MEMORE: Mediation and Moderation in Repeated Measures Designs

Amanda Kay Montoya
UCLA

Workshop: 1:00pm – 3:00pm PST

Please go to https://github.com/akmontoya/WPA2020.git , download the folder and open SPSS.

Workshop Procedures

Download files at
https://github.com/akmontoya/WPA2020.git

Assuming some familiarity with:
- Regression
- Mediation/Moderation
- SPSS

What we will learn:
- Repeated-Measures Data
- Mediation in Two-Instance Within-Participant Designs
- Short Break / Q&A (10 min)
- Moderation in Two-Instance Within-Participant Designs
- Q&A

How we will learn:
- Combination of theory and practice
- Follow along with the analysis as we go
  - Use syntax!
  - **Ask questions** about concepts or anything that is confusing

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Mediation

- Two-Condition Within Subjects Mediation
  - Judd Kenny and McClelland (2001)
  - Path analytic approach
  - Estimation of Indirect Effects
  - MEMORE
  - Reporting (Writing and Figures)
  - Common Questions
- Other Types of Repeated Measures Mediation
  - Multilevel (1 – 1 – 1 , 1 – 2 – 2 etc)
  - Longitudinal
  - Multilevel SEM

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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 mediation, it’s important to think about how/when/how many times the variables in your mediation model are measured
- *Multilevel* has a nice system referring to levels (1-1-1 mediation, 1-2-1, mediation etc.
- Is your causal variable (*X*) measured repeatedly?
- Is your causal variable (*X*) what differentiates your repeated measurements?

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Repeated Measures Data

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

X: varies between repeated measurements
M: measured in each of the two instances
Y: measured in each of the two instances

Examples:

- Participants read two scenarios. Interested in how scenario influences *Y* through *M*. Measure *M* and *Y* in each scenario.
- Pre-post test: Therapist measures certain symptoms and various outcomes before administering some intervention, and after administering the intervention.
- Researcher interested in if male partners in heterosexual relationships believe fights are less severe because they are less perceptive of small “squabbles”. Measure both male and female partners in relationships, self report number of small “squabbles” and severity of last fight.

Non-Examples:

- Does calorie consumption impact body image through weight gain over time?
- Any instance where repeated-measure factor is a “nuisance” (e.g. studying schools, but not interested in comparing schools directly).

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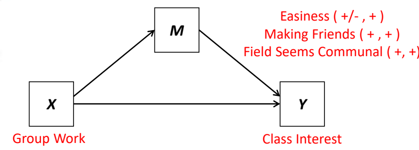
Mediation



A simple mediation model connects an **assumed** causal variable (*X*) to an **assumed** outcome variable (*Y*), through some mechanism (*M*).

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

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

Mediation can be found throughout the psychology literature and is particularly common in social psychology

A quick example: Name some possible mediators!

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A Brief Caution on Causality

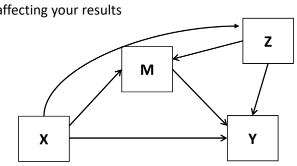
Mediation analysis is an inherently causal model. There are a variety of assumptions needed to know that the model is causal, and most of these are not testable.

1. Temporal precedence (i.e., the variable are in the right order).
   A **cause** must precede an **effect**. This means X must happen before M and Y, and M must happen before Y.
   - Measurement order is necessarily but not sufficient for supporting temporal precedence
   - There is a lot of difficulty in understanding temporal precedence for psychological variables (e.g., mood is a dynamic process, and not something that necessarily “occurs”).
   - Testing models in different orders **DOES NOT** tell us if the order is correct

A Brief Caution on Causality

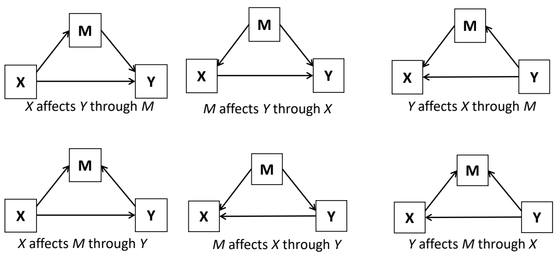
Mediation analysis is an inherently causal model. There are a variety of assumptions needed to know that the model is causal, and most of these are not testable.

2. No-**omitted** confounders
   If there is a variable which is a common cause (i.e., a confounder) of two variables which effect each other in a mediation analysis, we may over or under-estimate their **causal** relationship.
   - Include appropriate covariates in your models to account for potential confounding.
   - If a covariate is presumed to be caused by *X* you must include this as a *serial mediator*
   - Conduct **sensitivity analysis** to examine *how much* confounders might be affecting your results



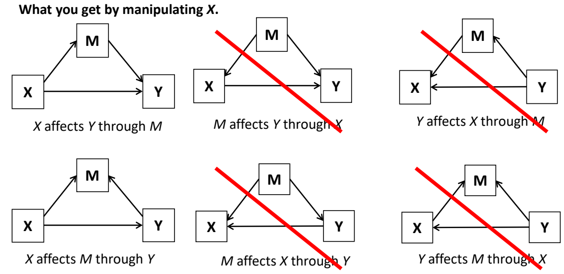
A Brief Caution on Causality

There are a number of alternative causal processes that may be occurring when a *statistical indirect effect* is present (and these are only three variable systems):



A Brief Caution on Causality

What you get by manipulating *X*.

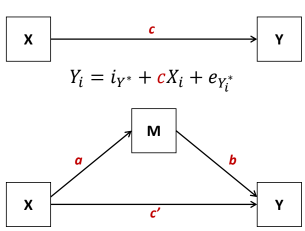


Even when *X* is manipulated, we can not provide evidence for the causal order between *M* and *Y*. This can only be supported using other experiments or previous research. *A statistically significant indirect effect does not lend credence to one model over another.*

Between Subjects Mediation: Path Analysis

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

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



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

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

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

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

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

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

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

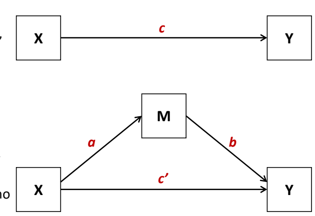
Interpreting the Coefficients

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

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

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

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



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

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). https://psyarxiv.com/ahgfy/

Within-Subjects Version (CompSci_WS.sav) :
Female participants (N = 51) read <u>two syllabi</u> 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 (same as BS version)
  - Two measures: `int_i` `int_g`
- Perceptions that the class has a communal environment.
  - Two measures: `comm_i` `comm_g`
  - Taking this class would assist me in _______________.
  - Helping others, serving the community, working with others, connecting with others, caring for others.
- How difficult would you rate the class you read about?
  - Two measures: `diff_i` `diff_g`

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 <u>fellow students</u> to ensure that you thoroughly understand each concept. Homework assignments may be completed <u>with other students</u>. You are <u>strongly encouraged</u> 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 <u>cited in your assignment</u>. You may seek help from University of Washington CSE 142 TAs, professors, <u>and classmates</u>.

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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You must abide by the following rules:
- You may not work with another student on homework assignments.
- You may not show another student your solution to an assignment, nor look at his/her solution.
- You may not have anyone describe in detail how to solve an assignment or sit with you as you write it.
- You may not post online about your homework to ask others for help.

Judd, Kenny, and McClelland (2001)

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

One of the few treatments of mediation analysis in this common research design.

A "causal steps", Baron and Kenny type logic to determining whether M is functioning as a mediator of X's effect on Y when both M and Y are measured twice in difference circumstances but on the same people.

1. On average, does Y differ by condition?
2. On average, does M differ by condition?
3. Does difference in M predict a difference in Y?
4. Does the difference in M account for all the difference in Y?

Computer Science Within-Subjects Data Example

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

Research Question: Can group work in computer science classes increase women's interest by increasing their perception that computer science is communal?

Data is in *wide form*: repeated measurements of the same variables are saved as separate variables (one row per participant). *Long form* is when there is a variable coding instance of repeated measurements (multiple rows per participant, one for each instance).

CompSci_WS.sav

int_I	int_G	comm_I	comm_G
1.50	4.00	1.00	6.80
2.75	3.25	2.00	5.40
5.75	2.50	3.20	3.60
3.50	5.75	1.60	5.20
2.25	2.00	4.40	4.60
1.50	1.75	3.00	5.00
2.50	4.25	4.20	4.40
6.00	1.75	4.80	2.40
3.00	2.00	2.60	5.80
4.00	5.25	1.60	5.00
5.00	5.00	4.60	6.20
2.00	1.75	3.80	4.20
1.00	1.75	2.60	3.20
1.25	4.50	1.00	6.00
5.75	4.50	2.60	6.00
3.25	4.75	3.00	6.20
2.75	2.25	4.80	4.60
5.50	2.00	4.00	7.00
1.75	5.25	1.60	5.60
4.00	5.50	1.80	5.40
2.25	4.00	2.20	4.80
4.00	6.50	2.00	6.80
5.00	4.50	3.20	6.00

Analysis using Judd et al. (2001)

1. On average, does *Y* differ by condition?

Setup a model of the outcome in each condition:

$$Y_{1i} = c_1 + e_{Y^*_{1i}}$$
$$Y_{2i} = c_2 + e_{Y^*_{2i}}$$

Is c_1 different from c_2?

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 $c_2 - c_1$):

$$Y_{2i} - Y_{1i} = (c_2 - c_1) + \left(e_{Y^*_{2i}} - e_{Y^*_{1i}}\right) = c + e_{Y^*_i}$$

Use intercept only regression analysis, or a paired sample t-test, or a one sample t-test on the differences to conduct inference on $c_2 - c_1$

With the data: On average, is class interest higher in the group work condition?

```
T-TEST PAIRS=int_G WITH int_I (PAIRED).
```

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference: Lower	Upper			
Pair 1	int_G - int_I	.37255	1.99585	.27948	-.18879	.93389	1.333	50	.189

Analysis using Judd et al. (2001)

2. On average, does *M* differ by condition?

Setup a model of the mediator in each condition:

$$M_{1i} = a_1 + e_{M_{1i}}$$
$$M_{2i} = a_2 + e_{M_{2i}}$$

Is a_1 different from a_2?

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 $a_2 - a_1$):

$$M_{2i} - M_{1i} = (a_2 - a_1) + \left(e_{M_{2i}} - e_{M_{1i}}\right) = a + e_{M_i}$$

Use intercept only regression analysis, or a paired sample t-test, or a one sample t-test on the differences to conduct inference on $a_2 - a_1$

With the data: On average, is communal goal affordance higher in the group work condition?

```
T-TEST PAIRS=comm_G WITH comm_I (PAIRED).
```

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference: Lower	Upper			
Pair 1	comm_G - comm_I	2.29412	1.77870	.24907	1.79385	2.79438	9.211	50	.000

Analysis using Judd et al. (2001)

3. Does difference in *M* predict a difference in *Y*? / Does *M* predict *Y* controlling for condition?

Setup a model of the outcome in each condition:

$$Y_{1i} = g_{10} + g_{11}M_{1i} + e_{Y_{1i}}$$
$$Y_{2i} = g_{20} + g_{21}M_{2i} + e_{Y_{2i}}$$

Note that there are **two estimates** of the effect of *M* on *Y*. Let's average them to estimate an average effect of *M* on *Y*. Setup a new model where you can directly estimate and conduct inference on what you are interested in (in this case $\frac{1}{2}(g_{21} + g_{11})$):

Optional board work

$$Y_{2i} - Y_{1i} = (g_{20} - g_{10}) + g_{21}M_{2i} - g_{11}M_{1i} + (e_{Y_{2i}} - e_{Y_{1i}})$$

$$Y_{2i} - Y_{1i} = \underbrace{(g_{20} - g_{10})}_{c'^*} + \underbrace{\frac{g_{21}+g_{11}}{2}}_{b}(M_{2i} - M_{1i}) + \underbrace{\frac{(g_{21}-g_{11})}{2}}_{d}(M_{2i} + M_{1i}) + (\underbrace{e_{Y_{2i}} - e_{Y_{1i}}}_{e_{Y_i}})$$

$$Y_{2i} - Y_{1i} = c'^* + b(M_{2i} - M_{1i}) + d(M_{2i} + M_{1i}) + e_{Y_i}$$

Analysis using Judd et al. (2001)

3. Does M predict Y controlling for condition?

With the data: Does communal goal affordance predict interest in the class?

```
compute int_diff = int_G - int_I.
compute comm_diff = comm_G - comm_I.
compute comm_sum = comm_G+comm_I.
EXECUTE.
regression dep = int_diff /method = enter comm_diff comm_sum.
```

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.310	1.877		.698	.489
	comm_diff	.590	.135	.526	4.385	.000
	comm_sum	-.275	.216	-.153	-1.272	.210

a. Dependent Variable: int_diff

✓

Analysis using Judd et al. (2001)

4. Does the difference in communal goal affordance account for all the difference in interest?

$$Y_{2i} - Y_{1i} = c'^{*} + b(M_{2i} - M_{1i}) + d(M_{2i} + M_{1i}) + e_{Yi}$$

Next we center the sum term, so the intercept has the interpretation of the predicted difference in Y for someone with no difference in M's but is average on M's.

$$Y_{2i} - Y_{1i} = c' + b(M_{2i} - M_{1i}) + d(M_{2i} + M_{1i} - (\overline{M_2 + M_1})) + (\epsilon_{Y2i} - \epsilon_{Y1i})$$

where $c' = \left(g_{20} - g_{10} + d(\overline{M_2 + M_1})\right)$

Intercept is predicted *outcome* when all regressors are zero. This means predicted difference in Y when there is no difference in M and a person is average on the sum of M.

Analysis using Judd et al. (2001)

4. Does the difference in communal goal affordance account for all the difference in interest?

With the data: Is there a significant difference in interest predicted when there is no difference in communal goals?

```
compute comm_sumc = comm_G+comm_I- 8.325490.
EXECUTE.
regression dep = int_diff /method = enter comm_diff comm_sumc.
```

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.981	.388		-2.527	.015
	comm_diff	.590	.135	.526	4.385	.000
	comm_sum	-.275	.216	-.153	-1.272	.210

a. Dependent Variable: int_diff

✗

Analysis using Judd et al. (2001)

1. ✗ On average, is interest higher in the group work condition?
2. ✓ On average, is communal goal affordance higher in the group work condition?
3. ✓ Does difference in communal affordance predict a difference in interest?
4. ✗ Does the difference in communal goal affordance account for all the difference in interest?

According to Judd, Kenny, and McClelland we do not have a mediated effect!

Because there is no evidence that interest is higher in the group work condition, the Judd et al. (2001) method would conclude there is not mediation.

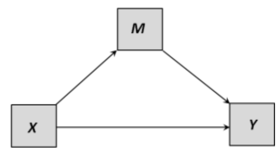
Judd et al. Criticisms and Misuses

Problems with this approach
- No estimate of the indirect effect
- No quantification of uncertainty about conclusion
  - *p*-value
  - Confidence Interval
- Requirement that the total effect is significant before looking for indirect effect
  - The direct and indirect effect could be of opposite sign
  - There is greater power to detect the indirect effect than direct effect *(Judd, Kenny, 2014, Psych Science)*
- Multiple testing problem
- Issues with *complete* and *partial* mediation

This method has been used by a variety of researchers:
- Approximately 600 citing papers
- Many researchers do not report or estimate the partial regression coefficient for the sum of the mediators
- Because the estimate of the indirect effect is not made explicit, researchers often misinterpret the coefficients
  - b_1 path is often interpreted as indirect effect
- Extensions to more complicated models have been poorly implemented

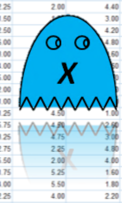
Can we think about it like a path analysis?

Analytic Goal: Can <u>group work</u> in computer science classes increase women's <u>interest</u> by increasing their perception that computer science is <u>communal</u>?



Where is *X* in the data?

Y_1	Y_2	M_1	M_2
int_I	int_G	comm_I	comm_G
1.50	4.00	1.00	6.80
2.75	3.25	2.00	5.40
5.75	2.50	3.20	3.60
3.50	5.75	1.60	5.20
2.25	2.00	4.40	4.60
1.50	[illegible]	3.00	5.00
2.50	[illegible]	4.20	4.40
6.00	[illegible]	4.80	2.40
3.00	[illegible]	[illegible]	5.80
4.00	[illegible]	[illegible]	5.00
5.00	[illegible]	[illegible]	6.20
2.00	[illegible]	[illegible]	4.20
1.00	[illegible]	[illegible]	3.20
1.25	4.50	1.00	6.00
5.75	4.80	2.60	6.00
3.25	4.75	3.00	6.20
2.75	2.25	4.80	4.60
5.50	2.00	4.00	7.00
1.75	5.25	1.60	5.60
4.00	5.50	1.80	5.40
2.25	4.00	2.20	4.80
4.00	6.50	2.00	6.80
5.00	4.50	3.20	6.00
5.00	3.75	4.00	4.80
4.75	5.25	1.20	6.60



Advantages of a path analytic approach

Provides an estimate of the indirect, total, and direct effects
- Allows us to conduct inferential tests directly on an estimate of the indirect effect

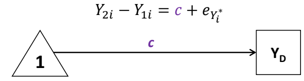
Connects researchers understanding of between-subjects mediation to within-subjects mediation
- Reduce misinterpretation of regression coefficients

Using a path analytic framework will help extend the simple mediation model to more complicated questions
- Multiple mediators
- Moderated mediation
- Integration of between and within-subjects designs

Path-Analytic Approach

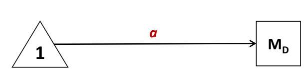
Total Effect (*c*): The effect of our presumed cause (*X*) on our outcome (*Y*), without controlling for any other variables. (i.e. mean difference in outcome between the two conditions).

$$Y_{2i} - Y_{1i} = c + e_{Y_i^*}$$



***a*-path:** The effect of our presumed cause (*X*) on our mediator *(M)*. (i.e. mean difference in mediator between the two conditions).

$$M_{2i} - M_{1i} = a + e_{M_i}$$

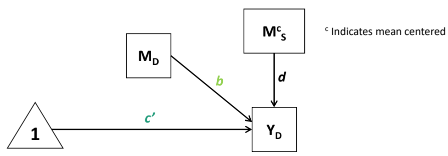


Path-Analytic Approach

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

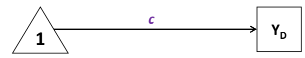
Direct effect (*c'*): The effect of our presumed cause (*X*) on *Y* while controlling for *M*. (i.e. predicted difference in *Y* for two people who differ by one unit on *X* but with the same score on *M*)

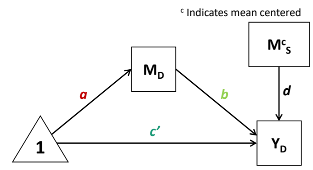
$$Y_{2i} - Y_{1i} = c' + b(M_{2i} - M_{1i}) + d(M_{2i} + M_{1i} - \overline{(M_2 + M_1)}) + e_{Y_i}$$



Path-Analytic Approach

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





Within Subjects: Path Estimates

Total Effect *c*: (Regress Y_D on a constant)

$\widehat{Y_D} = c$

$\widehat{Y_D} = .373$

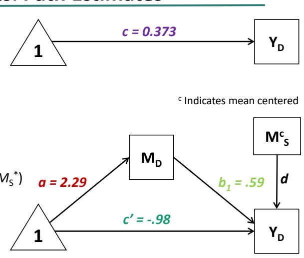
a path: (Regress M_D on a constant)

$\widehat{M_D} = a$

$\widehat{M_D} = 2.29$

b path and *c'* path: (Regress Y_D on M_D and M_S^*)

$$\widehat{Y_D} = c' + b_1 M_D + dM_S^c + e_3$$
$$\widehat{Y_D} = -.98 + .59 M_D - .28 M_S^c$$



A one unit increase in the difference in communal goal affordance is expected to result in a .59 unit increase in the difference in interest.
People with no difference in communal goal affordance perceptions are expected to be .98 units more interested in the individual class than the group work class .

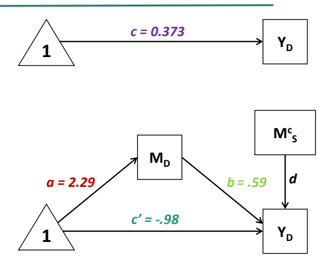
Note: M_S must be mean centered for c' to have intended interpretation

Data Example: Partitioning effect of X on Y

The effect of *X on Y* partitions into two components: direct and indirect, in the usual way.

c	=	c'	+	a	x	b
.373	=	-.98	+	2.29	x	.59
.373	=	-.98	+	1.35		

We can conduct inferential tests on the estimate of the indirect effect as in any other mediation analysis.



MEMORE has three methods of inference for the indirect effect available: bootstrapping, Monte Carlo confidence intervals, Sobel Tests

Inference about the Indirect Effect

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

- Why is this so hard?
  - The product of two normal distributions is not necessarily normal. The shape of the distribution of the indirect effect depends on the true indirect effect.
  - There are many instances where the indirect effect could be zero (either a or b could be zero, or both could be zero).

Causal Steps Method

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

Appeal
- Easy to do, just need regression
- Intuitive

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

This just the JKM Method but for Between Subjects Designs

Joint Significance

Method
1. Test if there is a significant effect of X on M ($a \neq 0$).
2. Test if there is a significant effect of M on Y controlling for X ($b \neq 0$).

Appeal
- Easy to do, just need regression
- Intuitive
- Solves issues of requirement of significant total effect to claim an indirect effect.
- Good method balance Type I Error and Power

What's wrong with it?
- No estimate of the indirect effect
- No quantification of uncertainty about conclusion
  - *p*-value
  - Confidence Interval
- Multiple testing problem

Bootstrap Confidence Intervals (Percentile)

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

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

Appeal
- No assumptions about the sampling distribution of the indirect effect
- Provides point estimate of indirect effect
- Can calculate confidence intervals
- Good method balance Type I Error and Power

What's wrong with it?
- Most software does not have this functionality built in
- Requires original data

Bootstrap Confidence Intervals

Original Data

M_D	M_s	Y_D
-0.35	-0.58	0.25
0.31	-0.50	1.89
-0.19	2.61	2.08
-1.30	-1.49	-0.54
0.59	1.14	1.74
-0.29	-0.29	1.04
1.80	0.08	1.23
-0.01	1.20	1.30
0.30	1.35	1.31
-0.98	0.90	-0.76

a = -.0120 *b* = .610

ab = -0.007

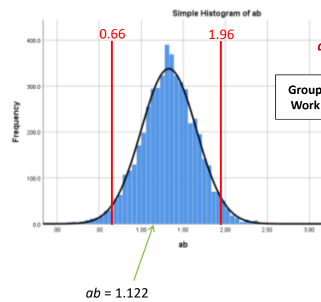
Bootstrap Sample

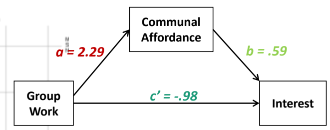
M_D	M_s	Y_D

a = 0.1550 *b* = 0.764

ab = 0.118

Bootstrap Confidence Intervals (CompSci_WS Data)



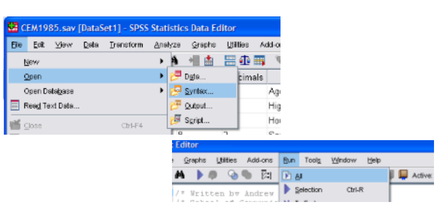


ab = 1.122

Zero is not contained in the 95% confidence interval [0.66, 1.96] so we conclude the indirect effect is different from zero with 95% confidence. This is the similar to rejecting the null hypothesis at α = .05.

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` or `W`)

```
MEMORE m= comm_G comm_I /y = int_G int_I /normal=1/samples=10000
    /conf = 90 /model = 1.
```

M is your list of mediators (order matters)
Y is you list of outcomes (order should be matched to the order in the M list)

Some other arguments:

- **model** specifies the model you are interested. The default is 1, mediation. Moderation models are 2 and 3.
- **normal = 1** asks for Sobel test
- **samples** corresponds to the number of bootstrap/MC samples you would like
- **conf** specifies level of confidence you want (default is 95)
- **mc = 1** asks for Monte Carlo confidence intervals
- **bc = 1** asks for bias corrected bootstrap confidence intervals

Using MEMORE for CASC WS data

```
MEMORE m= comm_G comm_I /y = int_G int_I /model = 1.
```

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

                         Written by Amanda Montoya

                  Documentation available at akmontoya.com

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

Model:
  1

Variables:
Y = int_G    int_I
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
```

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

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Using MEMORE for CASC WS data

```
MEMORE m= comm_G comm_I /y = int_G int_I /model = 1.
```

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

Model
         Effect        SE         t         p      LLCI      ULCI
'X'       .3725     .2795    1.3330     .1886    -.1888     .9339

Degrees of freedom for all regression coefficient estimates:
  50

***************************************************************************************
Outcome: Mdiff =  comm_G    -       comm_I

Model
         Effect        SE         t         p      LLCI      ULCI
'X'      2.2941     .2491    9.2108     .0000    1.7938    2.7944

Degrees of freedom for all regression coefficient estimates:
  50

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

Outcome variable

c = .37

a = 2.29

First few sections are regression models involved in the mediation analysis. This is the model of *Y* from *X*, therefore this is the model which produces the estimate of *c*

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Using MEMORE for CASC WS data

```
MEMORE m= comm_G comm_I /y = int_G int_I /model = 1.
```

```
***************************************************************************************
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
'X'          -.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
```

This is the model predicting Y_D from a constant, M_D, and M^c_{avg} therefore this model gives us an estimate of b and c'

c' = -.98

b = .590

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Using MEMORE for CASC WS data

```
MEMORE m= comm_G comm_I /y = int_G int_I /model = 1.
```

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

Total effect of X on Y
     Effect        SE         t        df         p      LLCI      ULCI
      .3725     .2795    1.3330   50.0000     .1886    -.1888     .9339

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

Indirect Effect of X on Y through M
         Effect    BootSE  BootLLCI  BootULCI
Ind1     1.3540     .3281     .6678    1.9608

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

Important effects for mediation and inference about these effects

Based on a 95% bootstrap confidence interval we have evidence of mediation!

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Using MEMORE for CASC WS data

```
MEMORE m= comm_G comm_I /y = int_G int_I /model = 1.

*************************** ANALYSIS NOTES AND WARNINGS ****************************

Bootstrap confidence interval method used: Percentile bootstrap.

Number of bootstrap samples for bootstrap confidence intervals:
  5000

The following variables were mean centered prior to analysis:
 (        comm_G     +        comm_I    )         /2

Level of confidence for all confidence intervals in output:
      95.00
```

Check here for error messages, warnings, and additional information

Writing up a Repeated Measures Mediation Analysis

Tips:

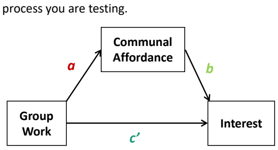
- Walk the reader through the **steps** of the mediation in a way that is intuitive.
  - Include interpretations of the results: b.e.g. "The total effect was significant, $p < .05$"
- Use equations and numbers *where helpful*.
- Avoid using computational variable names (e.g. RESPAPPR)
- Avoid causal language if it is not supported by your research design.
- Pick one inferential method and report it
- Read the write ups of other's mediation analyses

Is the effect of group work on class interest mediated by communal goal affordance of the class?

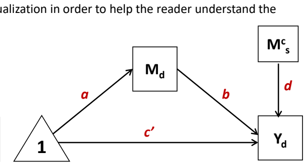
Overall there was not strong evidence of a total effect of group work on interest in computer science classes, we estimate that individuals were .37 units higher on interest in group work than individual work classes (p = .19). The class with group work was rated 2.29 units higher on communal goal affordance than the class with individual work (p < .001). A one unit increase in perception of communal goal affordance increased interest in the class by .59 units (p = .0001), and the relationship between communal goal affordance and interest in a class did not depend on condition (p = .21). The effect of group work on interest through communal goal fulfillment was different from zero (ab = 1.35, 95% Bootstrap CI [.68, 1.96]). This means that we expect women to be 1.35 units more interested in a computer science class with group work compared to one without group work, through the effect of group work on communal goal affordance, and the subsequent effect of communal goal affordance on interest. There was a significant direct effect between group work and interest (c' = -.98, p = .01). This indicates that there may be some other process, separate from communal goal affordance, which is actually deterring women from computer science classes with group work.

Visualizations

I suggest using both a conceptual and statistical visualization in order to help the reader understand the process you are testing.



Conceptual



Statistical

Tips:

- Providing a conceptual diagram helps the readers understand the process you are interested in.
- Providing a statistical diagram helps readers understand how you estimated the model, and that you did it correctly.
- Provide path estimates on statistical diagram or in a table.
- Don't forget to report the path estimates and statistics for the *d* path. It's important!

Planning Your Studies

Recent evidence suggests that p-hacking (or CI-hacking) is very common for mediation analyses in psychology.

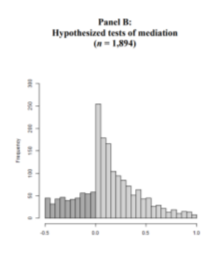
Increased skepticism of mediation analyses will mean you have to plan accordingly.

Preregister:

- Report your planned sample size and exclusion criteria
- Describe which variables play which role in your mediation analysis (X, M, Y, covariates)
- Describe how each variable will be calculated from your raw data (means, factor analysis, sum scores)
- Report which test of mediation you will use, at what level, how many bootstraps, and can even select a seed for your bootstrapping

Power analysis:

- Many tools available for power analysis for mediation (pwr2ppl, MCpowrMed, WebPower, Bmem, MedPower)
- Either need estimates of paths or correlations
- For MEMORE see included R script, coming soon with Montoya (*under review*).



Gotz, Gonzalez-Mule, Banks, Boyle, Bollman, *in press*

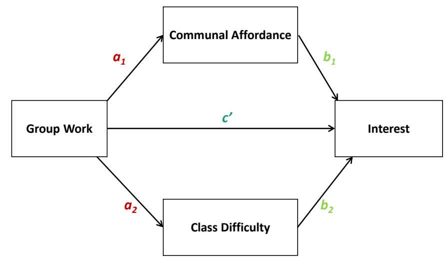
Common Questions

- Can this method be used for more than two conditions?
  YES! Judd, Kenny, and McClelland (2001) describe a system for setting up contrasts among conditions, and testing the indirect effects of those contrasts.
  I recommend reading Hayes & Preacher (2014) on mediation analysis with a multicategorical IV if you want to try this out. I am happy to give instructions on how to trick MEMORE into doing this. There will be functionality (soonish) for MEMORE to do 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 mediators?
  YES! MEMORE is already set up to do parallel mediation with up to 10 sets of mediators and serial mediation with up to two sets of mediators (See Montoya & Hayes, in press for instructions).
- Can we do conditional process models?
  Not yet, but we're working on it. If you want to use Mplus, there is example code available.
- 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.
  Sometimes there are covariates which change within a person across conditions that you want to account for, this can be done by treating this additional variable as another set of mediators.

Using MEMORE for CASC WS data

Do people just like group work classes because they are easier?



Using MEMORE for CASC WS data

Do people just like group work classes because they are easier?

```
MEMORE m = comm_I comm_G diff_I diff_G /y = int_I int_G.
```

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

Model Summary
         R       R-sq        MSE          F        df1        df2          p
     .6307      .3978     2.6073     7.5978     4.0000    46.0000      .0001

Model
              coeff         SE          t         df          p       LLCI       ULCI
'X'           .9172      .3815     2.4042    46.0000      .0203      .1493     1.6851
M1diff        .4847      .1448     3.3460    46.0000      .0016      .1931      .7762
M2diff       -.4123      .1878    -2.1952    46.0000      .0332     -.7904     -.0342
M1avg         .5160      .4157     1.2411    46.0000      .2209     -.3209     1.3528
M2avg        -.3781      .2879    -1.3133    46.0000      .1956     -.9577      .2014
```

Notice that we are now **controlling** for difficulty of the class when estimating the effect of communal goal affordance on interest!

Using MEMORE for CASC WS data

Do people just like group work classes because they are easier?

```
MEMORE m = comm_I comm_G diff_I diff_G /y = int_I int_G.
```

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

Total effect of X on Y
    Effect         SE          t         df          p       LLCI       ULCI
    -.3725      .2795    -1.3330    50.0000      .1886     -.9339      .1888

Direct effect of X on Y
    Effect         SE          t         df          p       LLCI       ULCI
     .9172      .3815     2.4042    46.0000      .0203      .1493     1.6851

Indirect Effect of X on Y through M
          Effect     BootSE   BootLLCI   BootULCI
Ind1     -1.1119      .3812    -1.8531     -.3522
Ind2      -.1779      .1160     -.4465      .0000
Total    -1.2897      .3507    -1.9566     -.5612

Indirect Key
Ind1  X       ->      M1diff    ->       Ydiff
Ind2  X       ->      M2diff    ->       Ydiff
```

Controlling for difficulty, there is still a significant indirect effect through communal affordance!

Other Types of Repeated Measures Mediation

- Multilevel Models
  - Bauer, Preacher, Gil (2006) *Psychological Methods*

  Covers Mediation and Moderated Mediation for 1-1-1 multilevel mediation
  - Kenny, Korchmaros, Bolger (2003) *Psychological Methods*

  Covers mediation for 1-1-1 multilevel models
  - MLMed Macro (njrockwood.com)
- Latent Growth Curve Models (Longitudinal Processes M-Y measured over time)
  - Choeng, MacKinnon, Khoo (2003) *Structural Equation Modeling*
- Structural Equation Modeling (Can be used for a variety of data types)
  - Cole & Maxwell (2003) *Journal of Abnormal Psychology*
    X, M, and Y all measured over time
  - Newsom (2009) *Structural Equation Modeling*
    Dyadic data using LGMs
  - Selig & Little (2012) *Handbook of Developmental Research Methods*
    Autoregressive models and cross-lagged panel models for longitudinal data X, M, and Y all measured over time.
- **Selig & Preacher (2009) *Research in Human Development***
  - **Longitudinal Models X, M, and Y measured across time. Cross-lagged panel models, latent growth models, latent difference score models**
- Multilevel SEM
  - Preacher, Zyphyr, Zhang, 2010
  - Preacher, Zhang, Zyphur, 2011

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Moderation

- Two-Condition Within Subjects Moderation
  - Judd Kenny and McClelland (2001, 1996)
  - Interpretations
  - Probing
  - MEMORE
  - Reporting (Writing and Figures)
  - Common Questions
- Other Types of Repeated Measures Moderation
  - Multilevel
  - Longitudinal
  - Multilevel SEM

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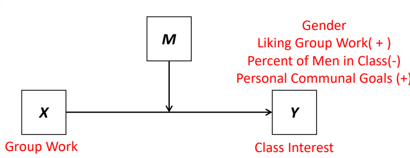
Moderation



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!

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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) :

Female participants (N = 51) read <u>two syllabi</u> 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 ($\alpha = .87$)
  - Same as between subjects version
- `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.

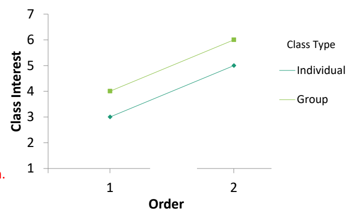
$$Y_{1i} = b_{10} + b_1 W_i + \epsilon_{1i}$$

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

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

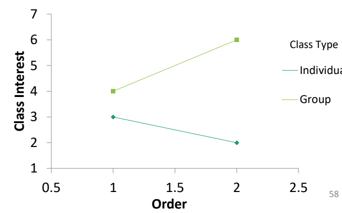
$$Y_{1i} = b_{10} + b_{11} W_i + e_{1i}$$

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

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

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.

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



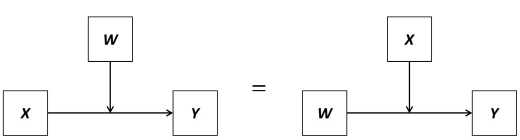
Symmetry in Within-Subjects Moderation

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.

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.

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

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Analysis using Judd et al. (1996)

2. Setup two regression equations, one for each condition

Setup a model of the outcome in each condition:

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

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.
```

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

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Analysis using Judd et al. (1996)

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

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

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

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.

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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

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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?

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

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

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

Conditional effects will become important when it comes to probing

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

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

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 $\theta_{X \to Y}(W)$ is

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

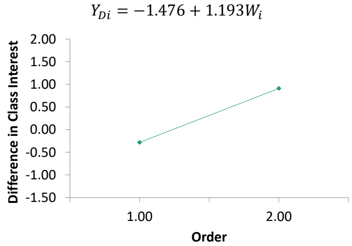
Squared standard error of b_0 Covariance of b_0 and b_1 Squared standard error of b_1

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:

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

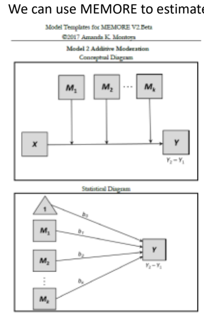


W	$\theta_{X \to Y \mid W}$	$s_{\theta_{X \to Y \mid W}}$	*p*
1	-.2826	0.4010	.4843
2	.9107	.3634	.0156

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.




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

- 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 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.
```

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.
```

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.
```

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

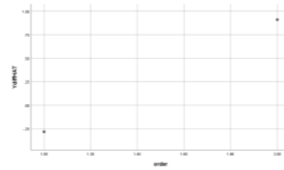
```
MEMORE w = order /y = int_G int_I /model = 2 /plot = 1.
```

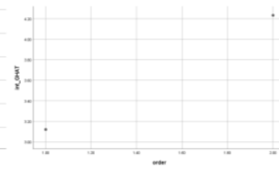
```
Data for visualizing conditional effect of X on Y.
Paste text below into a SPSS syntax window and execute to produce plot.

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.
```

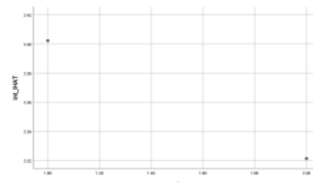
Code for plotting. You'll get three plots each with the moderator on the *X* axis and a different outcome on the *Y* axis.

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

Graphs







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

Summarizing

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 ($\theta_{X\to Y|W} = -.283, p = .48$). But among those who read the individual work syllabus first, they were significantly more interested in the group work class ($\theta_{X\to Y|W} = .9107, p = .0156$). 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 ($\theta_{W\to Y|X} = 1.1126, p = .0065$); whereas, order did not significantly predict interest in the individual work class ($\theta_{W\to Y|X} = -.0807, p = .8446$). 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

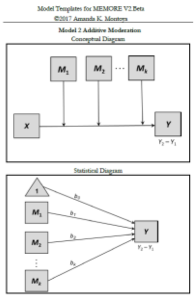
Does effect of <u>group work</u> on <u>interest</u> in computer science classes depend on an individual's <u>preference for group work</u>?

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.




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

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

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

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

Using MEMORE for CASC WS data

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

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

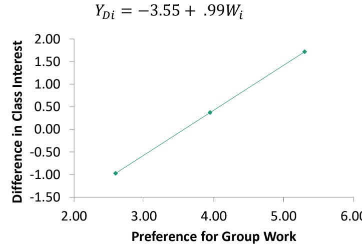
Strong evidence for moderation, where as preference for group work increases, the difference between interest in the two classes increases.

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	$\theta_{X\to Y\|W}$	$s_{\theta_{X\to Y\|W}}$	*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.
```

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

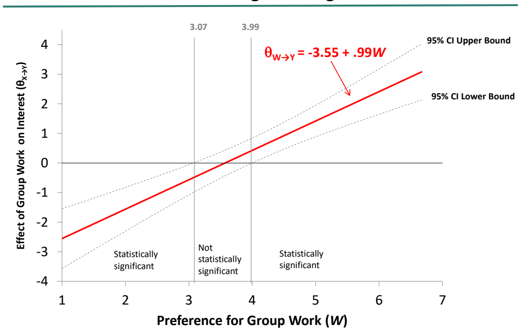
The Johnson-Neyman technique seeks to find the value or values of the moderator (*W*) within the data, if they exist, such that the *p*-value for the conditional effect of condition at that value or those values of *W* is exactly equal to some chosen level of significance α. Thus, no need to select values 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 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 <u>positively predicts</u> interest in **class with group work**

and <u>negatively predicts</u> 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:

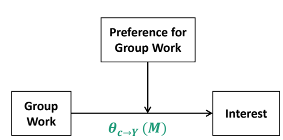
- Interpret the sign and the magnitude of the interaction coefficient with respect to *X*'s effect on *Y* (or *M*'s effect on *Y*; or both).
- Provide probing results with interpretations
- Read the write ups of other's moderation analyses
- Provide a graphical representation of the effect of interest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

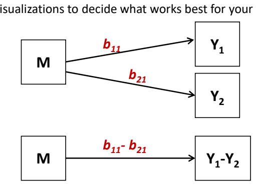
Overall, the impact of including group work in a computer science class on interest in the class depends on an individual's general preference for group work (b_1 = .49, p = .001). As preference for group work increases relative interest in the class with group work compared to the class with individual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

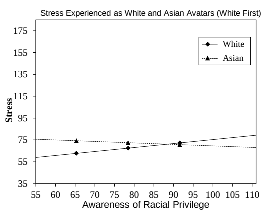
Tips:

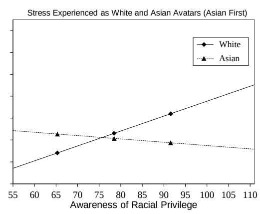
- Try the different scales of the *Y* axis (difference vs. raw Y score with two lines for each condition)
- I do not like bar graphs with the effect of the moderator in each condition
- Provide path estimates on statistical diagram or in a table.

Visualizations: A Case Study

Tawa, J., & **Montoya, A. K.** (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.



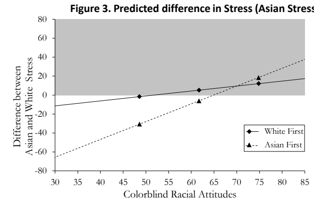


Visualizations: A Case Study

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.

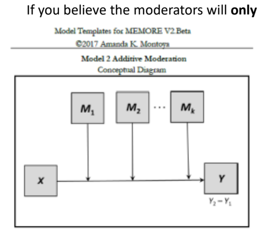
  ALTERNATIVES: Some of the other repeated-measures mediation options are more appropriate if you have more than two conditions (especially longitudinal), so take a look at those when thinking about these options.
- Can I use multiple moderators?
  YES! MEMORE models 2 and 3 accept up to 5 moderators. (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).

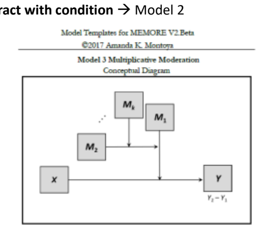
Multiple Moderator Models

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





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 two two-way interactions:
Condition x Group Preference
Condition x Order

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

Other Types of Repeated Measures Mediation

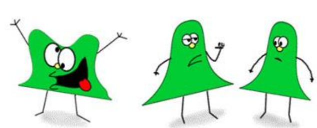
- Multilevel Models (Cross level interactions in particular)
  - Aguinis, Gottfredsom, Culpepper (2013) *Journal of Management*
  Very approachable article on estimating cross-level interactions
  - Bauer & Curran (2010) *Multivariate Behavioral Research*
  Estimating and probing interactions in multilevel models
  - Many many others!
- Latent Growth Curve Models
  - Preacher, Curran, Bauer (2006) *Journal of Educational and Behavioral Statistics*
    Also has MLM and regression
- Structural Equation Modeling (Can be used for a variety of data types)
  - Klein & Muthen (2007) *Multivariate Behavioral Research*
    Methods for including latent interactions
- Multilevel SEM
  - Preacher, Zhang, Zyphur (2016) *Psychological Methods*
    Very technical read, but deals with a lot of the issues of bias in MLM
  - Ryu (2015) *Structural Equation Modeling*
    Impact of centering in MSEM

Thank you!

I am available for questions after the workshop and via email at akmontoya@ucla.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.



"KEEP YOUR EYE ON THAT GUY, TOM. HE'S NOT, YOU KNOW...NORMAL!"

Other Kinds of Bootstrap Confidence Intervals

All bootstrap confidence intervals use the same basic sampling technique, just use different methods for choosing the end points of the confidence intervals

Bias-Corrected Confidence Interval

- Percentile bootstrapping assumes that your sample estimate (*ab*) is unbiased in estimating the population indirect effect
- Bias-corrected reduces this assumption to assuming that the bias of *ab* is a constant (i.e. as N goes to infinity *ab* will go to the population indirect effect plus some constant)
- Bias-corrected confidence intervals estimate the bias of *ab* then adjust edges of confidence interval to be "bias-corrected" (i.e. centered not around your original estimate of *ab*), but around the point based on the bias estimation.

Bias-Corrected and Accelerated

- Same principles as BC regarding bias correction
- Acceleration allows for the assumption that the standard error of the indirect effect depends on the population value of the indirect effect
- Acceleration parameter, which is used to adjust the ends of the confidence interval is estimated using leave-one-out estimates of skew of the estimates of the indirect effect.