ESTIMATING AND PROBING CONDITIONAL EFFECTS IN TWO INSTANCE REPEATED-MEASURES DESIGNS

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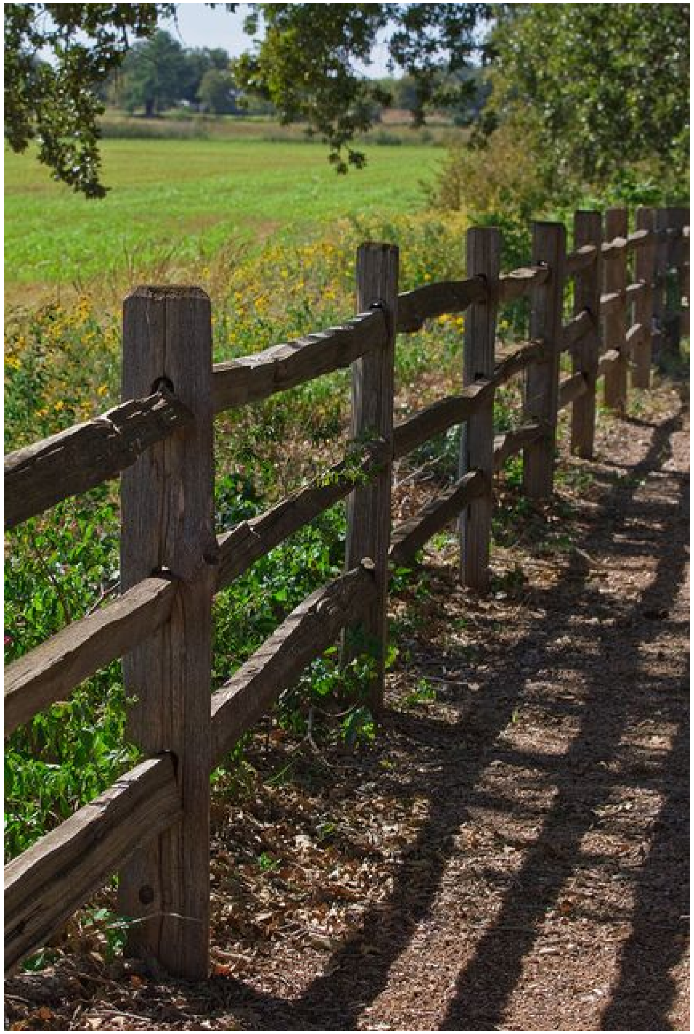
Slides available at github.com/akmontoya/EHEMarch2017

Overview

- Running Example
- Two-Condition Repeated Measures Data
- Between Subjects Moderation
- Two Instance Repeated-Measures Moderation
  - Judd Kenny and McClelland (2001, 1996)
  - Interpretations
  - Probing
  - MEMORE
  - Reporting (Writing and Figures)
  - Common Questions
- Resources



Running Example: Group Work in Computer Science

Montoya, A. K. (2013) Increasing Interest in Computer Science through Group Work: A Goal Congruity Approach (Undergraduate Honors Thesis).

Female participants (N = 51) read two syllabi for different computer science classes. One of the syllabi reported the class would have group projects, and the other syllabi stated the class would have individual projects.

- Syllabi also differed in professor's name (but not gender), and the primary programming language used in the class.

Measured Variables:

- Interest in each the class `int_i` `int_g`
- `Grppref`: Preference for group work ($\alpha = .60$)
- `Order`
  - 1 = Group First; 2 = Individual First

University of Washington
Computer Science & Engineering 142: Introduction to Programming I
Course Syllabus

Instructor

name: John Johnson
email: j.johnson@uw.edu
office: CSE 800
office phone: (206)555-1234
office hours: see course website

Course Overview

This course provides an introduction to computer science using the Java programming language. CSE 142 is primarily a programming course that focuses on common computational problem solving techniques. No prior programming experience is assumed, although students should know the basics of using a computer (e.g., using a web browser and word processing program) and should be competent with math through Algebra 1. The information, concepts, and analytical thinking introduced in lecture provide a unifying framework for the topics covered in CSE 143.

Lecture Time

MWF 12:00 PM - 1:00 PM, Classroom TBA

Discussion Sections

You will be expected to participate in a weekly discussion section, held on Thursdays (see course website for details). The TA who runs your section will grade your homework assignments. In section, we will answer questions, go over common errors in homework, and discuss sample problems in more detail than lecture.

Course Web Site

- http://www.cs.washington.edu/142/

Textbook

- Reges/Stepp, *Building Java Programs: A Back to Basics Approach (2nd Edition)*.

Grading

The primary assessment for your success in this class is exams. There will be 2 midterms and 1 final, and together they make up 85% of your grade. The homework assignments are designed to prepare you for your exams. The exams are designed to assess your ability to utilize the concepts you've learned from your homework and in lecture in new contexts.

5% participation
10% weekly homework assignments
25% midterm 1
25% midterm 2
35% final exam

Exams

Our exams are closed-book and closed-notes, although each student will be allowed to bring a single index card with hand-written notes (no larger than 5" by 8"). No electronic devices may be used, including calculators. Make-up exams will not be given except in case of a serious emergency.

Homework

Homework consists of weekly assignments done in optional groups and submitted electronically on the course web site. Disputes about homework grading must be made within 2 weeks of receiving the grade. If you don't make an honest effort on the homework, your exam score will reflect it.

Academic Integrity and Collaboration

Computer Science is best learned through interacting with your fellow students to ensure that you thoroughly understand each concept. Homework assignments may be completed with other students. You are strongly encouraged to discuss general ideas of how to approach an assignment with other students, and may discuss specific details about what to write with other students. Any help you receive from or provide to classmates should be cited in your assignment. You may seek help from University of Washington CSE 142 TAs, professors, and classmates.

You must abide by the following rules:

- You are highly encouraged to work with another student on homework assignments.
- You may not show another student outside of your class your solution to an assignment, nor look at his/her solution.
- You may not have anyone outside of your class describe in detail how to solve an assignment or sit with you as you write it.
- You may not post online about your homework, other than on the class discussion board, to ask others for help.

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COMPUTER SCIENCE WITHIN-SUBJECTS DATA EXAMPLE

Montoya, A. K. (2013) Increasing Interest in Computer Science thought Group Work: A Goal Congruity Approach (Undergraduate Thesis).

Data should be a in wide format, two-condition within-subjects design with a person level covariate.

Research Question: Does the degree to which <u>preference for group work</u> predicts <u>interest</u> in computer science depend on whether or not the class has <u>group work</u>?

Or

Does effect of <u>group work</u> on <u>interest</u> in computer science classes depend on an individual's <u>preference for group work</u>?

CompSci_WS.sav

Subject	int_I	int_G	grppref
300	1.50	4.00	6.67
301	2.75	3.25	6.33
325	5.75	2.50	2.67
342	3.50	5.75	6.00
349	2.25	2.00	4.00
350	1.50	1.75	3.67
305	2.50	4.25	4.00
348	6.00	1.75	2.33
318	3.00	2.00	4.67
320	4.00	5.25	4.00
332	5.00	5.00	3.67
338	2.00	1.75	3.00
310	1.00	1.75	3.00
304	1.25	4.50	5.67
306	5.75	4.50	4.00
308	3.25	4.75	4.00
315	2.75	2.25	4.33
322	5.50	2.00	2.33
343	1.75	5.25	6.00
314	4.00	5.50	3.00
319	2.25	4.00	5.00

Repeated Measures Data

There are many different kinds of "repeated measures data." What type of data you have will determine what kind of mediation analysis is appropriate.

Types of *Repeated Measurements:*

- Each person *over time*
- *Nested/Multilevel* data (individuals within schools, cohorts, etc)
- *Dyadic* data (twins, couples, labmates, roomates)
- Each person in a *variety of circumstances*
- and many more…

What is measured repeatedly?

- Specifically in moderation, it's important to think about how/when/how many times the variables in your model are measured
- *Multilevel* framework has a nice system referring to levels
- Is your independent variable measured repeatedly?
- Is your independent variable what differentiates your repeated measurements?

Repeated Measures Data

MEMORE is for two-instance repeated measures moderation analysis, where the independent variable of interest is the factor which differs by repeated measures.

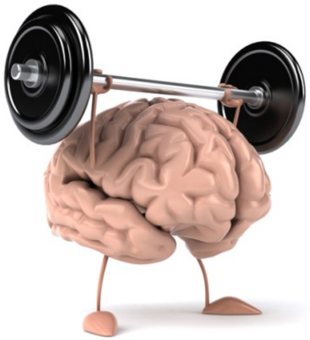
X: varies between repeated measurements
M: measured once, does not vary by instance
Y: measured in each of the two instances

Examples:

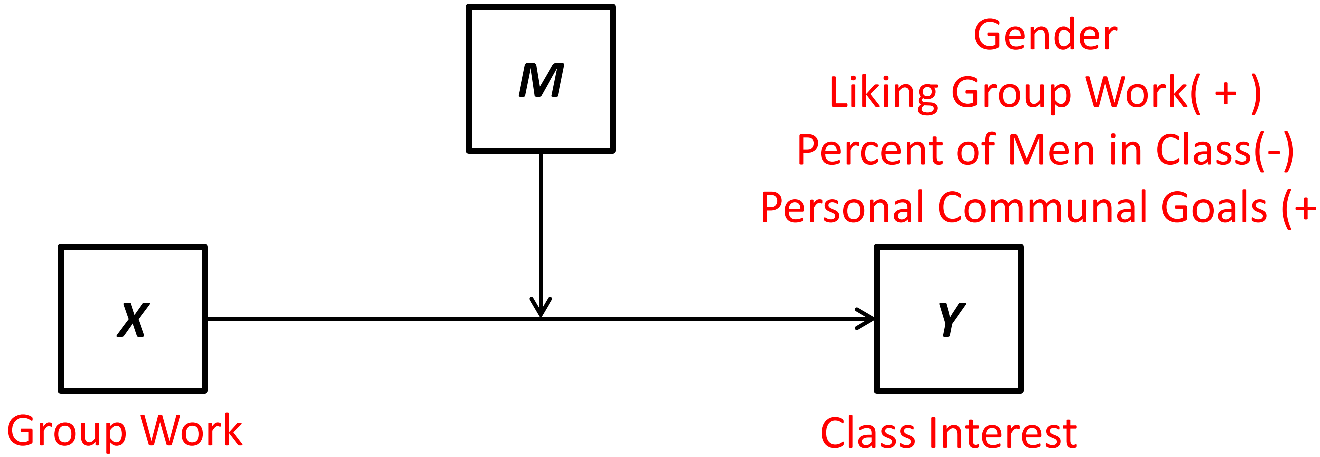
- Participants read two assignments which differ in framing. Interested in how assignment influences *motivation to complete* and whether effect of assignment depends on *current GPA*.
- Pre-post test: Educator measures learning outcomes before administering an intervention, and after administering the intervention. Does this relationship depend on person level variables (e.g. parent support)?
- Researcher interested in cross-gender partners, do team level variables impact the differences in outcomes for girls and boys?

Non-Examples:

- Does reading intervention's impact on language outcomes depend on change in reading? (Pre/post)
- Any instance where repeated-measure factor is a "nuisance" (e.g. studying schools, but not interested in comparing schools directly).



Moderation



The relationship between the focal predictor (*X*) and an outcome (*Y*) is said to be moderated when the size or direction depends on *M*. Moderation helps us understand boundary conditions of effect: for whom on when is the effect large or small, present or absent, positive or negative.

X and *M* are frequently described as “interacting” in their prediction of *Y*.

Many different kind of variables may act as moderators. Situational, individual level variables, cognitive variables, environmental variables, etc.

A quick example: Name some possible moderators!

Modeling Non-Contingent Relationships

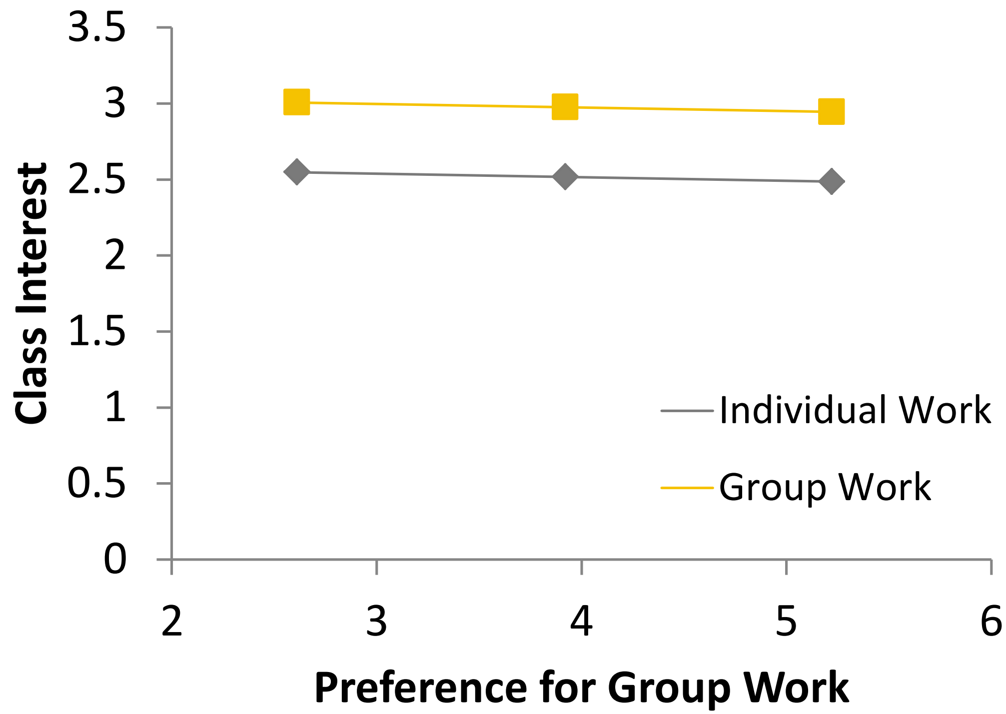
A multiple regression model without interaction terms, fixes the relationship between the predictors and the outcomes to be the same regardless of the level of other predictors.

$$Y_i = b_0 + b_1 X_i + b_2 M_i$$

Example:
Y: Interest in Class (1-7)
X: Group Work (0 No Group Work; 1 Group Work)
M: Preference for group work (1-7)

A one unit increase in group work results in a .46 unit increase in interest, regardless of preference for group work.

$\hat{Y}$	X	M
2.55	0	2.61
2.52	0	3.92
2.49	0	5.22
3.01	1	2.61
2.98	1	3.92
2.94	1	5.22

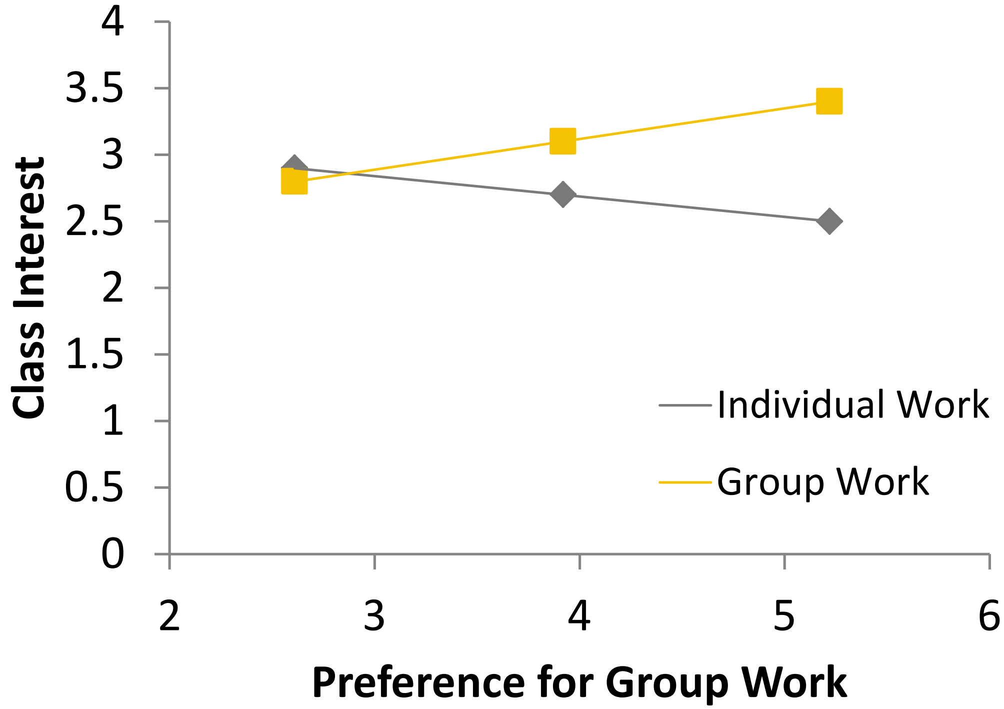


Modeling Contingent Relationships

What if instead we felt that the relationship between group work and interest depends on preference for group work?

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

Y	X	M
2.9	0	2.61
2.7	0	3.92
2.5	0	5.22
2.8	1	2.61
3.1	1	3.92
3.4	1	5.22



Symmetry in Moderation

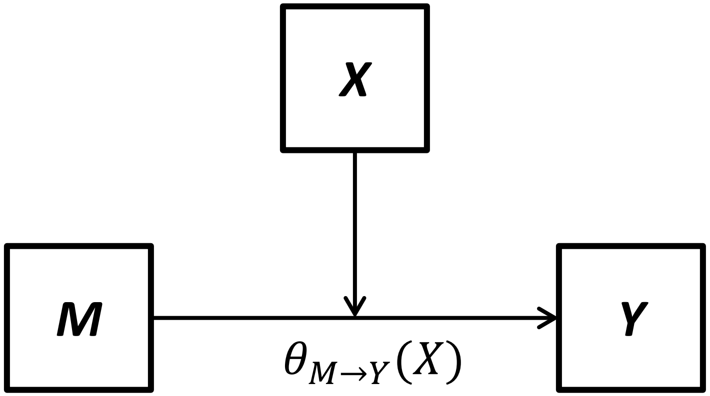
$$Y_i = b_0 + b_1X_i + b_2M_i + b_3M_iX_i$$

We saw that this model can be expressed such that it is clear that *X*'s effect on *Y* depends on *M*

$$Y_i = b_0 + (b_1 + b_3M_i)X_i + b_2M_i$$

But it can also be equivalently expressed that *M*'s effect on *Y* depends on *X*

$$Y_i = b_0 + (b_2 + b_3X_i)M_i + b_1X_i$$



Here *X* moderates the effect of *M* on *Y*. *X* is the moderator, with the conditional effect of *M* on *Y* given *X* expressed as $\theta_{M \to Y}(X)$. Which variable to think of as the moderator is not a mathematical concern, but rather a substantive research concern. These two models are mathematically equivalent.

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

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

Select a value of the moderator (*M*) 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.

Let's call the conditional effect:

$$\theta_{X \to Y}(M) = (b_1 + b_3 M_i)$$

The estimated standard error of θ is

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

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

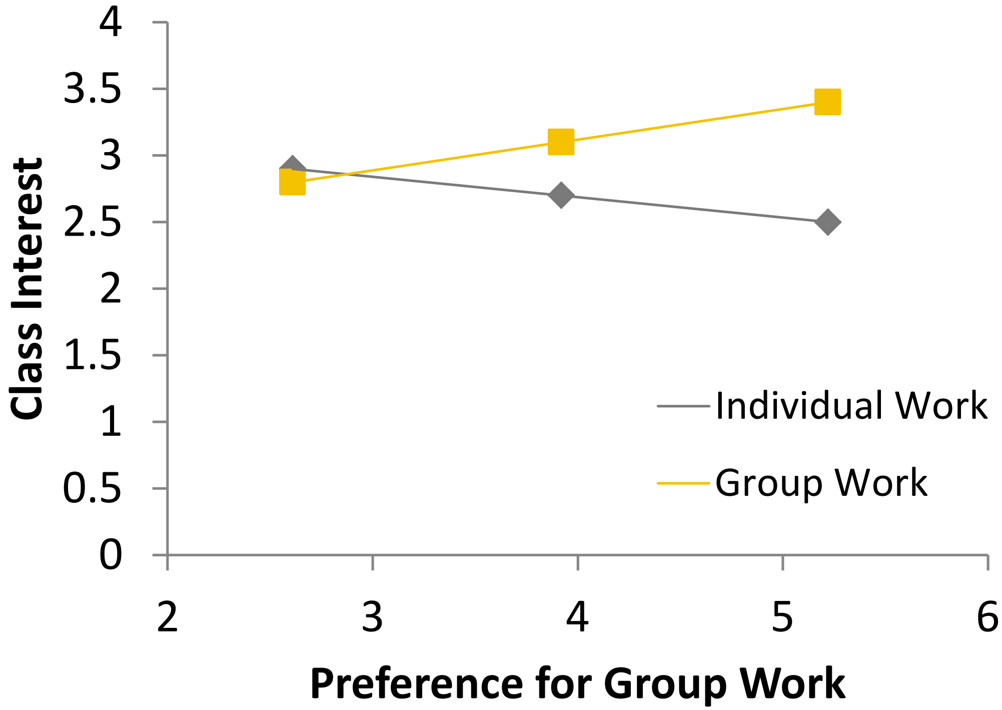
You must choose the points along the moderator to "probe" the effect of *X* on *Y*. There are some conventions for choosing to do so:

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

If *M* is continuous, choose the Mean ± 1 SD

Let's look at an example with our computer science data:

$$Y_i = 3.32 + (-1.07 + .39M_i)X_i - .16M_i$$



M	$\theta_{X\to Y\mid M}$	$s_{\theta_{X\to Y\mid M}}$	*p*
2.61	-0.06	0.41	0.89
3.92	0.45	0.29	0.12
5.22	0.96	0.40	0.02

Participants were more interested in the group work class than the individual work class when they had relatively high preference for group work.

The Johnson-Neyman Technique

The Johnson-Neyman technique seeks to find the value or values of the moderator (*M*) 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 *M* is exactly equal to some chosen level of significance α. Thus, no need to select values of *M* in advance.

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

$$t_{crit} = \frac{b_1 + b_3 M}{\sqrt{s_{b_1}^2 + 2Ms_{b_1 b_3} + M^2 s_{b_3}^2}}$$

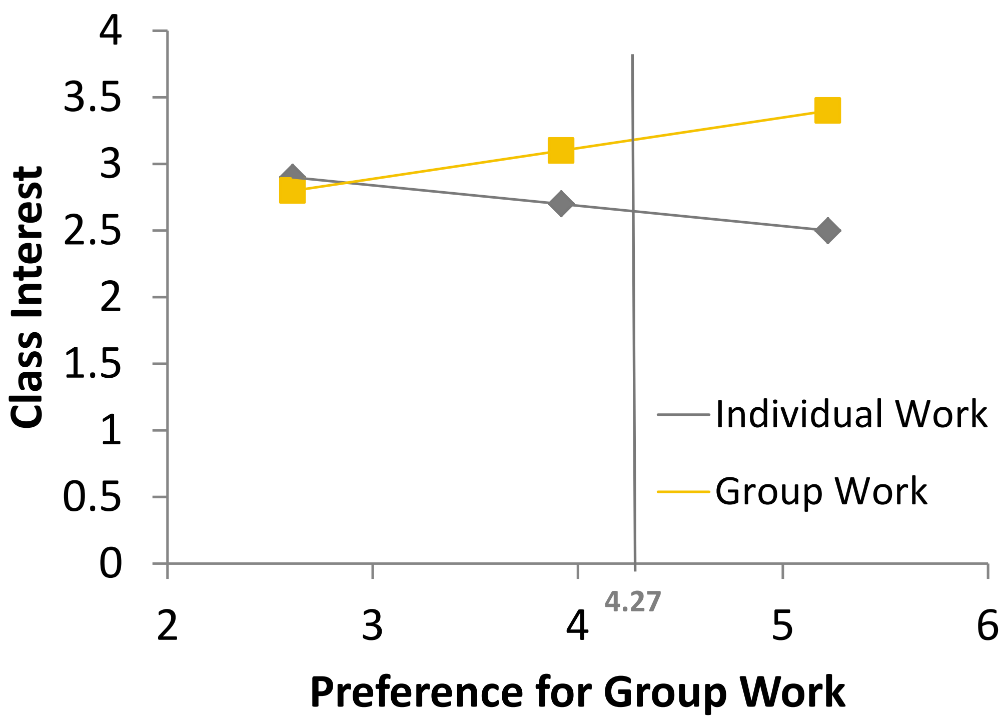
Isolating *M* yields to the solution in the form of a quadratic equation which always has two roots, though not always two that are interpretable.

The Johnson-Neyman Technique

For what values of preference for group work are there significant differences in interest between the group work and individual work class?

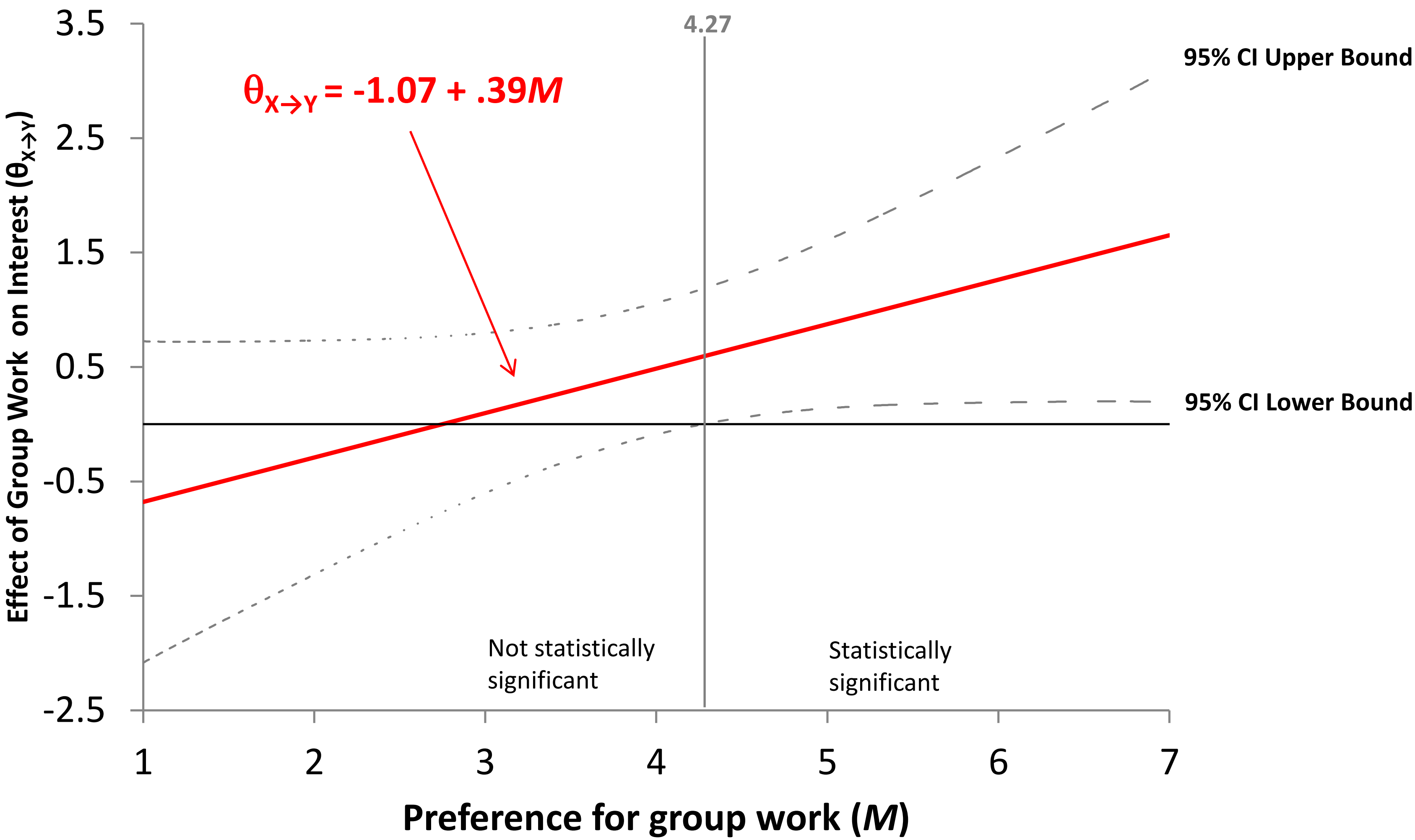
Let's look at an example with our computer science data:

$$Y_i = 3.32 + (-1.07 + .39M_i)X_i - .16M_i$$



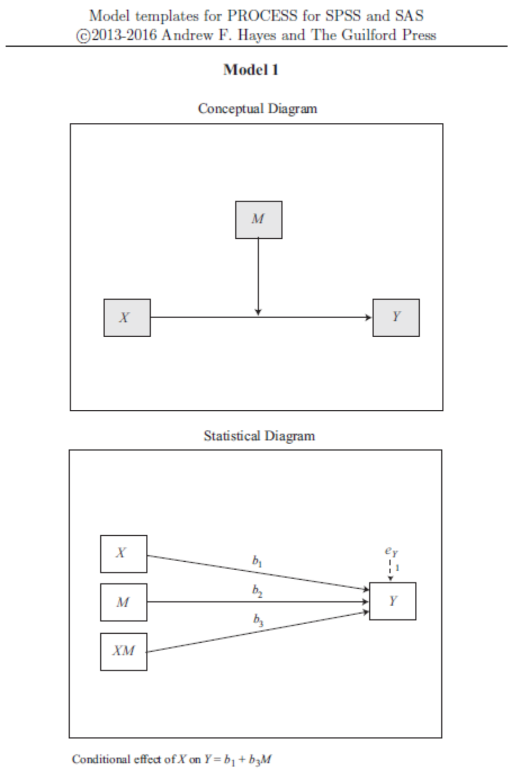
Participants were more interested in the group work class than the individual work class when they had preference for group work higher than 4.27 ($\alpha = 0.05$).

A Plot of the "Region of Significance"



PROCESS

PROCESS is a macro available for SPSS and SAS written by Andrew F. Hayes, documented in *Mediation, Moderation, and Conditional Process Analysis*, and available for free online at *processmacro.org*




```
PROCESS vars = cond interest grppref /x = cond
     /m = grppref /y = interest / model = 1
     /jn = 1 /plot = 1.
```

- List all variables involved in the model in `vars` argument.
- Assign variables roles (X, Y, M), and covariates don't get a role.
- 2-way interaction is `Model 1`
- `JN` option calls the Johnson-Neyman technique
- `PLOT` option calls a table of values for making a plot.

Judd, McClelland, and Smith (1996)

Judd, C. M., McClelland, G. H., and Smith, E. R. (1996). Testing Treatment by Covariate Interactions When Treatment Varies Within Subjects. *Psychological Methods*, *1*(4), 366-378.

Psychological Methods
1996, Vol. 1, No. 4, 366–378

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1082-989X/96/$3.00

Testing Treatment by Covariate Interactions When Treatment Varies Within Subjects

Charles M. Judd and Gary H. McClelland
University of Colorado at Boulder

Eliot R. Smith
Purdue University

In contrast to the situation when an independent or treatment variable varies between subjects, procedures for testing treatment by covariate interactions are not commonly understood when the treatment varies within subjects. The purpose of this article is to identify analytic approaches that test such interactions. Two design scenarios are discussed, one in which the covariate is measured only a single time for each subject and hence varies only between subjects, and the other in which the covariate is measured at each level of the treatment variable and hence varies both within and between subjects. In each case, alternative analyses are identified and their assumptions and relative efficiencies compared.

An issue that arises with some frequency in data analysis in psychological research concerns the relationship between some measured variable and the dependent variable and whether that relationship depends on or varies across levels of a manipulated or experimental independent variable. For instance, in a clinical intervention study, we might randomly assign patients to one of two conditions, either a treatment intervention or a placebo intervention control condition. Prior to treatment, we measure a characteristic of the patients, probably focusing on the prior course and severity of their illness. Following the treatment, we assess the outcome variable of symptom severity. The primary question of interest, of course, is whether the outcome variable is affected by the manipulated treatment: Did the treatment make a difference on subsequent symptom severity? Additionally, however, we may well want to know whether the relationship between the treatment and posttreatment symptom severity depends on the patient's pretreatment course of illness. It may be, for instance, that the treatment's effect is greater for patients whose pretreatment symptoms were relatively severe. Equivalently, it may be that posttreatment symptom severity is less well predicted by pretreatment course of illness in the case of patients in the intervention condition than in the case of patients in the control condition.

The pretreatment measure of illness course is typically called a *covariate*. The analysis that is of interest is an analysis of covariance (ANCOVA), including the treatment by covariate interaction (Judd & McClelland, 1989). The two questions of interest are (a) Is there an overall treatment main effect? and (b) Is there a Treatment × Covariate interaction? If the interaction is significant, it indicates that the covariate:outcome variable relationship depends on the treatment variable. Equivalently, it suggests that the effect of the treatment on the outcome variable depends on the level of the covariate.

The analysis is readily conducted using multiple regression, making the standard assumption that errors or residuals are independently sampled from a single normally distributed population. Assume that Y_i is the outcome variable, Z_i is the covariate, and X_i is the contrast-coded (Judd & McClelland, 1989; Rosenthal & Rosnow, 1985) treatment variable. One estimates two least squares regression models:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \varepsilon_i$$

and

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \beta_3 X_i Z_i + \varepsilon_i.$$

In the first equation, β_1 represents the magnitude of

Charles M. Judd and Gary H. McClelland, Department of Psychology, University of Colorado at Boulder; Eliot R. Smith, Department of Psychological Sciences, Purdue University.

This work was partially supported by National Institute of Mental Health Grant R01 MH45049.

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A regression approach to considering "cross level" interactions.

Approach is very simple:

1. Data should be a two-condition within-subjects design with a person level covariate.
2. Setup two regression equations, one for each condition
3. Take the difference between those two regression equations
4. Regression weight for person level covariate in Step 3 tests moderation.

Running Example: Group Work in Computer Science

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ANALYSIS USING JUDD ET AL. (1996)

2. Setup two regression equations, one for each condition

$$Y_{1\mathrm{i}} = b_{10} + b_{11}M_i + \epsilon_{1i}$$

$$Y_{2\mathrm{i}} = b_{20} + b_{21}M_i + \epsilon_{2i}$$

Is b_{11} different from b_{21}?

3. Based on these models, setup a new model where you can directly estimate and conduct inference on what you are interested in (in this case $b_{11} - b_{21}$):

$$Y_{2i} - Y_{1i} = (b_{10} - b_{20}) + (b_{11} - b_{21})M_i + (\epsilon_{1i} - \epsilon_{2i}) = b_0 + b_1 M_i + \epsilon_i$$

Use simple regression to conduct inference on $b_1 = b_{11} - b_{21}$

With the data: Does the relationship between preference for group work and interest depend on group work condition?

```
regression /dep = int_diff /method = enter grppref.
```

ANALYSIS USING JUDD ET AL. (1996)

4. Regression weight for person level covariate in Step 3 tests moderation.

$$Y_{1\mathrm{i}} = b_{10} + b_{11} M_i + \epsilon_{1i}$$

$$Y_{2\mathrm{i}} = b_{20} + b_{21} M_i + \epsilon_{2i}$$

$$Y_{2i} - Y_{1i} = (b_{10} - b_{20}) + (b_{11} - b_{21}) M_i + (\epsilon_{1i} - \epsilon_{2i}) = b_0 + b_1 M_i + \epsilon_i$$

```
regression /dep = int_diff /method = enter grppref.
```

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-3.550	.648		-5.474	.000
	grppref	.994	.156	.674	6.388	.000

a. Dependent Variable: int_diff

What does it mean that b_1 is positive?

$$b_1 = b_{11} - b_{21} = .994$$

$$b_{11} > b_{21}$$

Practically, this means that the relationship between preference for group work and interest is significantly stronger (more positive) in the group work condition.

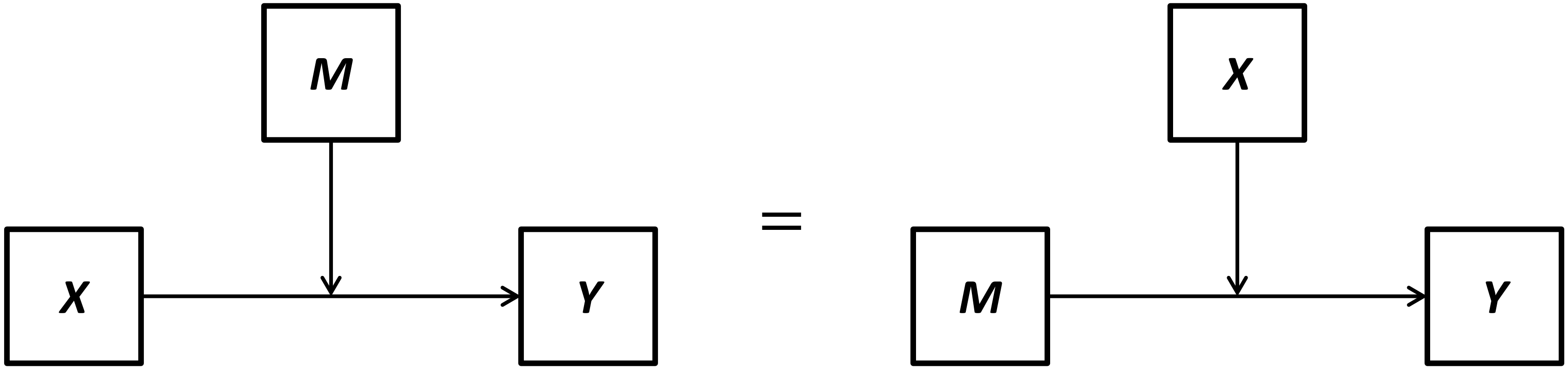
Symmetry in Within-Subjects Moderation

Does the effect of condition depend on *M*?

$$Y_{2i} - Y_{1i} = (b_{10} - b_{20}) + (b_{11} - b_{21})M_i + \ (\epsilon_{1i} - \epsilon_{2i}) = b_0 + b_1 M_i + \epsilon_i$$

$Y_{2i} - Y_{1i}$ is a quantification of the effect of condition, which means that if *M* predicts $Y_{2i} - Y_{1i}$ then the effect of condition depends on *M*.

$\boldsymbol{b_1}$ is a test of exactly that!



Conditional Effects in Within-Subjects Moderation

$$Y_{2i} - Y_{1i} = (b_{10} - b_{20}) + (b_{11} - b_{21})M_i + \ (\epsilon_{1i} - \epsilon_{2i}) = b_0 + b_1 M_i + \epsilon_i$$

Given a value of *M* what is the effect of condition on the outcome?

$Y_{2i} - Y_{1i}$ is a quantification of the effect of condition, which means that the conditional effect of condition $\theta_{X \to Y}(M) = b_0 + b_1 M$

Given a specific condition what is the effect of *M* on the outcome?

$$Y_{1\mathrm{i}} = b_{10} + b_{11} M_i + \epsilon_{1i}$$

$$Y_{2\mathrm{i}} = b_{20} + b_{21} M_i + \epsilon_{2i}$$

$$\theta_{M \to Y}(X) = b_{X1}$$

Conditional effects will become important when it comes to probing

Probing an Effect of Condition on Outcome: The "Pick-a-Point" Approach

$$\theta_{X\rightarrow Y}(M) = b_0 + b_1 M$$

Select a value of the moderator (*M*) at which you'd like to have an estimate of the condition's 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 condition is zero at that moderator value.

The estimated standard error of $\theta_{X\rightarrow Y}(M)$ is

$$s_{\theta_{X\rightarrow Y}(M)} = \sqrt{(s_{b_0}^2 + 2M s_{b_0 b_1} + M^2 s_{b_1}^2)}$$

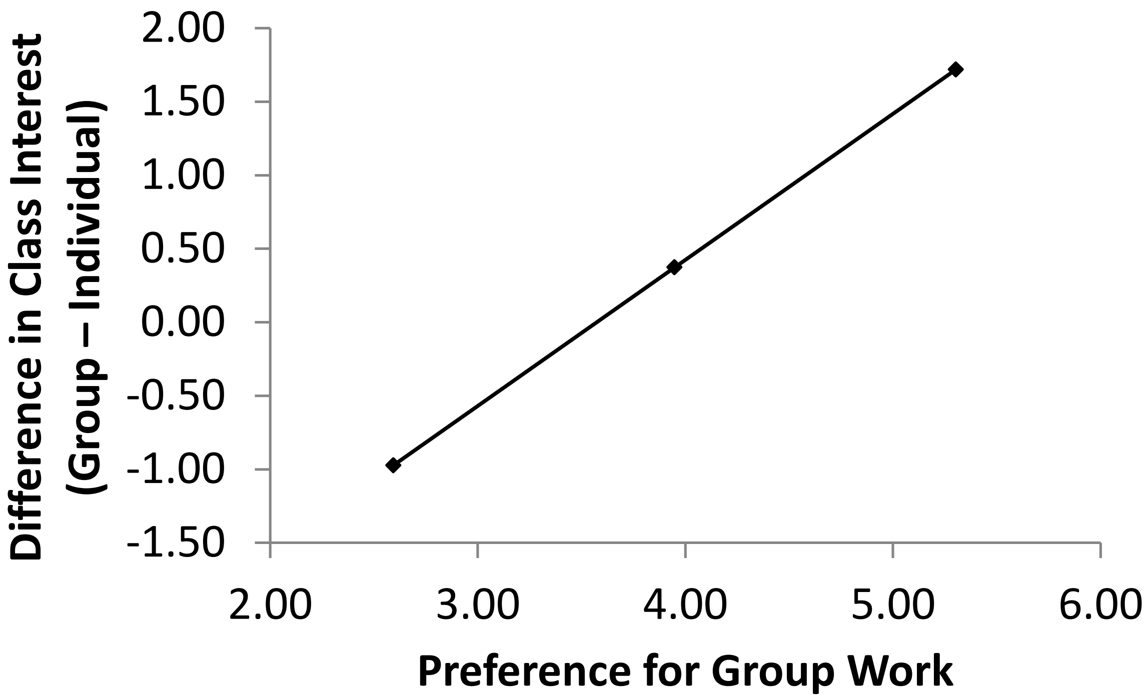
Squared standard error of b_0 Covariance of b_0 and b_1 Squared standard error of b_1

Probing an Effect of Condition on Outcome: The "Pick-a-Point" Approach

You must choose the points along the moderator to "probe" the effect of condition on Y.

Let's look at an example with our computer science data:

$$Y_{Di} = -3.55 + .99M_i$$



M	$\theta_{X\rightarrow Y\mid M}$	$s_{\theta_{X\rightarrow Y\mid M}}$	p
2.59	-0.97	0.30	0.00
3.95	0.37	0.21	0.08
5.30	1.72	0.30	0.00

Participants relatively low in preference for group work are more interested in the individual work class, and those high in preference for group work are more interested in the class with group work.

The Johnson-Neyman Technique

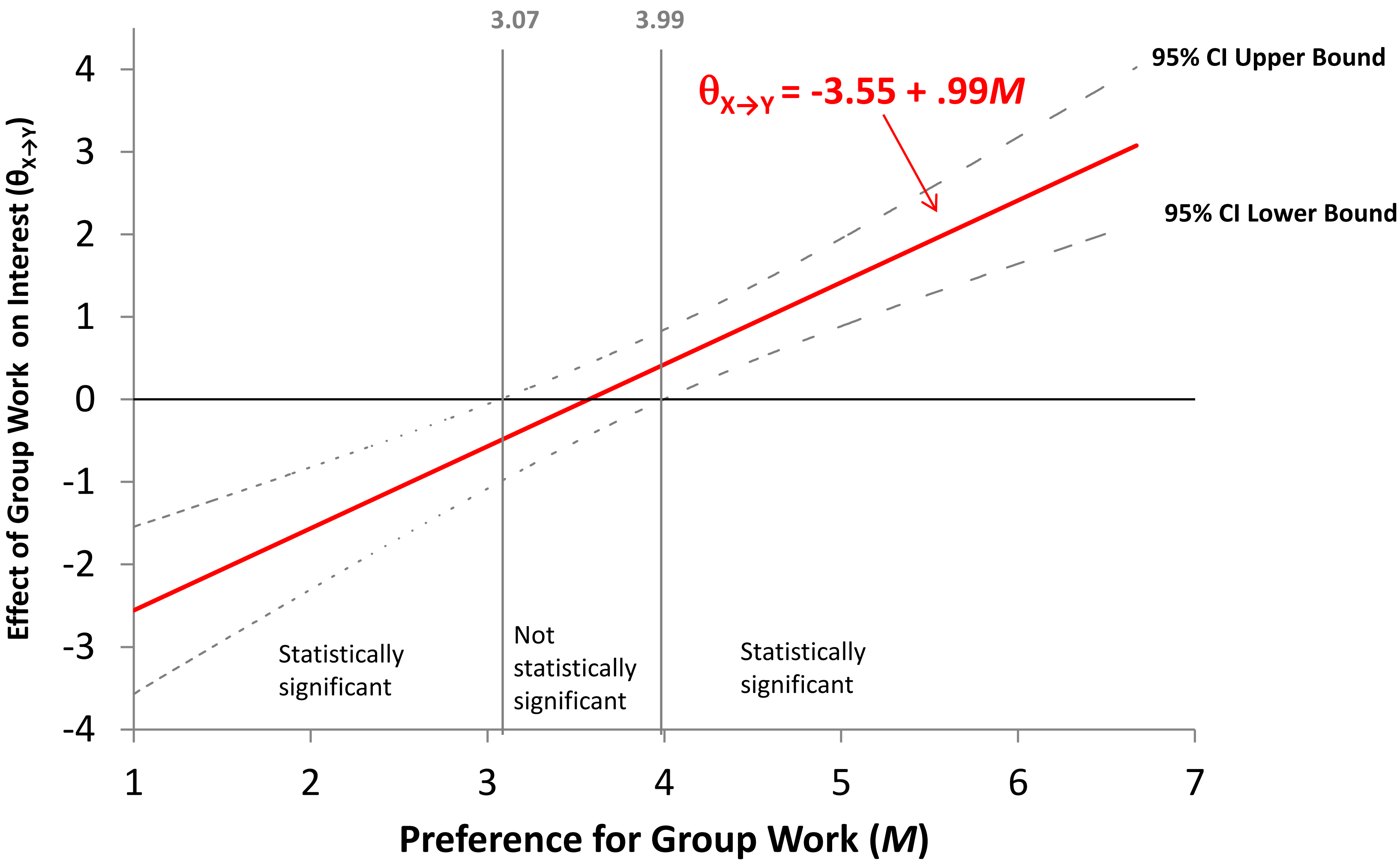
The Johnson-Neyman technique seeks to find the value or values of the moderator (*M*) within the data, if they exist, such that the *p*-value for the conditional effect of condition at that value or those values of *M* is exactly equal to some chosen level of significance α. Thus, no need to select values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

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

$$t_{crit} = \frac{b_0 + b_1 M}{\sqrt{s_{b_0}^2 + 2M s_{b_0 b_1} + M^2 s_{b_1}^2}}$$

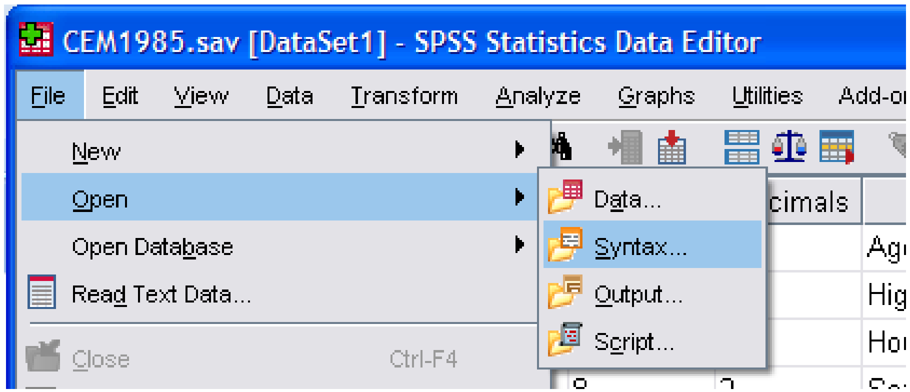
Isolating *M* yields to the solution in the form of a quadratic equation which always has two roots, though not always two that are interpretable.

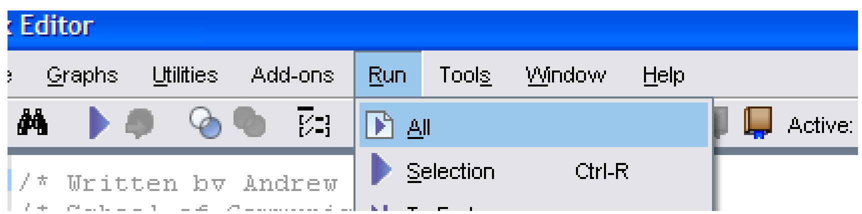
A Plot of the "Region of Significance"



Teaching your package MEMORE

MEMORE is a command which must be taught and re-taught to your statistical package (SPSS) every time you open the package. To teach your program the MEMORE command, open the memore.sps file and run the script exactly as is.





SPSS now knows a new command called MEMORE

Writing MEMORE Syntax

MEMORE has 2 required arguments: Y and M

```
MEMORE m = grppref /y = int_G int_I /model = 3 /jn = 1 /plot = 1.
```

M is your list of moderators
Y is you list of outcomes

Some other arguments:

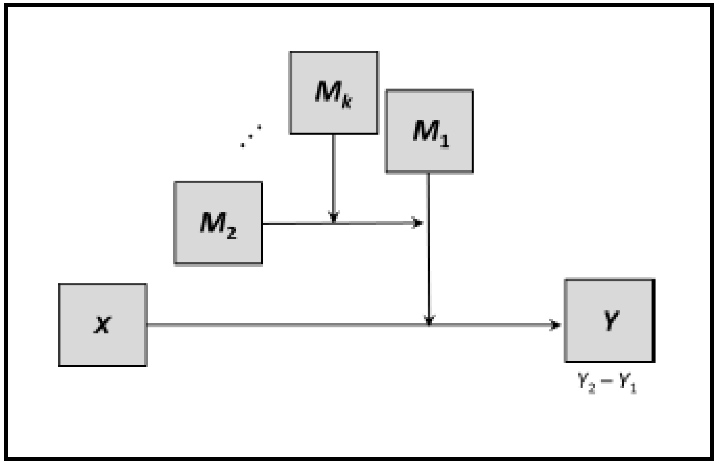
- **model** specifies the model you are interested. The default is 1, mediation. Moderation models are 2 and 3.
- **conf** specifies level of confidence you want (default is 95)
- **jn = 1** asks for Johnson-Neyman procedure
- **plot = 1** asks for plotting code
- **quantile = 1** probes at quantiles instead of Mean ± 1 SD

MEMORE

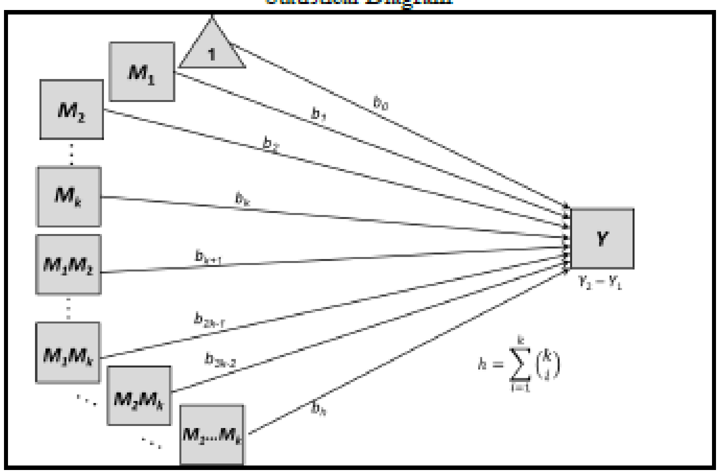
We can use MEMORE to estimate and probe this model.

Model 3 Multiplicative Moderation

Conceptual Diagram



Statistical Diagram




```
MEMORE m = grppref /y = int_G int_I
       /model = 3 /jn = 1 /plot = 1.
```

List moderator(s) in the `m` list
List outcomes in the `y` list
Can use `model 2` or `model 3` when you have 1 moderator there is no difference.
`JN` option calls the Johnson-Neyman technique
`PLOT` option calls a table of values for making a nice plot.

Using MEMORE for CASC WS data

```
MEMORE m = grppref /y = int_G int_I /model = 3 /jn = 1 /plot = 1.
```

```
********************** MEMORE Procedure for SPSS Version 2.Beta ***********************

                         Written by Amanda Montoya

                  Documentation available at akmontoya.com

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

Model:
  3

Variables:
Y = int_G    int_I
M = grppref

Computed Variables:
Ydiff =          int_G      -        int_I

Sample Size:
  51
```

First part of output repeats what you told MEMORE to do. Always double check that this is correct!

I double checked to make sure the order of subtraction was the same as when we did this by hand.

Using MEMORE for CASC WS data

```
MEMORE m = grppref /y = int_G int_I /model = 3 /jn = 1 /plot = 1.
```

Probing effect of condition on outcome at different values of the moderator

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

Conditional Effect of 'X' on Y at values of moderator(s)
    grppref     Effect         SE          t          p       LLCI       ULCI
     2.5938     -.9728      .2964    -3.2823      .0019    -1.5684     -.3772
     3.9478      .3725      .2085     1.7865      .0802     -.0465      .7916
     5.3019     1.7179      .2964     5.7963      .0000     1.1223     2.3135

Degrees of freedom for all conditional effects:
  49

Values for quantitative moderators are the mean and plus/minus one SD from the mean.
```

This is the default. You can change this to the 10th, 25th, 50th, 75th, and 90th quantiles by adding `quantile =1` to the command line

Using MEMORE for CASC WS data

```
MEMORE m = grppref /y = int_G int_I /model = 3 /jn = 1 /plot = 1.
```

```
****************************** JOHNSON-NEYMAN PROCEDURE *******************************

Moderator value(s) defining Johnson-Neyman significance region(s) and percent of
observed data above value:
      Value      % Abv
     3.0685    72.5490
     3.9949    54.9020

Conditional Effect of 'X' on Y at values of moderator
    grppref     Effect         SE          t          p       LLCI       ULCI
     1.0000    -2.5564      .5037    -5.0752      .0000    -3.5687    -1.5442
     1.2984    -2.2599      .4619    -4.8931      .0000    -3.1880    -1.3318
     1.5968    -1.9634      .4210    -4.6641      .0000    -2.8094    -1.1174
     1.8953    -1.6669      .3813    -4.3712      .0001    -2.4332     -.9006
     2.1937    -1.3704      .3434    -3.9905      .0002    -2.0605     -.6803
     2.4921    -1.0739      .3078    -3.4886      .0010    -1.6925     -.4553
     2.7905     -.7774      .2755    -2.8218      .0069    -1.3310     -.2238
     3.0685     -.5012      .2494    -2.0096      .0500    -1.0023      .0000
     3.0889     -.4808      .2477    -1.9416      .0579     -.9785      .0168
     3.3874     -.1843      .2260     -.8156      .4187     -.6385      .2699
     3.6858      .1122      .2125      .5279      .5999     -.3148      .5392
     3.9842      .4087      .2086     1.9591      .0558     -.0105      .8279
     3.9949      .4193      .2087     2.0096      .0500      .0000      .8387
     4.2826      .7052      .2149     3.2809      .0019      .2733     1.1371
     4.5811     1.0017      .2306     4.3435      .0001      .5382     1.4652
     4.8795     1.2982      .2539     5.1124      .0000      .7879     1.8085
     5.1779     1.5947      .2830     5.6350      .0000     1.0260     2.1634
     5.4763     1.8912      .3162     5.9804      .0000     1.2557     2.5267
     5.7747     2.1877      .3525     6.2070      .0000     1.4794     2.8961
     6.0732     2.4843      .3909     6.3560      .0000     1.6988     3.2697
     6.3716     2.7808      .4308     6.4546      .0000     1.9150     3.6465
     6.6700     3.0773      .4720     6.5200      .0000     2.1288     4.0258

Degrees of freedom for all conditional effects:
  49
```

This will only print when we include `jn =1` in the command line. JN technique does not work for multiple moderators.

Using MEMORE for CASC WS data

```
MEMORE m = grppref /y = int_G int_I /model = 3 /jn = 1 /plot = 1.
```

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

Conditional Effect of Moderator(s) on Y in each Condition

Condition 1 Outcome:
 int_G

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4488      .2014     1.7964    12.3612     1.0000    49.0000      .0010

Model
              coeff         SE          t          p       LLCI       ULCI
constant     1.7874      .5836     3.0624      .0036      .6145     2.9603
grppref       .4922      .1400     3.5158      .0010      .2109      .7735

Degrees of freedom for all conditional effects:
  49

--------------------------------------------------------------------------

Condition 2 Outcome:
 int_I

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4710      .2218     1.6502    13.9671     1.0000    49.0000      .0005

Model
              coeff         SE          t          p       LLCI       ULCI
constant     5.3374      .5594     9.5415      .0000     4.2132     6.4615
grppref      -.5014      .1342    -3.7373      .0005     -.7710     -.2318

Degrees of freedom for all conditional effects:
  49
```

Preference for group work positively predicts interest in **class with group work**

and negatively predicts interest in **class with individual work**.

Using MEMORE for CASC WS data

```
MEMORE m = grppref /y = int_G int_I /model = 3 /jn = 1 /plot = 1.
```

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

Data for visualizing conditional effect of X on Y.
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/grppref YdiffHAT int_GHAT int_IHAT.

BEGIN DATA.

     2.5938     -.9728     3.0640     4.0368
     3.9478      .3725     3.7304     3.3578
     5.3019     1.7179     4.3968     2.6789

END DATA.

GRAPH/SCATTERPLOT = grppref WITH YdiffHAT.
GRAPH/SCATTERPLOT = grppref WITH int_GHAT.
GRAPH/SCATTERPLOT = grppref WITH int_IHAT.
```

Code for plotting. You'll get three plots each with the moderator on the *X* axis and a different outcome on the *Y* axis.

1) Predicted Differences between *Y*'s
2) Predicted *Y* from first condition
3) Predicted *Y* from second condition

Writing up a Moderation Analysis

Tips:

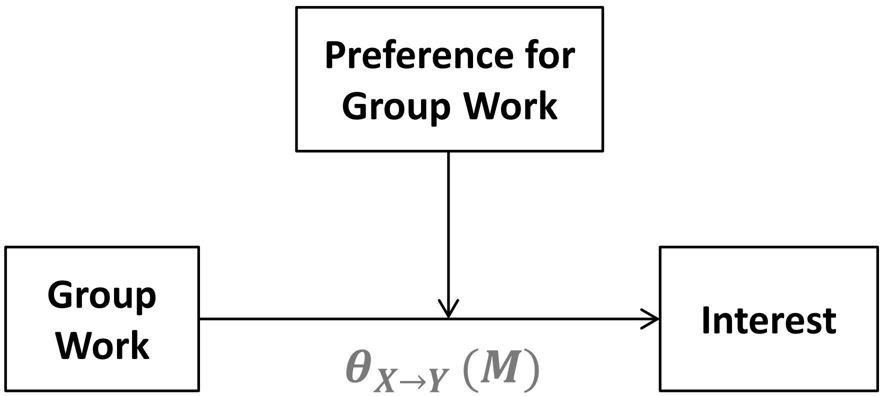
- Interpret the sign and the magnitude of the interaction coefficient with respect to *X*'s effect on *Y* (or *M*'s effect on *Y*; or both).
- Provide probing results with interpretations
- Read the write ups of other's moderation analyses
- Provide a graphical representation of the effect of interest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

Does the effect of group work on interest in a computer science class depend on preference for group work?

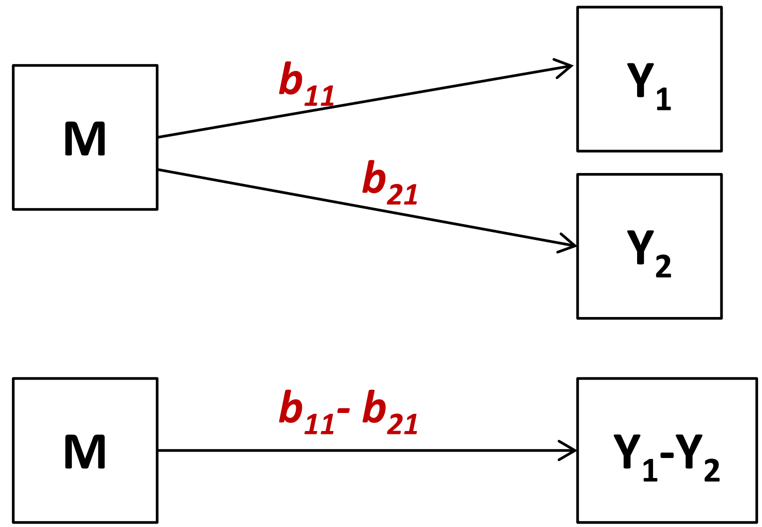
Overall, the impact of including group work in a computer science class on interest in the class depends on an individual's general preference for group work (b_1 = .49, *p* = .001). As preference for group work increases relative interest in the class with group work compared to the class with individual work increases as well. (i.e. the group work class is more preferred as general preference for group work increases). Indeed we found that those who were relatively low in preference for group work preferred the individual work class over the class with group work ($\theta_{X \rightarrow Y}(M$ =2.59) = -.97, *p* = .002). Whereas, those who were relatively moderate in preference for group work did not show a strong preference for one class over another, though they marginally preferred the class with group work ($\theta_{X \rightarrow Y}(M$=3.97) = .37, *p* = .08). Finally, those who showed a strong general preference for group work, unsurprisingly preferred the class with group work over the class with individual work ($\theta_{X \rightarrow Y}(M$=5.30) = 1.72, *p* < .001). The Johnson-Neyman procedure those whose preference for group work was less than 3.07 preferred the individual work class, and those who's preference for group work was greater than 3.99 preferred the group work class. Preference for group work was positively related to interest in the class with group work (*b* = .49, *p* = .001), and negatively related to interest in the class with individual work (*b* = -0.50, *p* = .001).

Visualizations

I recommend trying a number of different types of visualizations to decide what works best for your case.



Conceptual



Statistical

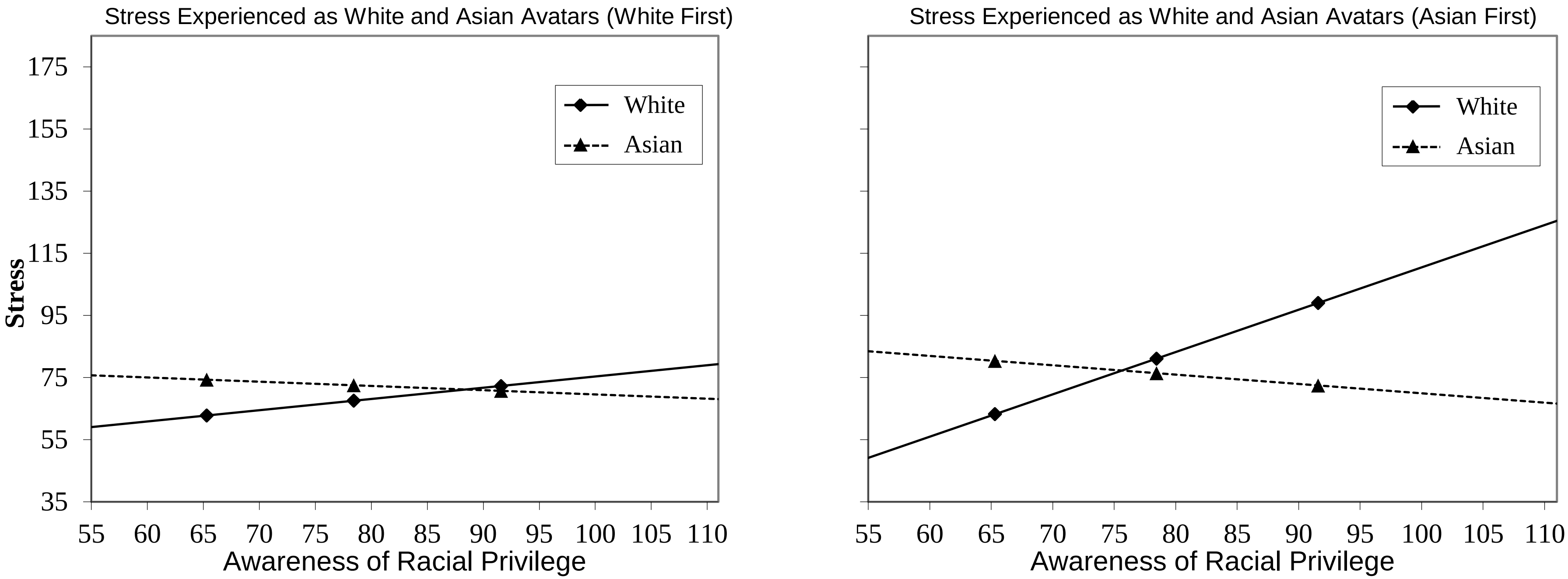
Tips:

- Try the different scales of the *Y* axis (difference vs. raw Y score with two lines for each condition)
- I do not like bar graphs with the effect of the moderator in each condition
- Provide path estimates on statistical diagram or in a table.

Visualizations: A Case Study

Tawa, J., & **Montoya, A. K.** (Under Review) White students' physiological stress while operating non-White avatars and the moderating role of awareness of racial privilege.

White participants operated avatars of three difference races (White, Black, and Asian) and wrote heart monitors to measure their stress while operating each avatar. We found that individual's awareness of racial privilege moderated the effect of avatar race on stress, and that this effect depended on the order of operating the avatars.



Visualizations: A Case Study

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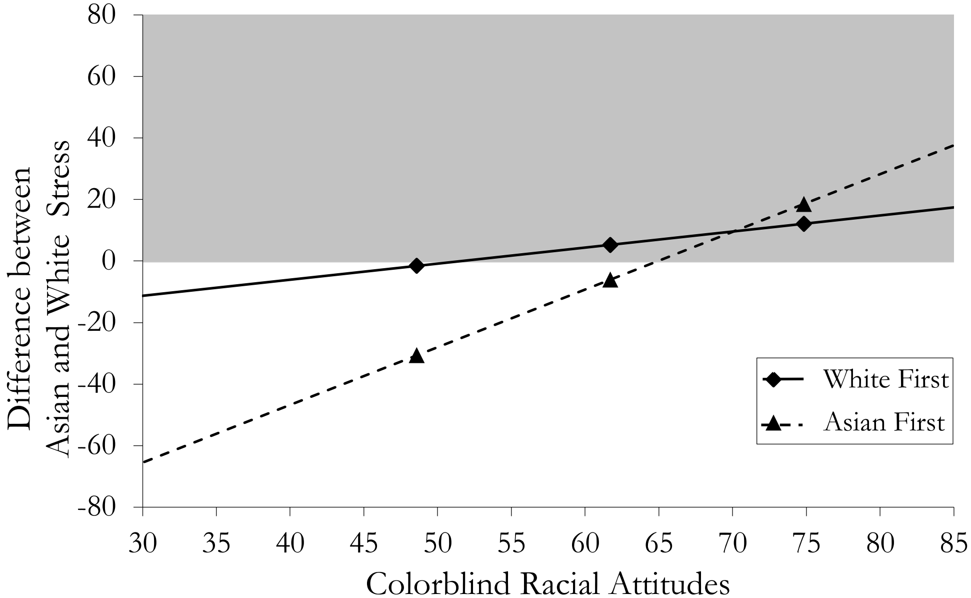
Figure 3. Predicted difference in Stress (Asian Stress – White Stress), split by order.



Note. Scores above zero on the Y-axis represent greater predicted stress while piloting the Asian avatar than while piloting the White avatar. Points marked by shapes indicate predicted stress differences at the mean plus/minus one standard deviation on CBA.

Common Questions

- Can this method be used for more than two conditions?

  YES! The same method for coming up with contrasts in Judd, Kenny, and McClelland (2001) describe a system for setting up contrasts among conditions can be used for moderation.

  I recommend reading Hayes & Montoya (*in press*) on moderation analysis with a multicategorical IV if you want to try this out. I am happy to give instructions on how to get MEMORE to doing this.

  ALTERNATIVES: Some of the other repeated-measures mediation options are more appropriate if you have more than two conditions (especially longitudinal), so take a look at those when thinking about these options.

- Can I use multiple moderators?

  YES! MEMORE models 2 and 3 accept up to 5 moderators. (See Documentation for instructions).

- How do I control for covariates?

  All of MEMORE's mediation analyses are within-person models, so you do not need to control for any between subjects variables such as age, gender, big-5. But you can include them as additional moderators (likely using model 2).

Multiple Moderator Models

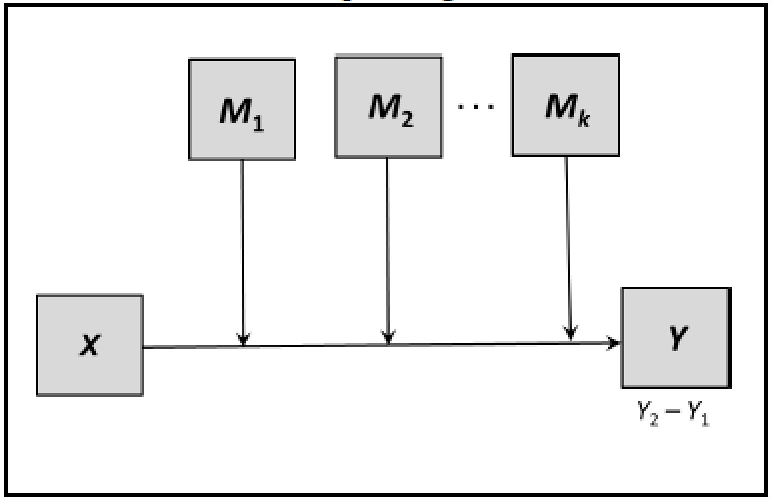
Model 2 vs. Model 3

When you have multiple moderators you are interested, consider whether you think those moderators will themselves interact or not.

If you believe the moderators will interact **with each other** → Model 3
If you believe the moderators will **only interact with condition** → Model 2

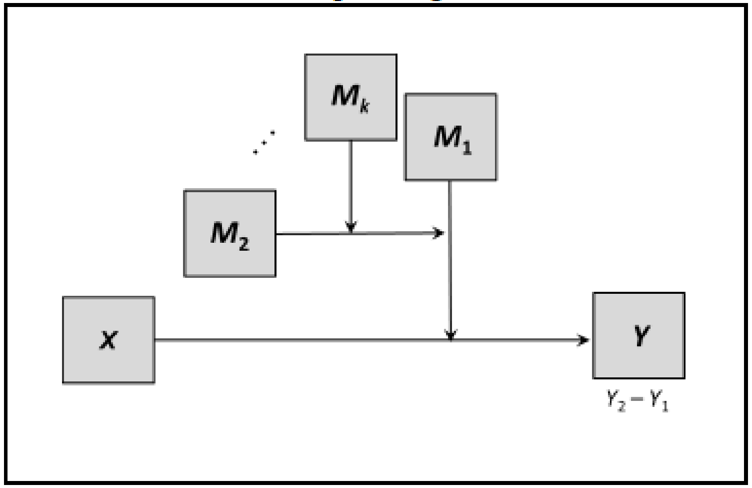
Model Templates for MEMORE V2.Beta
©2017 Amanda K. Montoya

Model 2 Additive Moderation
Conceptual Diagram



Model Templates for MEMORE V2.Beta
©2017 Amanda K. Montoya

Model 3 Multiplicative Moderation
Conceptual Diagram



Multiple Moderator Models

```
MEMORE m = grppref order/y = int_G int_I /model = 2.
```

```
Model:
  2

Variables:
Y =   int_G    int_I
M1 =  grppref
M2 =  Order

Computed Variables:
Ydiff =         int_G     -       int_I

Sample Size:
  51

**************************************************************************************
Outcome: Ydiff =  int_G     -       int_I

Model Summary
         R       R-sq        MSE          F        df1        df2          p
      .7113      .5059     2.0502    24.5734     2.0000    48.0000      .0000

Model
              coeff         SE          t          p       LLCI       ULCI
constant    -4.8074      .8394    -5.7269      .0000    -6.4952    -3.1196
grppref       .9562      .1505     6.3542      .0000      .6536     1.2588
Order         .9071      .4055     2.2372      .0300      .0918     1.7223

Degrees of freedom for all regression coefficient estimates:
  48
```

Think of it like 3 two-way interactions:

Condition x Group Preference

Condition x Order

Order x Group Preference

Multiple Moderator Models

```
MEMORE m = grppref order/y = int_G int_I /model = 3.
```

```
Model:
  3

Variables:
Y =   int_G    int_I
M1 =  grppref
M2 =  Order

Computed Variables:
Ydiff =          int_G     -       int_I
Int1  =          grppref   x       Order

Sample Size:
  51

*************************************************************************************
Outcome: Ydiff =  int_G     -       int_I

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .7125      .5077     2.0862    16.1569     3.0000    47.0000      .0000

Model
              coeff         SE          t          p       LLCI       ULCI
constant    -5.5239     1.9247    -2.8700      .0061    -9.3960    -1.6518
grppref      1.1401      .4690     2.4312      .0189      .1967     2.0836
Order        1.4057     1.2704     1.1065      .2742    -1.1501     3.9615
Int1         -.1263      .3048     -.4145      .6804     -.7395      .4868

Degrees of freedom for all regression coefficient estimates:
  47
```

Think of it like three-way interaction, and three two-way interactions:

Condition x Group Preference

Condition x Order

Group Preference x Order

Condition x Group Preference x Order

Resources

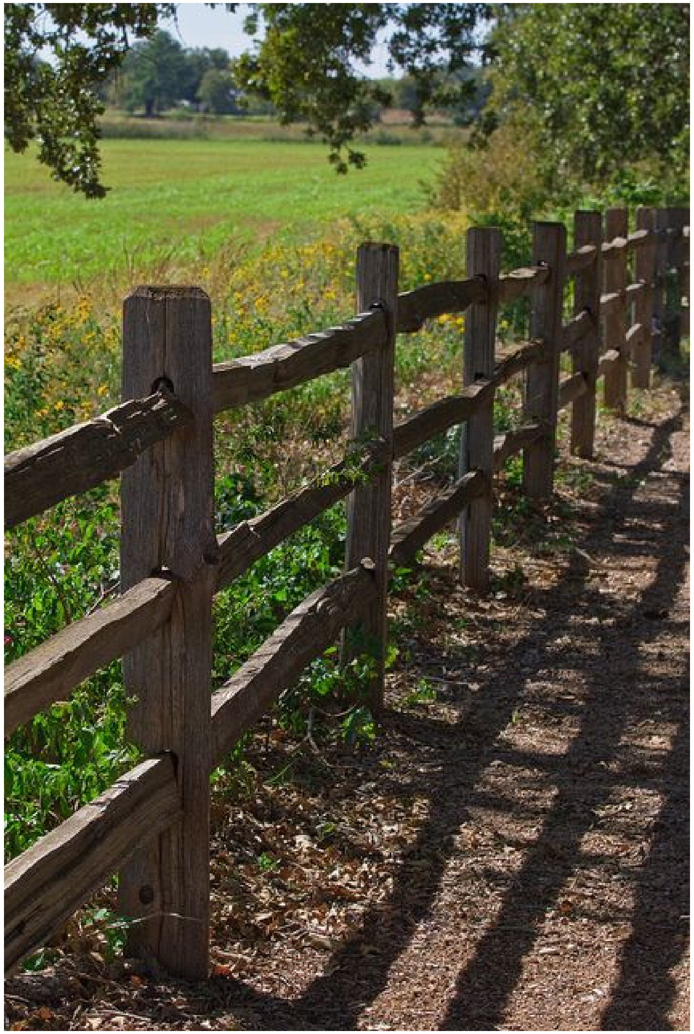
I am available for questions now and forever via email at montoya.29@osu.edu

Things to look forward to:

Hayes, A. F., Montoya, A. K., Preacher, K. J., & Page-Gould, E. (under contract). *Statistical mediation analysis: Within-participant designs*. New York: The Guilford Press.

MEMORE can be downloaded from akmontoya.com

Slides available at github.com/akmontoya/EHEMarch2017



Thank you!

The Mechanisms and Contingencies (MAC) Lab

The Ohio State University

Thank you, Dr. Hayes for his guidance on this project! Thanks to the Mechanisms and Contingencies Lab for your support, and to the National Science Foundation Graduate Research Fellowship, the Counsel of Graduate Students, and The Ohio State University Distinguished Dean's University Fellowship for supporting my research. And thanks to all of you for attending!