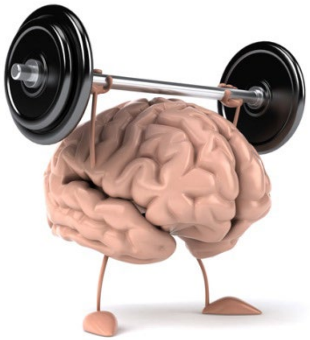
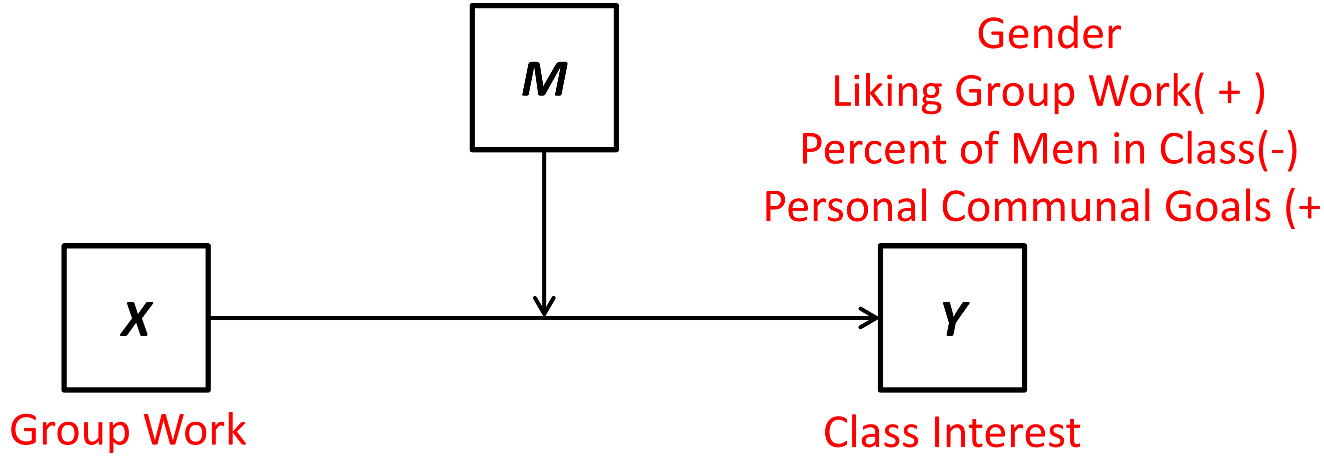


# Moderation




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.

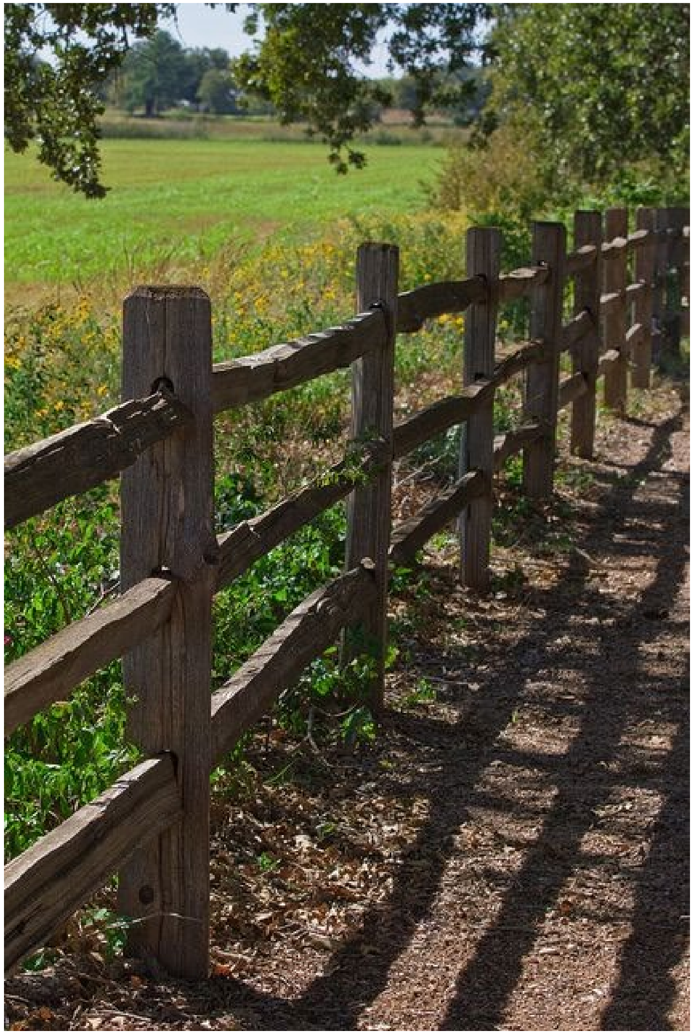
*X* and *M* are frequently described as “interacting” in their prediction of *Y*.

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

A quick example: Name some possible moderators!

# Moderation

- Between-Subject Moderation
- Two-Condition Within Subjects Moderation
  - Judd Kenny and McClelland (2001, 1996)
  - Interpretations
  - Probing
  - MEMORE
  - Reporting (Writing and Figures)
  - Common Questions
  - Multiple Moderator Models



# Moderation in Between-Subject Designs

Moderation analysis is **very common** with between-subject designs.

We focus on regression based moderation analysis, but it can also be examined using ANOVA (and these methods are largely equivalent)

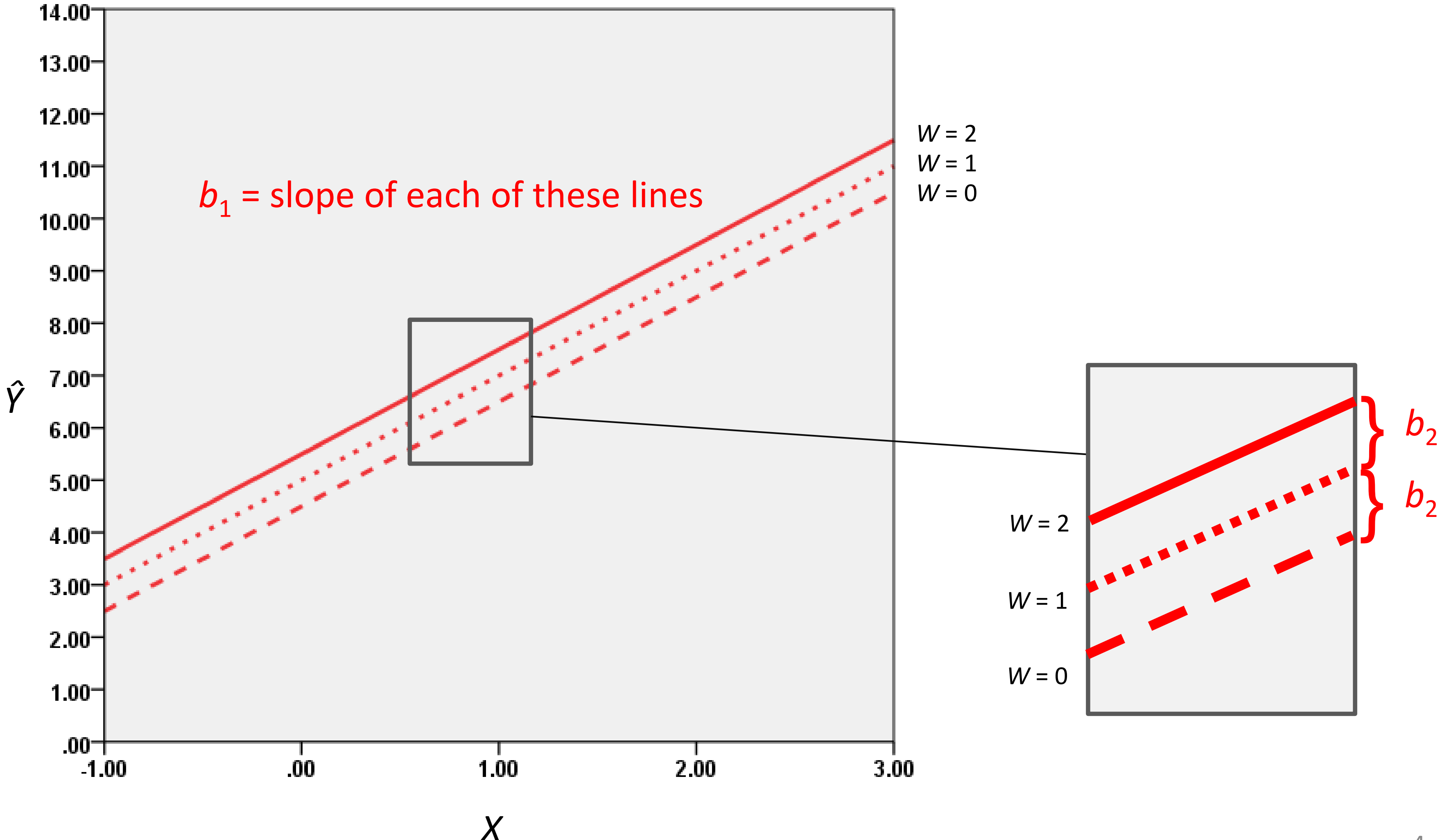
*X*: observed or assigned once per subject

*W*: observed or assigned once per subject

*Y*: observed once per subject

# Partial regression coefficients as *unconditional* effects

$$\hat{Y}_i = 4.50 + 2.00X_i + 0.50W_i$$



# Releasing this constraint

Suppose we let *X*'s effect be a function of *W*, *f*(*W*), as in

$$\widehat{Y}_i = b_0 + f(W_i)X_i + b_2W_i$$

For instance, let *f*(*W*) be a linear function of *W*, $b_1 + b_3W$. Thus,

$$\widehat{Y}_i = b_0 + (b_1 + b_3W_i)X_i + b_2W_i$$

This can be rewritten in an equivalent form as

$$\widehat{Y}_i = b_0 + b_1X_i + b_2W_i + b_3X_iW_i$$

This model, the "simple moderation model," allows *X*'s effect on *Y* to depend linearly on *W*. Other forms of moderation are possible, but this form is the one most frequently estimated.

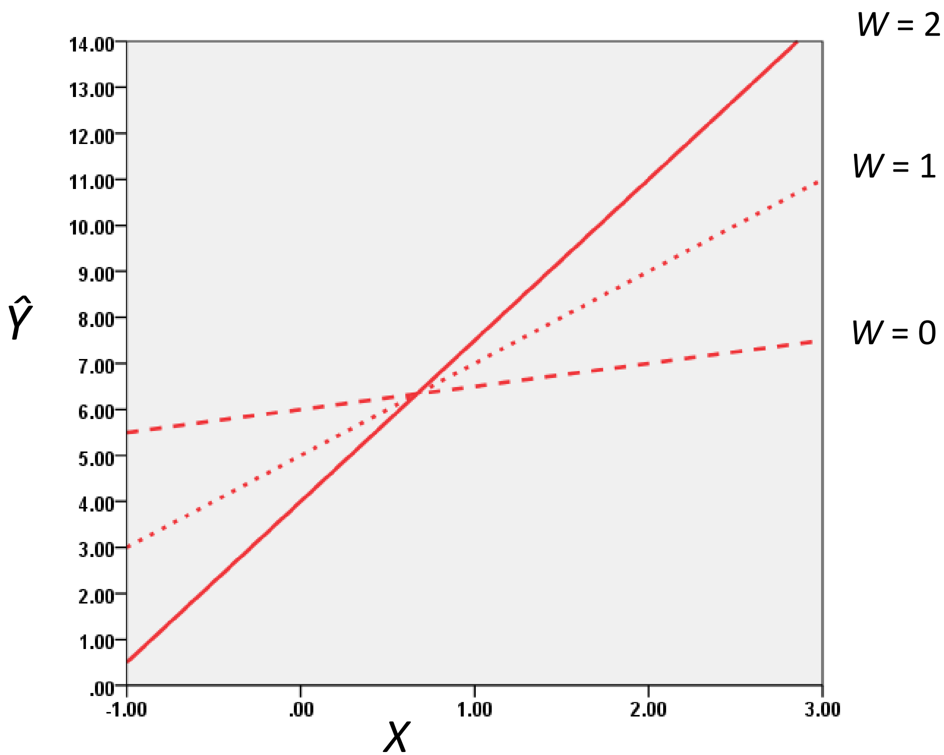
# $X$'s effect on $Y$ as a function of $W$

$b_0$ = 6.00
$b_1$ = 0.50
$b_2$ = -1.00
$b_3$ = 1.50

$$\hat{Y}_i = 6.00 + 0.50X_i - 1.00W_i + 1.50X_iW_i$$

| $X$ | $W$ | $\hat{Y}$ |
|---|---|---|
| -1 | 0 | 5.50 |
| -1 | 1 | 3.00 |
| -1 | 2 | 0.50 |
| 0 | 0 | 6.00 |
| 0 | 1 | 5.00 |
| 0 | 2 | 4.00 |
| 1 | 0 | 6.50 |
| 1 | 1 | 7.00 |
| 1 | 2 | 7.50 |
| 2 | 0 | 7.00 |
| 2 | 1 | 9.00 |
| 2 | 2 | 11.00 |

Observe that the amount by which two cases that differ by one unit on $X$ are estimated to differ on $Y$ **depends on** $W$.

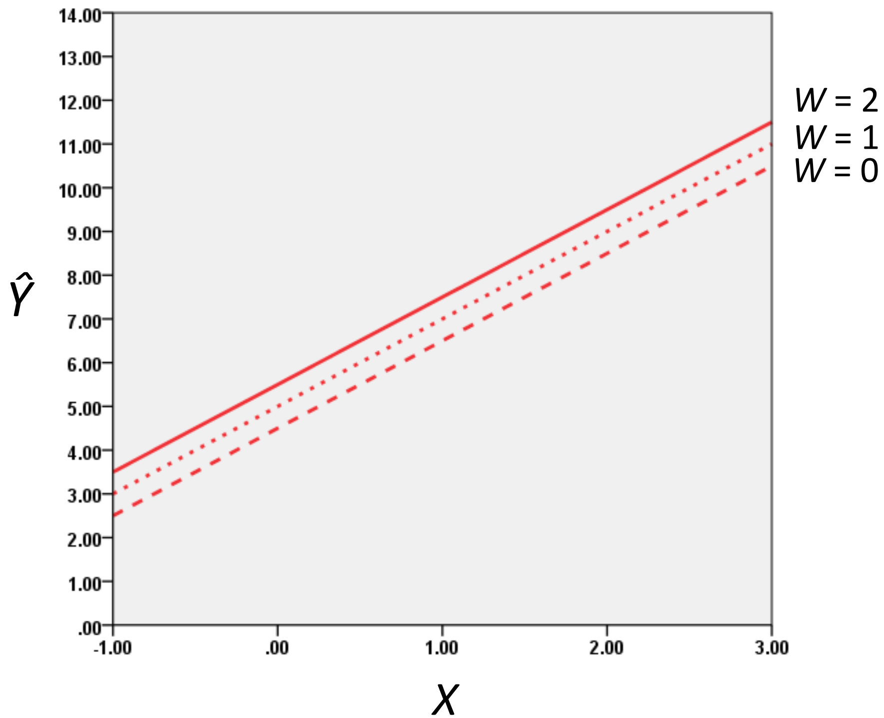


# Differences in interpretation

| | $\hat{Y}_i = b_0 + b_1X_i + b_2W_i$ | $\hat{Y}_i = b_0 + b_1X_i + b_2W_i + b_3X_iW_i$ |
|---|---|---|
| $b_0$ | The estimated value of *Y* when *X* and *W* = 0. | The estimated value of *Y* when *X* and *W* = 0. |
| $b_1$ | The effect of *X* on *Y* holding *W* constant. This is a *partial* effect. | The effect of *X* on *Y* when *W* = 0. This is a *conditional* effect. It is Not a "main effect" or "average effect" of *X*. |
| $b_2$ | The effect of *W* on *Y* holding *X* constant. This is a *partial* effect. | The effect of *W* on *Y* when *X* = 0. This is a *conditional* effect. It is not a "main effect" or "average effect" of *W*. |
| $b_3$ | | How much the effect of *X* on *Y* changes as *W* changes by 1 unit. |

# Importance of $b_3$

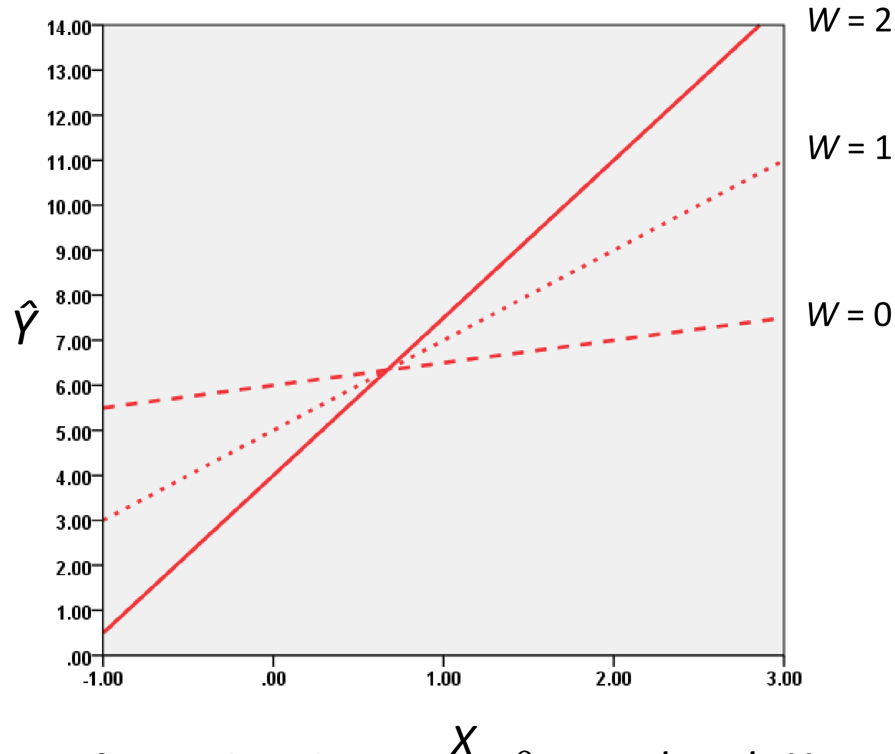
$$\widehat{Y}_i = 4.50 + 2.00X_i + 0.50W_i + 0X_iW_i$$




$\theta_{X\rightarrow Y} = b_1 + b_3W$
$= 2.00 + 0W$

$\theta_{W\rightarrow Y} = b_2 + b_3X$
$= 0.50 + 0X$

$$\widehat{Y}_i = 6.00 + 0.50X_i - 1.00W_i + 1.50X_iW_i$$




$\theta_{X\rightarrow Y} = b_1 + b_3W$
$= 0.50 + 1.50W$

$\theta_{W\rightarrow Y} = b_2 + b_3X$
$= -1.00 + 1.50X$

When $b_3 = 0$, a one unit change in $X$ has the same effect on $Y$ regardless of $W$, and a one unit change in $W$ has the same effect on $Y$ regardless of $X$. When $b_3 \neq 0$, the effect of a change in $X$ on $Y$ depends on $W$, and the effect of a change in $W$ on $Y$ depends on $X$. So we test a moderation hypothesis by testing whether $b_3$ is different from zero.

# Probing an Interaction

The coefficient for the product term carries information about how changes in one variable are related to changes in the effect of the other. A picture helps to understand how the focal variable's effect changes as a function of the moderator variable.

It is typically desirable to conduct statistical tests of the focal predictor variable's effect at values of the moderator. This allows you to make more definitive claims about where the focal predictor variables effect is zero versus where it is not.

## "Pick-a-Point" Approach

Select values of the moderator and estimate the conditional effect of the focal predictor at those values of the moderator, along with a hypothesis test or confidence interval.

## Johnson-Neyman Technique

Derive mathematically where on the moderator variable continuum the focal variable's effect transitions between statistically significant and nonsignificant.

# Pick-a-point approach

$$\widehat{Y}_i = b_0 + b_1 X_i + b_2 W_i + b_3 X_i W_i$$

Select a value of the moderator (*W*) at which you'd like to have an estimate of $\theta_{X \rightarrow Y}$, the focal predictor variable's (*X*) effect. 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, where $df_{\text{residual}}$ is the residual degrees of freedom from the regression model.

We already know that $\theta_{X \rightarrow Y} = b_1 + b_3 W$

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

$$s_{\theta_{X \rightarrow Y}} = \sqrt{s_{b_1}^2 + 2W s_{b_1 b_3} + W^2 s_{b_3}^2}$$

Squared standard error of $b_1$

Covariance of $b_1$ and $b_3$

Squared standard error of $b_3$

You could do this by hand, and instructions are available in various books on regression analysis (e.g., Aiken and West, 1991; Cohen et al., 2003). But there is no reason to, and the potential for mistakes is high. It is made easier using "**regression centering**."

# 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 ratio of the conditional effect of the focal predictor at that value or values of *W* is exactly equal to some chosen level of significance $\alpha$**

To do so, we ask what value of $W$ produces a ratio exactly equal to the critical $t$ value ($t_{crit}$) required to reject the null hypothesis that the conditional effect of $X$ is equal to zero?

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

Isolate $W$ and solve the polynomial that results. The quadratic formula finds the solutions:

$$W = \frac{-2(t_{crit}^2 s_{b_1 b_3}^{-} - b_1 b_3) \pm \sqrt{(2t_{crit}^2 s_{b_1 b_3} - 2b_1 b_3)^2 - 4(t_{crit}^2 s_{b_3}^2 - b_3^2)(t_{crit}^2 s_{b_1}^2 - b_1^2)}}{2(t_{crit}^2 s_{b_3}^2 - b_3^2)}$$

# The Johnson-Neyman Technique

**This will produce no values, one value, or two values of *W* that are within the range of the moderator variable data.**

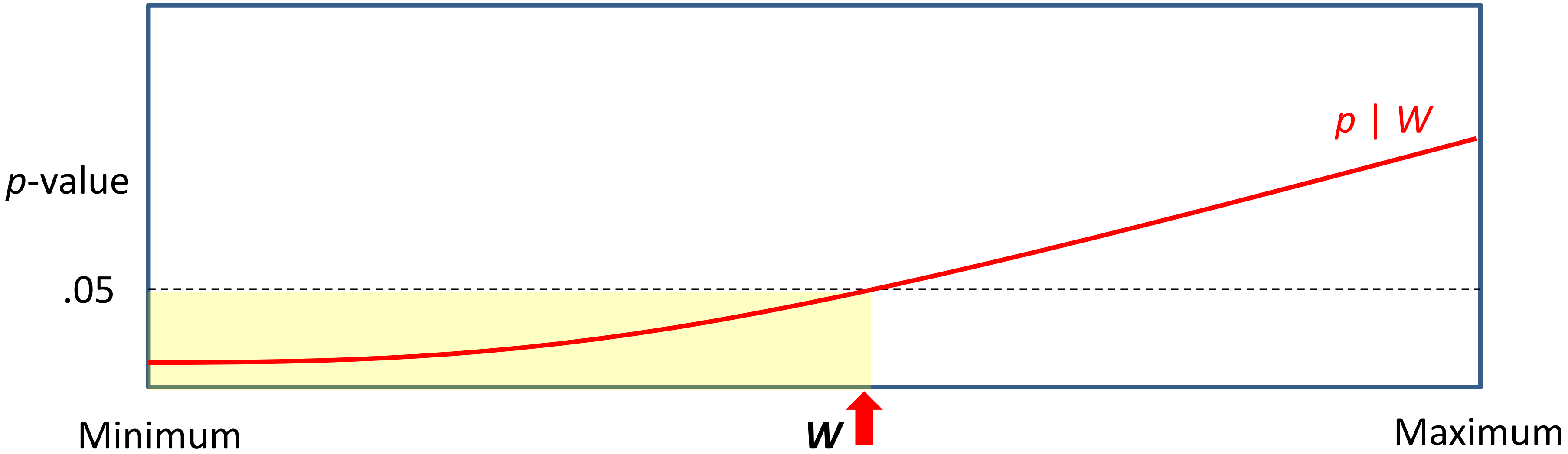
- If one value, this defines a single point of transition between a statistically significant and a statistically nonsignificant conditional effect of the focal predictor, such that $p \leq .05$ for either values of the moderator (1) equal to above *W* or (2) equal to and below *W*.

- If two values, this defines the two points of transition between a statistically significant and a statistically nonsignificant conditional effect of the focal predictor, such that the conditional effect is statistically significant for either (1) values of the moderator between the two values of *W*, or (2) values of the moderator at least as large as the larger *W* and at least as small as the smaller *W*.

- If no values, that means the conditional effect is statistically significant for ALL values of the moderator within the range of the data, or it NEVER is.

We would not attempt to do this by hand

# Examples of One Solution

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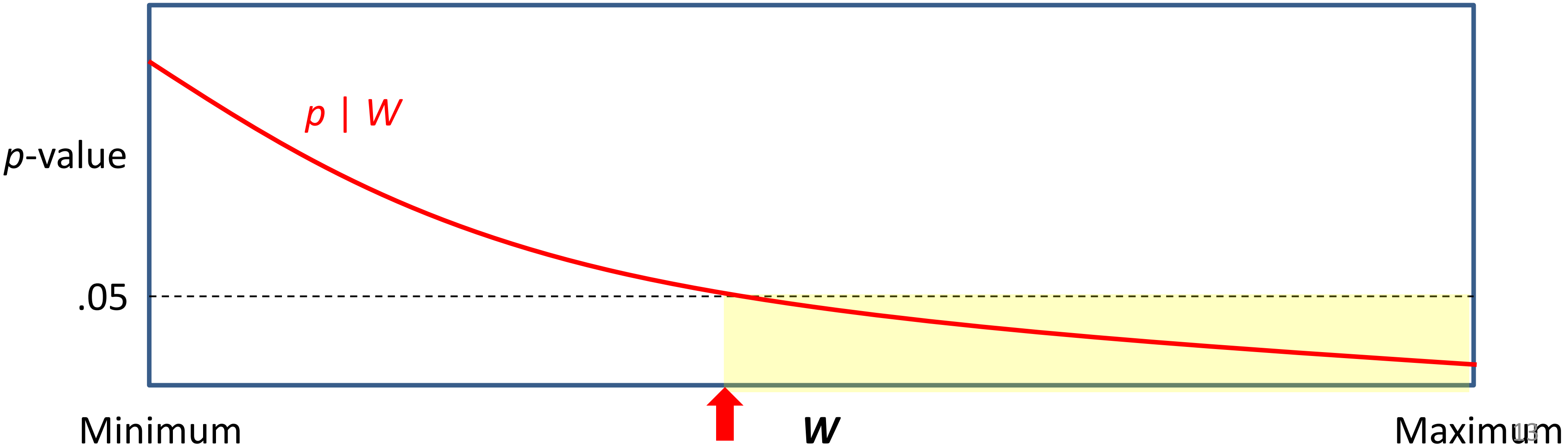
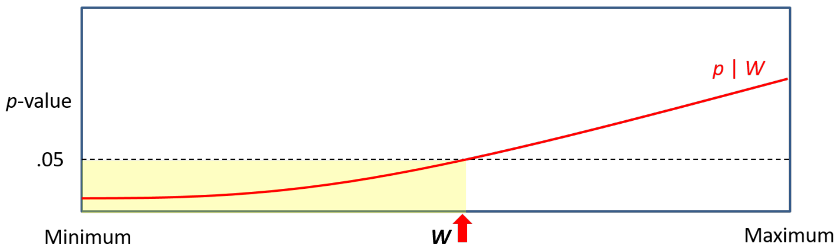
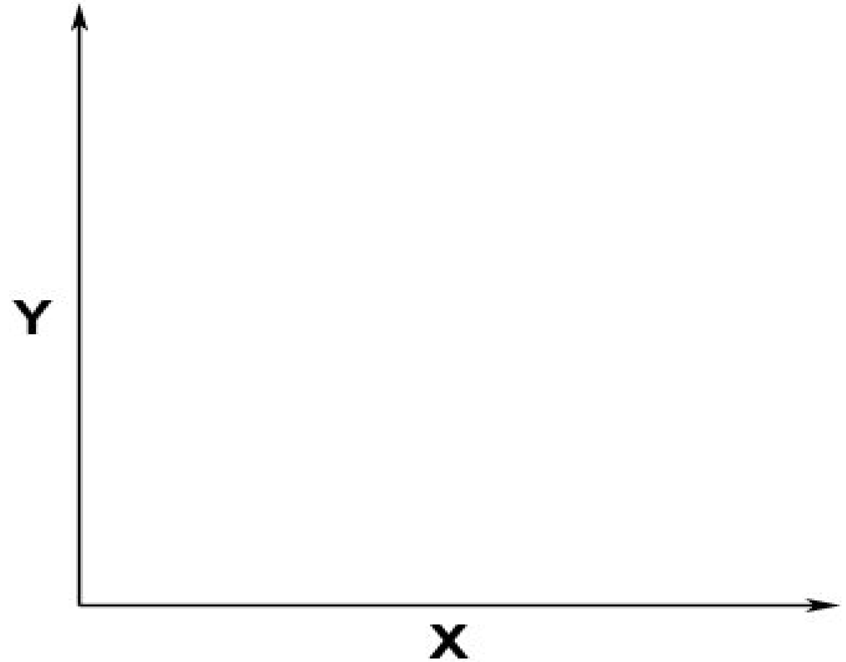
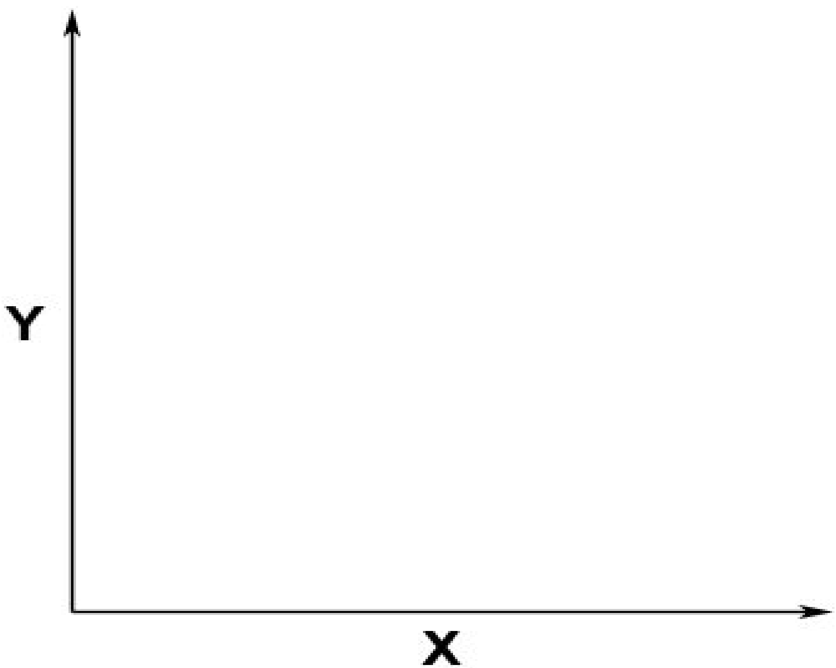
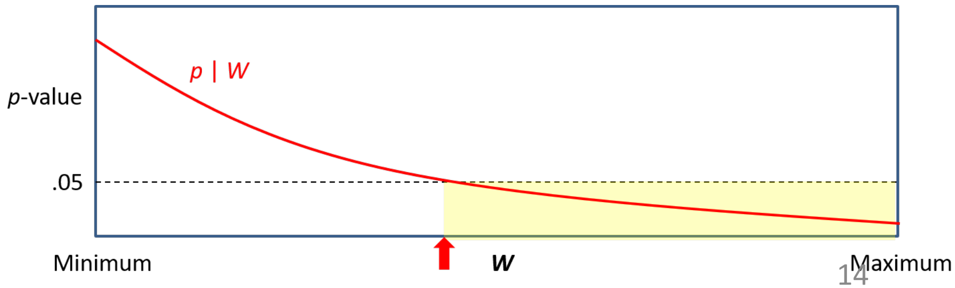


# One Solution: What would the graph look like?

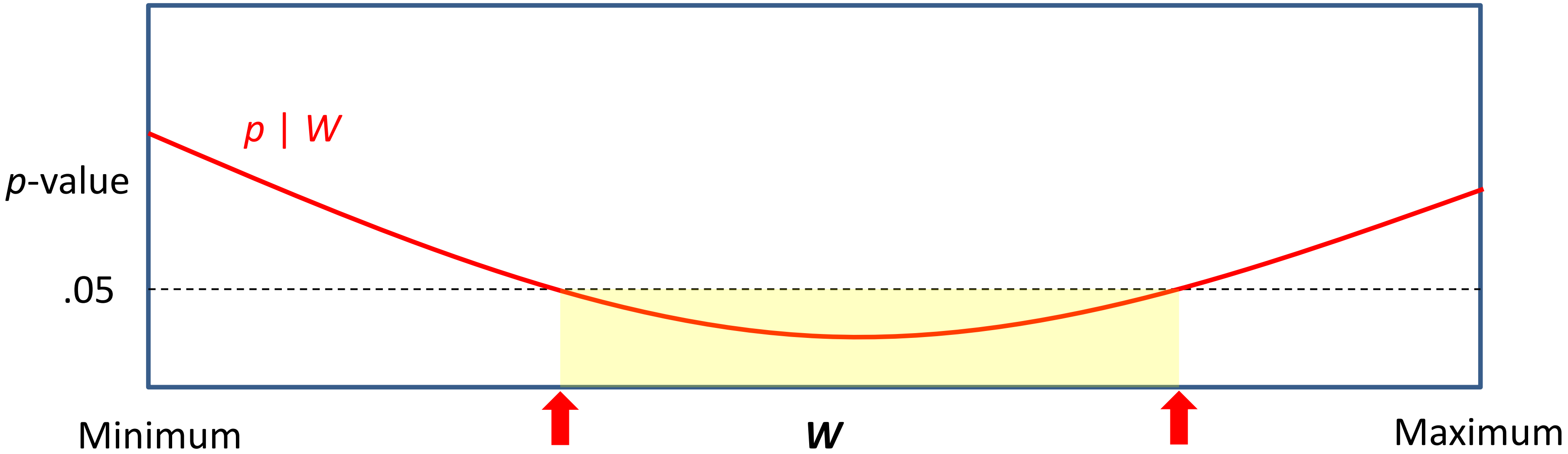


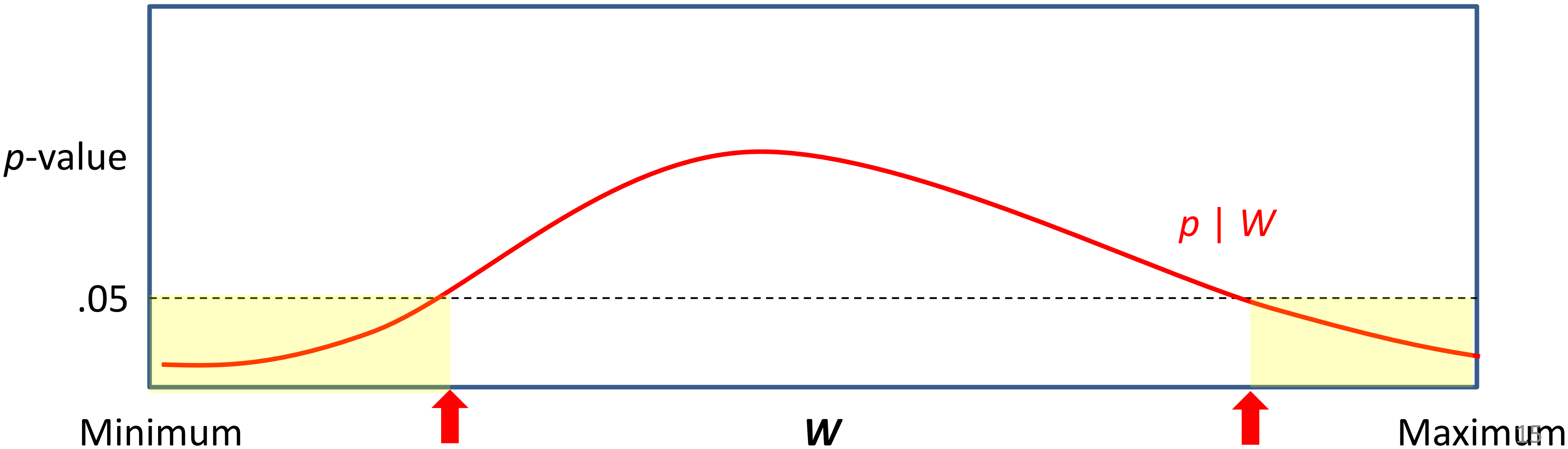



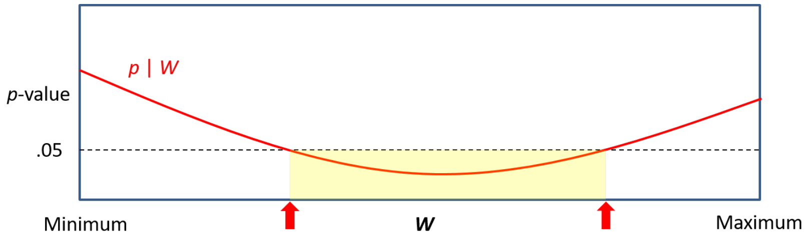
# Examples of two solutions

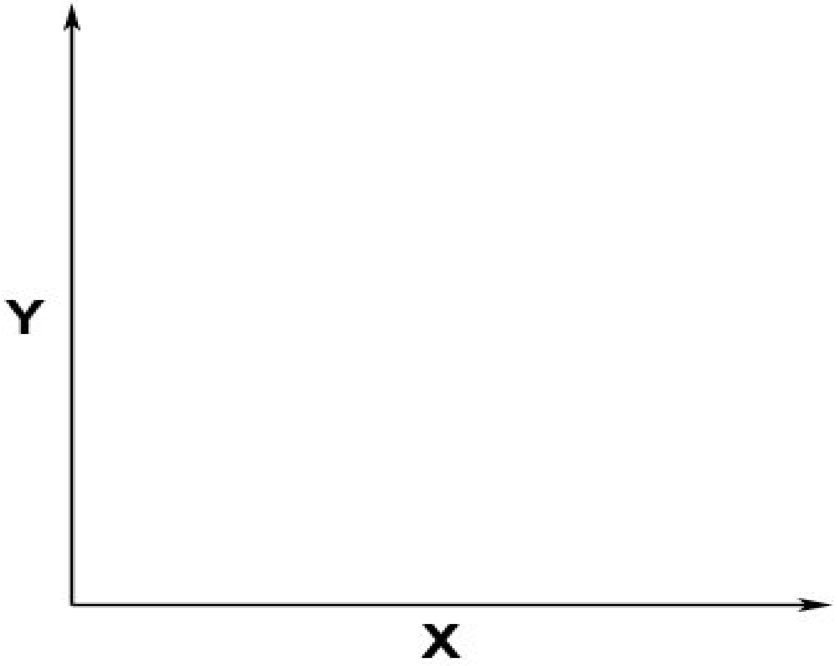


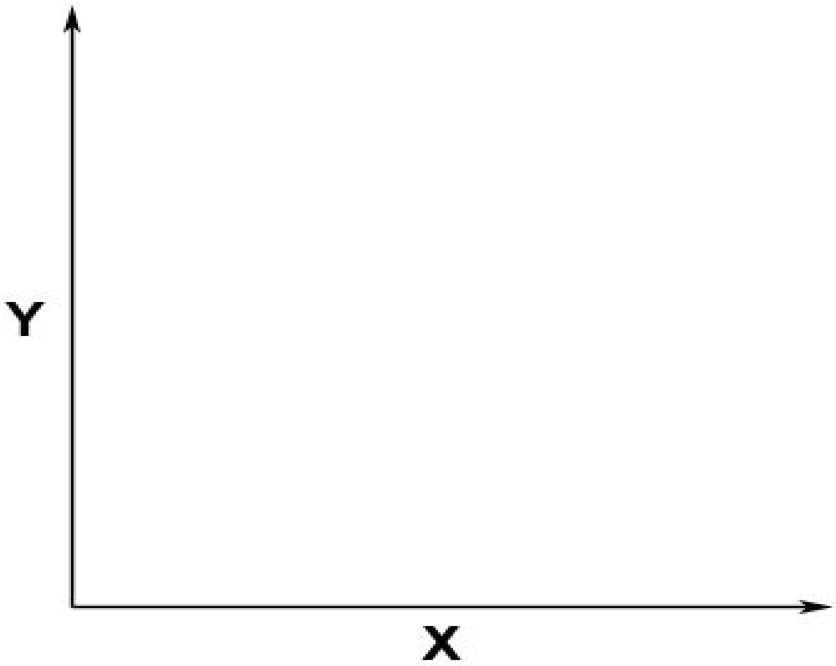

**OR**

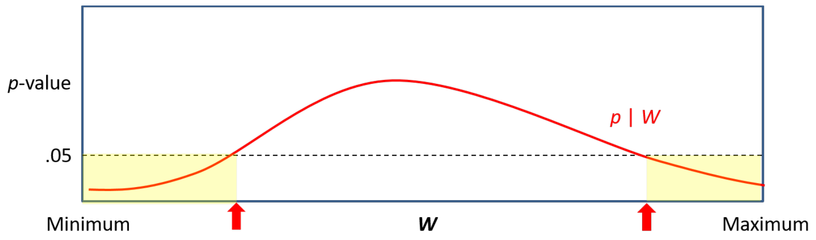


# Two Solutions: What would the graph look like?

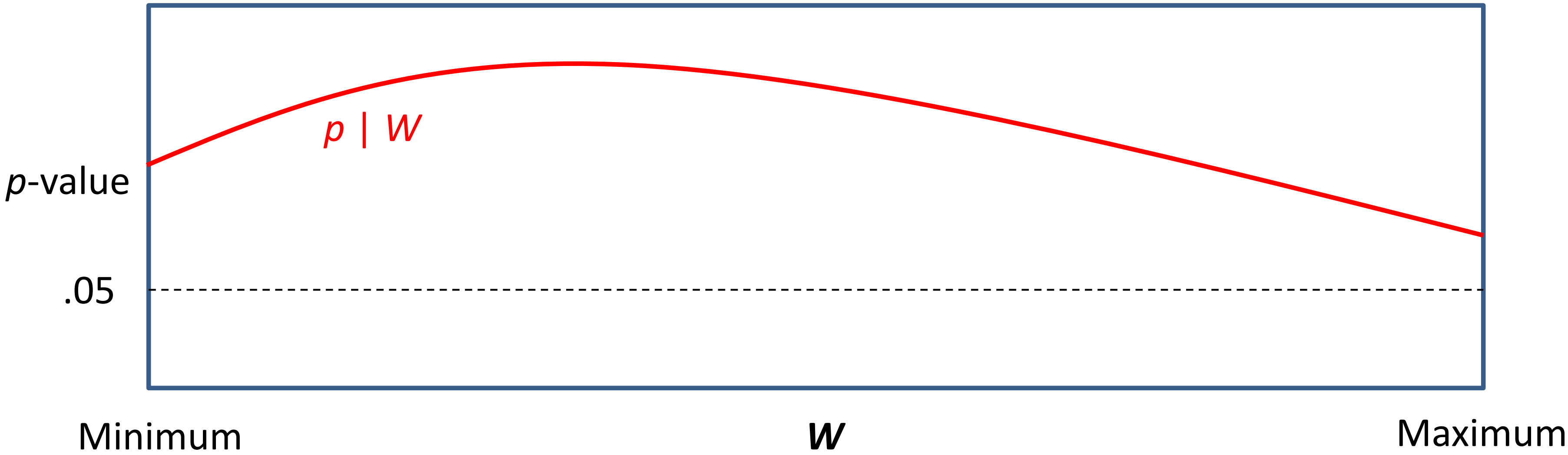


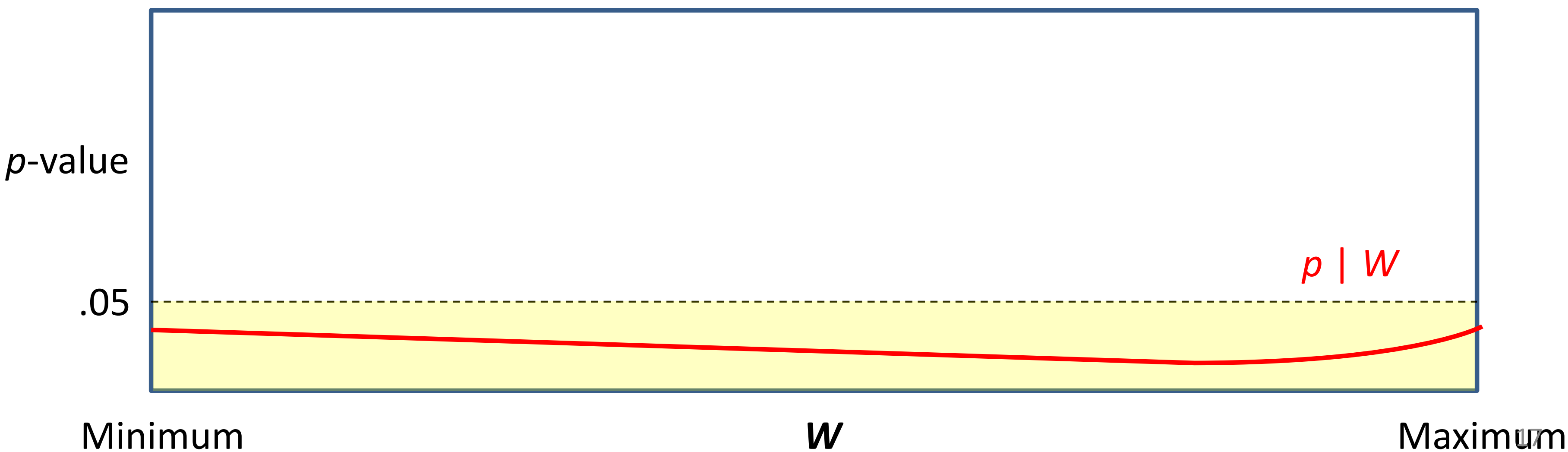



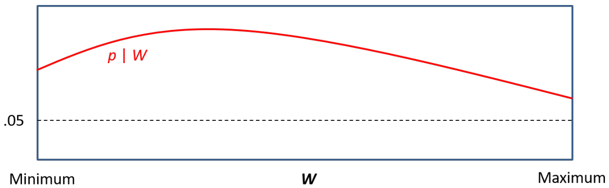
# Examples of No Solutions

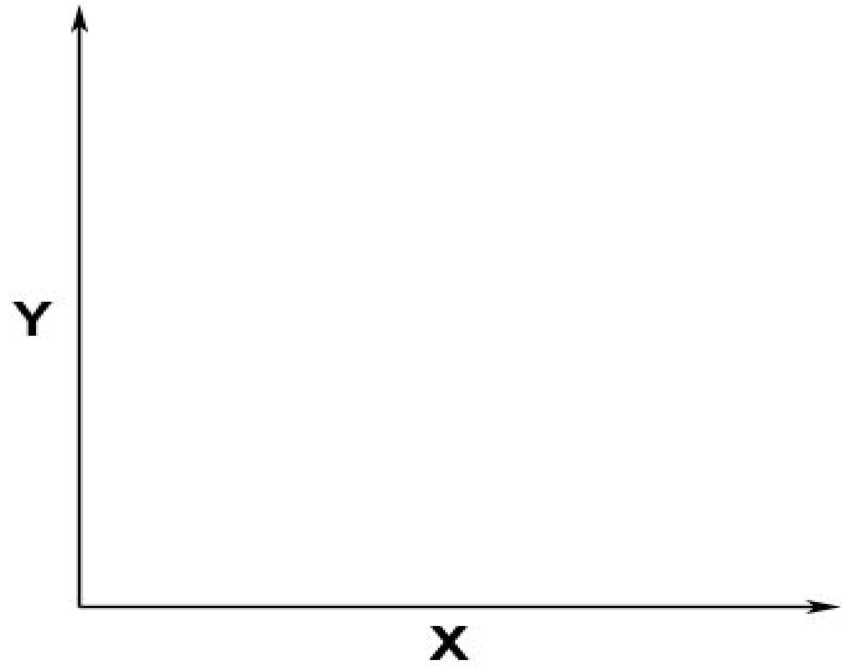



**OR**

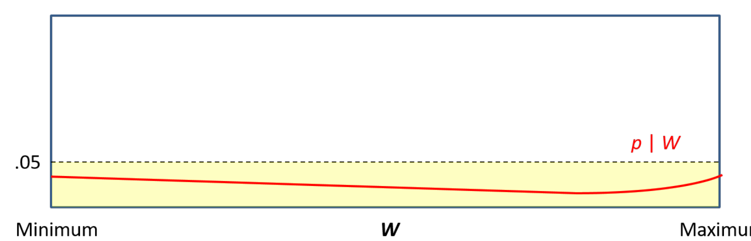


# No Solution: What would the graph look like?







# MODERATION IN WITHIN-SUBJECT DESIGNS

# Running Example: Group Work in Computer Science (WS)

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

**Within-Subjects Version (CompSci_WS.sav, CompSci_WS.sas) :**
Female participants (N = 51) read two syllabi for a different computer science classes. One of the syllabi reported the class would have group projects throughout, and the other syllabi stated that individual project would be scheduled throughout.

- 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`
- `Perscom` Personal Communal Goals ($\alpha = .87$)
- `Order`
  - 1 = Group First; 2 = Individual First

# Modeling Non-Contingent Relationships

When we consider non-contingent relationships in a repeated-measures design, this means the relationship between a variable (*W*) and the outcome (*Y*) is the same across conditions.

$$Y_{1\mathrm{i}} = b_{10} + b_1 W_i + \epsilon_{1i}$$

$$Y_{2\mathrm{i}} = b_{20} + b_1 W_i + \epsilon_{2i}$$

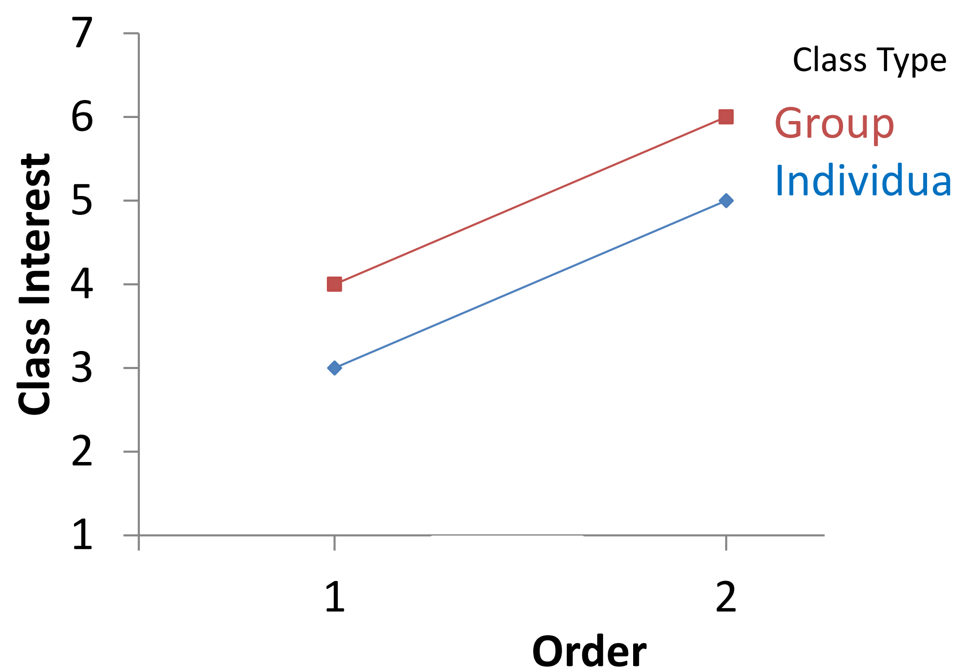
Example:

$Y_1$: Interest in Individual Work Class (1-7)

$Y_2$: Interest in Group Work Class

W: Order (1 = Group First, 2 = Individual First)

| $\hat{Y}_1$ | $\hat{Y}_2$ | W |
|---|---|---|
| 3 | 4 | 1 |
| 5 | 6 | 2 |




A one unit increase in order results in a 2 unit increase in interest, regardless of condition.

# Modeling Contingent Relationships

What if instead we felt that the relationship between Order and Interest depends on condition? Thus the relationship between Order and Interest *differs* across the two conditions

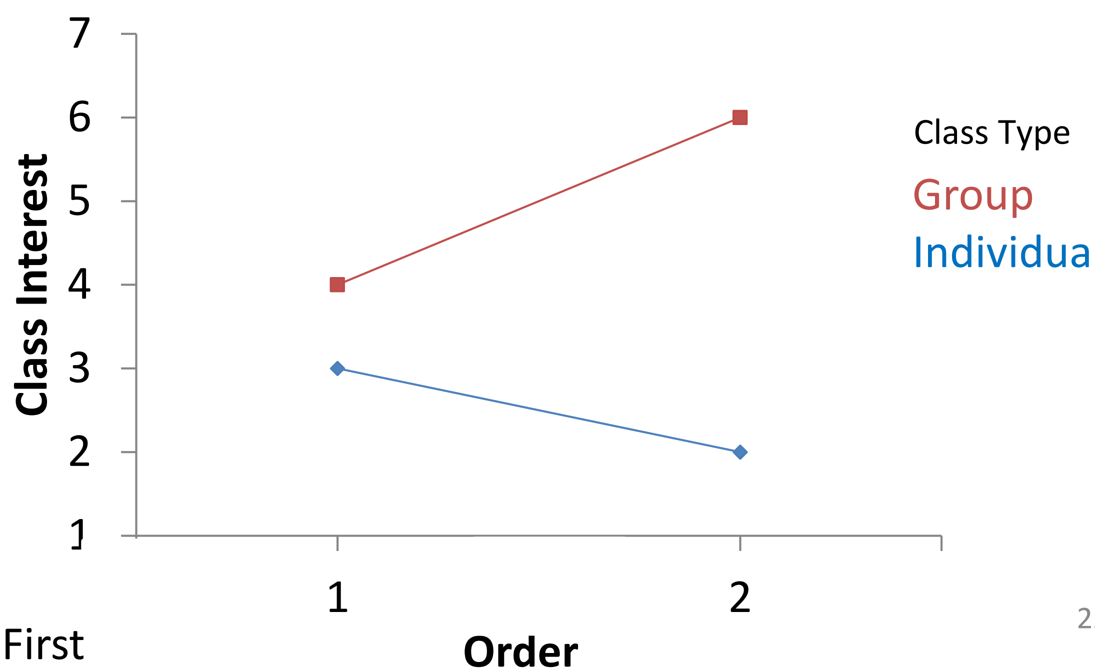
$$Y_{1\mathrm{i}} = b_{10} + b_{11}W_i + e_{1i}$$

$$Y_{2\mathrm{i}} = b_{20} + b_{21}W_i + e_{2i}$$

$$Y_{2i} - Y_{1i} = (b_{10} - b_{20}) + (b_{11} - b_{21})W_i + \ (e_{1i} - e_{2i}) = b_0 + b_1 W_i + e_i$$

The difference between $b_{11}$ and $b_{21}$ tells us how much the relationship between *W* and *Y* differs across conditions. So $b_1$ tells us if there is moderation.

| $\hat{\boldsymbol{Y}}_1$ | $\hat{\boldsymbol{Y}}_2$ | **W** |
|---|---|---|
| 3 | 4 | 1 |
| 2 | 6 | 2 |




1 = Group First, 2 = Individual First

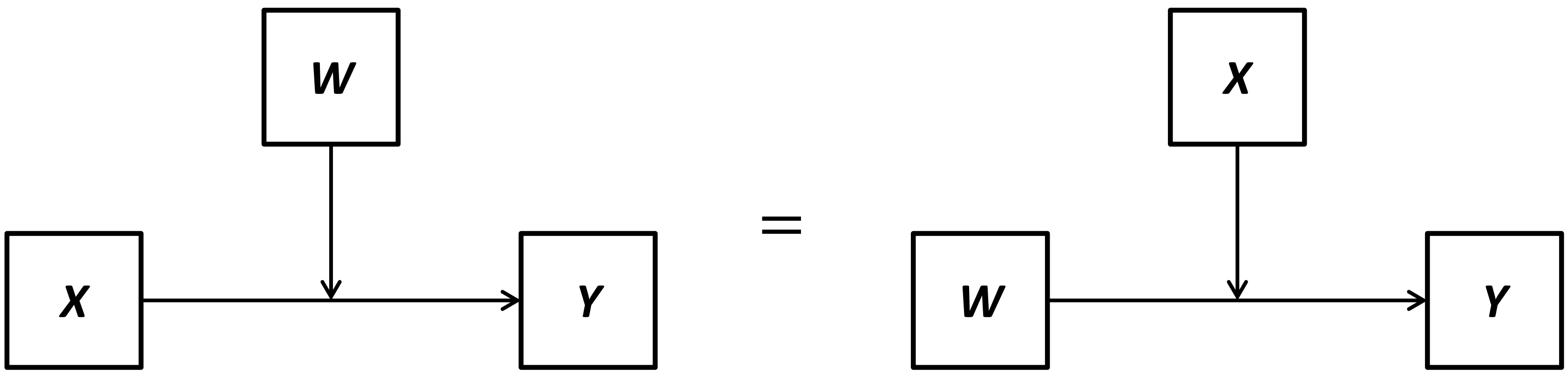
# Symmetry in Within-Subjects Moderation

**Does the effect of condition depend on *W*?**

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

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

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



# 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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## Testing Treatment by Covariate Interactions When Treatment Varies Within Subjects

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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.

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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, $\beta_1$ represents the magnitude of

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

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A regression approach to considering a "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.

# Computer Science Within-Subjects Data Example

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

1. Data should be a two-condition within-subjects design with a person level covariate.

**Research Question: Does the degree to which class order predicts interest in computer science depend on whether the class has group work or not?**

Or

**Does effect of group work on interest in computer science classes depend on an the order they read the syllabi?**

CompSci_WS.sav

| | Subject | int_I | int_G | Order | grppref |
|---|---|---|---|---|---|
| 1 | 300 | 1.50 | 4.00 | 1 | 6.67 |
| 2 | 301 | 2.75 | 3.25 | 1 | 6.33 |
| 3 | 325 | 5.75 | 2.50 | 1 | 2.67 |
| 4 | 342 | 3.50 | 5.75 | 1 | 6.00 |
| 5 | 349 | 2.25 | 2.00 | 1 | 4.00 |
| 6 | 350 | 1.50 | 1.75 | 1 | 3.67 |
| 7 | 305 | 2.50 | 4.25 | 1 | 4.00 |
| 8 | 348 | 6.00 | 1.75 | 1 | 2.33 |
| 9 | 318 | 3.00 | 2.00 | 1 | 4.67 |
| 10 | 320 | 4.00 | 5.25 | 1 | 4.00 |
| 11 | 332 | 5.00 | 5.00 | 1 | 3.67 |
| 12 | 338 | 2.00 | 1.75 | 1 | 3.00 |
| 13 | 310 | 1.00 | 1.75 | 1 | 3.00 |
| 14 | 304 | 1.25 | 4.50 | 2 | 5.67 |
| 15 | 306 | 5.75 | 4.50 | 2 | 4.00 |
| 16 | 308 | 3.25 | 4.75 | 2 | 4.00 |
| 17 | 315 | 2.75 | 2.25 | 2 | 4.33 |
| 18 | 322 | 5.50 | 2.00 | 2 | 2.33 |
| 19 | 343 | 1.75 | 5.25 | 2 | 6.00 |
| 20 | 314 | 4.00 | 5.50 | 2 | 3.00 |
| 21 | 319 | 2.25 | 4.00 | 2 | 5.00 |
| 22 | 330 | 4.00 | 6.50 | 2 | 5.67 |
| 23 | 334 | 5.00 | 4.50 | 2 | 3.33 |
| 24 | 309 | 5.00 | 3.75 | 2 | 1.00 |
| 25 | 329 | 4.75 | 5.25 | 2 | 4.00 |
| 26 | 333 | 1.75 | 5.25 | 2 | 6.33 |
| 27 | 336 | 4.50 | 2.25 | 2 | 3.67 |
| 28 | 341 | 1.00 | 3.75 | 2 | 4.33 |
| 29 | 302 | 1.75 | 1.75 | 2 | 4.00 |

# Analysis using Judd et al. (1996)

2. Setup two regression equations, one for each condition

Setup a model of the outcome in each condition:

$$Y_{1\mathrm{i}} = b_{10} + b_{11}W_i + e_{1i}$$
$$Y_{2\mathrm{i}} = b_{20} + b_{21}W_i + e_{2i}$$

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 $b_{11} - b_{21}$):

$$Y_{2i} - Y_{1i} = (b_{20} - b_{10}) + (b_{21} - b_{11})W_i + (e_{2i} - e_{1i}) = b_0 + b_1 W_i + e_i$$

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

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

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

```
proc reg data=CompSci_WS;model int_diff=order;run;
```

```
summary(lm(int_diff~Order, data = CompSci_WS))
```

What sign do you expect $b_1$ to be? **Remember:** int_diff = int_G – int_i.

# Analysis using Judd et al. (1996)

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

$$Y_{2\mathrm{i}} = b_{20} + b_{21}W_i + e_{2i}$$

$$Y_{1\mathrm{i}} = b_{10} + b_{11}W_i + e_{1i}$$

$$Y_{2i} - Y_{1i} = (b_{20} - b_{10}) + (b_{21} - b_{11})W_i + \ (e_{2i} - e_{1i}) = b_0 + b_1 W_i + e_i$$

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | -1.476 | .880 | | -1.676 | .100 |
| | Order | 1.193 | .541 | .300 | 2.205 | .032 |

a. Dependent Variable: int_diff

What does it mean that $b_1$ is positive?

$$b_1 = b_{21} - b_{11} = 1.193$$

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

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

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

```
proc reg data=CompSci_WS;model int_diff=order;run;
```

```
summary(lm(int_diff~Order, data = CompSci_WS))
```

# Interpreting the Coefficients

$$Y_{2i} - Y_{1i} = (b_{20} - b_{10}) + (b_{21} - b_{11})W_i + (e_{2i} - e_{1i}) = b_0 + b_1 W_i + e_i$$

$b_0$ is the expected difference in *Y* when *W* = 0

We can think of this as the effect of "condition" on *Y* when *W* is zero.

In the Computer Science example, W can only be 1 or 2, so we do not interpret this parameter in this case.

$b_1$ is the degree to which the relationship between *W* and *Y* differs by condition.

Alternatively: the degree to which the effect of condition on *Y* depends on *W. i.e.,* if W increases by one unit the effect of condition on *Y* will increase by $b_1$ units

# Conditional Effects in Within-Subjects Moderation

$$Y_{2i} - Y_{1i} = (b_{20} - b_{10}) + (b_{21} - b_{11})W_i + \ (e_{2i} - e_{1i}) = b_0 + b_1 W_i + e_i$$

**Given a value of *W* 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 $\theta_{X \to Y}(W) = b_0 + b_1 W$

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

$$Y_{1\mathrm{i}} = b_{10} + b_{11} W_i + e_{1i}$$

$$Y_{2\mathrm{i}} = b_{20} + b_{21} W_i + e_{2i}$$

$$\theta_{W \to Y}(X) = b_{x1}$$

Conditional effects will become important when it comes to probing

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

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

Select a value of the moderator (*W*) 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 $\theta_{X\rightarrow Y}(W)$ is

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

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

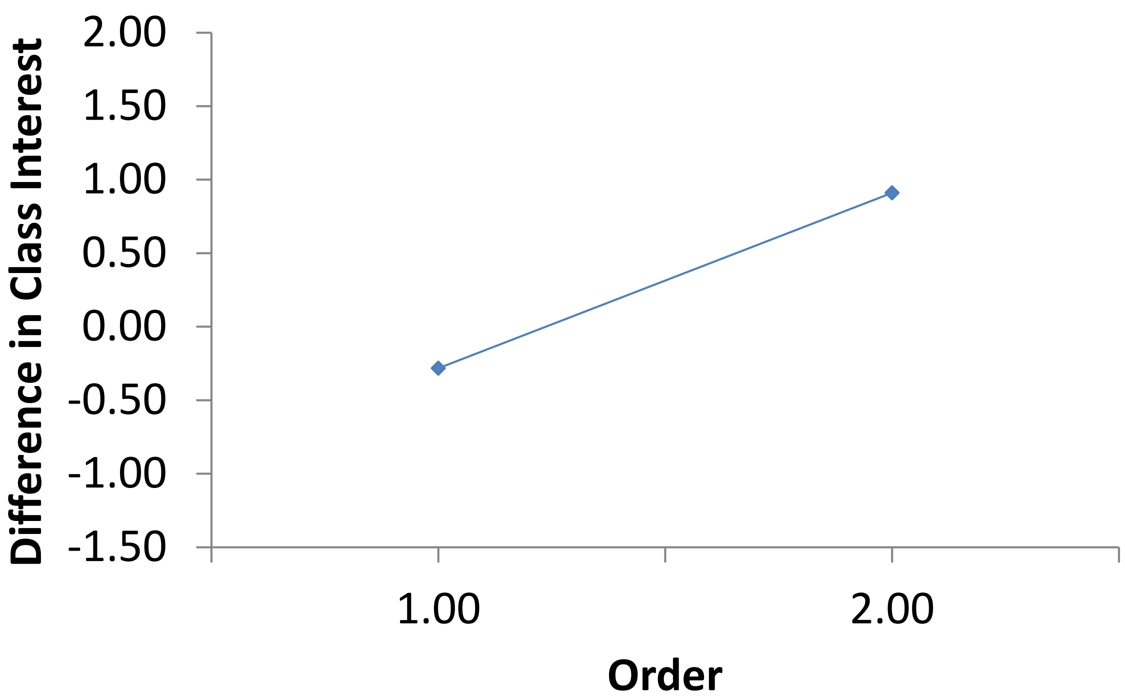
# Probing an Effect of Condition on Outcome: The "Pick-a-Point" Approach

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:

$$Y_{Di} = -1.476 + 1.193W_i$$

| W | $\theta_{X \to Y \mid W}$ | $s_{\theta_{X \to Y \mid W}}$ | *p* |
|---|---|---|---|
| 1 | -.2826 | 0.4010 | .4843 |
| 2 | .9107 | .3634 | .0156 |



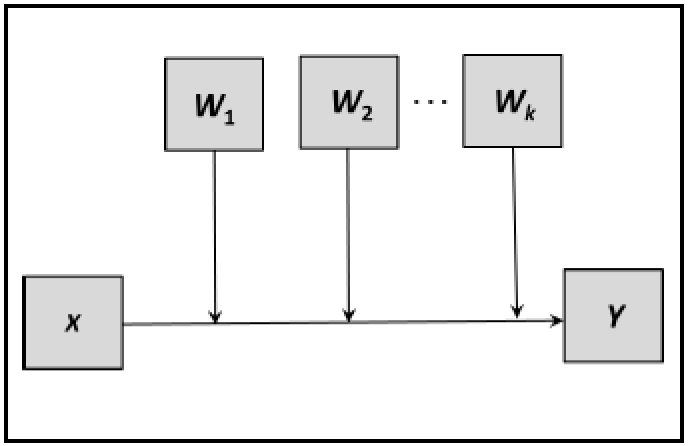

Participants who saw the group work class first did not show a difference in interest between the two classes. However, those who saw the individual work class first showed a larger effect of condition such students were significantly more interested in the group class.

# MEMORE

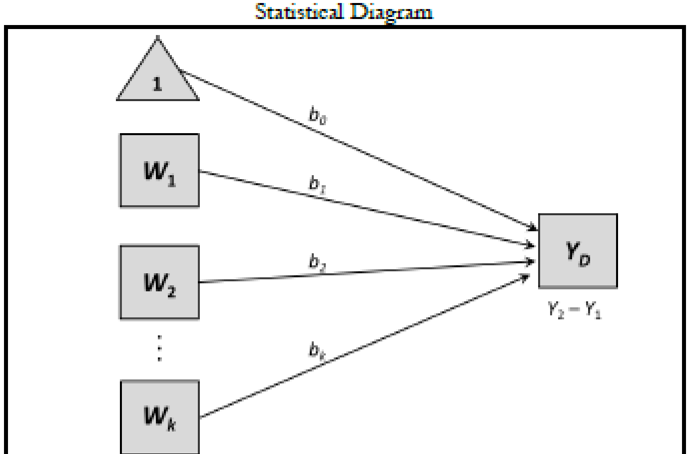
We can use MEMORE to estimate and probe this model.

Model Templates for MEMORE V3.Beta
©2022 Amanda K. Montoya

**Model 2 Additive Moderation**
Conceptual Diagram




Statistical Diagram




Subscript *k* indicates moderators. Model can have up to 5 moderators

```
MEMORE w = order /y = int_G int_I
/model = 2 /plot = 1.
```

```
%memore(w=order,y = int_G int_I,
model = 2, plot = 1, data =
CompSci_WS);
```

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

# Using MEMORE for CASC WS data

```
MEMORE w = order /y = int_G int_I /model = 2 /plot = 1.
```

```
%memore(w=order,y = int_G int_I, model = 2, plot = 1, data =
CompSci_WS);
```

```
********************* MEMORE Procedure for SPSS Version 2.1 ***********************

                    Written by Amanda Montoya

             Documentation available at akmontoya.com

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

Model:
  2

Variables:
Y = int_G    int_I
W = Order

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 w = order /y = int_G int_I /model = 2 /plot = 1.
```

```
%memore(w=order,y = int_G int_I, model = 2, plot = 1, data =
CompSci_WS);
```

```
Outcome: Ydiff =  int_G      -       int_I

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3005      .0903     3.6978     4.8629     1.0000    49.0000      .0322

Model
              coeff         SE          t          p       LLCI       ULCI
constant    -1.4759      .8804    -1.6764      .1000    -3.2452      .2934
Order        1.1933      .5411     2.2052      .0322      .1058     2.2808

Degrees of freedom for all regression coefficient estimates:
  49
```

Regression results are the same as when we did this using `regression` command

# Using MEMORE for CASC WS data

```
MEMORE w = order /y = int_G int_I /model = 2 /plot = 1.
```

```
%memore(w=order,y = int_G int_I, model = 2, plot = 1, data =
CompSci_WS);
```

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

```
Conditional Effect of 'X' on Y at values of moderator(s)
      Order     Effect        SE         t         p      LLCI      ULCI
     1.0000     -.2826     .4010    -.7048     .4843   -1.0884     .5232
     2.0000      .9107     .3634    2.5061     .0156     .1804    1.6410

Degrees of freedom for all conditional effects:
  49

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

Values for dichotomous moderators are the two values of the moderator.
```

# Using MEMORE for CASC WS data

```
MEMORE w = order /y = int_G int_I /model = 2 /plot = 1.
```

```
%memore(w=order,y = int_G int_I, model = 2, plot = 1, data = CompSci_WS);
```

```
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
      .3766      .1418     1.9306     8.0962     1.0000    49.0000      .0065

Model
              coeff         SE          t          p       LLCI       ULCI
constant     2.0070      .6362     3.1548      .0027      .7285     3.2854
Order        1.1126      .3910     2.8454      .0065      .3268     1.8984

Degrees of freedom for all conditional effects:
  49

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

Condition 2 Outcome:
 int_I

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0281      .0008     2.1189      .0389     1.0000    49.0000      .8446

Model
              coeff         SE          t          p       LLCI       ULCI
constant     3.4829      .6665     5.2260      .0000     2.1436     4.8222
Order        -.0807      .4096     -.1971      .8446     -.9039      .7425

Degrees of freedom for all conditional effects:
  49

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

Order positively predicts interest in **class with group work**

and does not significantly predict interest in **class with individual work**.

# Using MEMORE for CASC WS data

```
MEMORE w = order /y = int_G int_I /model = 2 /plot = 1.
```

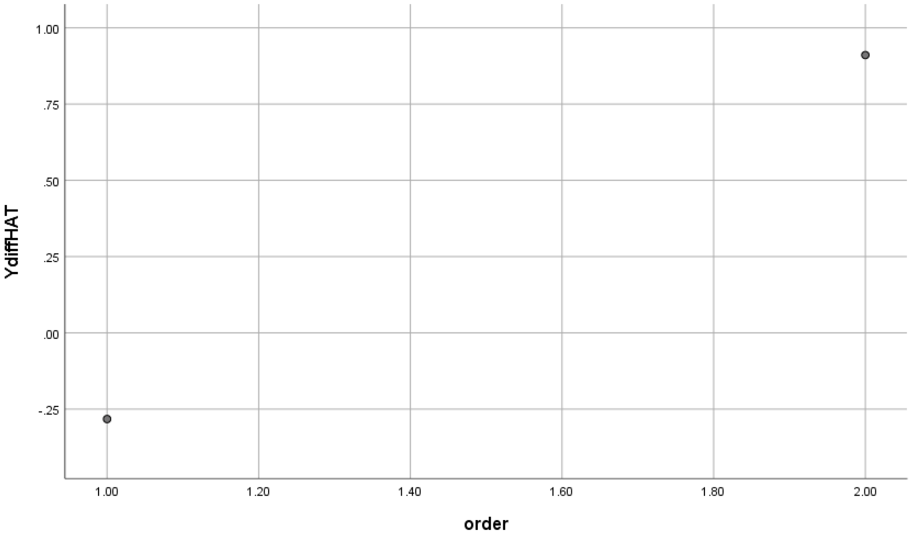
```
%memore(w=order,y = int_G int_I, model = 2, plot = 1, data =
CompSci_WS);
```

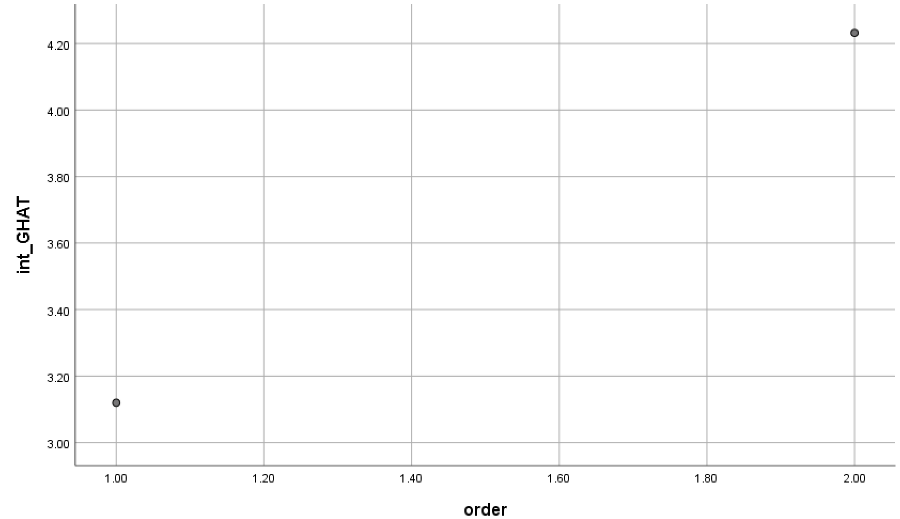
```
Data for visualizing conditional effect of X on Y.
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/order YdiffHAT int_GHAT int_IHAT.

BEGIN DATA.

     1.0000     -.2826     3.1196     3.4022
     2.0000      .9107     4.2321     3.3214

END DATA.

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

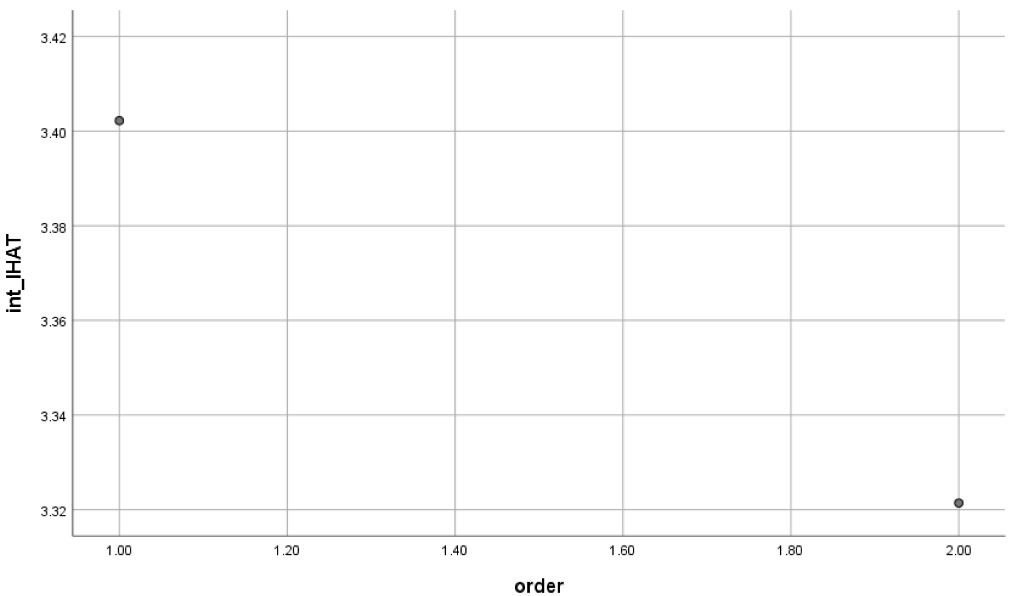
Code for plotting. You'll get three plots each with the moderator on the *X* axis and a different outcome on the *Y* axis.

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

# SPSS Graphs




You can snaz these up in SPSS or export the data to something more fit for preparing graphs (e.g., R or Excel)

# Using MEMORE for CASC WS data

```
MEMORE w = order /y = int_G int_I /model = 2 /plot = 1.
```

```
%memore(w=order,y = int_G int_I, model = 2, plot = 1, data =
CompSci_WS);
```

| Data for visualizing conditional effect of 'X' on Y. | | | | |
|---|---|---|---|---|
| | ORDER | Ydiff | INT_G | INT_I |
| | 1.0000 | -0.2826 | 3.1196 | 3.4022 |
| | 2.0000 | 0.9107 | 4.2321 | 3.3214 |

Only table with values is produced

```
data;
input order Ydiff int_G int_I;
datalines;
1       -0.2826                   3.1196         3.4022
2       0.9107          4.2321          3.3214
run;
proc sgplot;reg x=order y=Ydiff;run;
proc sgplot;reg x=order y=int_G;run;
proc sgplot;reg x=order y=int_I;run;
```

# Writing Up Results

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 order of syllabus presentation?**

Overall, the impact of including group work in a computer science class on interest in the class depends on the order that students read the syllabus ($b_1$ = 1.19, $p$ = .001). Among those who read the individual work syllabus first, we observed a 1.19 unit larger difference between interest in group work and interest in individual work classes. Among those who read the group work syllabus first, they did not significantly differ on their interest in the two classes ($\theta_{X\rightarrow Y|W} = -.283, p = .48$). But among those who read the individual work syllabus first, they were significantly more interested in the group work class ($\theta_{X\rightarrow Y|W} = .9107, p = .0156$). Considering the interaction another way, this result shows that order predicts interest differently across the conditions. Those who read the individual work syllabus first were significantly higher on interest in the group work class than those who read the group work syllabus first ($\theta_{W\rightarrow Y|X} = 1.1126, p = .0065$); whereas, order did not significantly predict interest in the individual work class ($\theta_{W\rightarrow Y|X} = -.0807, p = .8446$). Overall, this suggests that there may be some unique aspect of reading about the individual work class first, and then the group work class which is driving differences in interest between the two conditions. It is worth considering whether it is ecologically valid to rely on order of presentation occurring in one way versus another, and leads to many limitations of the utility of introducing group work into computer science classes as an effective method for recruiting and retaining women.

# Computer Science Within-Subjects Data Example

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

1. Data should be a 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 |

# MEMORE

We can use MEMORE to estimate and probe this model.

Model Templates for MEMORE V3.Beta

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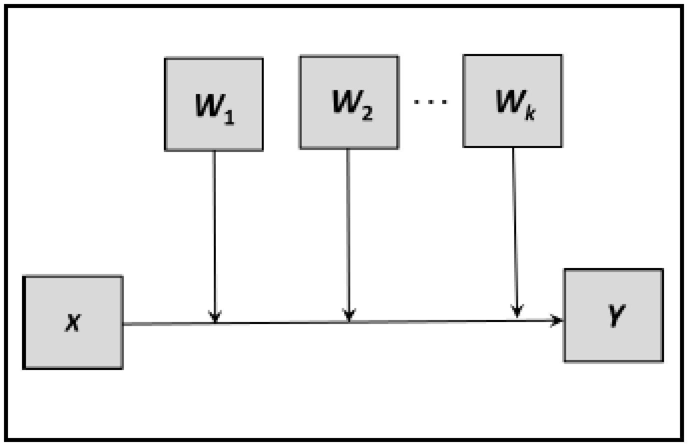
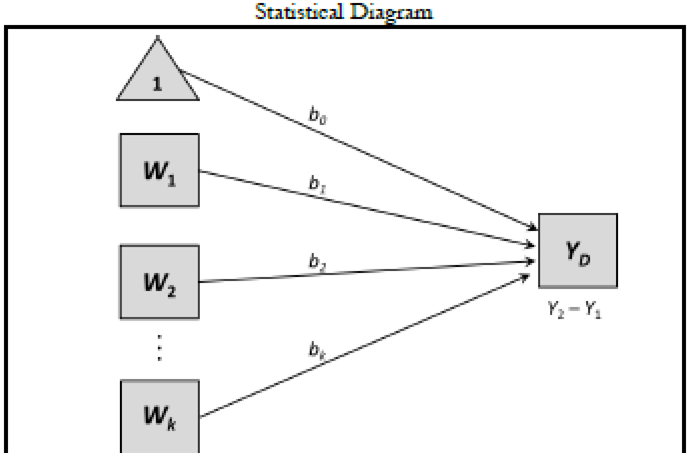
**Model 2 Additive Moderation**

Conceptual Diagram




Statistical Diagram




Subscript *k* indicates moderators. Model can have up to 5 moderators

```
MEMORE w = grppref /y = int_G int_I
/model = 2/jn = 1 /plot = 1.
```

```
%memore(w=grppref,y = int_G int_I, model =
2, jn = 1, plot = 1, data = CompSci_WS);
```

- List moderator(s) in the `w` 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 w = grppref /y = int_G int_I /model = 2/jn = 1 /plot = 1.
```

```
%memore(w=grppref,y = int_G int_I, model = 2, jn = 1, plot = 1,
data = CompSci_WS);
```

```
********************** MEMORE Procedure for SPSS Version 2.1 ************************

                         Written by Amanda Montoya

                  Documentation available at akmontoya.com

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

Model:
  2

Variables:
Y = int_G    int_I
W = 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 w = grppref /y = int_G int_I /model = 2/jn = 1 /plot = 1.
```

```
%memore(w=grppref,y = int_G int_I, model = 2, jn = 1, plot = 1,
data = CompSci_WS);
```

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

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6741      .4544     2.2178    40.8067     1.0000    49.0000      .0000

Model
               coeff         SE          t          p       LLCI       ULCI
constant     -3.5500      .6485    -5.4742      .0000    -4.8532    -2.2468
grppref        .9936      .1555     6.3880      .0000      .6810     1.3062

Degrees of freedom for all regression coefficient estimates:
  49
```

Strong evidence for moderation, where as preference for group work increases, the difference between interest in the two classes increases.

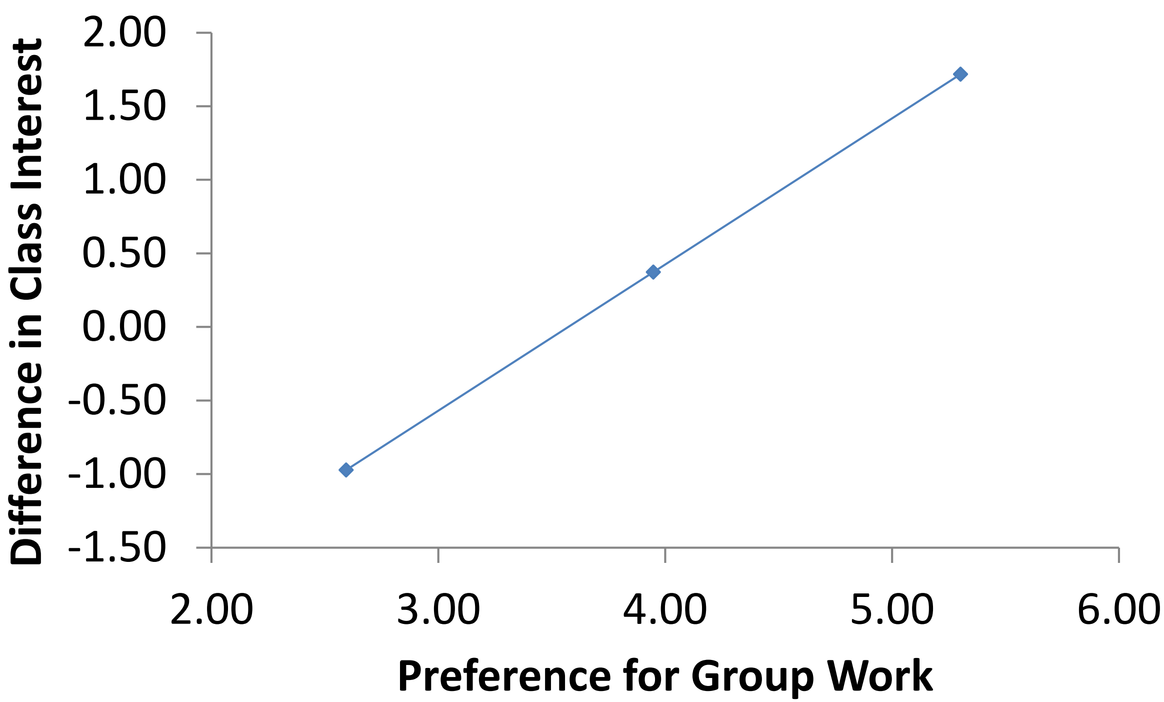
# Probing an Effect of Condition on Outcome: The "Pick-a-Point" Approach

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:

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

| W | $\theta_{X\rightarrow Y\mid W}$ | $s_{\theta_{X\rightarrow Y\mid W}}$ | $p$ |
|---|---|---|---|
| 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.

# Using MEMORE for CASC WS data

```
MEMORE w = grppref /y = int_G int_I /model = 2/jn = 1 /plot = 1.
```

```
%memore(w=grppref,y = int_G int_I, model = 2, jn = 1, plot = 1,
data = CompSci_WS);
```

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

# The Johnson-Neyman Technique

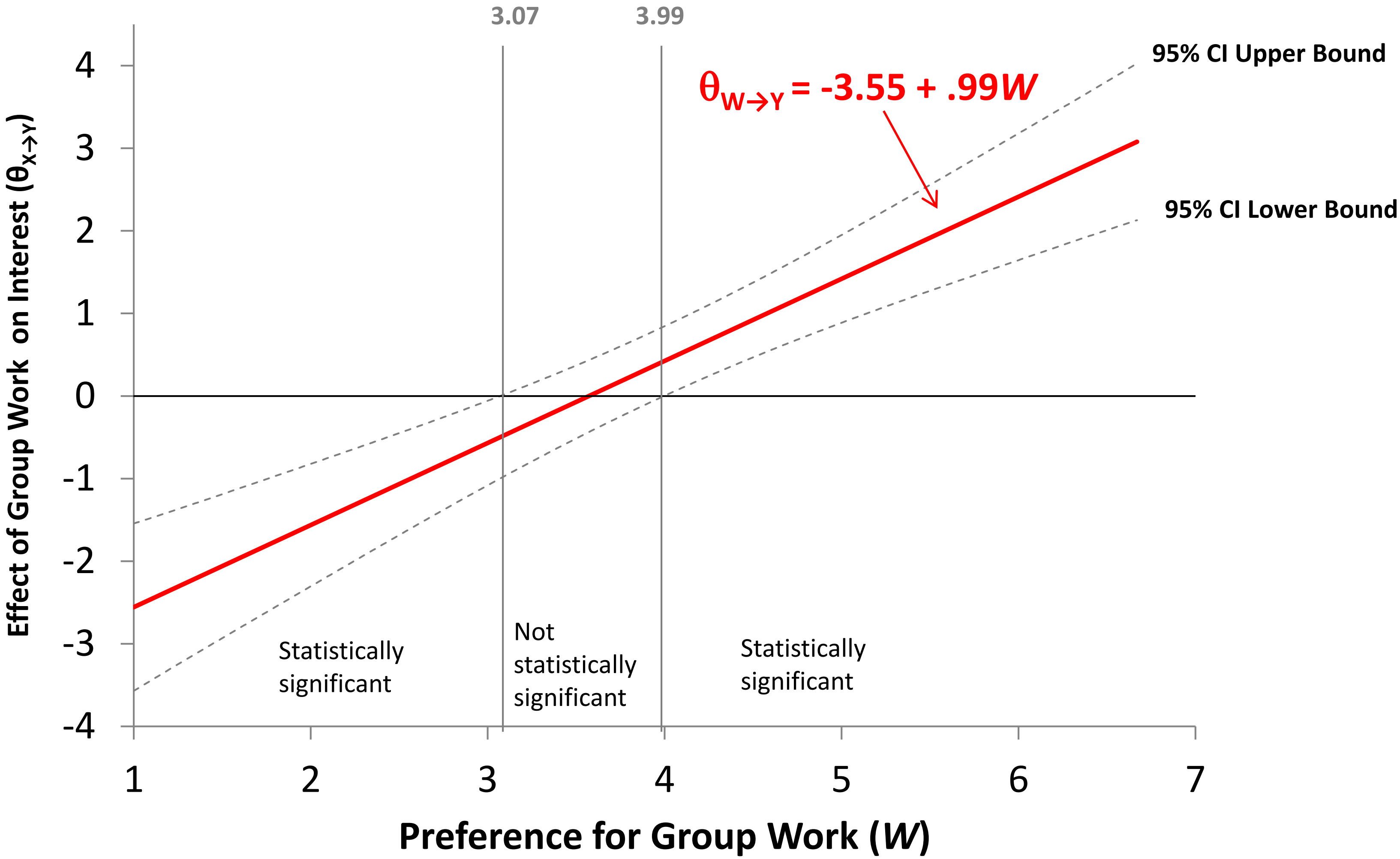
The Johnson-Neyman technique seeks to find the value or values of the moderator (*W*) within the data, if they exist, such that the *p*-value for the conditional effect of condition at that value or those values of *W* is exactly equal to some chosen level of significance $\alpha$. Thus, no need to select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

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

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.

# A Plot of the "Region of Significance"



# Using MEMORE for CASC WS data

```
MEMORE w = grppref /y = int_G int_I /model = 2/jn = 1 /plot = 1.
```

```
%memore(w=grppref,y = int_G int_I, model = 2, jn = 1, plot = 1,
data = CompSci_WS);
```

```
****************************** 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 w = grppref /y = int_G int_I /model = 2/jn = 1 /plot = 1.
```

```
%memore(w=grppref,y = int_G int_I, model = 2, jn = 1, plot = 1,
data = CompSci_WS);
```

```
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 w = grppref /y = int_G int_I /model = 2/jn = 1 /plot = 1.
```

```
%memore(w=grppref,y = int_G int_I, model = 2, jn = 1, plot = 1,
data = CompSci_WS);
```

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

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

# Using MEMORE for CASC WS data

```
MEMORE w = grppref /y = int_G int_I /model = 2/jn = 1 /plot = 1.
```

```
%memore(w=grppref,y = int_G int_I, model = 2, jn = 1, plot = 1,
data = CompSci_WS);
```

| Data for visualizing conditional effect of 'X' on Y. | | | | |
|---|---|---|---|---|
| | GRPPREF | Ydiff | INT_G | INT_I |
| | 2.5938 | -0.9728 | 3.0640 | 4.0368 |
| | 3.9478 | 0.3725 | 3.7304 | 3.3578 |
| | 5.3019 | 1.7179 | 4.3968 | 2.6789 |

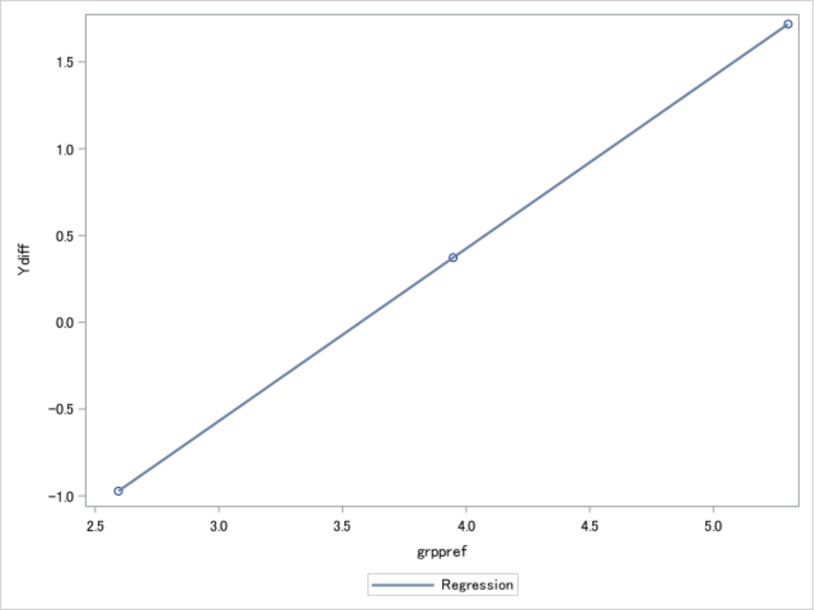
Only data table is generated, then write separate code to make the graphs

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

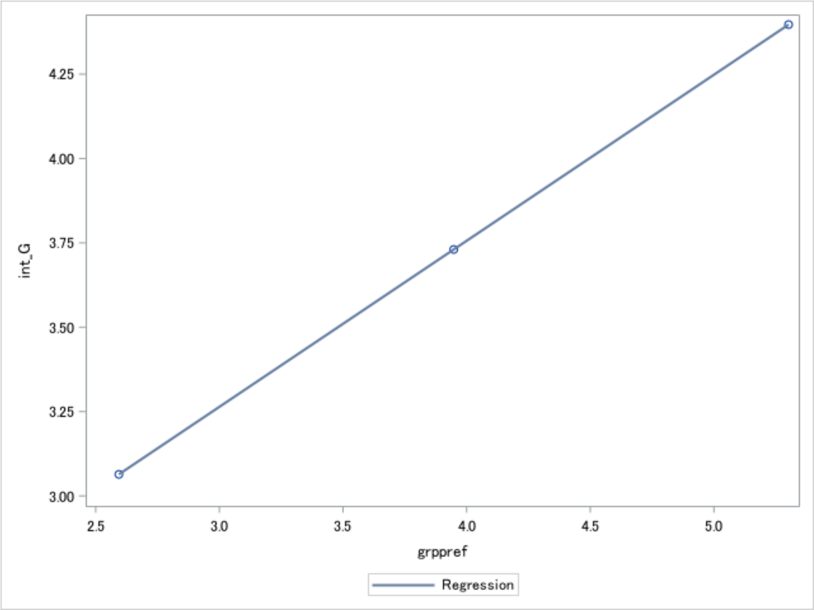
```
data;
input grppref Ydiff int_G int_I;
datalines;
  2.5938 -0.9728 3.0640 4.0368
  3.9478 0.3725 3.7304 3.3578
  5.3019 1.7179 4.3968 2.6789

run;
proc sgplot;reg x=grppref y=Ydiff;run;
proc sgplot;reg x=grppref y=int_G;run;
proc sgplot;reg x=grppref y=int_I;run;
```

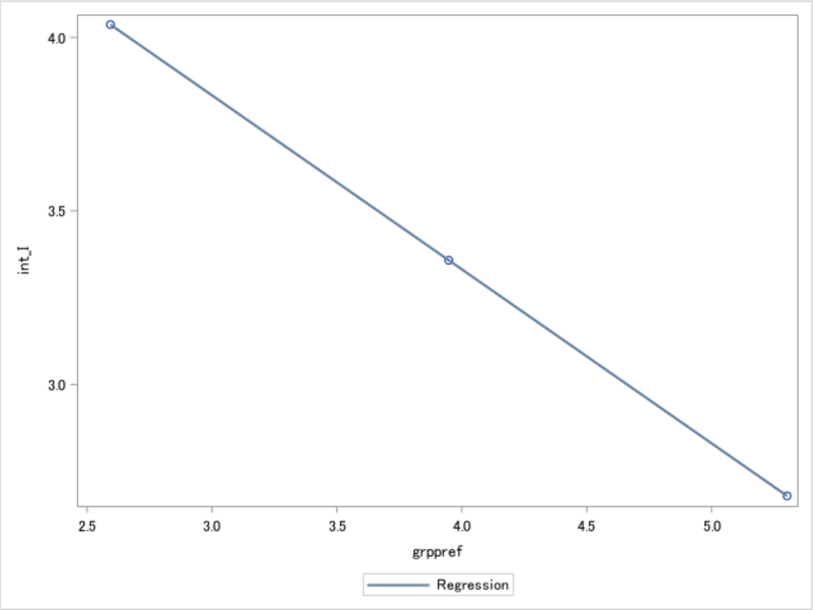
# SAS Graphs



Ydiff
1.5
1.0
0.5
0.0
−0.5
−1.0
2.5
3.0
3.5
4.0
4.5
5.0
grppref
Regression

int_G
4.25
4.00
3.75
3.50
3.25
3.00
2.5
3.0
3.5
4.0
4.5
5.0
grppref
Regression

int_I
4.0
3.5
3.0
2.5
3.0
3.5
4.0
4.5
5.0
grppref
Regression

# Writing up a Moderation Analysis

Tips:

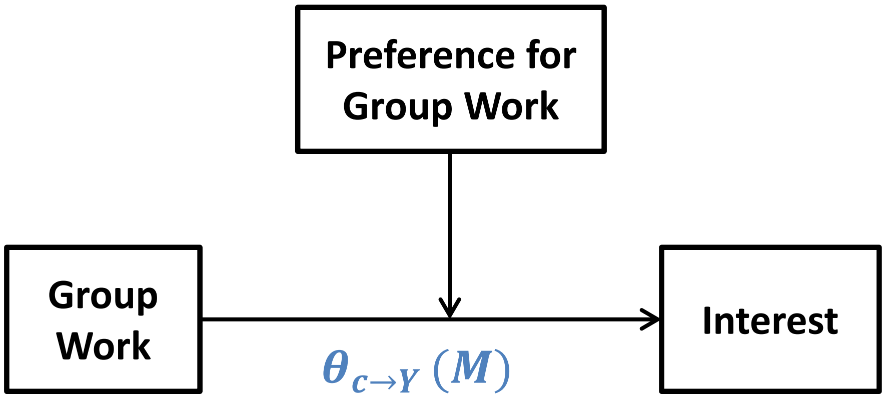
- Interpret the sign and the magnitude of the interaction coefficient with respect to *X*'s effect on *Y* (or *M*'s effect on *Y*; or both).
- Provide probing results with interpretations
- Read the write ups of other's moderation analyses
- Provide a graphical representation of the effect of interest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

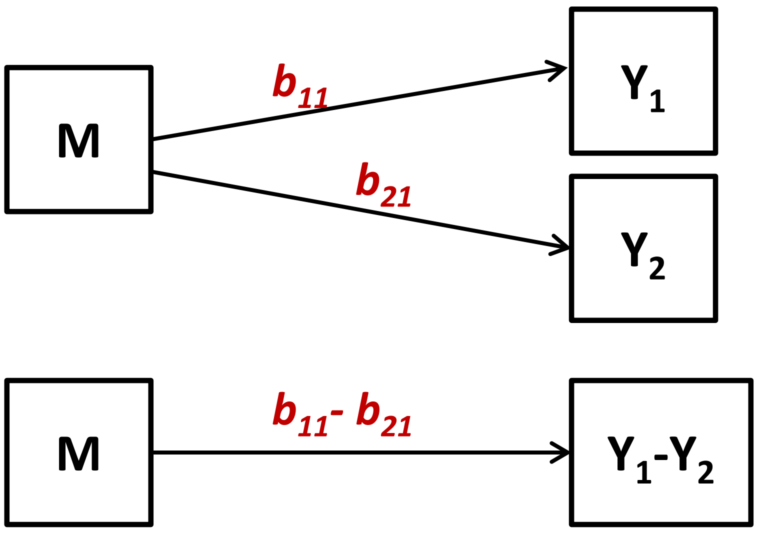
Overall, the impact of including group work in a computer science class on interest in the class depends on an individual's general preference for group work ($b_1$ = .49, $p$ = .001). As preference for group work increases relative interest in the class with group work compared to the class with individual 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**

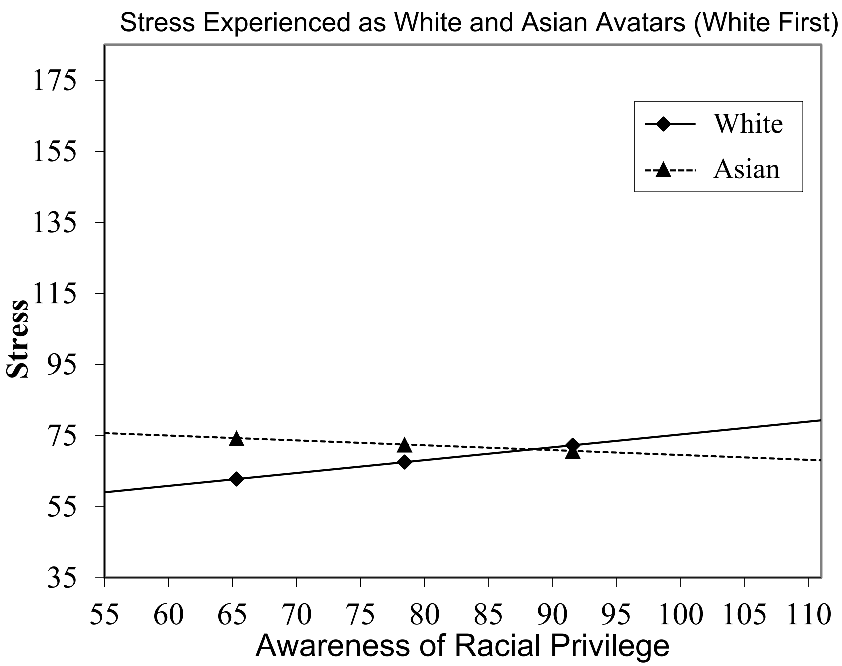
Tips:

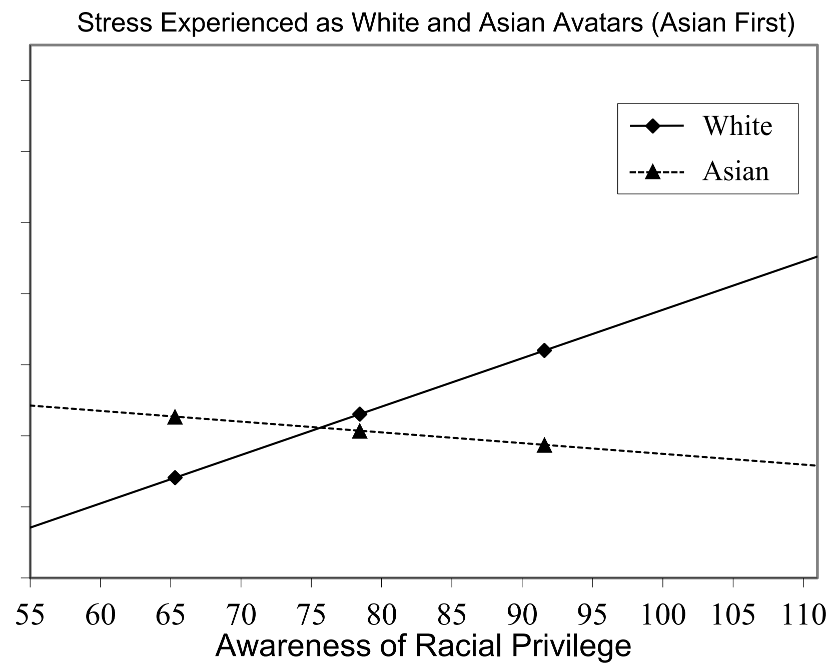
- Try the different scales of the *Y* axis (difference vs. raw Y score with two lines for each condition)
- I do not like bar graphs with the effect of the moderator in each condition
- Provide path estimates on statistical diagram or in a table.

# Visualizations: A Case Study

Tawa, J., & **Montoya, A. K.** (white paper) 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.



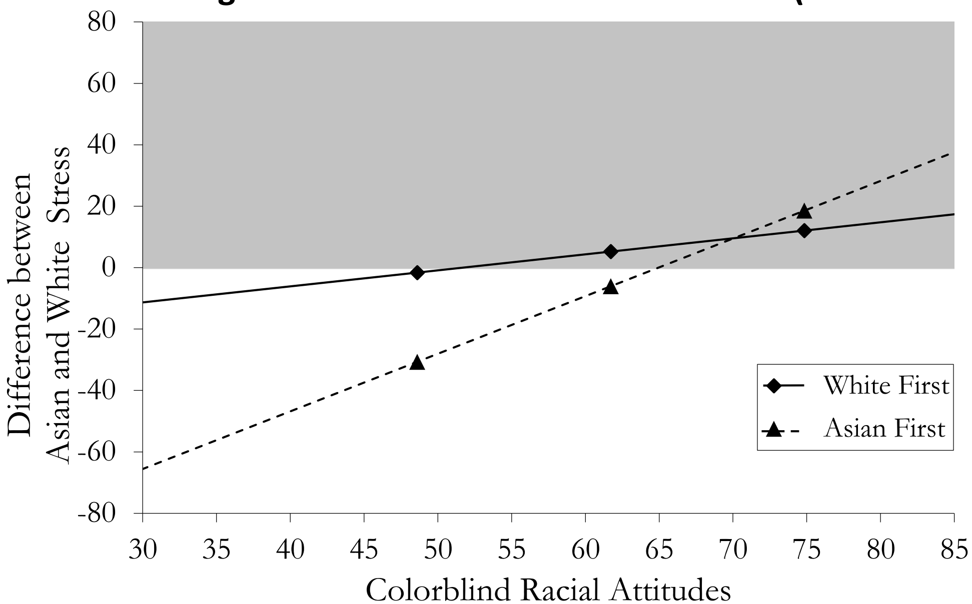



# Visualizations: A Case Study

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.

**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).

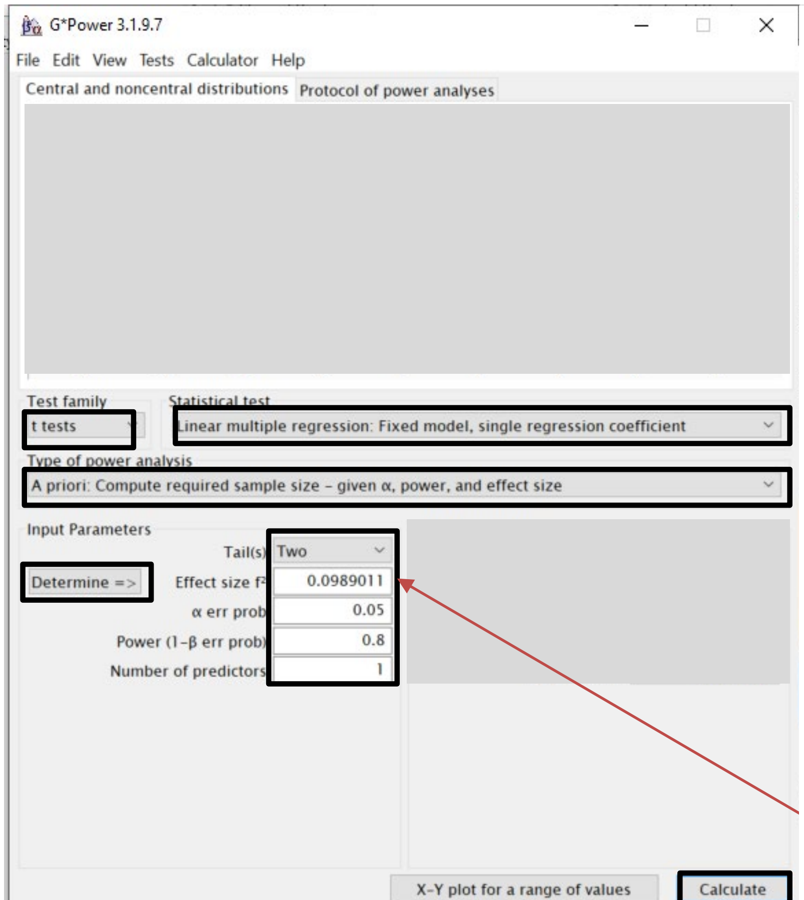
- How do I control for covariates?

  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).

# Power Analysis

Power analysis for within-subject moderation can be conducted with any tool that does power analysis for regression.

G*Power is a commonly used tool for power analysis.



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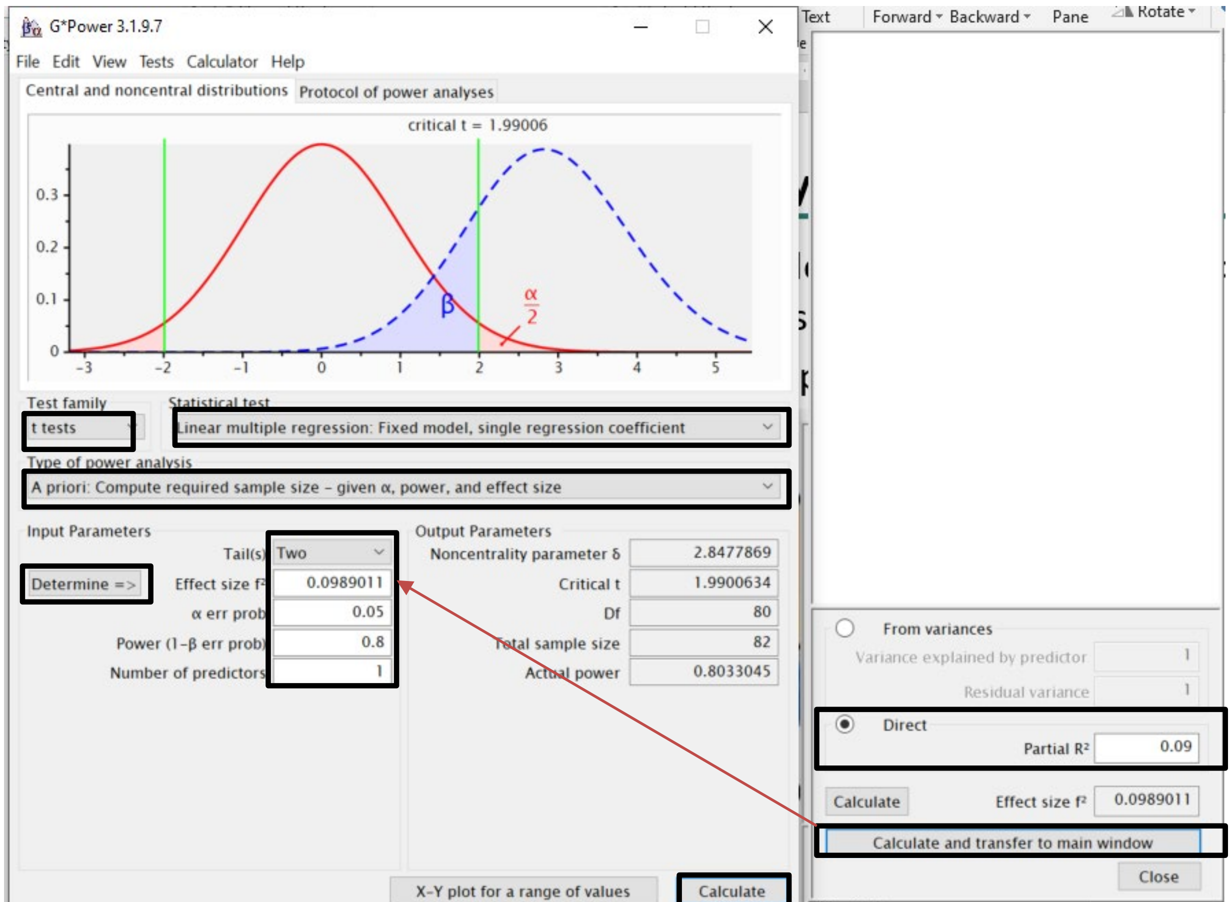



**Recommended sample size for this case is 82**

# Generating Effect Size Estimates

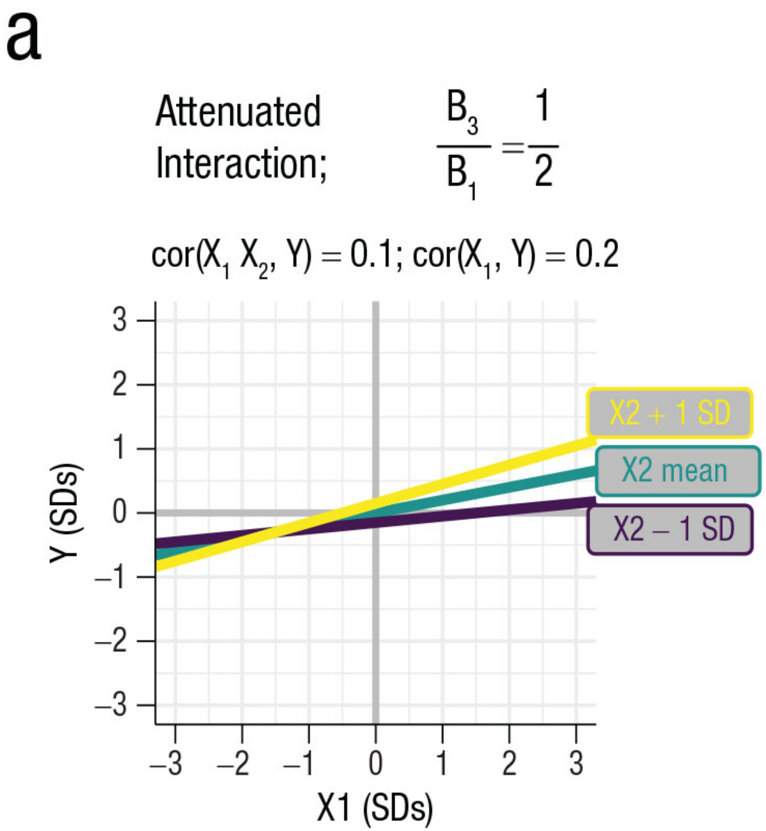
Power analysis itself is often not difficult, but coming up with an effect size estimate is.

**Possible approaches:**

- Pilot studies
  - Often cannot produce a precise enough estimate to be useful or will be biased
- Effect sizes from prior studies, literature, or meta-analysis
  - *Beware publication bias*
- Smallest effect size of interest (SESOI)
  - Lakens, 2017 & Anvari & Lakens, 2021

# Moderation Specific Issues

Generating a predicted effect size for an interaction can be difficult an unintuitive, especially when it depends on many other effects.




[Baranger et al., 2023](Baranger et al., 2023)

# Moderation Specific Issues

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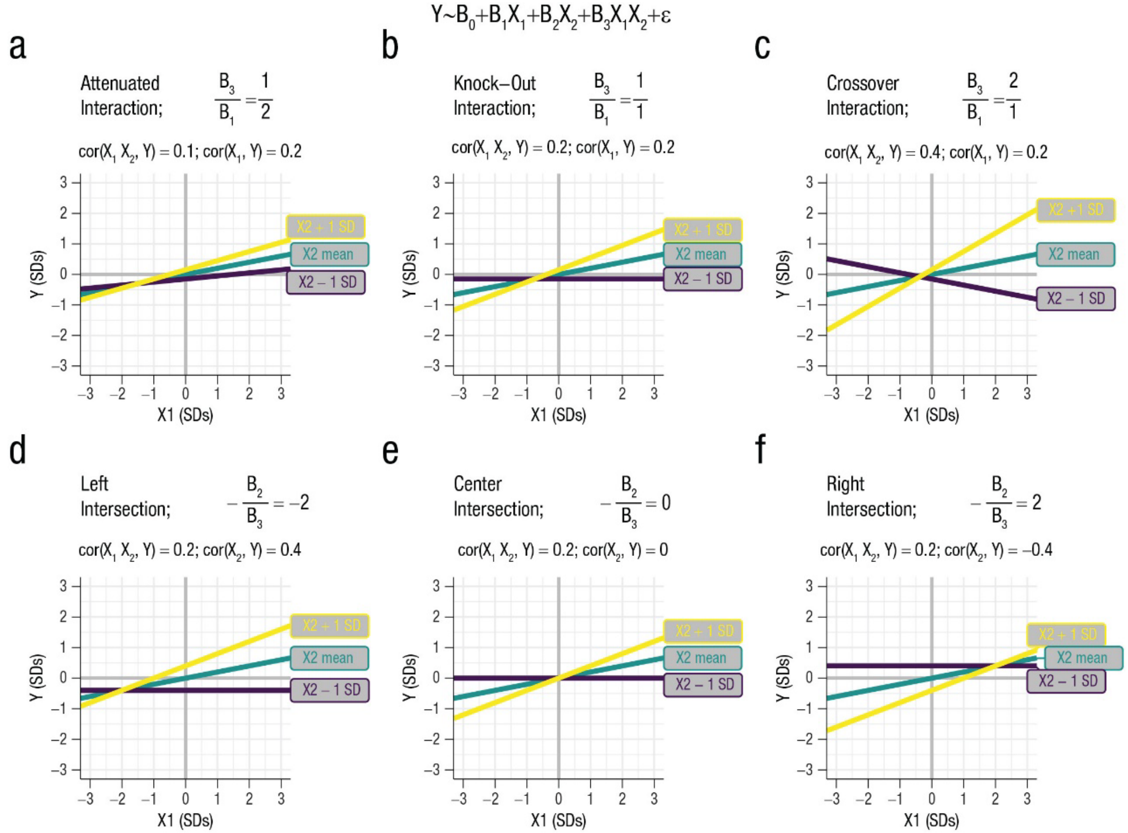



[Baranger et al., 2023](Baranger et al., 2023)

# Preregistration

**Preregistration:** A process where you create a time-stamped, publicly accessible record of your plan for a specific study.

- ❑ Planned sample size
- ❑ α-level/CI-level for each test
- ❑ Role of different variables in the analysis (e.g., independent variable, moderator, outcome), and how they are computed
- ❑ Estimation Method
- ❑ Plans for probing: simple slopes, JN, probing at specific values of the moderator
- ❑ **Tools and specifications**

# Finding Examples

DataStudio for finding examples

https://lookerstudio.google.com/s/gFgefAkOjKA

Publication Year | Research Areas | ModelNumb... (1) | Xtype | levelsX | numYvars

Journal Title | Covariates | Sample Size | Article Count 50

| Article Title (link) | Authors | Journal Title | Publication... | Research Areas | Study Num... | SampleSize | ModelNumb... | numXvars | Xtype | levelsX | numYvars |
|---|---|---|---|---|---|---|---|---|---|---|---|
| When should retail... | Jeong, H; Ye,... | JOURNAL O... | 2021 | Business & Economics | 1 | 271 | 1 (Mediation) | 1 | Pre-post | 2 | 1 |
| What hinders resi... | Dong, XJ | TOURISM A... | 2022 | Social Sciences - Other... | 2 | 130 | 1 (Mediation) | 1 | Experimental | 2 | 1 |
| The role of metad... | Hartley, S; P... | GROUP PRO... | 2022 | Psychology | 3 | 239 | 1 (Mediation) | 1 | Experimental | 2 | 2 |
| The connotative ... | Motoki, K; P... | JOURNAL O... | 2022 | Business & Economics | 1 | 154 | 1 (Mediation) | 1 | Experimental | 2 | 3 |
| The Self-Other Div... | Ring, C; Kav... | JOURNAL O... | 2020 | Social Sciences - Other... | 1 | 100 | 1 (Mediation) | 1 | Experimental | 2 | 1 |
| The Impact of Mix... | Huang, XZ; Z... | INTERNATIO... | 2022 | Environmental Science... | 2 | 434 | 1 (Mediation) | 1 | Experimental | 2 | 1 |
| The Hypoalgesic E... | Song, JS; Ka... | RESEARCH ... | 2022 | Social Sciences - Other... | 1 | 40 | 1 (Mediation) | 1 | Experimental | 2 | 1 |
| Testing the effecti... | Brochu, PM | JOURNAL O... | 2023 | Psychology | 1 | 45 | 1 (Mediation) | 1 | Pre-post | 2 | 2 |
| Suicidality and so... | Breitborde, ... | EARLY INTE... | 2021 | Psychiatry | 1 | 38 | 1 (Mediation) | 1 | Pre-post | 2 | 1 |
| Putting the Me in ... | Hamilton, K... | NEW MEDIA... | 2021 | Communication | 1 | 119 | 1 (Mediation) | 1 | Experimental | 2 | 1 |
| Positive reputatio... | Inoue, Y; Mif... | FRONTIERS ... | 2023 | Psychology | 2 | 293 | 1 (Mediation) | 1 | Experimental | 2 | 1 |
| Perceptions of a P... | Pals, AM; Go... | JOURNAL O... | 2022 | Psychology; Family Stu... | 1 | 52 | 1 (Mediation) | 3 | Experimental | 2 | 1 |
| Pandemic Pedago... | Armstrong, ... | SOUTHERN ... | 2022 | Communication | 1 | 163 | 1 (Mediation) | 1 | Pre-post | 2 | 4 |
| Mind the ad: How ... | Kocak, A; Ro... | JOURNAL O... | 2022 | Psychology; Business ... | 1 | 123 | 1 (Mediation) | 1 | Experimental | 2 | 1 |
| Mind the ad: How ... | Kocak, A; Ro... | JOURNAL O... | 2022 | Psychology; Business ... | 2 | 151 | 1 (Mediation) | 1 | Experimental | 2 | 1 |
| Mediation and Mo... | Wong, CL; C... | JOURNAL O... | 2020 | Public, Environmental ... | 1 | 1001 | 1 (Mediation) | 1 | Pre-post | 2 | 1 |

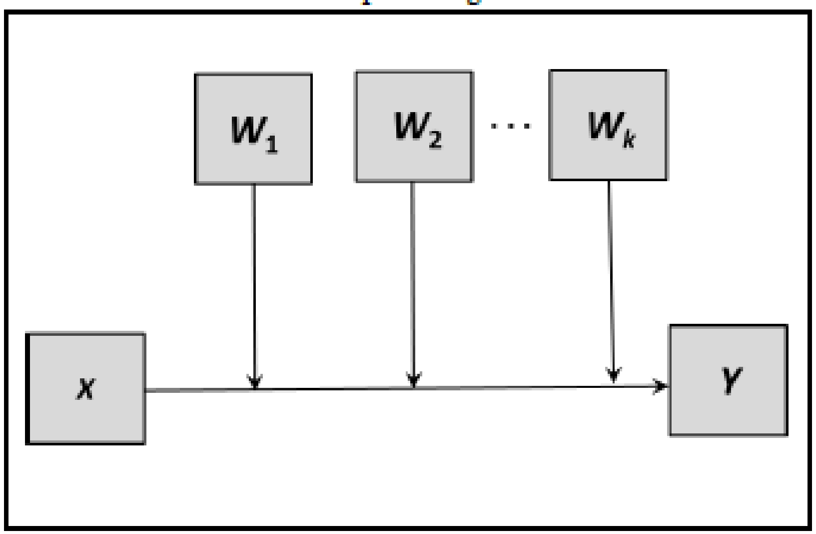
# Multiple Moderator Models

Model 2 vs. Model 3

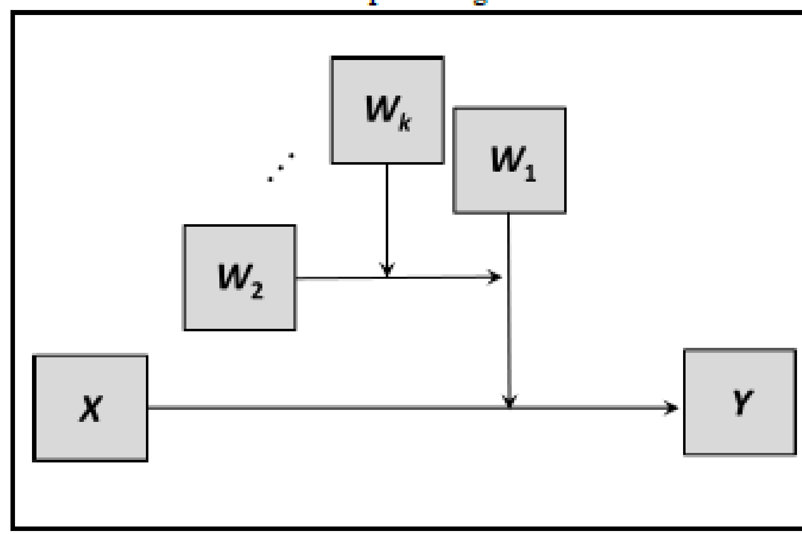
When you have multiple moderators you are interested, consider whether you think those moderators will themselves interact or not.

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 2 Additive Moderation
Conceptual Diagram




Model 3 Multiplicative Moderation
Conceptual Diagram



# Multiple Moderator Models

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

```
%memore(w=grppref order,y = int_G int_I, model = 2,
        data = CompSci_WS);
```

```
********************** MEMORE Procedure for SPSS Version 3.0 ***********************

                        Written by Amanda Montoya

                  Documentation available at akmontoya.com

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

Model:
  2

Variables:
Y =  int_G    int_I
W1 = grppref
W2 = 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 two two-way interactions:
Condition x Group Preference
Condition x Order

# Multiple Moderator Models

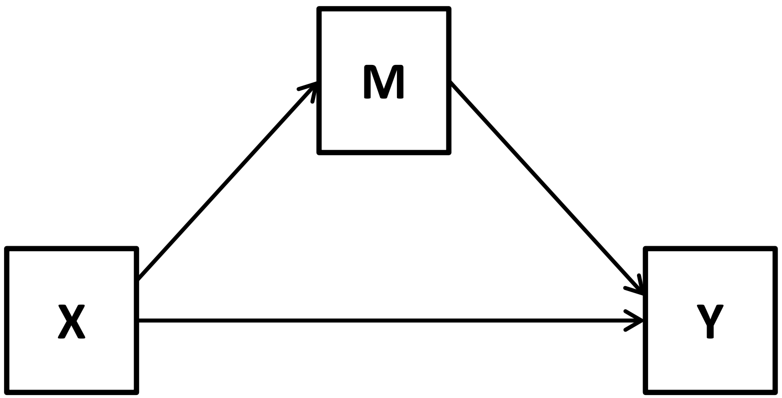
```
MEMORE w = grppref order/y = int_G int_I /model = 3.
```

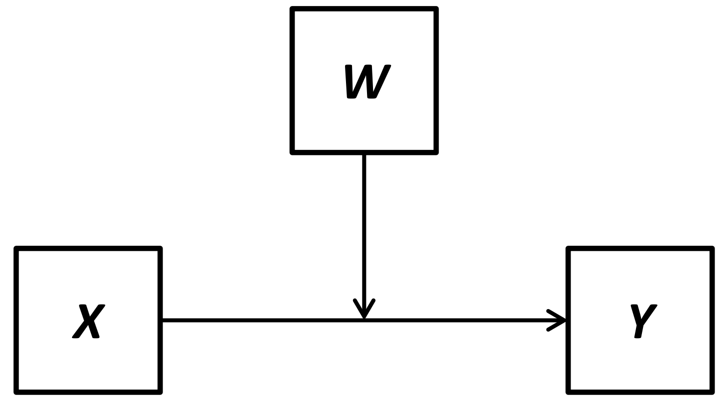
```
%memore(w=grppref order,y = int_G int_I, model = 3,
        data = CompSci_WS);
```

```
Model:
  3

Variables:
Y =  int_G    int_I
W1 = grppref
W2 = Order

Computed Variables:
Ydiff =          int_G      -       int_I
Intl  =          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
Intl         -.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

# Combining mediation and moderation




Research questions:

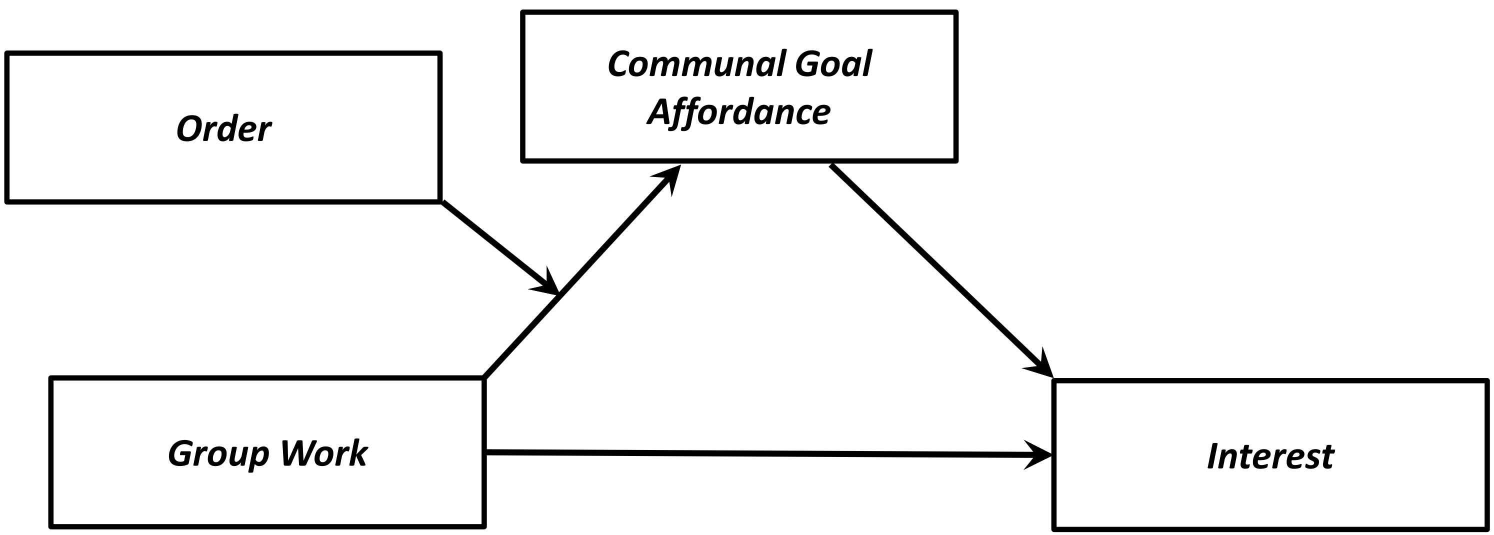
- Does the process through which *X* affects *Y* through *M* depend on *W*?
- Are there certain groups where *X* affects *Y* through *M* and certain groups where this process does not occur?

**Conditional process analysis** allows a mediated process to be moderated. Now the indirect effect can be defined as a *function of the moderator.*

# CPA in Two-instance repeated-measures designs

Extending the path analytic from Montoya & Hayes (2017) we can now allow for moderation of a mediated pathway.

**First stage moderated mediation** allows *W* to moderate the path between the within-subjects factor and the mediator.






Montoya, *under review (https://psyarxiv.com/wrtb6)*

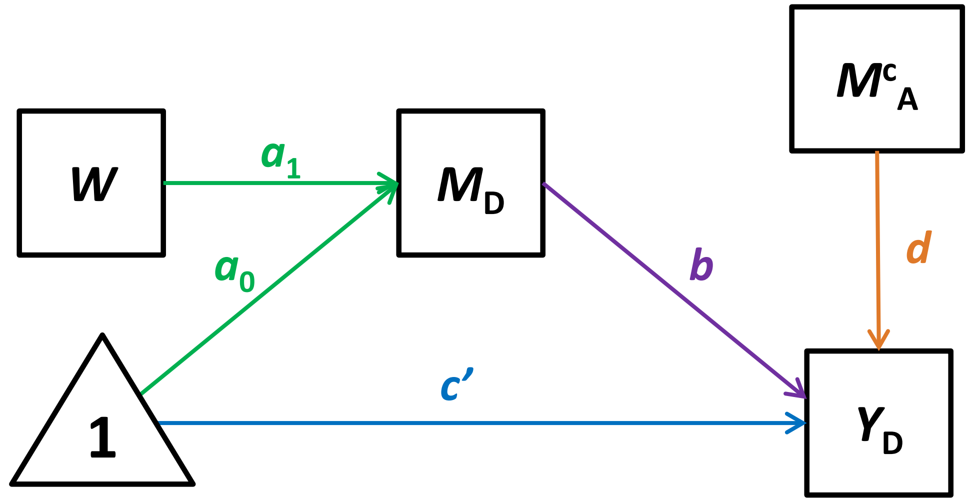
# Equations and Path Diagram

**First stage moderated mediation** allows *W* to moderate the path between the within-subjects factor and the mediator.

$$M_{2i} - M_{1i} = a_0 + a_1 W_i + \epsilon_{Mi}$$

$$\theta_{X \to M}(W) = a_0 + a_1 W_i$$

$$Y_{Di} = c' + bM_{Di} + dM^c_{Ai} + \epsilon_{Yi}$$




What is the indirect effect?

$$\theta_{X \to M}(W) \times b = (a_0 + a_1 W)b = a_0 b + a_1 bW$$

Indirect effect is a *function* of the moderator



Montoya, *under review (https://psyarxiv.com/wrtb6)*

# Inference

$$\theta_{X\rightarrow M}(W) \times b = (a_0 + a_1 W)b = a_0 b + a_1 bW$$

**Conditional Indirect Effects**
Select a value of *W*, plug that into the equation for the indirect effect, and use bootstrapping to make inference about the indirect effect at that value

Does the indirect effect *depend* on the moderator?

If $a_1 b = 0$ then the indirect effect *does not* depend on W

$$\theta_{X\rightarrow M}(W) \times b = a_0 b + 0 * W = a_0 b$$

$a_1 b$ can be called the **index of moderated mediation**

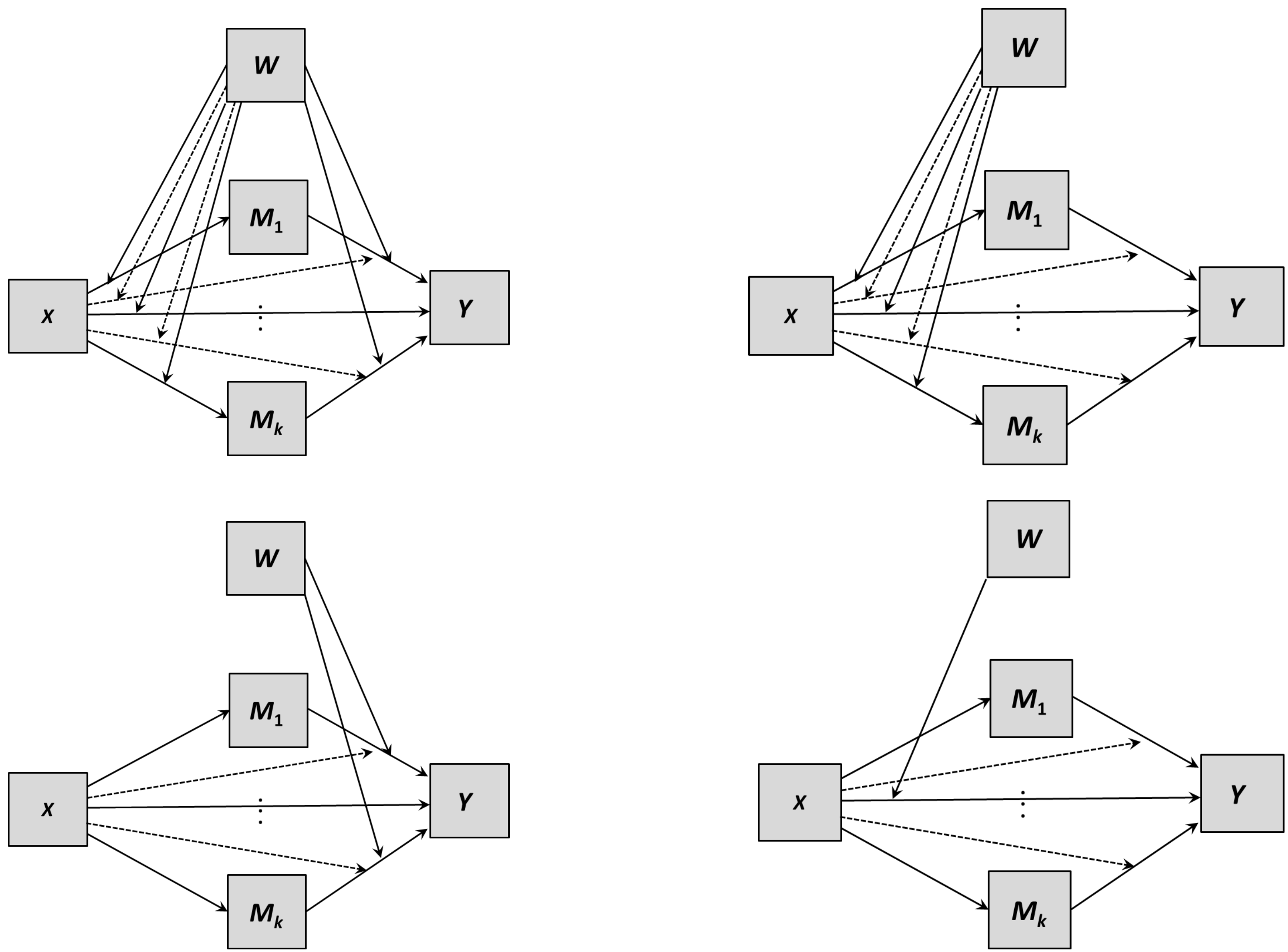
A test on the index will indicate if the indirect effect depends on *W.* We can do this formal test using bootstrapping.



Montoya, *under review (https://psyarxiv.com/wrtb6)*

# MEMORE V3: Models 4 - 18

The latest version of MEMORE has expanded to models with a single moderator on any combination of paths in the mediation.






Montoya, *under review (https://psyarxiv.com/wrtb6)*

# MEMORE

```
MEMORE m = comm_G comm_I /w = order/y = int_G int_I /model = 15.
```

```
%memore(m=comm_G comm_I, w=order,y=int_G int_I,model=15,
         data = CompSci_WS);
```

```
*********************** MEMORE Procedure for SPSS Version 3.0 ************************

                         Written by Amanda Montoya

                  Documentation available at akmontoya.com

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

Model:
  15

Variables:
Y = int_G    int_I
W = Order
M = comm_G   comm_I

Computed Variables:
Ydiff =          int_G     -      int_I
Mdiff =          comm_G    -      comm_I
Mavg =  (        comm_G    +      comm_I   )       /2                       Centered

Sample Size:
  51
```

# Moderated Mediation with MEMORE

```
MEMORE m = comm_G comm_I /w = order/y = int_G int_I /model = 15.
```

```
%memore(m=comm_G comm_I, w=order,y=int_G int_I,model=15,
         data = CompSci_WS);
```

```
Outcome: Ydiff =  int_G     -       int_I

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3005      .0903     3.6978     4.8629     1.0000    49.0000      .0322

Model
             Effect         SE          t          p       LLCI       ULCI
constant    -1.4759      .8804    -1.6764      .1000    -3.2452      .2934
W            1.1933      .5411     2.2052      .0322      .1058     2.2808

Degrees of freedom for all regression coefficient estimates:
  49

Conditional Effect of Focal Predictor on Outcome at values of Moderator(s)
 Focal:   'X'       (X)
 Outcome: Ydiff     (Y)
 Mod:     Order     (W)


      Order     Effect         SE          t          p       LLCI       ULCI
     1.0000     -.2826      .4010     -.7048      .4843    -1.0884      .5232
     2.0000      .9107      .3634     2.5061      .0156      .1804     1.6410

     Values for dichotomous moderators are the two values of the moderator.

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

# Moderated Mediation with MEMORE

```
MEMORE m = comm_G comm_I /w = order/y = int_G int_I /model = 15.
```

```
%memore(m=comm_G comm_I, w=order,y=int_G int_I,model=15,
        data = CompSci_WS);
```

```
Outcome: Mdiff =  comm_G    -       comm_I

Model Summary
         R       R-sq        MSE          F        df1        df2          p
     .3393      .1151     2.8567     6.3752     1.0000    49.0000      .0149

Model
              Effect          SE           t           p        LLCI        ULCI
constant       .4339       .7738       .5606       .5776     -1.1213      1.9890
W             1.2009       .4756      2.5249       .0149       .2451      2.1568

Degrees of freedom for all regression coefficient estimates:
  49

Conditional Effect of Focal Predictor on Outcome at values of Moderator(s)
 Focal:    'X'        (X)
 Outcome: Mdiff       (M)
 Mod:     Order       (W)


     Order     Effect          SE           t           p        LLCI        ULCI
    1.0000     1.6348       .3524      4.6387       .0000       .9266      2.3430
    2.0000     2.8357       .3194      8.8779       .0000      2.1938      3.4776

    Values for dichotomous moderators are the two values of the moderator.

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

# Moderated Mediation with MEMORE

```
MEMORE m = comm_G comm_I /w = order/y = int_G int_I /model = 15.
```

```
%memore(m=comm_G comm_I, w=order,y=int_G int_I,model=15,
         data = CompSci_WS);
```

```
Outcome: Ydiff =  int_G     -        int_I

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5639      .3180     2.8299    11.1909     2.0000    48.0000      .0001

Model
              coeff         SE          t          p       LLCI       ULCI
constant     -.9814      .3884    -2.5269      .0149    -1.7623    -.2005
Mdiff         .5902      .1346     4.3845      .0001      .3195      .8608
Mavg         -.5505      .4328    -1.2718      .2096    -1.4208      .3198

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

# Moderated Mediation with MEMORE

```
MEMORE m = comm_G comm_I /w = order/y = int_G int_I /model = 15.
```

```
%memore(m=comm_G comm_I, w=order,y=int_G int_I,model=15,
        data = CompSci_WS);
```

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

Conditional Total Effect of X on Y at values of the Moderator(s)
      Order     Effect         SE          t         df          p       LLCI       ULCI
     1.0000     -.2826      .4010     -.7048    49.0000      .4843    -1.0884      .5232
     2.0000      .9107      .3634     2.5061    49.0000      .0156      .1804     1.6410

     Values for dichotomous moderators are the two values of the moderator.

Direct effect of X on Y
     Effect         SE          t         df          p       LLCI       ULCI
     -.9814      .3884    -2.5269    48.0000      .0149    -1.7623     -.2005

Conditional Indirect Effect of X on Y through Mediator at values of the Moderator
  Ind:       Ind1
  Med:       Mdiff      (M)


      Order     Effect     BootSE   BootLLCI   BootULCI
     1.0000      .9648      .2835      .4278     1.5511
     2.0000     1.6736      .4349      .7777     2.4990

     Values for dichotomous moderators are the two values of the moderator.

Indirect Key
Ind1  'X'      ->      Mdiff     ->      Ydiff
```

Indirect effect is significant and positive in both order conditions

# Moderated Mediation with MEMORE

```
MEMORE m = comm_G comm_I /w = order/y = int_G int_I /model = 15.
```

```
%memore(m=comm_G comm_I, w=order,y=int_G int_I,model=15,
         data = CompSci_WS);
```

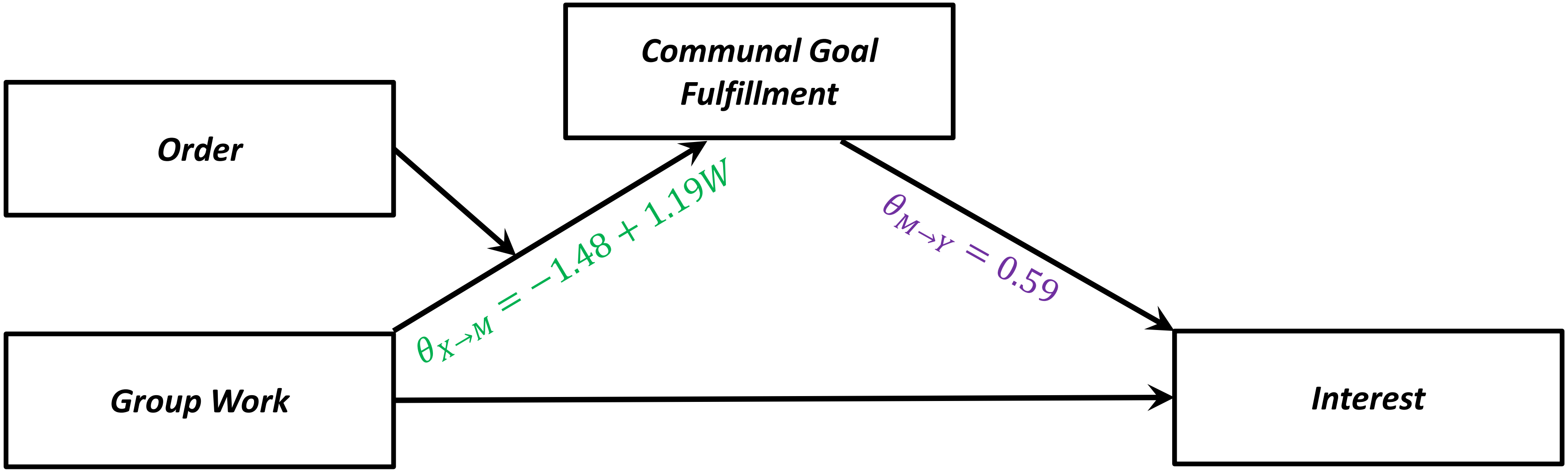
```
******************************** INDICES OF MODERATION ********************************

Test of Moderation of the Total Effect
      Effect         SE          t         df          p       LLCI       ULCI
W     1.1933      .5411     2.2052    49.0000      .0322      .1058     2.2808

Index of Moderated Mediation for each Indirect Effect.
          Effect     BootSE   BootLLCI   BootULCI
Ind1       .7088      .3629      .1035     1.5004
```

The indirect effect is statistically larger when participants read about the individual work class first.

# Computer Science Study

```
MEMORE m = comm_G comm_I /w = order/y = int_G int_I /model = 15.
```

```
%memore(m=comm_G comm_I, w=order,y=int_G int_I,model=15,
         data = CompSci_WS);
```




The indirect effect for both orders was such that **the group work class increased interest through communal goal fulfillment** (Group-first: 0.96 [0.43, 1.55], Individual-First: 1.67 [1.78, 2.50]).

The *index of moderated mediation* was significantly different from zero (0.71 [0.10, 1.50]), meaning the **indirect effect through drawing on the communal goals was stronger for those who read the individual work syllabus first, compared to reading group work first**.

# Wrapping Up

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Upcoming versions of MEMORE expanding functionality

- More moderated mediation
- Dichotomous outcomes
- More than 2 observations

Feel free to contact me with questions or consultation for data with other structures, extensions. This is frequently how new methods get developed!

Mediation for Between Subject Data: PROCESS (Available for SPSS, SAS, and R)
Mediation for Dyadic Data: MEDYAD (Available for SPSS, SAS, and R)
Mediation for Multilevel Models: MLMED (Available for SPSS)

Github.com/akmontoya/SHwithin