 3 |
|---|---|---|
| **Number of preprogrammed models** | 76 | 55 |
| **Multicategorical independent variable (X)** | Models 1 and 4 | All models |
| **Multicategorical moderators** | Model 1 only | All models |
| **Maximum number of moderators** | 4 | 2 |
| **User-constructed models** | No | Yes |
| **Customization of preprogrammed models** | No | Yes |
| **Moderated serial mediation models** | No | Yes |
| **Dichotomous Y** | Yes | Yes (V3.1) |
| **Bootstrapping** | Indirect effects only | All model coefficients |
| **Probing and visualizing interactions** | Models 1,2,3 only | All models with product |
| **Heteroscedasticity-consistent standard errors** | HC3 | HC0,HC1,HC2,HC3,HC4 |

## PROCESS v2 versus v3

Version 2 dialog box




Version 3 dialog box




Changes in the dialog box as well as the syntax structure means that many things you will find on the internet produced by others about the use of PROCESS are obsolete. *Introduction to Mediation, Moderation, and Conditional Process* (2nd edition) is a better resource than Google.

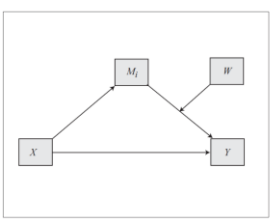
## PROCESS syntax

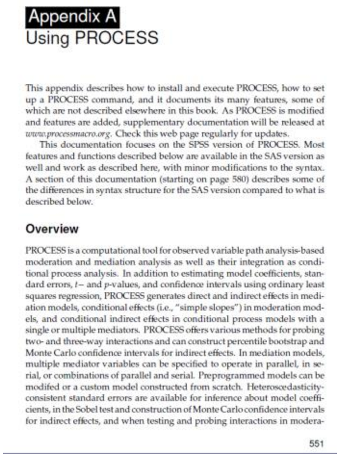
I recommend learning how to interact with PROCESS using syntax rather than the dialog box in SPSS. Not all features of PROCESS can be accessed through the dialog box.

Minimum required specifications

- Which variables play which role in the model (**`y=`** **`x=`** **`m=`** and so forth)
- Model number (**`model=`**)
- SAS only: Data file (**`data=`**)

Model 14



Appendix A
Using PROCESS

This appendix describes how to install and execute PROCESS, how to set up a PROCESS command, and it documents its many features, some of which are not described elsewhere in this book. As PROCESS is modified and features are added, supplementary documentation will be released at *www.processmacro.org*. Check this web page regularly for updates.

This documentation focuses on the SPSS version of PROCESS. Most features and functions described below are available in the SAS version as well and work as described here, with minor modifications to the syntax. A section of this documentation (starting on page 580) describes some of the differences in syntax structure for the SAS version compared to what is described below.

**Overview**

PROCESS is a computational tool for observed variable path analysis-based moderation and mediation analysis as well as their integration as conditional process analysis. In addition to estimating model coefficients, standard errors, $t$– and $p$-values, and confidence intervals using ordinary least squares regression, PROCESS generates direct and indirect effects in mediation models, conditional effects (i.e., "simple slopes") in moderation models, and conditional indirect effects in conditional process models with a single or multiple mediators. PROCESS offers various methods for probing two- and three-way interactions and can construct percentile bootstrap and Monte Carlo confidence intervals for indirect effects. In mediation models, multiple mediator variables can be specified to operate in parallel, in serial, or combinations of parallel and serial. Preprogrammed models can be modifed or a custom model constructed from scratch. Heteroscedasticity-consistent standard errors are available for inference about model coefficients, in the Sobel test and construction of Monte Carlo confidence intervals for indirect effects, and when testing and probing interactions in modera-

551

```
process y=yvar/x=xvar/m=mvlist/w=wvar/model=14.
```

## What's new in PROCESS v3

- In version 3, **vars=** is no longer used. You do not need to tell which variables are being used in the model prior to assigning them roles. So, for example,

```
process vars=pmi import reaction cond/x=cond/m=import pmi/
   y=reaction/model=4.
```

becomes the more streamlined

```
process x=cond/m=import pmi/y=reaction/model=4.
```

- Whereas in version 2, covariates were listed in **vars=** but not assigned a role anywhere in the model. In version 3, covariates are specified following **cov=**. So, for example,

```
process vars=pmi import reaction cond age sex/x=cond
   /m=import pmi/y=reaction/model=4.
```

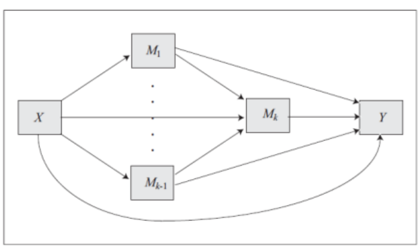
becomes

```
process x=cond/m=import pmi/y=reaction/cov=age sex/model=4.
```

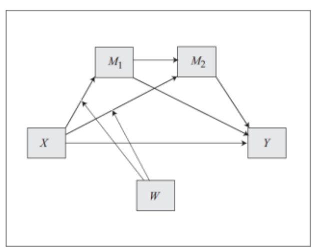
## What's new in PROCESS v3

- PROCESS version 2 was built around a model numbering system. This is the only way of telling PROCESS v2 what you are trying to do.
- Version 3 retains the model numbering system. The number of models has been reduced by eliminating all models with more than two moderators.
- Version 3 has 13 new numbered models that combine moderation with serial mediation, and that combine parallel and serial mediation. Examples:

Model 80

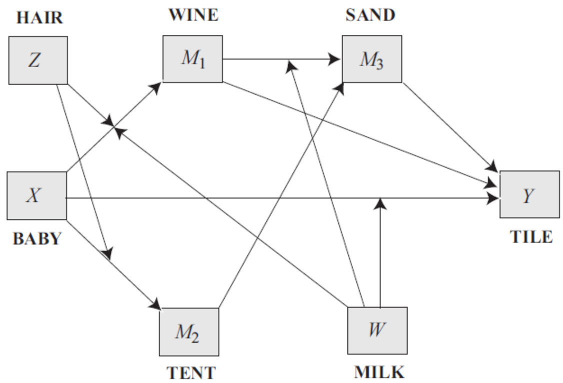



Model 84



## Customizing and creating models

In version 3, preprogrammed model numbers are shortcuts for populating four matrices that define a model. You can directly program these matrices in version 3 to create your own models. No model number needed.




This model could not be estimated in version 2. In version 3, it is easy. You get a budget of six mediators and two moderators when designing your own model.

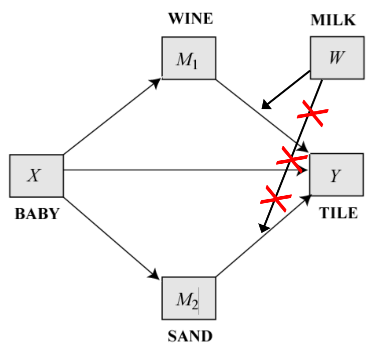
## What's new in PROCESS v3

- In version 2, numbered models are fixed. If you don't like something about the model, too bad. Choose another model, or abandon PROCESS. Version 3 allows you to edit numbered models to tailor them to your specific wants.

For example, this is model 14:

But what if you don't want *W* to moderate the path from $M_2$ to *Y*. In version 2, tough luck.

- In version 3, just reprogram the *W* matrix to eliminate the undesired moderation specification.




```
process y=tile/m=wine sand/x=baby/w=milk/model=14
    /wmatrix=0,0,0,0,1,0.
```

## Multicategorical independent variables and moderators

- PROCESS v2 had limited features for dealing with multicategorical independent variables. This is a frequently asked question, so we wrote about this and, eventually, added features to PROCESS v2 only for models 1 (simple moderation) and 4 (single and parallel multiple mediator models).

Hayes, A. F. & Preacher, K. J. (2014). Statistical mediation analysis with a multicategorical independent variable. *British Journal of Mathematical and Statistical Psychology, 67*, 451-470.

Hayes, A. F. & Montoya, A. K. (2017). A tutorial on testing, visualizing, and probing interaction involving a multicategorical variable in linear regression analysis. *Communication Methods and Measures*, *11*, 1-30.

- In version 3, *X* (causal antecedent) and moderators *W* and *Z* can be multicategorical with up to nine categories in **all** models PROCESS can estimate, using the **mcx**, **mcw**, and/or **mcz** options. Four coding systems are preprogrammed (indicator, sequential, Helmert, effect).
- Chapters added to the second edition of *Introduction to Mediation, Moderation, and Conditional Process* Analysis on this material, with examples using PROCESS v3.

## Multicategorical independent variables and moderators

- If you don’t like the preprogrammed coding systems, you can program your own system with the **xcatcode**, **wcatcode**, and **zcatcode** options. For example:

| | X1 | X2 | X3 |
|---|---|---|---|
| Group 1 | -0.5 | -0.5 | 0 |
| Group 2 | -0.5 | 0.5 | 0 |
| Group 3 | 0.5 | 0 | -0.5 |
| Group 4 | 0.5 | 0 | 0.5 |

```
process y=tile/m=wine/x=baby/w=milk/mcx=5/model=14/
  xcatcode=-0.5,-0.5,0,-0.5,0.5,0,0.5,0,-0.5,0.5,0,0.5
```

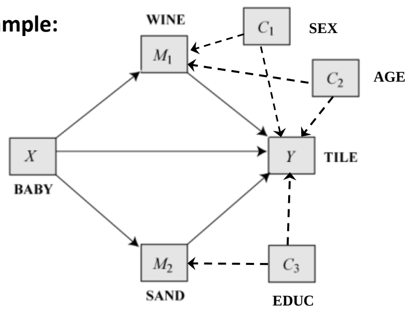
In this code, *X* is specified as a multicategorical variable in a second stage conditional process model, with a custom coding system used to represent the four groups. These codes represent three orthogonal contrasts that produce relative conditional indirect effects of *X* on *Y* through *M*

**X1 represents a contrast of groups 1 and 2 vs 3 and 4.**
**X2 represents a contrast of group 1 vs 2.**
**X3 represents a contrast of group 3 vs 4.**

## Covariates are assignable to equations now

- Version 2 offers little flexibility in how covariates are assigned to equations. All covariates go in models of *Y* and mediator(s) *M*, or just *M*, or just *Y*. You can't split covariates up and assign them to different equations.
- With a new **cmatrix** option in version 3, covariates can now be assigned to different equations in whatever configuration you desire, rather than being forced to all be in the models of *M*s, *Y*, or both.

**For example:**




```
process y=tile/m=wine sand/x=baby/cov=sex age educ/model=4/
   cmatrix=1,1,0,0,0,1,1,1,1.
```

## Customizing the assignment of covariates

By default, all covariates are assigned to all equations, but this can be overridden with the **cmatrix** option. The assignment of covariates to equations is internally represented with the *C* matrix.

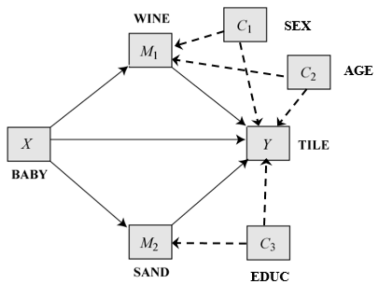
```
PROCESS y=yvar/x=xvar/m=med1 med2 ... medj/cov=cov1 cov2 … covk/model= ...
```

| | cov1 | cov2 | … | covk |
|---|---|---|---|---|
| med1 | 0/1 | 0/1 | … | 0/1 |
| med2 | 0/1 | 0/1 | … | 0/1 |
| . | . | . | … | . |
| . | . | . | … | . |
| . | . | . | … | . |
| medj | 0/1 | 0/1 | … | 0/1 |
| yvar | 0/1 | 0/1 | … | 0/1 |

C matrix

A one in the cell means the covariate in that column is to be included in the model of the variable in that row. A zero means the covariate in that column is to be excluded from the model of the variable in that row. By default, all entries in the *C* matrix are set to one.

## Customizing the assignment of covariates

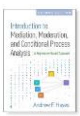



*C* matrix

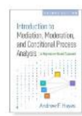
| | sex | age | educ |
|---|---|---|---|
| wine | 0 | 1 | 1 |
| sand | 1 | 1 | 1 |
| tile | 0 | 0 | 1 |

The **cmatrix** option does the assignment of covariates to equations. Read the matrix left to right, top to bottom, assigning the zeros and ones. Separate by commas in SPSS.

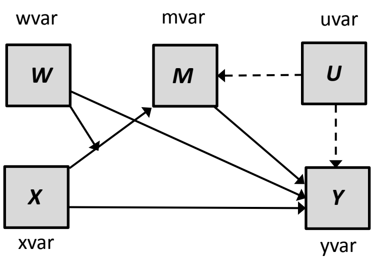
```
process y=tile/x=baby/m=wine sand/cov=sex age educ/model=6
   /cmatrix=0,1,1,1,1,1,0,0,1.
```




## An useful application of the cmatrix option




A limitation of PROCESS is that a variable can play only one role in a model (such as independent variable, moderator, mediator, and so forth). But sometimes we want a variable to play more than one role. For example:




| | uvar | wvarcopy |
|---|---|---|
| mvar | 1 | 0 |
| yvar | 1 | 1 |

In this model, *W* plays the role of moderator in the model of *M* and covariate in the model of *Y*. This couldn't be done in PROCESS v2.

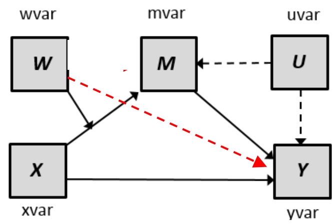
In version 3, the code is:

```
compute wvarcopy=wvar.
process y=yvar/x=xvar/m=mvar/w=wvar/cov=uvar wvarcopy/model=7/cmatrix=1,0,1,1.
```

## Why does this trick work?

```
process y=yvar/x=xvar/m=mvar/w=wvar/cov=uvar/model=7.
```

This is model 7 with one covariate *U* assigned to both *M* and *Y*




$$\widehat{M} = i_M + a_1X + a_2W + a_3XW + d_1U$$

$$\hat{Y} = i_Y + b_1M + d_2U + d_3W$$

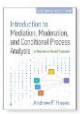
You might consider doing this:

```
process y=yvar/x=xvar/m=mvar/w=wvar/cov=uvar wvar/model=7.
```

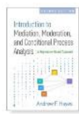
But *W* is being assigned twice here. A variable cannot be assigned more than one role in a PROCESS command. And even if it could, this would produce a singularity, as it would add *W* to the model of *M*, but it is already there in model 7. So *W* would appear in the equation for *M* twice.

```
compute wvarcopy=wvar.
process y=yvar/x=xvar/m=mvar/w=wvar/cov=uvar wvarcopy/model=7/cmatrix=1,1,0,1.
```

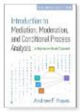
Creating a copy of *W* tricks PROCESS by disguising it with a different name. The cmatrix option keeps the copy of *W* out of the model of *M* but puts it in the model of *Y*.



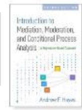
## Enhanced options/output for models with interactions



- In version 2, the **plot** option works only in models 1, 2, and 3. If you want to visualize interactions in other models, you have to express the moderated component of the model in terms of models 1, 2, and 3.
- In version 2, features for probing interactions work only in models 1, 2, and 3. To probe interactions in any other model, you have to express the moderated component in terms of models 1, 2, and 3.
- In version 3, the plot option works for **all** models that include a moderation component anywhere in the system of equations. And PROCESS automatically probes all interactions, regardless of whether they exist in the model.
- In complex models, the resulting output can be lengthy. PROCESS by default only probes interactions when the corresponding *p*-value is 0.10 or less. But this is only a default and can be changed with an argument (`intprobe = 1`).



## Some new moderation-related features

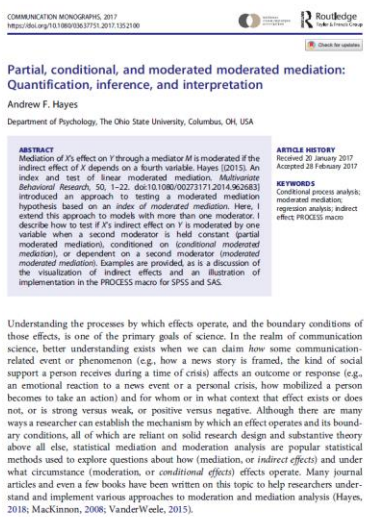


- When probing interactions, the default is to condition continuous moderators on the 16th, 50th, and 84th percentiles of the moderator distribution. Use of the mean, a standard deviation below, and a standard deviation above the mean is still possible with a new **moments** option.
- The **wmodval** and **zmodval** options now allow you to list more than one value for conditioning effects (e.g., **wmodval = 3.5, 5, 6.5** to estimate a conditional effect when moderator *W* equals 3.5, 5, and 6.5)
- An implementation of a "slope difference" test in moderation-only models with more than one moderator (models 2 and 3). For example, to test the difference between the conditional effect of *X* on *Y* when moderator *W* = 3 and moderator *Z* = 2 compared to when *W* = 1 and *Z* = 4:

```
process x=baby/y=tile/w=milk/z=hair/model=3/contrast=3,2;1,4.
```

## Partial, conditional, and moderated moderated mediation

Hayes, A. F. (2018). Partial, conditional, and moderated moderated mediation: Quantification, inference, and interpretation. *Communication Monographs, 85*, 4-40.



COMMUNICATION MONOGRAPHS, 2017
https://doi.org/10.1080/03637751.2017.1352100

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**Partial, conditional, and moderated moderated mediation: Quantification, inference, and interpretation**

Andrew F. Hayes
Department of Psychology, The Ohio State University, Columbus, OH, USA

**ABSTRACT**
Mediation of *X*'s effect on *Y* through a mediator *M* is moderated if the indirect effect of *X* depends on a fourth variable. Hayes [(2015). An index and test of linear moderated mediation. *Multivariate Behavioral Research*, 50, 1–22. doi:10.1080/00273171.2014.962683] introduced an approach to testing a moderated mediation hypothesis based on an *index of moderated mediation*. Here, I extend this approach to models with more than one moderator. I describe how to test if *X*'s indirect effect on *Y* is moderated by one variable when a second moderator is held constant (partial moderated mediation), conditioned on (*conditional moderated mediation*), or dependent on a second moderator (*moderated moderated mediation*). Examples are provided, as is a discussion of the visualization of indirect effects and an illustration of implementation in the PROCESS macro for SPSS and SAS.

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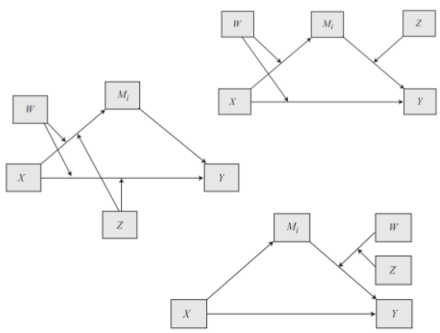
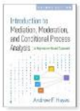
**KEYWORDS**
Conditional process analysis; moderated mediation; regression analysis; indirect effect; PROCESS macro

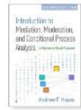
Understanding the processes by which effects operate, and the boundary conditions of those effects, is one of the primary goals of science. In the realm of communication science, better understanding exists when we can claim *how* some communication-related event or phenomenon (e.g., how a news story is framed, the kind of social support a person receives during a time of crisis) affects an outcome or response (e.g., an emotional reaction to a news event or a personal crisis, how mobilized a person becomes to take an action) and for whom or in what context that effect exists or does not, or is strong versus weak, or positive versus negative. Although there are many ways a researcher can establish the mechanism by which an effect operates and its boundary conditions, all of which are reliant on solid research design and substantive theory above all else, statistical mediation and moderation analysis are popular statistical methods used to explore questions about how (mediation, or *indirect effects*) and under what circumstance (moderation, or *conditional effects*) effects operate. Many journal articles and even a few books have been written on this topic to help researchers understand and implement various approaches to moderation and mediation analysis (Hayes, 2018; MacKinnon, 2008; VanderWeele, 2015).




PROCESS v3 includes statistics for testing ***partial moderated mediation***, ***conditional moderated mediation***, and ***moderated moderated mediation*** in conditional process models with two moderators.



## Many limitations still exist



- Still only one *X* and one *Y* allowed in a model.
- PROCESS is an OLS modeling tool. Categorical mediators never allowed, all models allow for dichotomous *Y* (with version 3.1).
- Up to 10 mediators in numbered models, 6 in custom models.
- No more than two moderators can be used in any model (down from 4 in v2)
- PROCESS is a single-level observed variable modeling system. No multilevel problems can be analyzed with PROCESS.
- PROCESS requires complete data. Listwise deletion is used for cases missing on any variable in the model.

## Some older features eliminated in v3

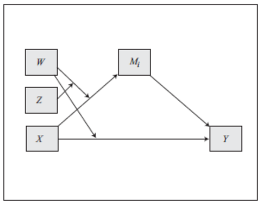
- All preprogrammed models in version 2 with more than two moderators have been eliminated in version 3.
- Moderators are always represented as *W* or *Z*. Never in version 3 is a moderator labeled *M*, *V*, or *Q* as in version 2.
- Percentile bootstrap confidence intervals are the only bootstrapping option available in version 3. Bias-correction is no longer available.
- *Y* cannot be dichotomous in version 3.0 but can be in 3.1
- The **ws** option for within-subject mediation analysis as described in Judd, Kenny, & McClelland (2001, *Psychological Methods*) available in v2 has been eliminated. The new MEMORE macro makes this obsolete. See *akmontoya.com* and

  Montoya, A. K., & Hayes, A. F. (2017). Mediation analysis in the two-instance repeated measures design: A path analytic perspective. *Psychological Methods, 22*, 6-27.
- The **cluster** option for dealing with nesting is gone. Use the MLMED macro for SPSS for multilevel mediation and conditional process analysis. See *www.njrockwood.com*

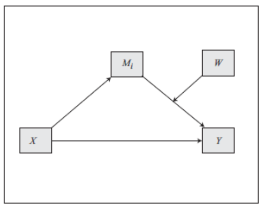
## Constructing and editing models in PROCESS

Historically, PROCESS has operated by a model number system. The model numbers and the models those numbers represent can be found in the documentation. Choose the model number that corresponds to the model you would like to estimate.

Model 13




Model 14



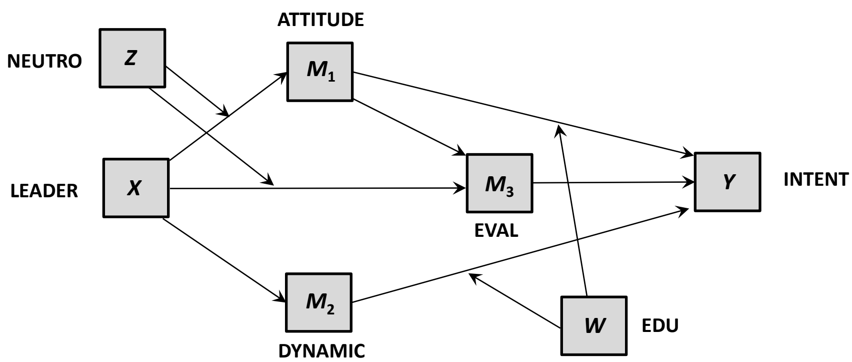

Many of the preprogrammed numbered models you will find useful.

But what if the model you want to estimate does not correspond to any preprogrammed model represented by a model number?

Version 2: Too bad. Nothing you can do about it (unless you know some tricks).

Version 3: Within certain constraints, you can create your own model from scratch, or edit an existing model number to make it correspond to the model you want to estimate.

## A complex model




Such a complex model is not preprogrammed into PROCESS as a model number. In version 2, this model could not be estimated. By the end of the day, you will know how to program this model in PROCESS v3.

## The *B* matrix

The *B* matrix is the heart of the representation of a model in PROCESS. It is a matrix of 0s and 1s specifying whether (1) or not (0) the variable in the column sends an effect to the variable in the row.

**Variables sending effects (i.e., arrow points away)**

**Variables receiving effects (an arrow points at)**

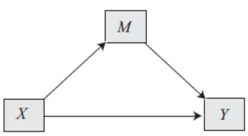
| | $X$ | $M_1$ | $M_2$ | ... | $M_k$ |
|---|---|---|---|---|---|
| $M_1$ | 0/1 | ■ | ■ | ■ | ■ |
| $M_2$ | 0/1 | 0/1 | ■ | ■ | ■ |
| ... | 0/1 | 0/1 | 0/1 | ■ | ■ |
| $M_k$ | 0/1 | 0/1 | 0/1 | 0/1 | ■ |
| $Y$ | 0/1 | 0/1 | 0/1 | 0/1 | 0/1 |

A model you program can contain one *X*, one *Y*, and up to 6 mediators. Certain cells are fixed to zero (the black squares above) to ensure the model is recursive (no feedback loops; PROCESS cannot estimate nonrecursive models).

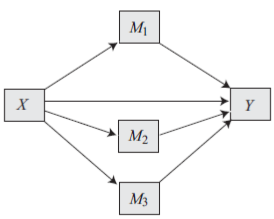
## Examples

**Model in conceptual form**

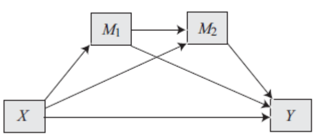
**Model in *B* matrix form**




| | $X$ | $M$ |
|---|---|---|
| $M$ | 1 | ■ |
| $Y$ | 1 | 1 |



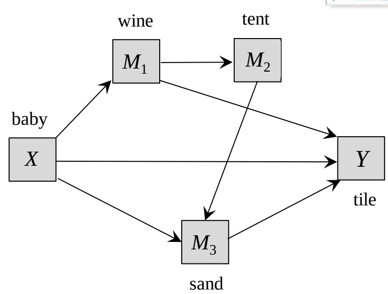

| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 1 | ■ | ■ | ■ |
| $M_2$ | 1 | 0 | ■ | ■ |
| $M_3$ | 1 | 0 | 0 | ■ |
| $Y$ | 1 | 1 | 1 | 1 |

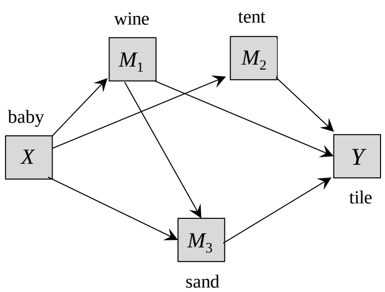



| | $X$ | $M_1$ | $M_2$ |
|---|---|---|---|
| $M_1$ | 1 | ■ | ■ |
| $M_2$ | 1 | 1 | ■ |
| $Y$ | 1 | 1 | 1 |

## Examples

| | | $X$ baby | $M_1$ wine | $M_2$ tent | $M_3$ sand |
|---|---|---|---|---|---|
| $M_1$ | wine | 1 | ■ | ■ | ■ |
| $M_2$ | tent | 0 | 1 | ■ | ■ |
| $M_3$ | sand | 1 | 0 | 1 | ■ |
| $Y$ | tile | 1 | 1 | 0 | 1 |

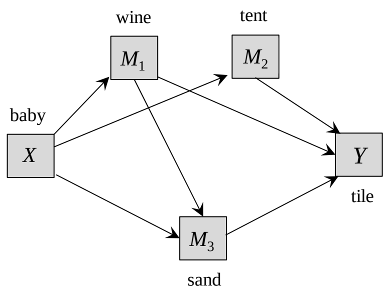



| | | $X$ baby | $M_1$ wine | $M_2$ tent | $M_3$ sand |
|---|---|---|---|---|---|
| $M_1$ | wine | **1** | ■ | ■ | ■ |
| $M_2$ | tent | **1** | **0** | ■ | ■ |
| $M_3$ | sand | **1** | **1** | **0** | ■ |
| $Y$ | tile | **0** | **1** | **1** | **1** |

## Programming the *B* matrix

The mediation component of a model is programmed using the **bmatrix=** statement followed by a sequence of zeros and ones.

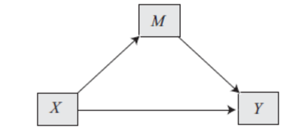



| | | $X$ baby | $M_1$ wine | $M_2$ tent | $M_3$ sand |
|---|---|---|---|---|---|
| $M_1$ | wine | **1** | ■ | ■ | ■ |
| $M_2$ | tent | **1** | **0** | ■ | ■ |
| $M_3$ | sand | **1** | **1** | **0** | ■ |
| $Y$ | tile | **0** | **1** | **1** | **1** |

Read the *B* matrix from left to right, top to bottom, skipping the black squares, and enter the zeros and ones in the sequence as they are encountered in the B matrix. Separate with commas in SPSS, but not in SAS.

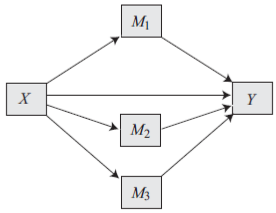
```
process y=tile/x=baby/m=wine tent sand/bmatrix=1,1,0,1,1,0,0,1,1,1.
```

## Examples



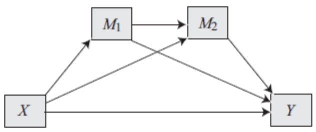

| | X | M |
|---|---|---|
| M | 1 | ■ |
| Y | 1 | 1 |

**bmatrix=1,1,1**




| | X | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 1 | ■ | ■ | ■ |
| $M_2$ | 1 | 0 | ■ | ■ |
| $M_3$ | 1 | 0 | 0 | ■ |
| Y | 1 | 1 | 1 | 1 |

**bmatrix=1,1,0,1,0,0,1,1,1,1**




| | X | $M_1$ | $M_2$ |
|---|---|---|---|
| $M_1$ | 1 | ■ | ■ |
| $M_2$ | 1 | 1 | ■ |
| Y | 1 | 1 | 1 |

**bmatrix=1,1,1,1,1,1**

## Moderation: The *W* and *Z* matrices

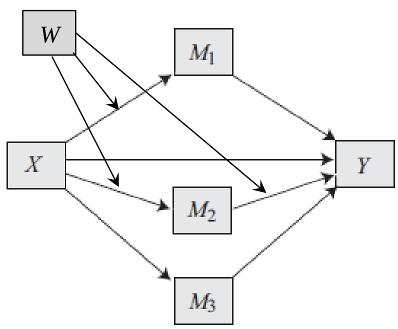
The *W* and *Z* matrices define which paths specified in the *B* matrix are moderated (1) and (0) not moderated. These matrices have the same form and size as the *B* matrix.

*B* matrix

| | X | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 1 | ■ | ■ | ■ |
| $M_2$ | 1 | 0 | ■ | ■ |
| $M_3$ | 1 | 0 | 0 | ■ |
| Y | 1 | 1 | 1 | 1 |

*W* matrix

| | X | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 1 | ■ | ■ | ■ |
| $M_2$ | 1 | 0 | ■ | ■ |
| $M_3$ | 0 | 0 | 0 | ■ |
| Y | 0 | 0 | 1 | 0 |




Note: A path fixed at zero in the *B* matrix cannot be moderated.

## Moderation: The *W* and *Z* matrices

A second moderator *Z* can be specified. But *Z* can only be used if *W* has already been used. That is, if your model has only one moderator, it must be called *W*.

*B* matrix

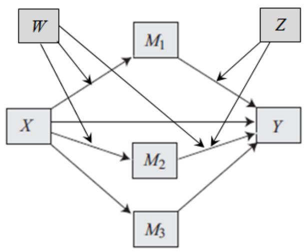
| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 1 | ■ | ■ | ■ |
| $M_2$ | 1 | 0 | ■ | ■ |
| $M_3$ | 1 | 0 | 0 | ■ |
| $Y$ | 1 | 1 | 1 | 1 |

*W* matrix

| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 1 | ■ | ■ | ■ |
| $M_2$ | 1 | 0 | ■ | ■ |
| $M_3$ | 0 | 0 | 0 | ■ |
| $Y$ | 0 | 0 | 1 | 0 |

*Z* matrix

| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 0 | ■ | ■ | ■ |
| $M_2$ | 0 | 0 | ■ | ■ |
| $M_3$ | 0 | 0 | 0 | ■ |
| $Y$ | 0 | 1 | 1 | 0 |




## Programming the *W* and *Z* matrices

*B* matrix

| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 1 | ■ | ■ | ■ |
| $M_2$ | 1 | 0 | ■ | ■ |
| $M_3$ | 1 | 0 | 0 | ■ |
| $Y$ | 1 | 1 | 1 | 1 |

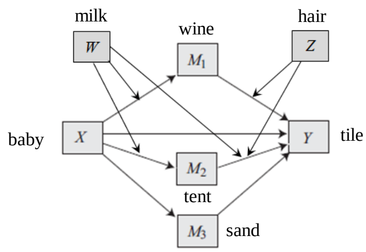
*W* matrix

| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 1 | ■ | ■ | ■ |
| $M_2$ | 1 | 0 | ■ | ■ |
| $M_3$ | 0 | 0 | 0 | ■ |
| $Y$ | 0 | 0 | 1 | 0 |

*Z* matrix

| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 0 | ■ | ■ | ■ |
| $M_2$ | 0 | 0 | ■ | ■ |
| $M_3$ | 0 | 0 | 0 | ■ |
| $Y$ | 0 | 1 | 1 | 0 |

The *W* and *Z* matrices are programmed with the **wmatrix=** and **zmatrix=** statements. Use the same procedure as for the *B* matrix.



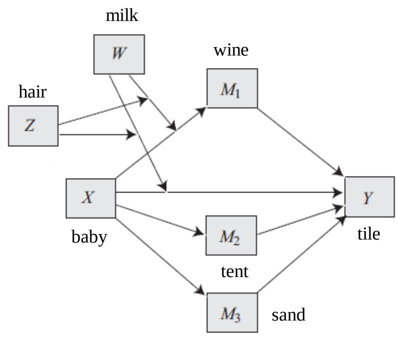

```
process y=tile/x=baby/m=wine tent sand/w=milk/z=hair
   /bmatrix=1,1,0,1,0,0,1,1,1,1/wmatrix=1,1,0,0,0,0,0,0,1,0
   /zmatrix=0,0,0,0,0,0,0,1,1,0.
```

## Moderated moderation: The *WZ* matrix

Moderated moderation, also known as three-way interaction, is held in the *WZ* matrix. *W* is the primary moderator, and *Z* is the secondary moderator. Program using the **wzmatrix=** statement, using the same 0/1 system.

*WZ* matrix

| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 1 | ■ | ■ | ■ |
| $M_2$ | 0 | 0 | ■ | ■ |
| $M_3$ | 0 | 0 | 0 | ■ |
| $Y$ | 1 | 0 | 0 | 0 |




```
process y=tile/x=baby/m=wine tent sand/w=milk/z=hair/
   bmatrix=1,1,0,1,0,0,1,1,1,1/wzmatrix=1,0,0,0,0,0,1,0,0,0.
```

Note: if you don't use **wmatrix** or **zmatrix**, this implies all cells are zero

## Putting it all together

This system allows for the construction of some very complex models.

*B* matrix

| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 1 | ■ | ■ | ■ |
| $M_2$ | 1 | 0 | ■ | ■ |
| $M_3$ | 1 | 0 | 0 | ■ |
| $Y$ | 1 | 1 | 1 | 1 |

*W* matrix

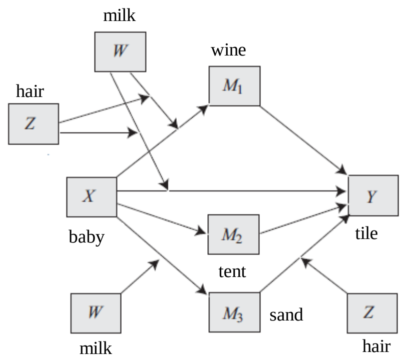
| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 0 | ■ | ■ | ■ |
| $M_2$ | 0 | 0 | ■ | ■ |
| $M_3$ | 1 | 0 | 0 | ■ |
| $Y$ | 0 | 0 | 0 | 0 |

*Z* matrix

| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 0 | ■ | ■ | ■ |
| $M_2$ | 0 | 0 | ■ | ■ |
| $M_3$ | 0 | 0 | 0 | ■ |
| $Y$ | 0 | 0 | 0 | 1 |

*WZ* matrix

| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 1 | ■ | ■ | ■ |
| $M_2$ | 0 | 0 | ■ | ■ |
| $M_3$ | 0 | 0 | 0 | ■ |
| $Y$ | 1 | 0 | 0 | 0 |

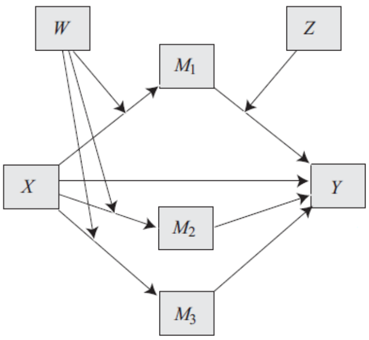



```
process y=tile/x=baby/m=wine tent sand/w=milk/z=hair
  /bmatrix=1,1,0,1,0,0,1,1,1,1/wmatrix=0,0,0,1,0,0,0,0,0,0
  /zmatrix=0,0,0,0,0,0,0,0,0,1/wzmatrix=1,0,0,0,0,0,1,0,0,0.
```

## Editing a numbered model

Many preprogrammed numbered models are likely to be close to the model you want to estimate. You can edit a modeled number, adding a desired interaction, or removing one you don't want. This is done by reprogramming the *W*, *Z*, and/or *WZ* matrices.

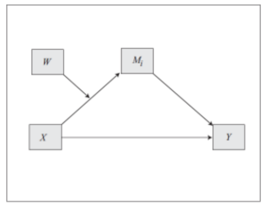
**Example**




**NOTE: When using a model number, the *B* matrix cannot be edited.**

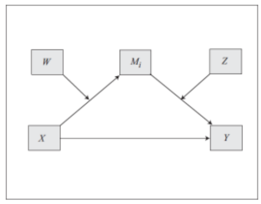
This is like model 7, except model 7 doesn't include moderation of any *M* to *Y* paths.

Model 7



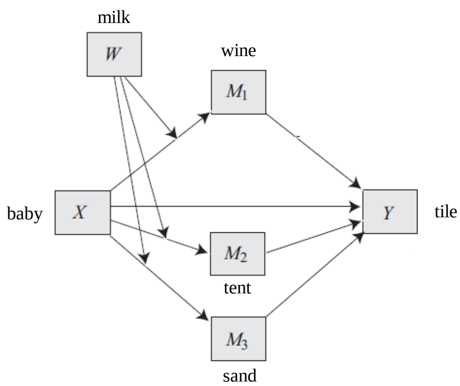

This is like model 21, except model 21 would includes moderation by *Z* of the $M_2$ and $M_3$ to *Y* paths as well as the $M_1$ to *Y* path.

Model 21




## Option 1: Edit model 7

In model 7, the *Z* matrix is all zeros because there is no *Z* in model 7. So program the *Z* matrix to include the moderation of the desired path by *Z*.



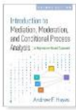

Preprogrammed Z matrix

| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 0 | ■ | ■ | ■ |
| $M_2$ | 0 | 0 | ■ | ■ |
| $M_3$ | 0 | 0 | 0 | ■ |
| $Y$ | 0 | 0 | 0 | 0 |

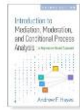
Desired *Z* matrix

| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 0 | ■ | ■ | ■ |
| $M_2$ | 0 | 0 | ■ | ■ |
| $M_3$ | 0 | 0 | 0 | ■ |
| $Y$ | 0 | 1 | 0 | 0 |

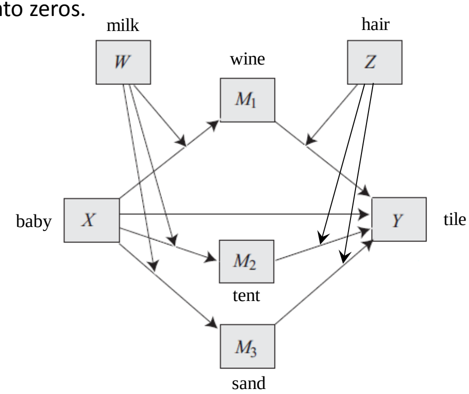
```
process y=tile/x=baby/m=wine tent sand/w=milk/z=hair/model=7/
    zmatrix=0,0,0,0,0,0,0,1,0,0.
```



## Option 2: Edit model 21



In model 21, the $Z$ matrix contains ones in certain cells that allow the $M_2$ and $M_3$ paths to $Y$ to be moderated by $Z$. We can reprogram the $Z$ matrix, turning the offensives ones into zeros.




Preprogrammed $Z$ matrix

| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 0 | ■ | ■ | ■ |
| $M_2$ | 0 | 0 | ■ | ■ |
| $M_3$ | 0 | 0 | 0 | ■ |
| $Y$ | 0 | 1 | 1 | 1 |

Desired $Z$ matrix

| | $X$ | $M_1$ | $M_2$ | $M_3$ |
|---|---|---|---|---|
| $M_1$ | 0 | ■ | ■ | ■ |
| $M_2$ | 0 | 0 | ■ | ■ |
| $M_3$ | 0 | 0 | 0 | ■ |
| $Y$ | 0 | 1 | 0 | 0 |

```
process y=tile/x=baby/m=wine tent sand/w=milk/z=hair/model=21/
    zmatrix=0,0,0,0,0,0,0,1,0,0.
```

## The MATRICES statement

If you want to check to make sure you have programmed the matrices correctly, or you want to see what the matrices of a preprogrammed model look like, add **matrices=1** to a PROCESS command.

```
process y=tile/x=baby/m=wine tent
  sand/w=milk/z=hair/model=7/
  zmatrix=0,0,0,0,0,0,0,1,0,0
  /matrices=1.
```

```
********** MODEL DEFINITION MATRICES **********

BMATRIX: Paths freely estimated (1) and fixed
to zero (0):
     baby wine tent sand
wine  1
tent  1    0
sand  1    0    0
tile  1    1    1    1

WMATRIX: Paths moderated (1) and not moderated
(0) by W:
     baby wine tent sand
wine  1
tent  1    0
sand  1    0    0
tile  0    0    0    0

ZMATRIX: Paths moderated (1) and not moderated
(0) by Z:
     baby wine tent sand
wine  0
tent  0    0
sand  0    0    0
tile  0    1    0    0
```

Matrices that don’t appear in the output have zeros in all cells. If your model includes covariates, the $C$ matrix will appear here too.

## Exercise #1

**What model does this set of matrices represent?**

*B* Matrix

| | $X$ | $M_1$ | $M_2$ |
|---|---|---|---|
| $M_1$ | 1 | ■ | ■ |
| $M_2$ | 1 | 1 | ■ |
| $Y$ | 0 | 1 | 1 |

*W* Matrix

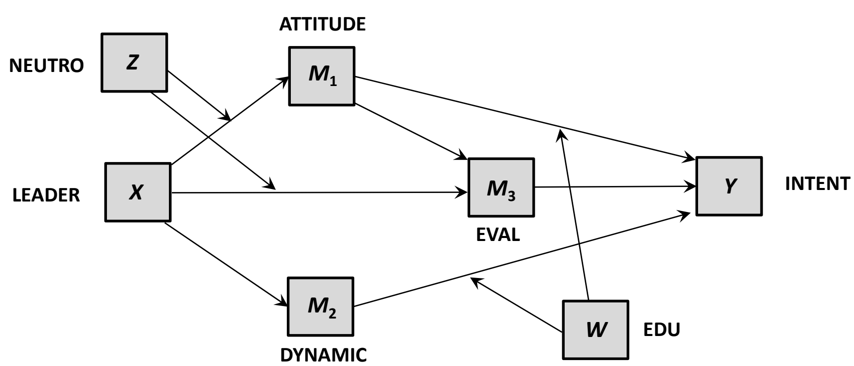
| | $X$ | $M_1$ | $M_2$ |
|---|---|---|---|
| $M_1$ | 1 | ■ | ■ |
| $M_2$ | 0 | 1 | ■ |
| $Y$ | 0 | 0 | 1 |

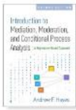
*C* Matrix

| | $U_1$ | $U_2$ | $U_3$ |
|---|---|---|---|
| $M_1$ | 1 | 0 | 0 |
| $M_2$ | 0 | 1 | 1 |
| $Y$ | 1 | 1 | 0 |

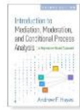
## Exercise #2

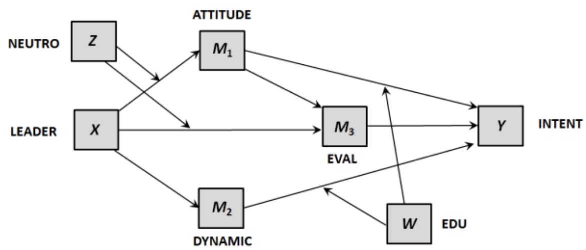
**Write the PROCESS command that estimates this model:**





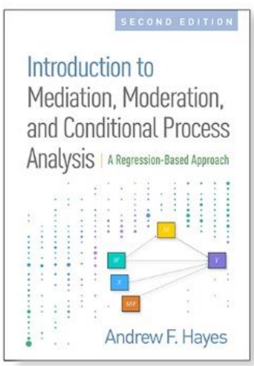
## Exercise #2



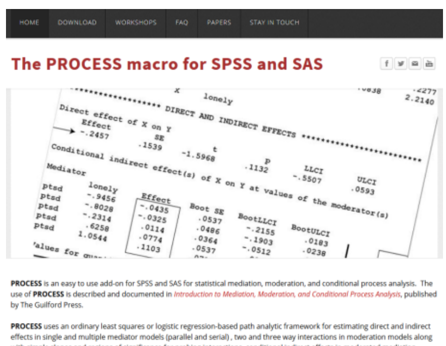



## Where to learn more…

**www.guilford.com**




**www.processmacro.org**




**Mediation, Moderation, and Conditional Process Analysis I and II**. Global School in Empirical Research Methods, University of St. Gallen, Switzerland, June 11-15 and June 18-22, 2018. www.gserm.ch

## Where to learn more…

**Mediation, Moderation, and Conditional Process Analysis I (5-days)**.
University of Ljubljana, Slovenia, August 27-31 2019.
www.gserm.ch **Instructor: Amanda Montoya**

**Mediation, Moderation, and Conditional Process Analysis I (5-days)**.
BI Norwegian Business School, Oslo, Norway, January 14-18 2019.
www.gserm.ch **Instructor: Amanda Montoya**

**Mediation, Moderation, and Conditional Process Analysis 2-day course**. Statistical Horizons, Ft. Lauderdale, FL, February 1-2 2019.
Link Here **Instructor: Andrew Hayes**

**Mediation, Moderation, and Conditional Process Analysis I and II**. Global School in Empirical Research Methods, University of St. Gallen, Switzerland, June 2019.
www.gserm.ch **Instructor: Andrew Hayes**

**Mediation, Moderation, and Conditional Process Analysis 5-day course**. Statistical Horizons, Chicago, IL, July 15-19 2019. **Instructor: Andrew Hayes**

akmontoya@ucla.edu

## Pertinent Publications

Rockwood, N. J., & Hayes, A. F. (2018). Mediation, moderation, and conditional process analysis: Regression-based approaches for clinical research. Draft submitted and to appear in A. G. C. Wright and M. N. Hallquist (Eds.) *Handbook of research methods in clinical psychology.* Cambridge University Press.

Rockwood, N. J., & Hayes, A. F. (2018). Multilevel mediation analysis. Draft submitted and to appear in A. A. O'Connell, D. B. McCoach, and B. Bell (Eds). *Multilevel modeling methods with introductory and advanced applications.* Information Age Publishing.

Hayes, A. F. (2018). Partial, conditional, and moderated moderated mediation: Quantification, inference, and interpretation. *Communication Monographs*, *85*, 4-40. [PDF]

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Hayes, A. F., Montoya, A. K., & Rockwood, N. J. (2017). The analysis of mechanisms and their contingencies: PROCESS versus structural equation modeling. *Australasian Marketing Journal, 25,* 76-81. [PDF and Mplus code]

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

Hayes, A. F. (2015). *An index and test of linear moderated mediation*. *Multivariate Behavioral Research, 50,* 1-22.
Hayes, A. F., & Preacher, K. J. (2014). Statistical mediation analysis with a multicategorical independent variable. *British Journal of Mathematical and Statistical Psychology*, *67*, 451-470.

Hayes, A. F., & Scharkow, M. (2013). The relative trustworthiness of inferential tests of the indirect effect in statistical mediation analysis: Does method really matter? *Psychological Science, 24*, 1918-1927.

## Pertinent Publications


Hayes, A. F., & Preacher, K. J. (2013). Conditional process modeling: Using structural equation modeling to examine contingent causal processes. In G. R. Hancock & R. O. Mueller (Eds.) *Structural equation modeling: A second course* (2nd Ed). Greenwich, CT: Information Age Publishing.

Hayes, A. F., Glynn, C. J., & Huge, M. E. (2012). Cautions regarding the interpretation of regression coefficients and hypothesis tests in linear models with interactions. *Communication Methods and Measures, 6,* 1-11.

Hayes, A. F., Preacher, K. J., & Myers, T. A. (2011). Mediation and the estimation of indirect effects in political communication research. In E. P. Bucy & R. L. Holbert (Eds), *Sourcebook for political communication research: Methods, measures, and analytical techniques.* (p. 434-465). *New York:* Routledge.

Hayes, A. F., & Preacher, K. J. (2010). Estimating and testing indirect effects in simple mediation models when the constituent paths are nonlinear. *Multivariate Behavioral Research, 45,* 627-660.

Hayes, A. F. (2009). Beyond Baron and Kenny: Statistical mediation analysis in the new millenium. *Communication Monographs, 76,* 408-420.

Hayes, A. F., & Matthes, J. (2009). Computational procedures for probing interactions in OLS and logistic regression: SPSS and SAS implementations. *Behavior Research Methods, 41,* 924-936.

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.

Preacher, K. J., Rucker, D. D., & Hayes, A. F. (2007). Assessing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivariate Behavioral Research, 42,* 185-227.

Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, and Computers, 36,* 717-731.