Mediation with Repeated-Measures and Multilevel Data

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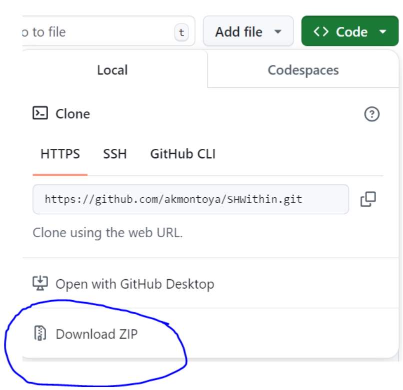
University of California, Los Angeles

September 12 & 13, 2024

Please go to https://github.com/akmontoya/SHWithin.git
Download the whole folder.



General Outline

Day 1

Introduction

- Within- and between-subject designs
- Overview of between-subject mediation

Within-Subject Mediation

- Estimation & Inference
- MEMORE Macro
- Issues of Causality
- Power Analysis
- Preregistration and writing guides
- Visuals for Publication
- Multiple Mediator Models

Wrap Up: Extensions and Next Steps

General Outline

Day 2

Between-subject moderation (review)

Within-Subject Moderation

- Estimation & Inference
- Visualizations
- Probing interactions
- MEMORE Macro
- Power Analysis
- Preregistration and writing guides

(If time) Within-Subject Moderated Mediation

- Estimation & Inference
- Visualizations
- Probing Conditional Effects
- MEMORE Macro
- Preregistration and Writing Guides

Wrap Up

Workshop Procedures

Assuming some familiarity with:

- Linear Regression
- (Some) Mediation & Moderation in BS-Design
- SPSS or SAS

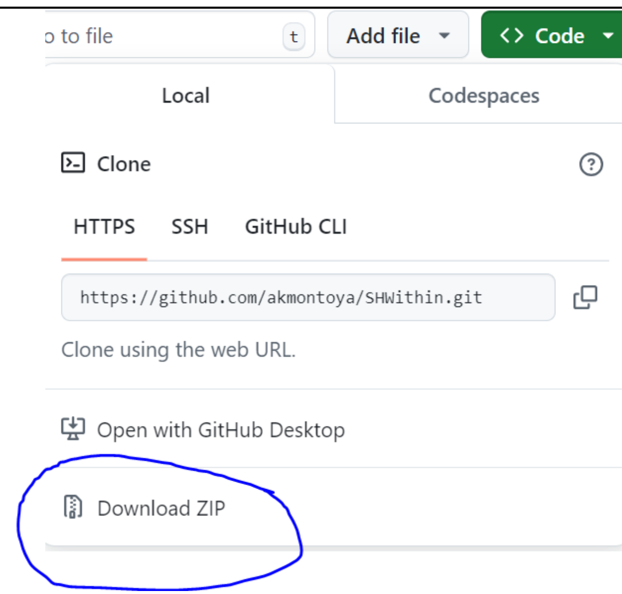
Class time:

10:30am – 12:30pm EST

BREAK/Activity

1pm – 3pm EST

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



How we will learn:

- Combination of theory and practice
- Follow along with the analysis as we go
  - Use syntax!
  - **<u>Ask questions</u>** about concepts or anything that is confusing

What You'll Need

- **This course is hands-on. Hopefully you brought a laptop with R 3.6.1, SPSS 19+ or SAS 9.1+ with PROC IML. If not, that is ok. You'll still benefit.**

SPSS Code	SAS Code	R Code

- **Various files available on GitHub.**
  - SPSS, SAS, and R data folders. SPSS data files are ready to go. SAS files are programs thus must be executed to make them "work" files. R files are CSV and need to be read into R.
  - Macro files. This contains the MEMORE macro we'll heavily rely on, and some documents related to it.
  - Miscellaneous folder. Various files, including some PDFs and other miscellaneous things of relevance to this course.

- **A lot of stamina.**

Setting Up in R

A few packages I'm going to use throughout the workshop:

```
install.packages(c("mosaic", "ggformula", "jtools", "dplyr"))
library(mosaic)
library(ggformula)
library(jtools)
library(dplyr)
```

Loading in data:

```
filelocation <- "C:\\Your\\Path\\Here\\harass.csv"
harass <- read.csv(filelocation, header = TRUE)
```

You are welcome to deviate from the way I do things, if you have a preferred package for certain types of operations, feel free to do so.

Experimental Designs

This course focuses on two types of designs:

- Between-subject
- Within-subject

Whether we are doing mediation or moderation, there will always be a focal predictor (X) and an outcome (Y).

To determine the type of design, we only need to focus on X and Y.

Between-Subject Design

- X is observed only once per subject
  - Randomly assigned (e.g., condition in a study)
  - Observed (e.g., handedness)

- Y is observed only once per subject
  - Only observed (e.g., typing speed)

Examples of Between-Subject Designs

Human participants are randomly assigned to complete a math test in either a hot or cold (X = temperature) room. Their performance on that math test (Y) is then measured.

Assigned

Researchers want to compare start-ups in finance to those in health (*X* = type of company) on their number of employees in their first two years (*Y*)

Observed

In this course X will typically be categorical, but it can also be continuous.

Within-Subject Design

- *X* is observed or assigned multiple times per subject
  - Assigned (e.g., participate in both conditions)
    - Every subject is observed under the same values of *X*
  - Observed (e.g., measured across time)
    - Values of *X* may differ across participants

- *Y* is observed under each instance of *X*
  - Only observed (e.g., typing speed)

Examples of Within-Subject Designs

Human participants are complete a math test both a hot and a cold (*X* = temperature) room. Their performance on that math test (*Y*) is then measured.

Assigned

Number of employees (*Y*) is measured at the end of the first year and second year (*X* = age of startup) across many start-ups.

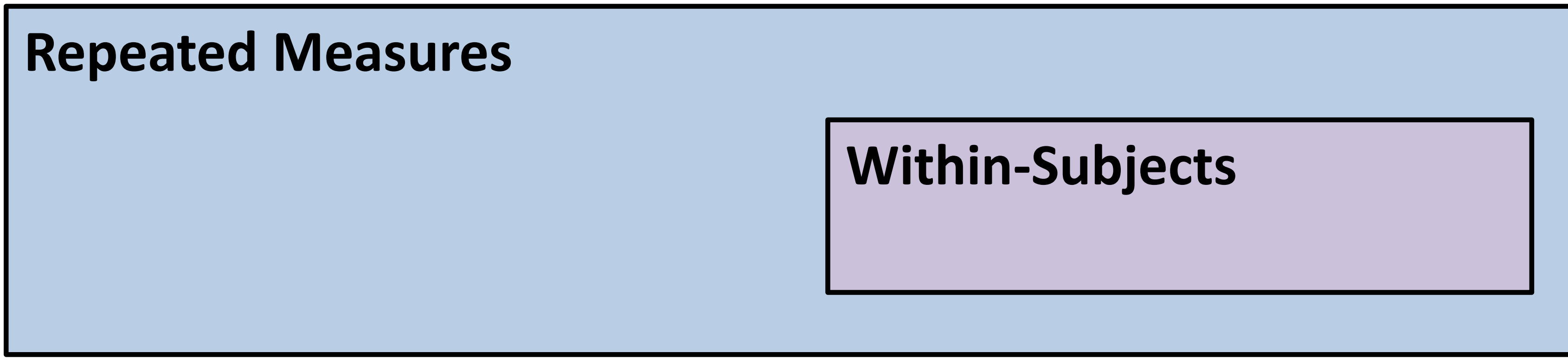
Assigned

Number of employees (*Y*) is measured one year apart for each start-up (*X* = age of startup)

Observed

Repeated-Measures vs Within-Subjects

Used very similarly



Types of Repeated-Measuresments

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

Repeated Measures Data

It's important to think about how/when/how many times the variables in your mediation model are measured

- Within-Subject: X and Y are assigned/observed repeatedly
- *Multilevel* has a nice system referring to levels (1-1-1 mediation, 2-2-1, mediation etc.
- Is your focal predictor measured repeatedly?
- Is your focal predictor what differentiates your repeated measurements?

Our Focus: Two Instance Repeated-Measures

The focal predictor is the factor which differs by repeated measures.

X: is assigned twice
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.

Counter Examples

- Does calorie consumption (*X*) impact body image (*Y*) through weight gain (*M*) over time?
  - *X* is observed (not assigned), so difference subjects have different *X*s. Can be dealt with in Multilevel or Latent Growth approaches.
- Any instance where repeated-measure factor is a “nuisance” (e.g. studying schools, but not interested in comparing schools directly).
  - *X* is observed and doesn’t vary within subjects of study

Mediation

- Between Subjects
  - Path analytic approach
  - Interpretation
  - Estimation
  - Inference

- Two-Instance Repeated-Measures
  - Judd Kenny and McClelland (2001)
  - Path analytic approach
  - Estimation of Indirect Effects
  - MEMORE
  - Reporting (Writing and Figures)
  - Causal inference
  - Study Planning (Power Analysis & Preregistration)
  - Multiple Mediator Models

Running Example: Group Work in Computer Science (BS)

Montoya, A. K. (2013) Increasing Interest in Computer Science thought Group Work: A Goal Congruity Approach. https://osf.io/preprints/psyarxiv/ahgfy

Between-Subjects Version (CompSci_BS.sav, CompSci_BS.sas) :
Female participants (N = 107) read *one of two* syllabi for a computer science class. One of the syllabi reported the class would have group projects throughout (`cond = 1`), and the other syllabi stated that there would be individual projects (`cond = 0`) throughout the class.

Measured Variables:

– `Interest` in the class ($\alpha = .89$)
  - How interested are you in taking the class you read about?
  - How much would you want to take the class you read about?
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  - How interested are you in majoring in computer science?
  - 1 Not at All – 7 Very much

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

Instructor

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

Course Overview

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

Lecture Time

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

Discussion Sections

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

Course Web Site

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

Textbook

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

Grading

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

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

Exams

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

Homework

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

Academic Integrity and Collaboration

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

You must abide by the following rules:

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

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Computer Science & Engineering 142: Introduction to Programming I
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name: John Johnson
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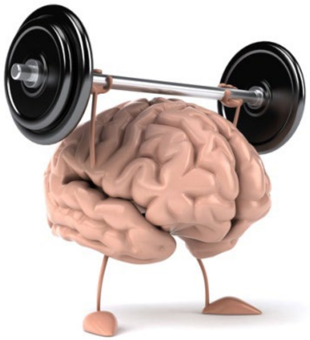
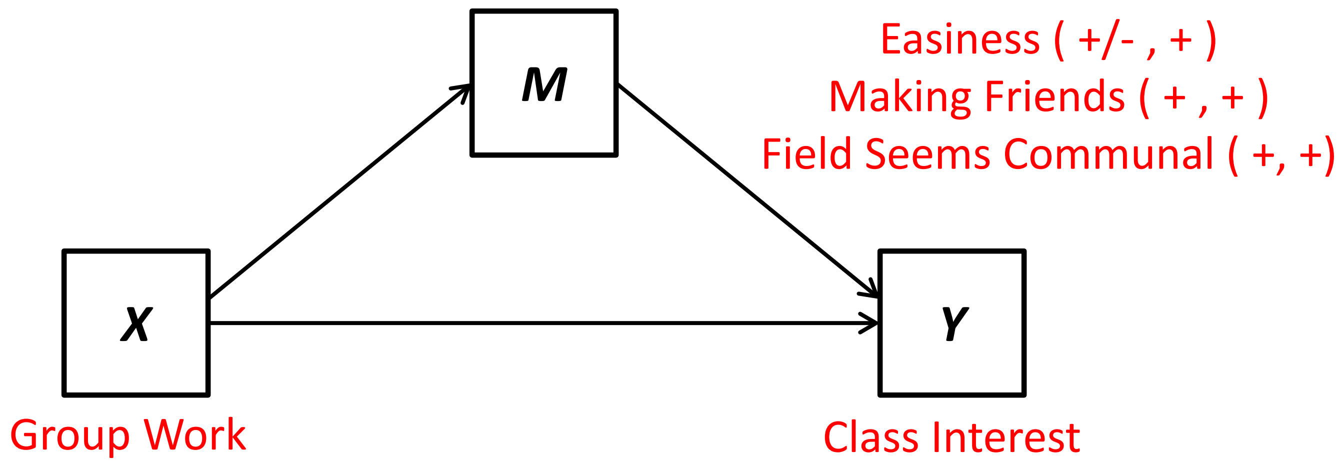
- You may not post online about your homework to ask others for help.



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, intermediary variable,* or *surrogate 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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  - How interested are you in taking the class you read about?
  - How much would you want to take the class you read about?
  - How likely would you be to choose the class you read about?
  - How interested are you in majoring in computer science?
  - 1 Not at All – 7 Very much
- `CSComm`: Perceptions that computer science is communal ($\alpha = .90$)
  - Computer science would assist me in _______________.
  - Helping others, serving the community, working with others, connecting with others, caring for others.
  - 1 Strongly Disagree – 7 Strongly Agree

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.

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

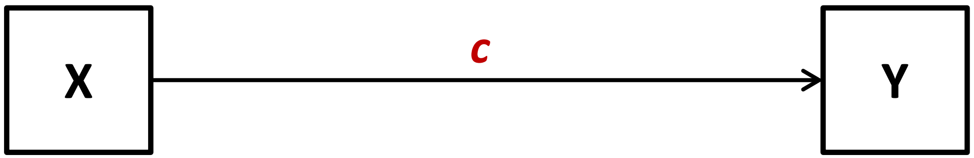
Direct effect of *X* on *Y* (not through *M*) = *c′*

Indirect effect = total effect - direct effect

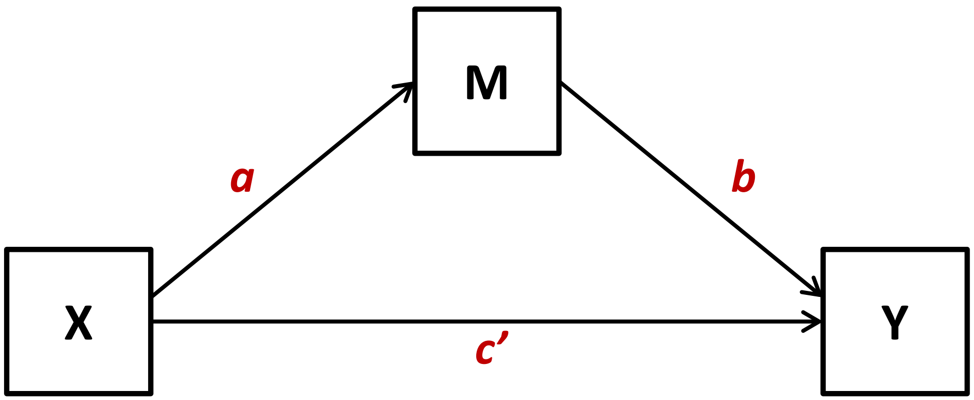
a × *b* = *c* - *c′*

Total effect = direct effect + indirect effect

c = *c′* + *a* × *b*



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

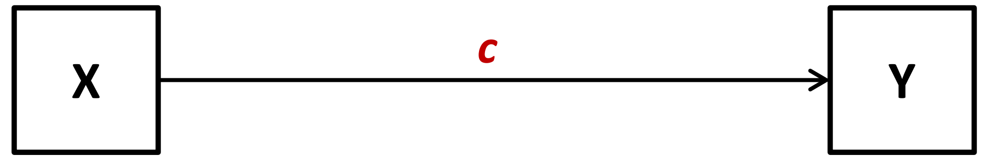


$$M_i = i_M + aX_i + e_{M_i}$$

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

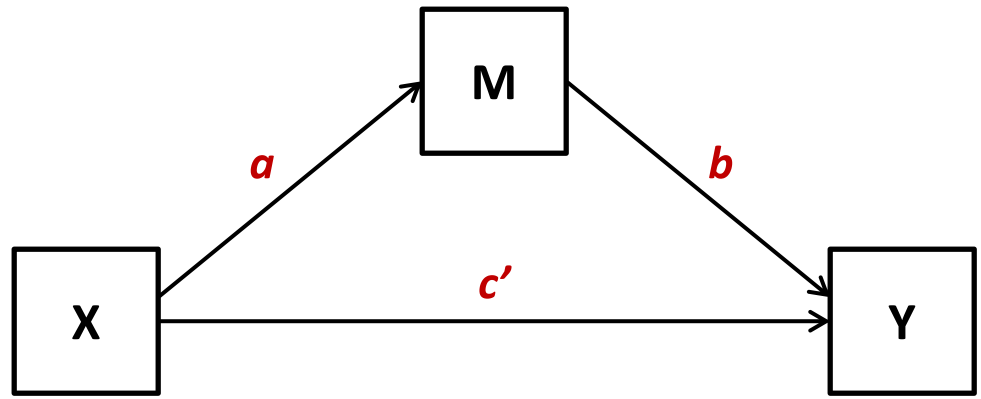
Interpreting the Coefficients

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



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

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



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

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

The Data: CompSci_BS

SPSS

CompSci_BS.sav [DataSet5] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Graphs

	Subject	Cond	Interest
1	101	1.00	4.00
2	102	1.00	4.00
3	108	1.00	4.67
4	111	1.00	1.67
5	117	.00	4.00
6	118	.00	2.33
7	119	1.00	4.67
8	120	1.00	1.67
9	122	.00	1.00
10	123	.00	1.00
11	125	.00	6.00
12	126	1.00	3.33

The SPSS file is ready for analysis.

SAS

```
data CompSci_BS;
input Subject Cond Interest CSComm grppref
datalines;
101 1   4    4.2 6    6
102 1   4    5.2 6.33333333333333     6.3333
108 1   4.66666666666667     5.6 5.33333333
111 1   1.66666666666667     2    6.33333333
117 0   4    1.8 3.66666666666667     0
118 0   2.33333333333333     4.8 3    0
119 1   4.66666666666667     5    3.66666666
120 1   1.66666666666667     4    4    4
122 0   1    3    5    0
123 0   1    1    3.66666666666667     0
125 0   6    4.2 3.33333333333333     0
126 1   3.33333333333333     3.6 1.66666666
127 1   3    4.2 4.33333333333333     4.3333
128 0   4    3.6 2    0
129 1   6.66666666666667     4.8 3    3
130 0   1    1    5.33333333333333     0
133 1   2.33333333333333     1.8 5.66666666
134 1   2    4    5    5
```

The SAS version is a SAS program that must be executed to produce a temporary work data file.

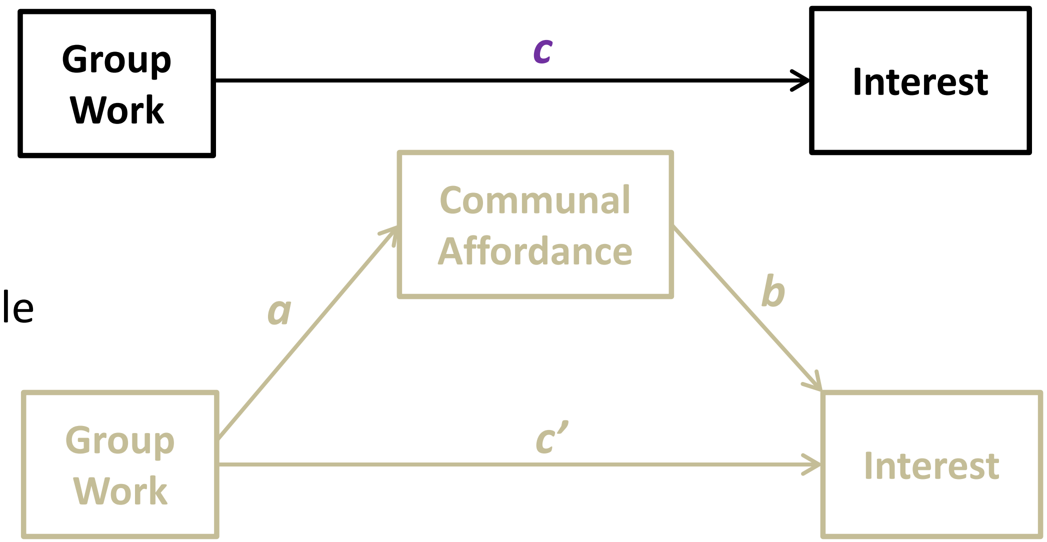
R

Subject	Cond	Interest	CSComm	grppref	condxgrppr
101	1	4	4.2	6	6
102	1	4	5.2	6.333333	6.333333
108	1	4.666667	5.6	5.333333	5.333333
111	1	1.666667	2	6.333333	6.333333
117	0	4	1.8	3.666667	0
118	0	2.333333	4.8	3	0
119	1	4.666667	5	3.666667	3.666667
120	1	1.666667	4	4	4
122	0	1	3	5	0
123	0	1	1	3.666667	0
125	0	6	4.2	3.333333	0
126	1	3.333333	3.6	1.666667	1.666667
127	1	3	4.2	4.333333	4.333333
128	0	4	3.6	2	0
129	1	6.666667	4.8	3	3

```
filelocation <-
"C:\\Data\\CompSci_BS.csv"
CompSci_BS <- read.csv(filelocation,
header = TRUE)
```

Estimation with CompSci_BS Data

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



The *c*-path can be estimated in a sample using the regression equation below.

$$Y_i = c_0 + cX_i + e_{Y_i^*}$$

```
regression /dep = interest /method = enter cond.
```

```
proc reg data=CompSci_BS;model interest = cond/stb clb;run;
```

```
summary(lm(interest~cond, data = CompSci_BS)
```

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.701	.193		14.002	.000
	Cond	.462	.285	.156	1.621	.108

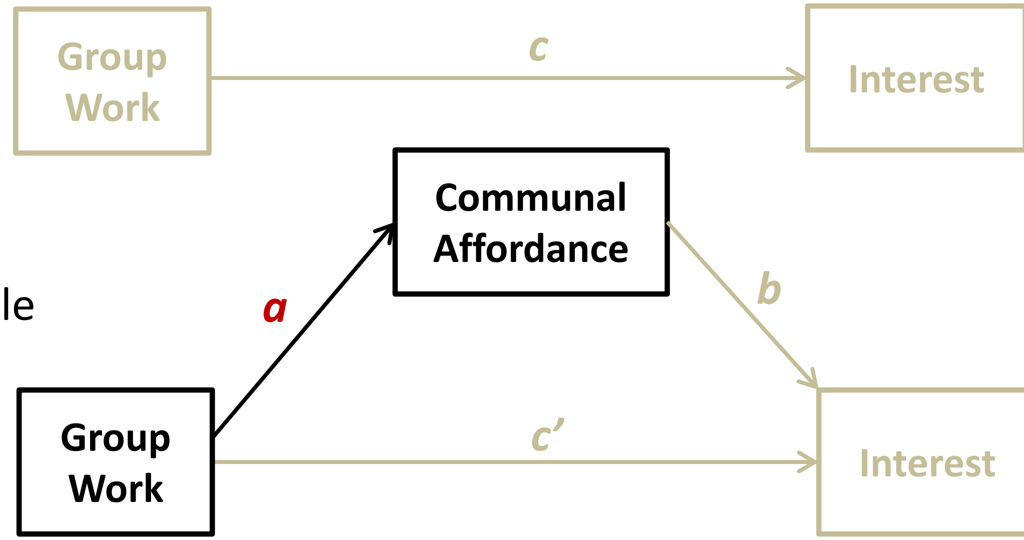
a. Dependent Variable: Interest

Overall women were .462 units more interested in the class with group work.

$c = .462$

Estimation with CompSci_BS Data

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



The *a*-path can be estimated in a sample using the regression equation below.

$$M_i = a_0 + aX_i + e_{M_i}$$

```
regression /dep = CScomm /method = enter cond.
```

```
proc reg data=CompSci_BS;model CScomm = cond/stb clb;run;
```

```
summary(lm(CScomm~cond, data = CompSci_BS)
```

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.421	.159		21.472	.000
	Cond	.488	.237	.198	2.060	.042

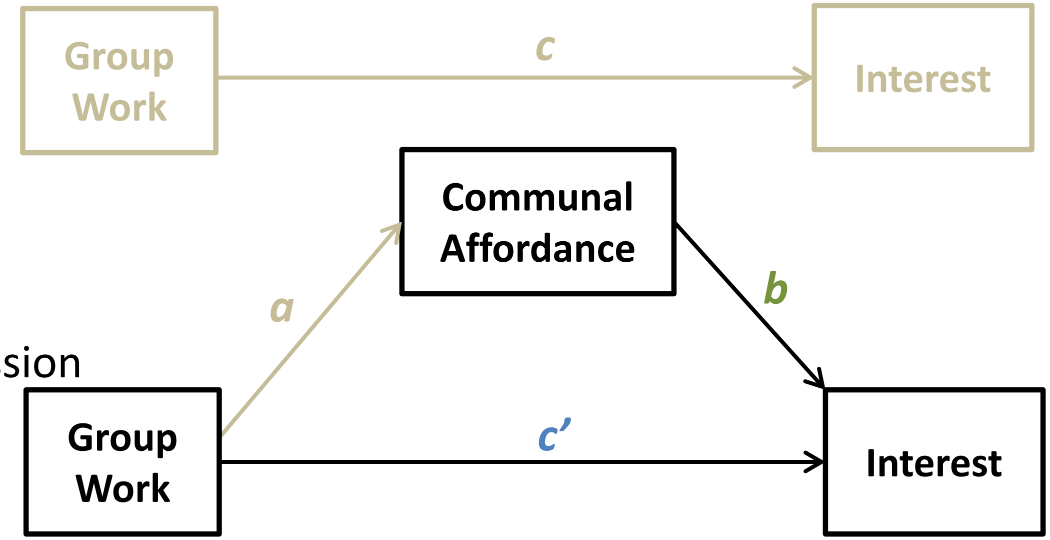
a. Dependent Variable: CSComm

Women saw computer science as .488 units more communal after reading a syllabus with group work.

a = .488

Estimation with CompSci_BS Data

Research Question: 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>?



The *b*-path and direct effect can be estimated in a sample using the regression equation below.

$$Y_i = i_Y + c' X_i + b M_i + e_{Y_i}$$

```
regression /dep = interest /method = enter cond  CScomm.
```

```
proc reg data=CompSci_BS;model interest = cond CScomm/stb clb;run;
```

```
summary(lm(interest~cond+CScomm, data = CompSci_BS)
```

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.964	.413		2.336	.021
	Cond	.218	.268	.073	.812	.419
	CSComm	.508	.109	.421	4.663	.000

a. Dependent Variable: Interest

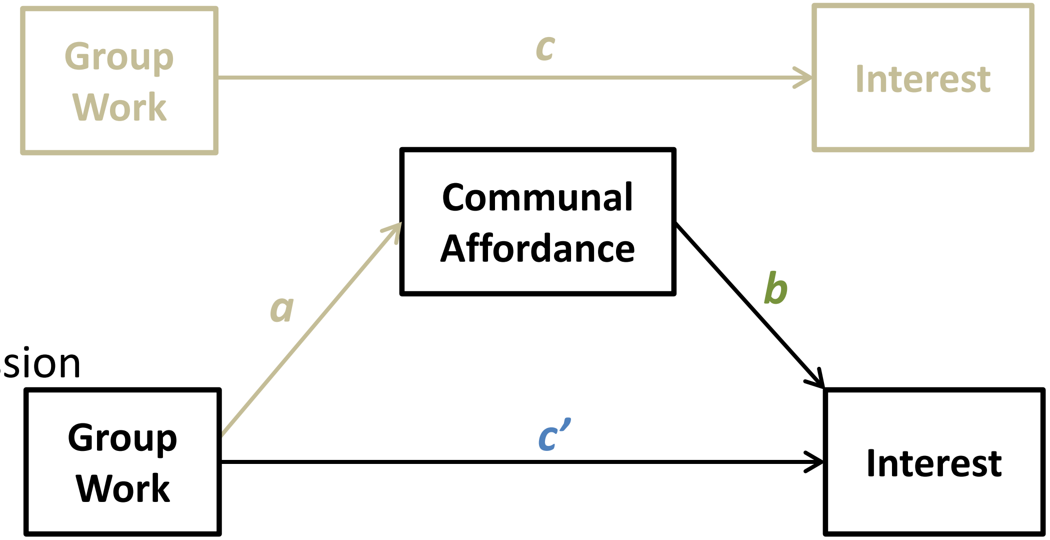
Controlling for communal affordance, women in the group work condition were .218 units more interested in the class with group work.

$c' = 0.218$

$b = .508$

Estimation with CompSci_BS Data

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



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	CSComm	.508	.109	.421	4.663	.000

a. Dependent Variable: Interest

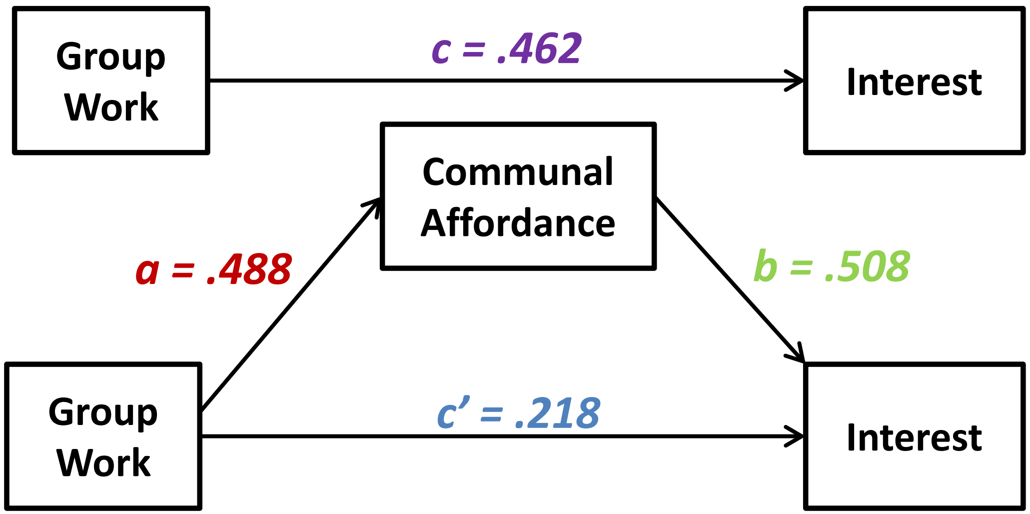
c' = 0.218

For two people in the same condition, a one unit difference in communal goals results in a 0.51 unit difference in interest, on average.

Interpreting the Coefficients

Research Question: 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>?

On average, women were .46 units more interested in the class with group work (*p* = .108). Similarly, computer science was perceived as .49 units more communal after reading a syllabus with group work (*p* = .042). Controlling for condition, a one unit increase in communal affordance resulted in a .508 unit increase in interest (*p* < .001). Controlling for communal affordance, group work did not predict additional interest (*c'* = .22, *p* = .42).



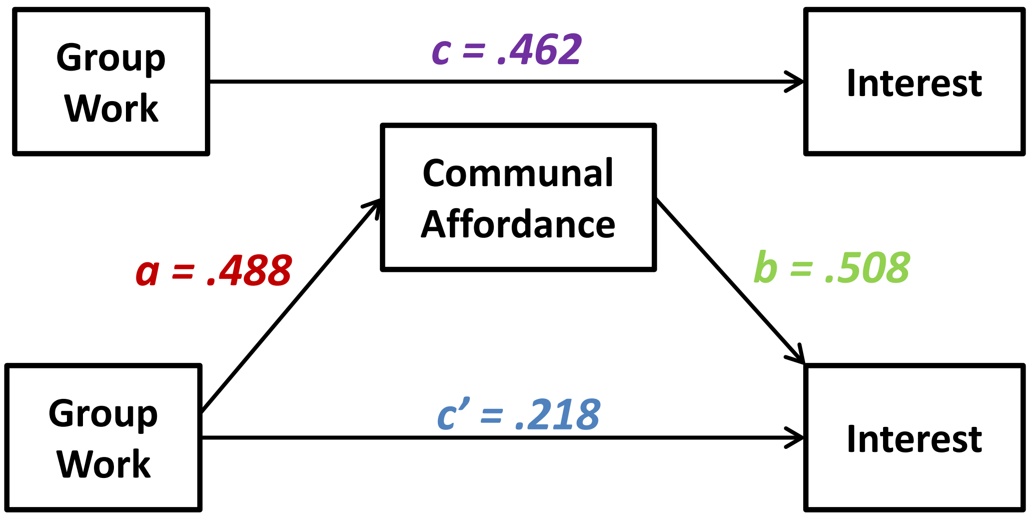
But what about the indirect effect?

Interpreting Indirect, Direct, and Total Effects

Indirect Effect

$a \times b = .488 \times .508 = .249$

Group work increased interest by .249 units indirectly through communal affordance. Where group work increased perceptions of communal affordance by .488 units, and a one unit increase in communal affordance resulted in a .508 unit increase in interest.



Direct Effect

$c' = .218$

Group work increased interest by .218 units directly (not through communal affordance).

Total Effect

$c = .462$

Group work increased interest by .462 units in total.

Inference for the direct and total effects can be drawn from the regression results because these are based on a single regression parameter.

$p = .419$

$p = .108$

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
- Issues with *complete* and *partial* mediation

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

Sobel Test / Normal Theory / Delta Method

Method

1. Calculate a Z-statistic

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

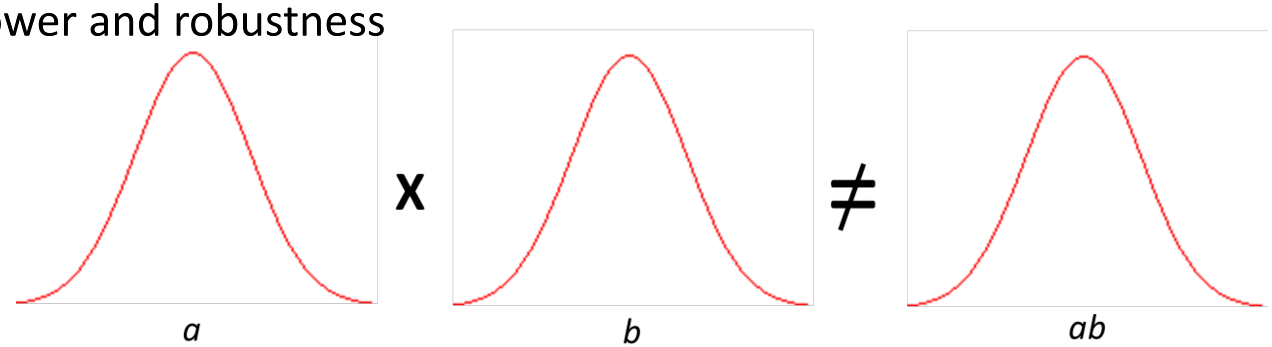
2. Calculate a p-value from Z-statistic

Appeal

- Very similar to process from regression
- Single test of the indirect effect
- Follows from asymptotic theory

What's wrong with it?

- Assumes indirect effect is normally distributed, which is not the case at finite sample sizes
- Poor power and robustness



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 2.5th and 97.5th 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?

- Not all software has this built in
- Requires original data

Bootstrap Confidence Intervals

Original Data

X	M	Y
-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 = .2931 b = .3099

ab = .0908

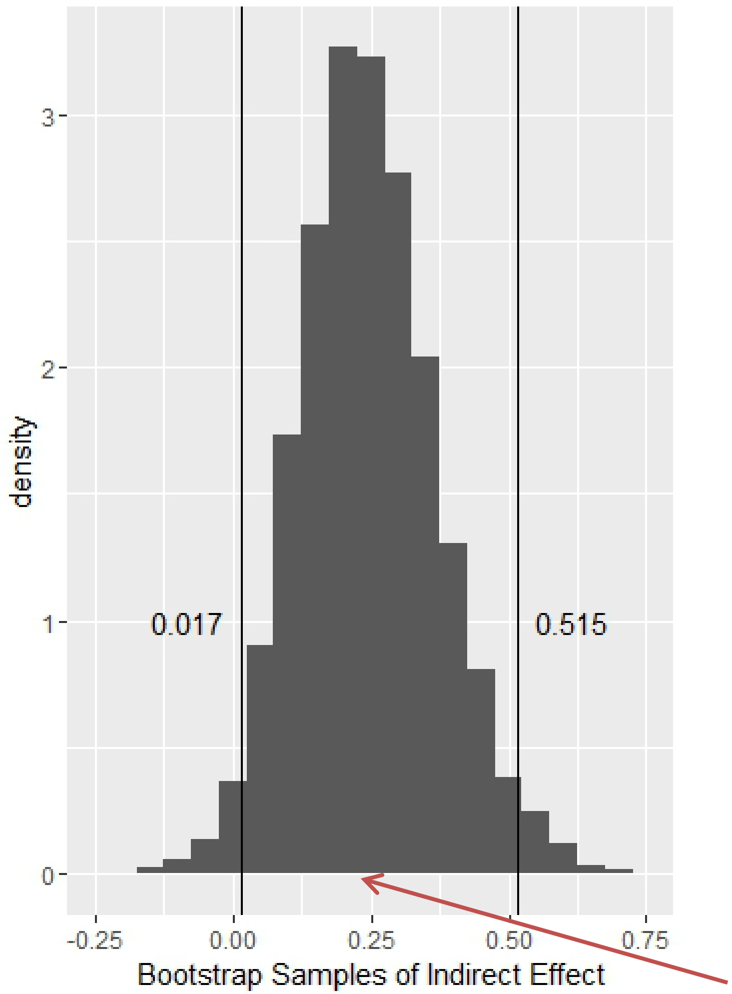
Bootstrap Sample

X	M	Y

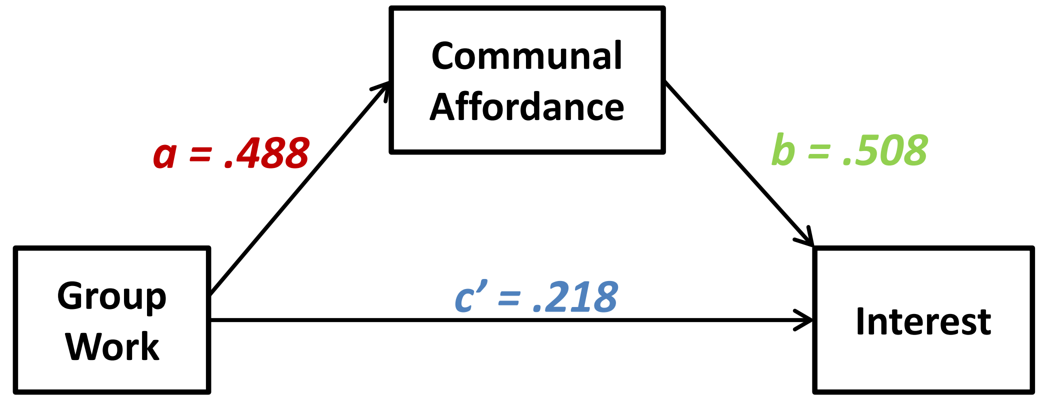
a = -.1035 b = .1495

ab = -.0155

Bootstrap Confidence Intervals (CompSci Data)



ab = .249



ab = .249

Zero is not contained in the confidence interval [0.017, 0.515] so we conclude the indirect effect is different from zero with 95% confidence. This is similar to rejecting the null hypothesis at α = .05.

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.

BC and BCA Bootstrap Confidence Intervals have been shown to have inflated Type I Error rates compared to other methods and are **not recommended**

The Monte Carlo Interval

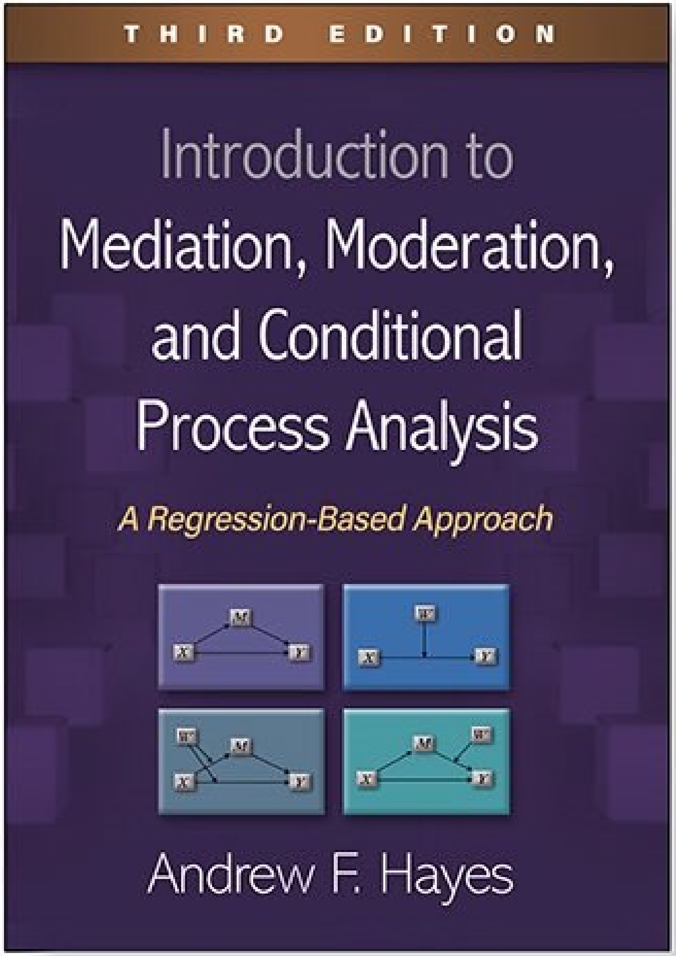
Monte Carlo empirically estimate the sampling distribution of the indirect effect and generate a confidence interval (CI) for estimation and hypothesis testing. This simulation based method assumes each individual path (*a* and *b*) are normally distributed.

(1) Generate k samples from a normal distribution with mean a and standard deviation s_a
(2) Generate k samples from a normal distribution with mean b and standard deviation s_b
(3) Multiply samples together to get a distribution of k estimates of ab.
(4) Rank order estimates and select estimates which define the lower percentile of sorted k estimates and upper percentile of sorted estimates which define CI of interest.
(5) For 95% CI lower and upper bounds are 2.5^{th} and 97.5^{th} percentile in k bootstrap estimates of the indirect effect.

This method performs well (similarly to bootstrapping) in a variety of simulation studies, but is still less popular.

This method makes stronger assumptions than bootstrapping, but does not seem to result in greater power.

PROCESS Macro



Published in January 2022 and available through The Guilford Press, Amazon.com, and elsewhere.

- First released in beta form in March of 2012 and later documented in Hayes (2013, IMMCPA, published by The Guilford Press).
- Available for both SPSS (in macro and "custom dialog" form), SAS, and R.
- An integration of functions available in my other published macros for mediation and moderation analysis (SOBEL, INDIRECT, MODMED, MODPROBE, MED3C) and a whole lot more, all in one command.
- A handy tool for both "confirmatory" and "exploratory" approaches to data analysis.
- Freely available at www.processmacro.org. The current release is v4.3

For more on the use of PROCESS take my Statistical Horizons Course

THINKING DEEPLY ABOUT CAUSALITY

Understanding Cause and Effect

As scientists we're often looking to support a claim that "X causes Y." Many of us are familiar with the phrase "correlation is not causation." But what then is needed to support a claim of cause?

Often we rely on experimentation to help us support the claim of cause. But what happens when we cannot (ethically or practically) manipulate our causal variable?

Consider the claim "Smoking tobacco causes lung cancer." Is it unethical to randomize people to smoke or not smoke. How then do we know this claim is true?

Necessary Conditions for Cause:

1. Covariation
2. Temporal Ordering
3. Elimination of competing explanations

Research on tobacco use easily found evidence for 1 & 2, and slowly over time accumulation of evidence supported 3.

Understanding Cause and Effect

Necessary Conditions for Cause:

1. Covariation
2. Temporal Ordering
3. Elimination of competing explanations

The following methods are frequently used to support the claim of cause. Which conditions for cause are supported by each method?

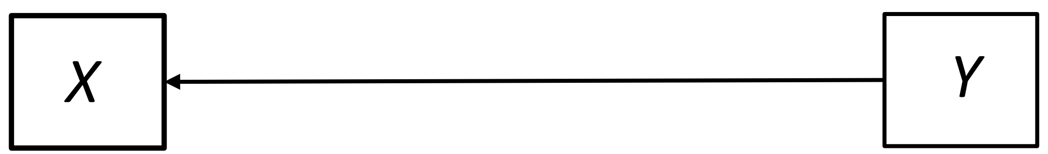
Experimental Manipulation:

Longitudinal Studies:

Cross-sectional Data Collection analyzed using Linear Regression:

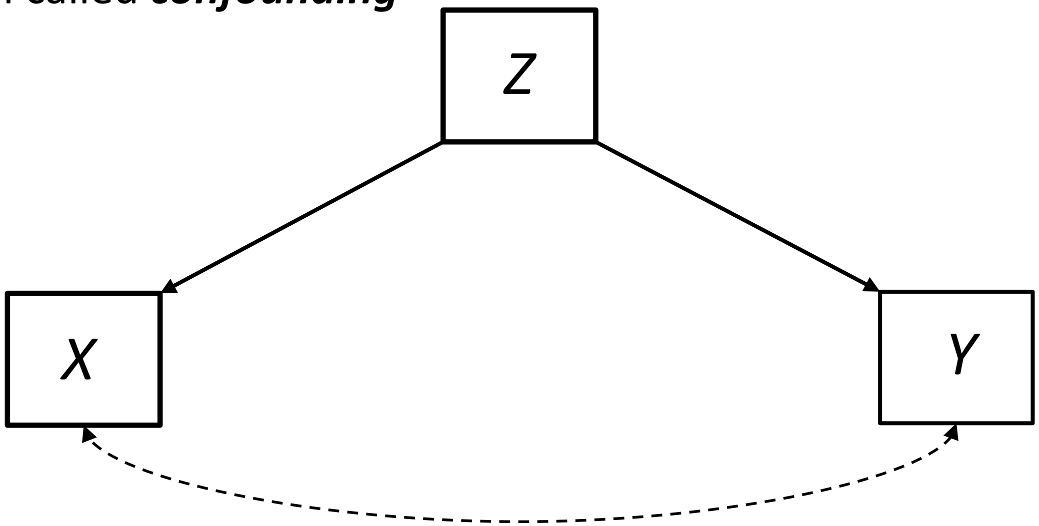
If it's not a cause, what is it?

Effect/Reverse Causation: It's possible that *X* is an effect of *Y*, rather than *Y* being an effect of *X*



If it's not a cause, what is it?

Spurious association: when relationship between X and Y is induced by a shared cause.
This is often called ***confounding***

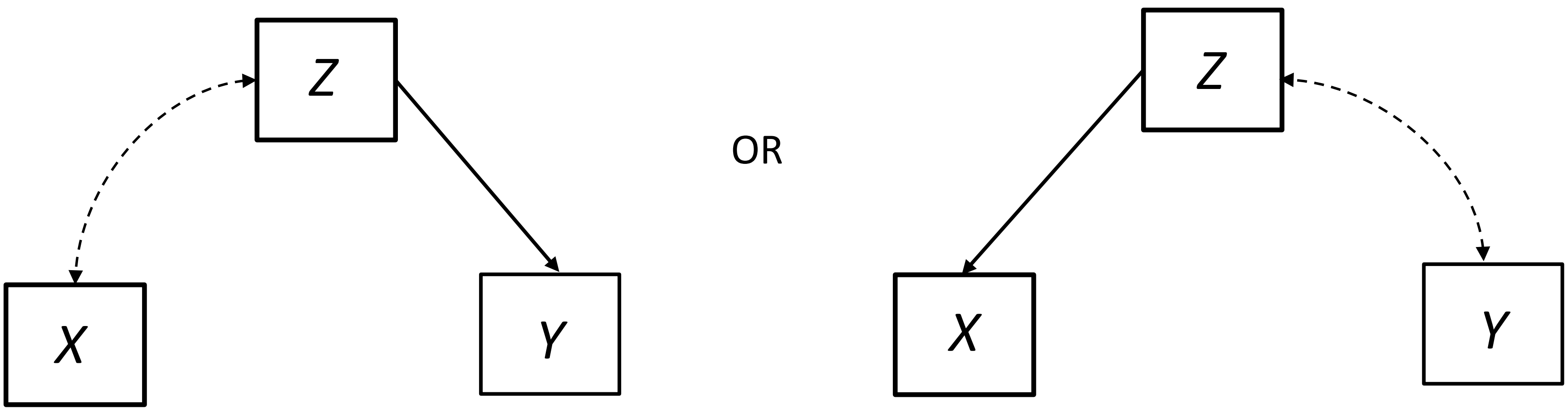


Example: Skirt length theory is one that suggests that skirt lengths predict the stock market (short skirt → market going up). Likely this is not a causal relationship but rather both skirt length and market trends are influenced by other larger cultural/economic trends.

Controlling for *Z* helps us eliminate spurious explanations.

If it’s not a cause, what is it?

Epiphenominality: X and Y are related because X is correlated with a cause of Y

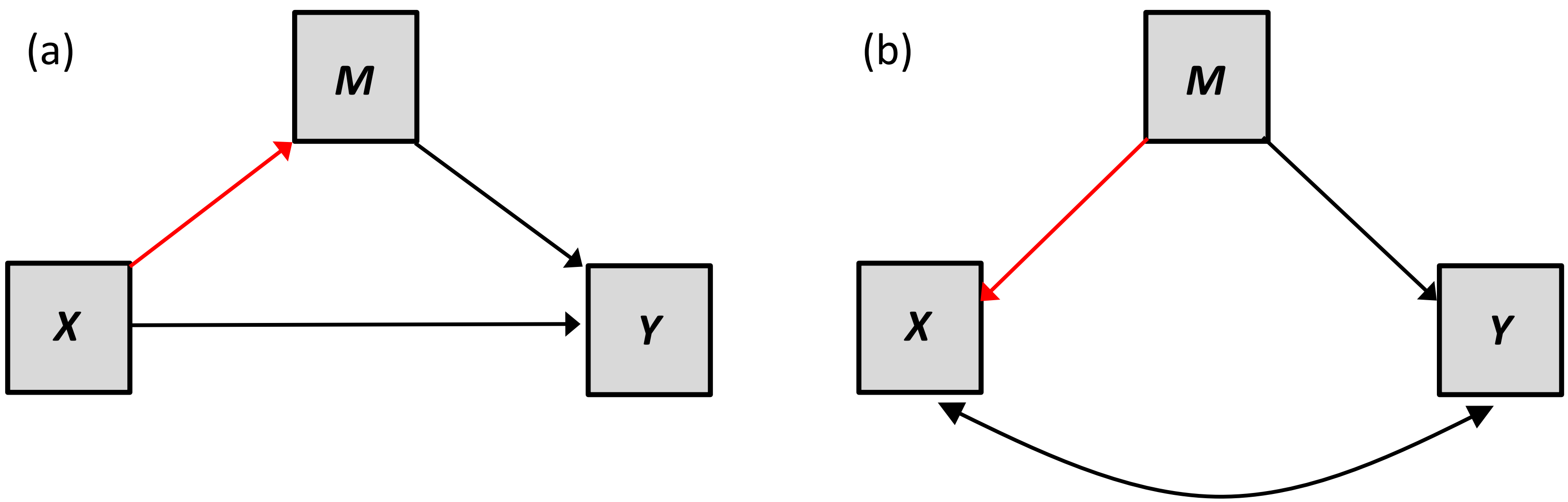


Example: Having an increased risk of breast cancer (Y) concurrent with taking an antibiotic is an **epiphenomenon**. It is not the antibiotic that is causing the increased risk, but the increased inflammation associated with the bacterial infection (Z) that prompted the taking of an antibiotic (X).

Controlling for *Z* helps us eliminate epiphenomenal explanations.

Mediation and spuriousness

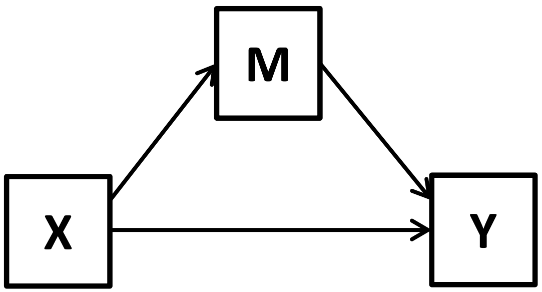
Mediation analysis cannot distinguish between (a)mediation and (b)spuriousness. If (b) can be deemed plausible, that weakens the case for (a) regardless of what the data analysis tells you.



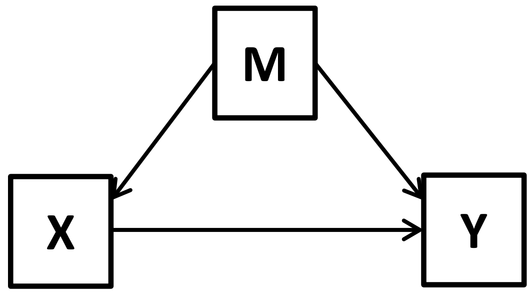
Inferences are always design-bound.
Mediation is a causal process, but causal claims are only justified if the design allows such claims, regardless of what the statistics say.

Mediation and Causality

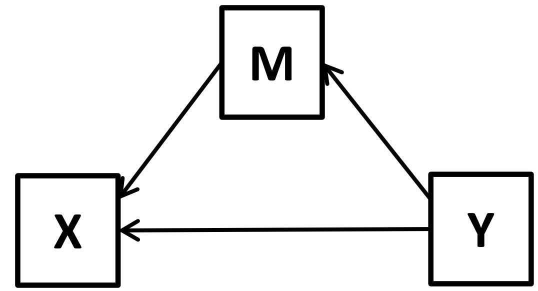
There are a number of alternative causal processes that may be occurring when a *statistical indirect effect* is present:



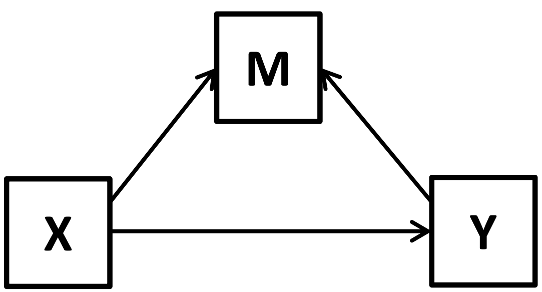
X affects *Y* through *M*



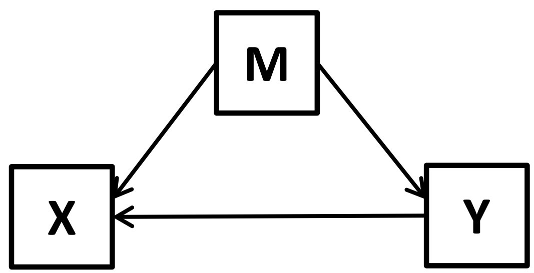
M affects *Y* through *X*



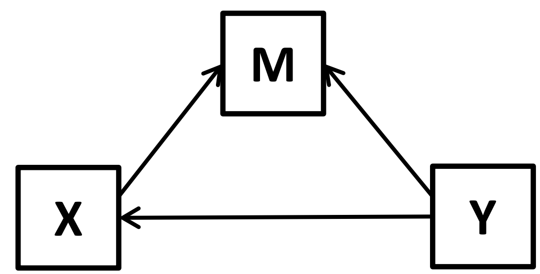
Y affects *X* through *M*



X affects *M* through *Y*



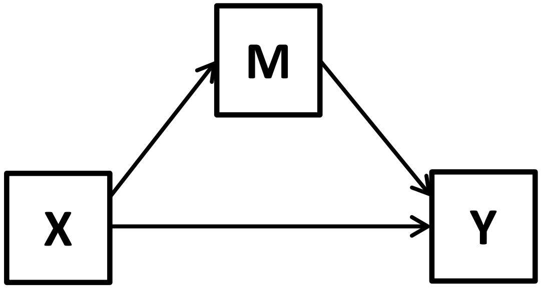
M affects *X* through *Y*



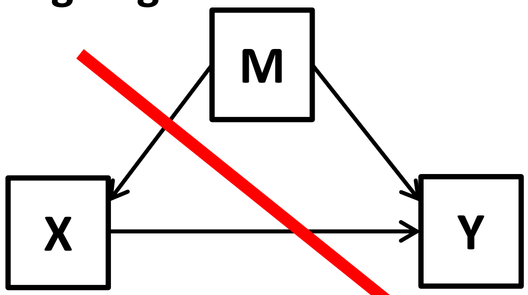
Y affects *M* through *X*

Mediation and Causality

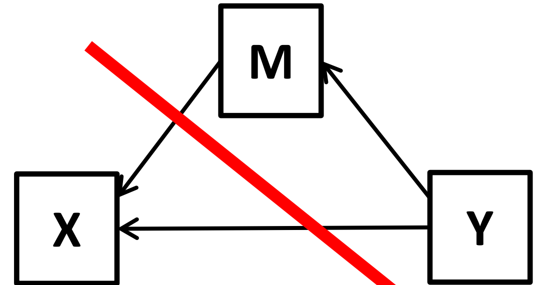
What you get by randomly assigning *X*.



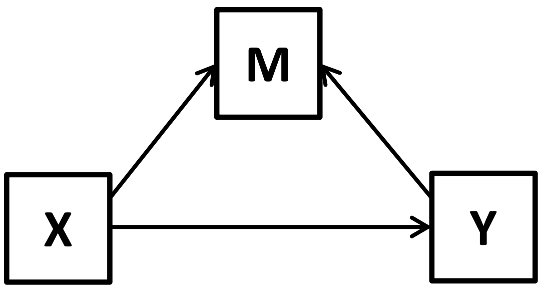
X affects *Y* through *M*



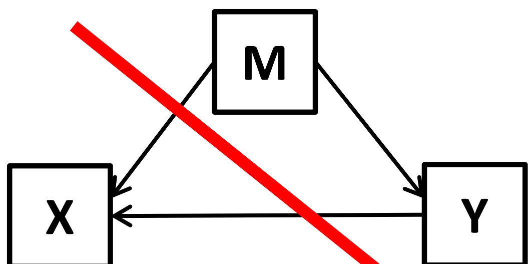
~~*M* affects *Y* through *X*~~



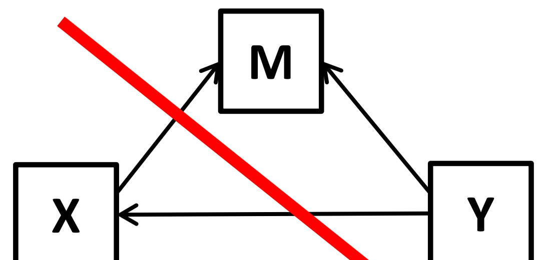
~~*Y* affects *X* through *M*~~



X affects *M* through *Y*



~~*M* affects *X* through *Y*~~



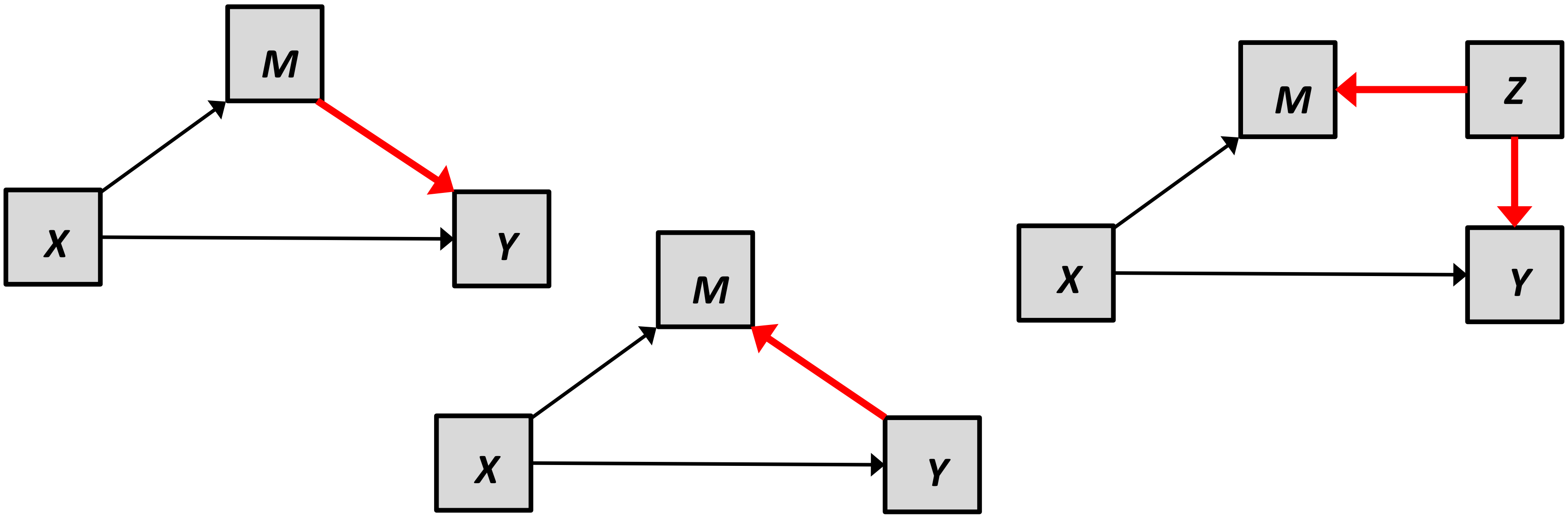
~~*Y* affects *M* through *X*~~

Even when *X* is randomly assigned, 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 (Thoemmes, 2015, *Basic and Applied Social Psychology).*

Manipulation of X

Manipulation of and random assignment to *X* affords causal inference for the effect of *X* on *M* and *Y*, but not the effect of *M* on *Y*. We cannot establish causal order for the *M*-*Y* path using the methods that are the focus here. Theory is important. Multiple studies can help, one of which involves manipulation of *M*.



When *X* is not experimentally manipulated, all paths are subject to potential alternative causal orders or confounding.

MacKinnon, D. P. & Pirlott, A. G. (2015). Statistical Approaches for Enhancing Causal Interpretation of the M to Y Relation in Mediation Analysis. *Personality and Social Psychology Review, 19*(1), 30 – 43.

Understanding Cause and Effect

Consider two male, Caucasian politicians. One of these two has been convicted of political corruption. Which one is it?

Understanding causal effects

Never Convicted

Convicted

Understanding causal effects

Lin, C., Adolphs, R., & Alvarez, R. M. (2018). Inferring whether officials are corruptible from looking at their faces. *Psychological Science, 29*(11), 1807-1823.

Table 1. Results for Correctly Categorized Officials Based on Aggregate-Level Trait Inferences and Individual-Level Trait Inferences From Study 1

	Aggregate-level accuracy				Average individual-level accuracy[a]				
Trait	Percentage of correctly categorized officials ($N = 72$)	Lower bound of 95% CI	$\chi^2(1)$	p	Mean accuracy ($N = 82$)	SD	Lower bound of 95% CI	$t(81)$	Cohen's d
Corruptibility	69.44%	59.22%	10.13	< .001	55.73%	6.95%	54.46%	7.47	0.82
Dishonesty	70.83%	60.67%	11.68	< .001	54.82%	6.41%	53.64%	6.81	0.75
Selfishness	66.67%	56.36%	7.35	.003	55.10%	6.76%	53.86%	6.83	0.75
Trustworthiness	68.06%	57.79%	8.68	.002	55.03%	6.41%	53.85%	7.10	0.78
Generosity	63.89%	53.53%	5.01	.013	54.97%	5.99%	53.87%	7.51	0.83

Note: CI = confidence interval.
[a]All ps for this variable are less than .001.

Research Article

Psychological Science
2018, Vol. 29(11) 1807–1823

DOI: 10.1177/0956797618788882
www.psychologicalscience.org/PS

Inferring Whether Officials Are Corruptible From Looking at Their Faces

Chujun Lin, Ralph Adolphs, and R. Michael Alvarez
Division of Humanities and Social Sciences, California Institute of Technology

Abstract
While inferences of traits from unfamiliar faces prominently reveal stereotypes, some facial inferences also correlate with real-world outcomes. We investigated whether facial inferences are associated with an important real-world outcome closely linked to the face bearer's behavior: political corruption. In four preregistered studies ($N = 325$), participants made trait judgments of unfamiliar government officials on the basis of their photos. Relative to peers with clean records, federal and state officials convicted of political corruption (Study 1) and local officials who violated campaign finance laws (Study 2) were perceived as more corruptible, dishonest, selfish, and aggressive but similarly competent, ambitious, and masculine (Study 3). Mediation analyses and experiments in which the photos were digitally manipulated showed that participants' judgments of how corruptible an official looked were causally influenced by the face width of the stimuli (Study 4). The findings shed new light on the complex causal mechanisms linking facial appearances with social behavior.

Keywords
face perception, corruption, social attribution, stereotyping, political psychology, open data, open materials, preregistered

Received 9/25/17; Revision accepted 6/3/18

Faces are rich in information: They provide clues about gender, race, age, and trait attributes, which are inferred spontaneously and ubiquitously (Engell, Haxby, & Todorov, 2007; Todorov, 2017). Moreover, such inferences often guide our social behavior—for instance, we decide whom to trust on the basis of how trustworthy a face looks (Rezlescu, Duchaine, Olivola, & Chater, 2012; Van't Wout & Sanfey, 2008). Many trait judgments made by participants across generations and cultures show consensus (Cogsdill, Todorov, Spelke, & Banaji, 2014; Lin, Adolphs, & Alvarez, 2017; Rule et al., 2010). But are trait judgments from faces accurate?

Previous research has shown that trait judgments from faces can be associated with important real-world social outcomes, such as dating and mating (Olivola et al., 2014; Valentine, Li, Penke, & Perrett, 2014), earnings and fundraising (Genevsky & Knutson, 2015; Hamermesh, 2011; Ravina, 2012), science communication (Gheorghiu, Callan, & Skylark, 2017), sentencing decisions (Berry & Zebrowitz-McArthur, 1988; Blair, Judd, & Chapleau, 2004; Wilson & Rule, 2015; Zebrowitz & McDonald, 1991), and leader selection (Todorov, Mandisodza, Goren, & Hall, 2005; for reviews, see Antonakis & Eubanks, 2017; Todorov, Olivola, Dotsch, & Mende-Siedlecki, 2015). Yet this prior research on the association between trait judgments from faces and real-world outcomes leaves open two important questions. First, most associations have focused on prosocial outcomes (e.g., correlations between competence judgments and election success; Todorov et al., 2005). Second, most associations are plausibly driven not by the behavior of the targets whose face is being judged but by the interests of the perceivers who are making the judgments (e.g., correlations between interesting-looking scientists and the perceiver's interest in their work). Here, we investigated an antisocial judgment that

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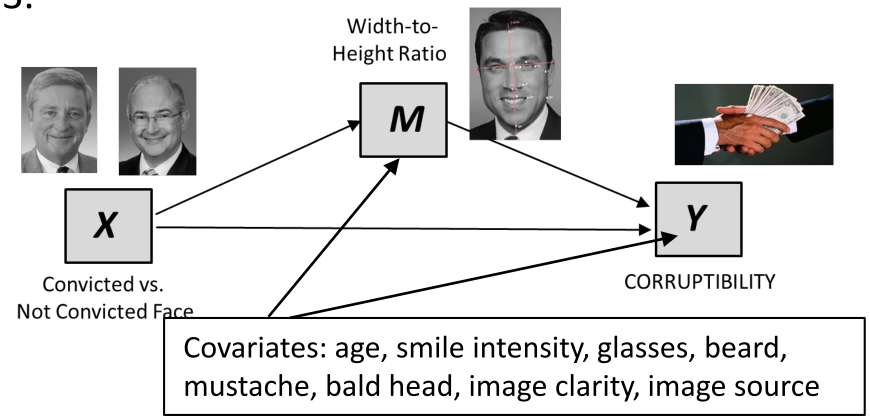
Understanding Cause and Effect

Lin, C., Adolphs, R., & Alvarez, R. M. (2018). Inferring whether officials are corruptible from looking at their faces. *Psychological Science, 29*(11), 1807-1823.

Necessary Conditions for Cause:

1. Covariation
2. Temporal Ordering
3. Elimination of competing explanations



1. Data from Studies 1 – 3 were combined to run the above mediation analysis. Have the necessary conditions for cause been met? Which necessary conditions does the mediation analysis support? Which require further support?
   (Hint: Think about what would make you feel more confident in this causal order)

2. Study 4b experimentally manipulated the width-to-height ratios of faces to measure the impact on corruptibility. Which condition for cause does this help support? Are we now completely convinced about the causal claims of this mediation analysis?

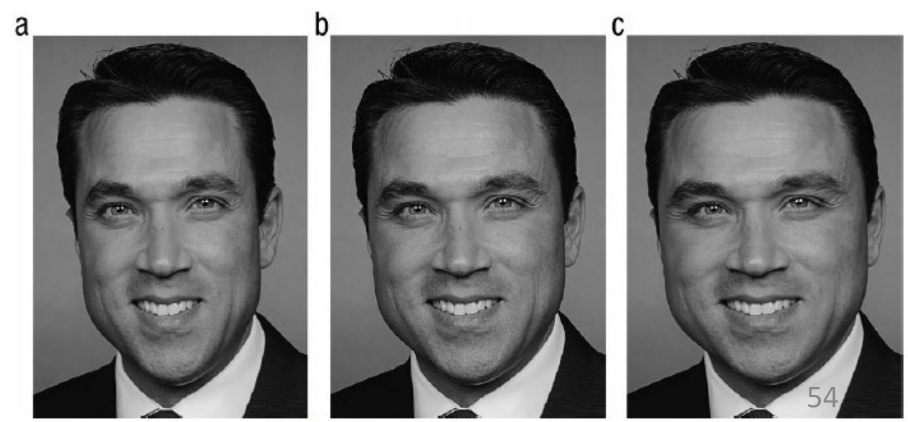


Fig. 6. Example of the same face in (a) slim, (b) original, and (c) fat versions.

MEDIATION 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, CompSci_WS.csv) :
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`

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.

Psychological Methods
2001, Vol. 6, No. 2, 115–134

1082-989X/01/$5.00 DOI: 10.1037//1082-989X.6.2.115

Estimating and Testing Mediation and Moderation in Within-Subject Designs

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Analyses designed to detect mediation and moderation of treatment effects are increasingly prevalent in research in psychology. The mediation question concerns the processes that produce a treatment effect. The moderation question concerns factors that affect the magnitude of that effect. Although analytic procedures have been reasonably well worked out in the case in which the treatment varies between participants, no systematic procedures for examining mediation and moderation have been developed in the case in which the treatment varies within participants. The authors present an analytic approach to these issues using ordinary least squares estimation.

The issues of mediation and moderation have received considerable attention in recent years in both basic and applied research (Baron & Kenny, 1986; James & Brett, 1984; Judd & Kenny, 1981b; MacKinnon & Dwyer, 1993). In addition to knowing whether a particular intervention has an effect, the researcher typically wants to know about factors that affect the magnitude of that effect (i.e., moderation) and mechanisms that produce the effect (i.e., mediation). Such knowledge helps in both theory development and intervention application.

To illustrate the difference between mediation and moderation, consider a design in which a researcher is interested in whether students who are taught with a new curriculum (the treatment condition) show higher performance on a subsequent standardized test than students taught under the old curriculum (the control condition). Assuming that a performance difference is found, one might plausibly hypothesize different mediating mechanisms for this effect. The new curriculum might increase students' interest in the subject matter; it might cause students to study harder outside of class; or it might convey the material more clearly. These are alternative reasons why the performance difference is found, that is, alternative mediators of the treatment effect. The researcher might also be interested in factors that affect the magnitude of the difference between performance following the old curriculum and performance following the new one. That difference might be larger or smaller for different types of students or in different types of classrooms or when taught by different kinds of teachers. All of these then are potential moderators of the treatment effect.

It is possible that the same variable may serve as both a mediator and a moderator. For instance, study time might serve both roles. First, as a mediator, the new curriculum might lead to higher performance because it causes students to study more. Second, as a moderator, the treatment might be especially effective for students who spend more time studying.

Procedures for assessing mediation and moderation have been relatively well worked out through ordinary least squares regression and analysis of variance procedures. Mediation is assessed through a four-step procedure (Baron & Kenny, 1986; Judd & Kenny,

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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?

Paired Samples Test

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

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

```
PROC TTEST DATA=CompSci_WS; PAIRED int_G*int_I; RUN;
```

```
t.test(Pair(int_G, int_I)~1, data = CompSci_WS)
```

Analysis using Judd et al. (2001)

2. On average, does M differ by condition?

Setup a model of the mediator in each condition:

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

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?

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

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

```
PROC TTEST DATA=CompSci_WS; PAIRED comm_G*comm_I; RUN;
```

```
t.test(Pair(comm_G, comm_I)~1, data = CompSci_WS)
```

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:

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

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

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

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.
```

```
data CompSci_WS;set CompSci_WS;int_diff=int_g-int_I;
comm_diff = comm_G - comm_I; comm_sum = comm_G+comm_I;run;
proc reg data=CompSci_WS;model int_diff=comm_diff comm_sum;run;
```

```
CompSci_WS <- transform(CompSci_WS,
                        int_diff = int_G - int_I,
                        comm_diff = comm_G - comm_I,
                        comm_sum = comm_G +comm_I)
summary(lm(int_diff~comm_diff+comm_sum, data = CompSci_WS))
```

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.
```

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
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?

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

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.

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

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 significance difference in interest predicted when there is no difference in communal goals?

```
compute comm_sumc = comm_sum- 8.325490.
EXECUTE.
regression dep = int_diff /method = enter comm_diff comm_sumc.
```

```
data CompSci_WS;set CompSci_WS;comm_sumc = comm_sum-8.325490;run;
proc reg data=CompSci_WS;model int_diff=comm_diff comm_sumc;run;
```

```
CompSci_WS <- transform(CompSci_WS,
                        comm_sumc = comm_sum-8.325490)
summary(lm(int_diff~comm_diff+comm_sumc, data = CompSci_WS))
```

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
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

All criticisms of the causal steps approach apply to this approach:

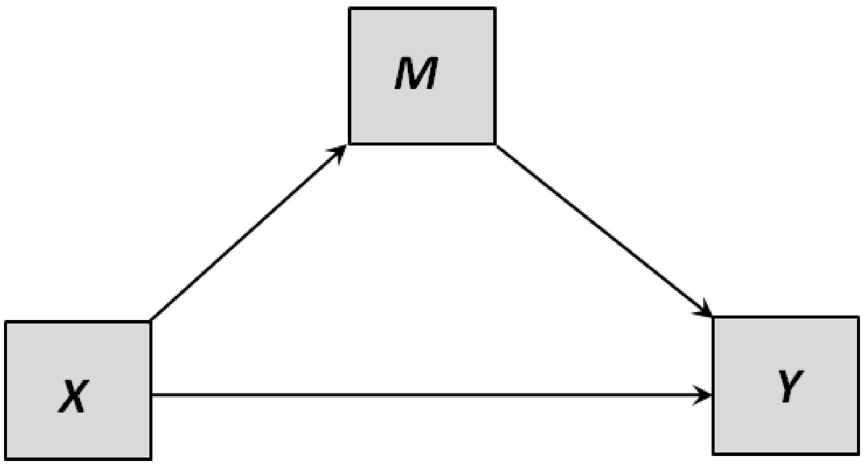
- There is no explicit quantification of the indirect effect
  - Inference about an indirect effect should be the result of a test on a *quantification* of the indirect effect
- Requiring that there must be a total effect is too restrictive
  - The direct and indirect effect could be of opposite sign
  - There is greater power to detect the indirect effect than total effect *(Judd, Kenny, 2014, Psych Science)*

This method has been used by a variety of researchers:

- Approximately 1150 citing papers, with around 1/3 using this method
- 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* path is often interpreted as indirect effect
- Extensions to more complicated models have been poorly implemented until recently

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	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
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

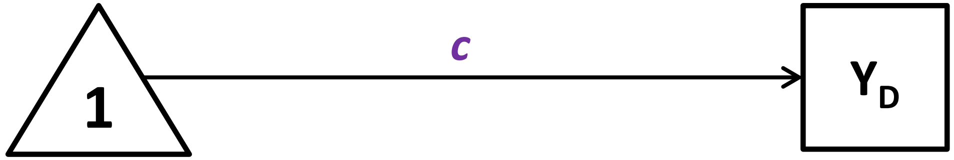
Using a path analytic framework will help extend the simple mediation model to more complicated questions

- Multiple mediators
- Moderated mediation
- Integration of between and within-subjects designs

Path-Analytic Approach

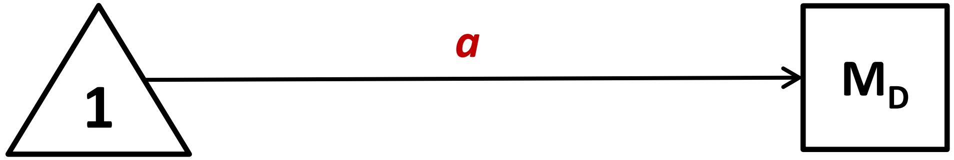
Total Effect (*c*): The effect of our presumed cause (*X*) on our outcome (*Y*), without controlling for any other variables. (i.e. mean difference in outcome between the two conditions).

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



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

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

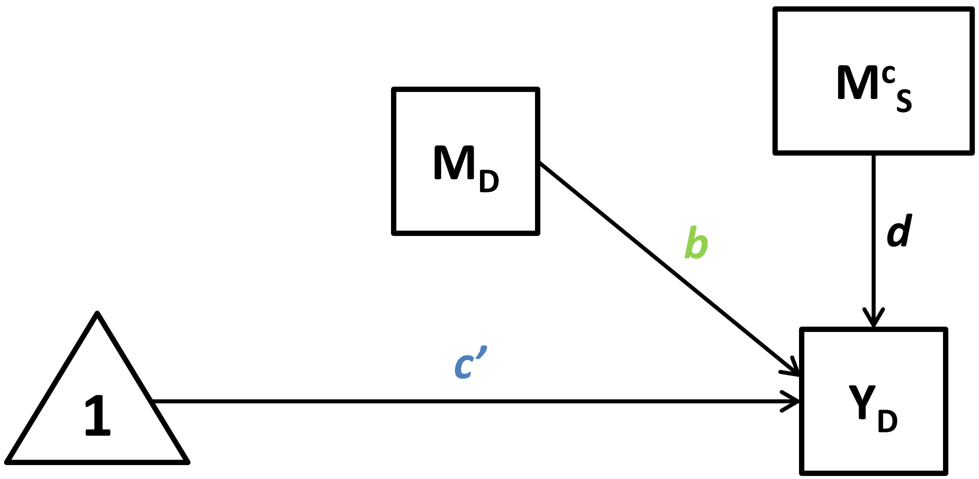


Path-Analytic Approach

***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*)

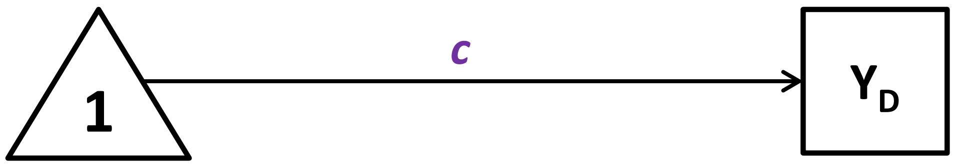
$$Y_{2i} - Y_{1i} = c' + b(M_{2i} - M_{1i}) + d(M_{2i} + M_{1i} - (\overline{M_2 + M_1})) + e_{Y_i}$$

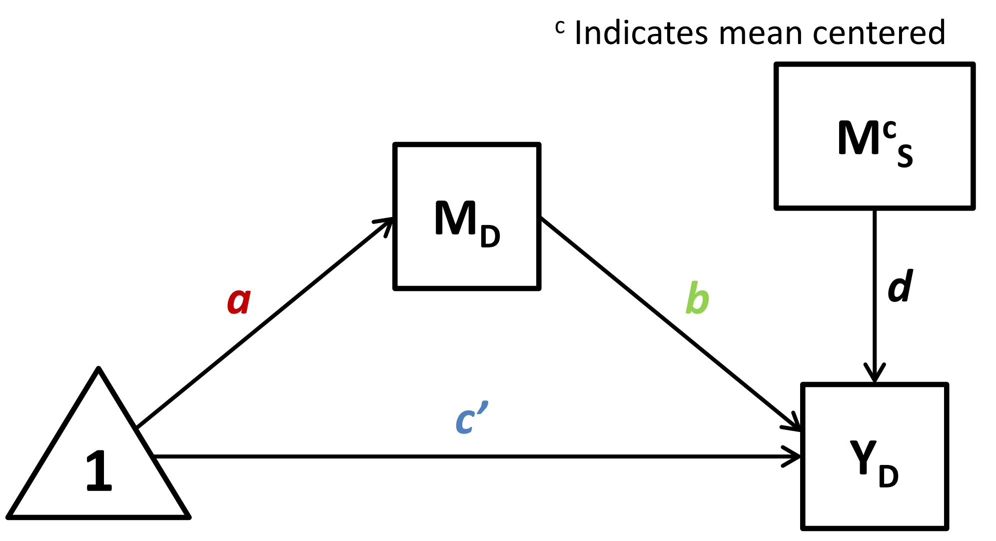


[c] Indicates mean centered

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*.

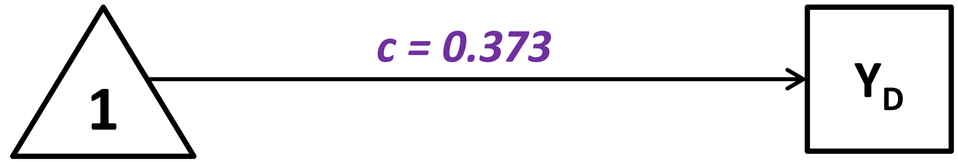




Within Subjects: Path Estimates

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

$$\widehat{Y_D} = c$$
$$\widehat{Y_D} = .373$$



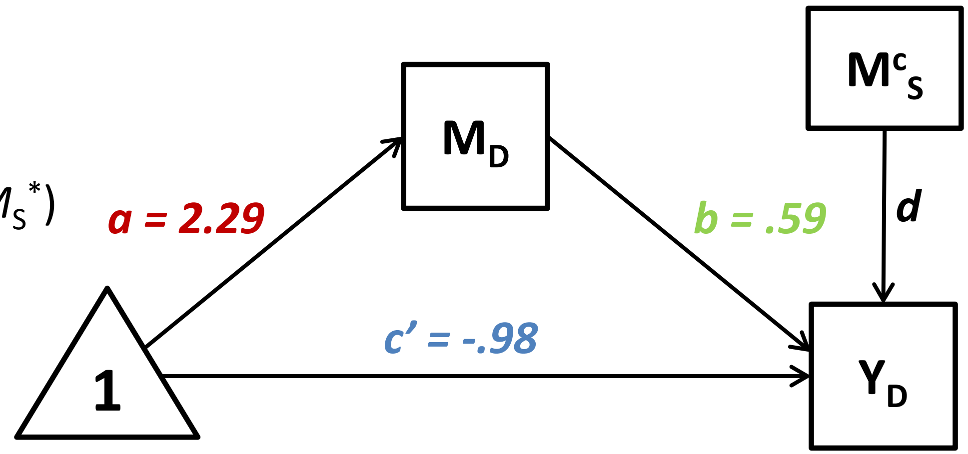
a path: (Regress M_D on a constant)

$$\widehat{M_D} = a$$
$$\widehat{M_D} = 2.29$$

^{c} Indicates mean centered

b path and *c′* path: (Regress Y_D on M_D and $M_S{}^*$)

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



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

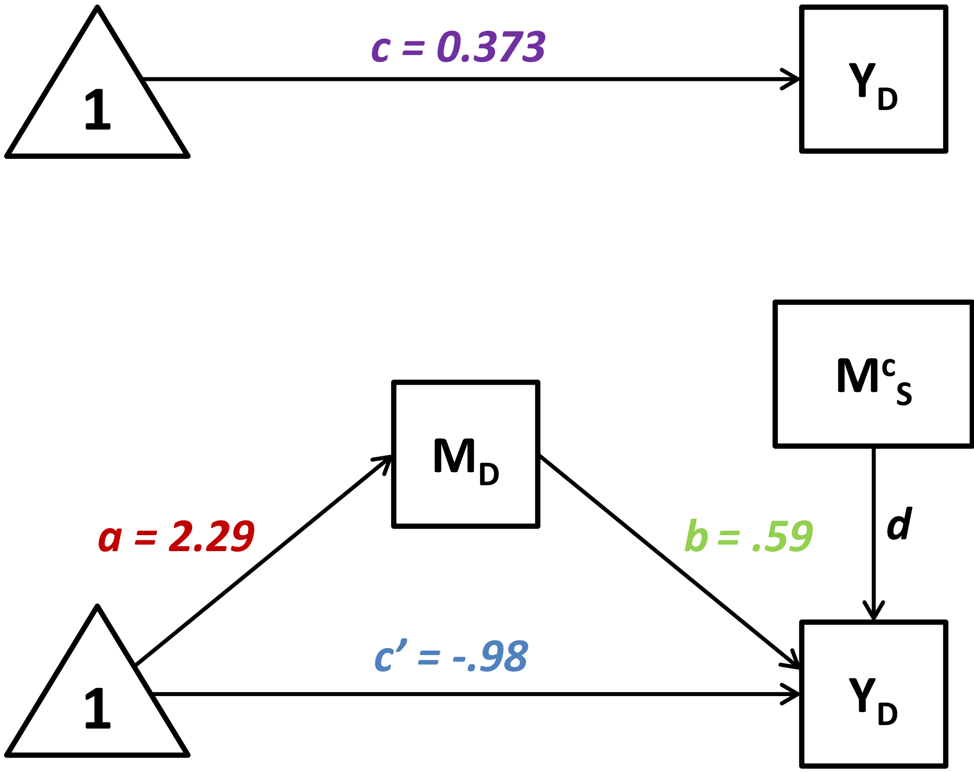
The effect of *X on Y* partitions into two components: direct and indirect, in the usual way.

$$c = c' + a \times b$$

$$.373 = -.98 + 2.29 \times .59$$

$$.373 = -.98 + 1.35$$

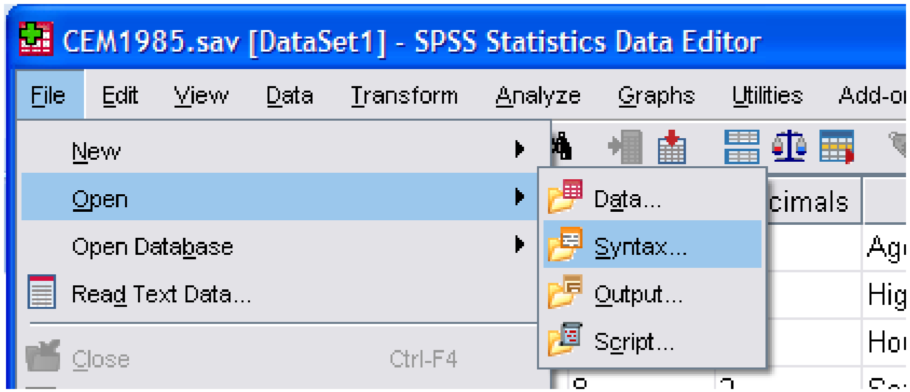
We can conduct inferential tests on the estimate of the indirect effect as in any other mediation analysis.

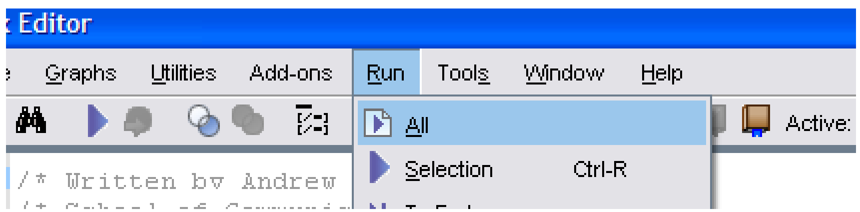


MEMORE has three methods of inference for the indirect effect available: bootstrapping, Monte Carlo confidence intervals, Sobel Tests

Teaching your package MEMORE (SPSS)

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.

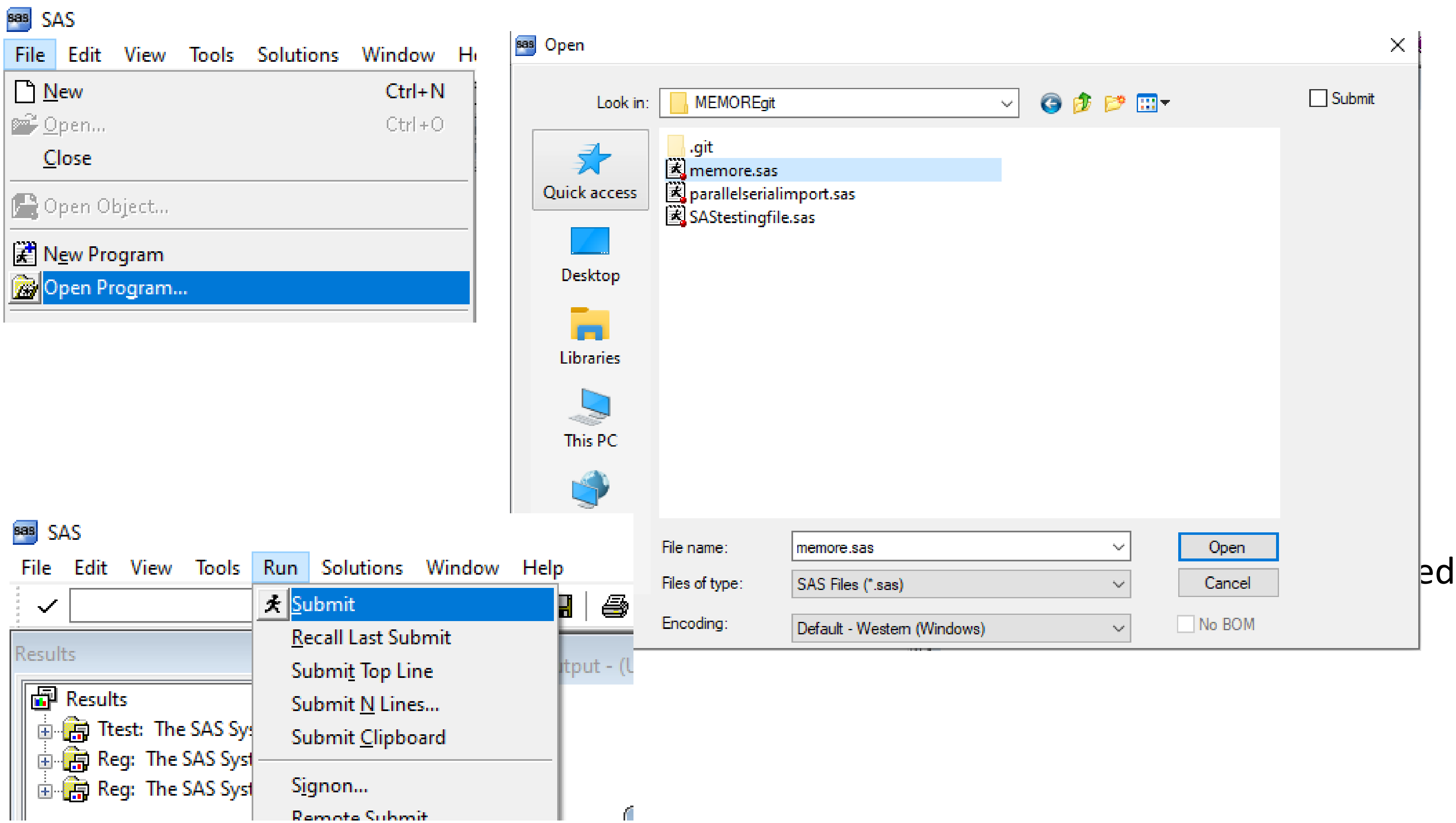




SPSS now knows a new command called MEMORE

Teaching your package MEMORE (SAS)

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



Writing MEMORE Syntax

MEMORE has 2 required arguments: `Y` and `M`, `data` is required for SAS

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

```
%memore(m = comm_G comm_I, y = int_G int_I, normal = 1, samples =
10000, conf = 90, model = 1, data = CompSci_WS);
```

`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)

Arguments:

- **`model`** specifies the model you are interested. The default is 1, mediation. Moderation models are 2 and 3, 4+ are moderation.
- **`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 CompSci WS data

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

```
%memore(m=comm_G comm_I, y=int_G int_I, model=1, data=CompSci_WS);
```

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

                          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!

Using MEMORE for CompSci WS data

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

```
%memore(m=comm_G comm_I, y=int_G int_I, model=1, data=CompSci_WS);
```

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

Using MEMORE for CompSci WS data

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

```
%memore(m=comm_G comm_I, y=int_G int_I, model=1, 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
'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**

Using MEMORE for CompSci WS data

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

```
%memore(m=comm_G comm_I, y=int_G int_I, model=1, data=CompSci_WS);
```

```
********************** 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      .3260      .6827     1.9653

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

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

Important effects for mediation and inference about these effects

Turning off the *XM* interaction

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

When we estimate this regression model, we allow the relationship between *M* and *Y* to differ by instance (*X*). This is like allowing for an interaction between *X* and *M* when estimating *Y*.

We do this by including the sum/average term in the regression model.

d estimates the difference in the relationship between M_1 → Y_1 and M_2 → Y_2. If we fix this coefficient to zero (do not include the sum term in the model) we fix the interaction to zero.

```
MEMORE m= comm_G comm_I /y = int_G int_I /xmint = 0/model = 1.
```

```
%memore(m=comm_G comm_I, y=int_G int_I, model=1, xmint = 0,
data=CompSci_WS);
```

Turning off the XM interaction

```
MEMORE m= comm_G comm_I /y = int_G int_I /xmint = 0/model = 1.
```

```
%memore(m=comm_G comm_I, y=int_G int_I, model=1, xmint = 0,
data=CompSci_WS);
```

No interaction **Interaction**

```
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

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

c = .3725 (.2795)

a = 2.2941 (.2491)

Turning off the XM interaction

```
MEMORE m= comm_G comm_I /y = int_G int_I /xmint = 0/model = 1.
```

```
%memore(m=comm_G comm_I, y=int_G int_I, model=1, xmint = 0,
data=CompSci_WS);
```

No interaction | **Interaction**

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

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5432      .2950     2.8655    20.5060     1.0000    49.0000      .0000

Model
           coeff         SE          t          p       LLCI       ULCI
'X'      -1.0257      .3893    -2.6349      .0112    -1.8079     -.2434
Mdiff      .6095      .1346     4.5284      .0000      .3390      .8799


 Indirect Effect of X on Y through M
           Effect     BootSE   BootLLCI   BootULCI
 Ind1      1.3982      .3082      .8034     2.0156
```

c = -.9814(.2795)

b = .5902 (.1346)

d = -.5505 (.4328)

ab = 1.3540 [.6827,1.9653]

Ultimately results are mostly unchanged, but that is not always the case.

Testing the *XM* interaction

There are three potential approaches to testing the *XM* interaction that you might take:

1. **Include the *XM* interaction by default**
   - This is what is recommended in causal mediation analysis (Vo et al., 2020)
   - Use the `xmint=1` option in MEMORE always (this is the default)
2. **Test/Evaluation *XM* interaction as a pre-step**
   - Estimate coefficient and use a hypothesis test or effect size measure to evaluate whether it should be included
   - Include your threshold in your preregistration
   - Final model will depend on whether *XM* is included or not
3. **Robustness Check**
   - Fit the model as hypothesized (*XM* in or out)
   - Afterwards fit the other model and evaluate whether the results are sensitive to the choice (change in effect size or significance level)

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?

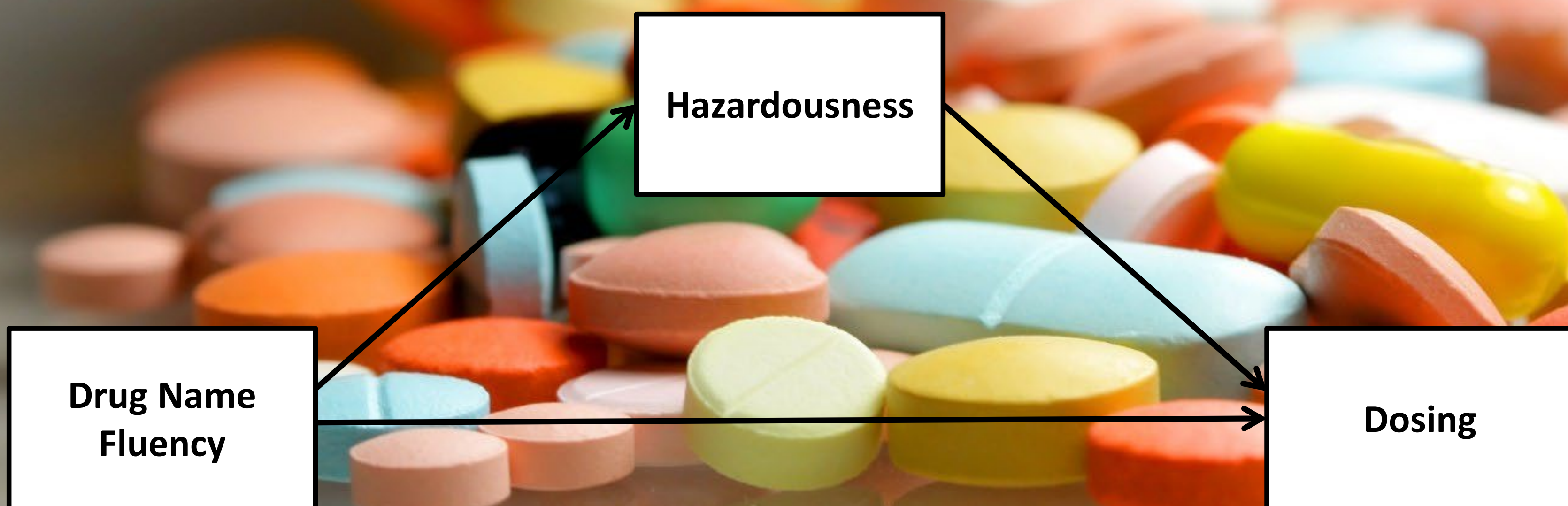
Overall there was no evidence of a total effect of group work on interest in computer science classes, we estimate that individuals were .37 units higher on interest in group work than individual work classes ($p = .19$). The class with group work was rated 2.29 units higher on communal goal affordance 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.

Example: Drug Name Fluency

Dohle, S., & Montoya, A. K. (2017). The dark side of fluency: Fluent names increase drug dosing. *Journal of Experimental Psychology: Applied*, *23*(3), 231 – 239.

Research Question: Can the name of drugs impact how hazardous they seem and how much people are willing to dose the drugs?

Imagine you have a cold, and there are a variety of medications available including (a) Fastinorbine and (b) Cytrigmcmium. Which seems more hazardous? Which are you willing to dose more of?



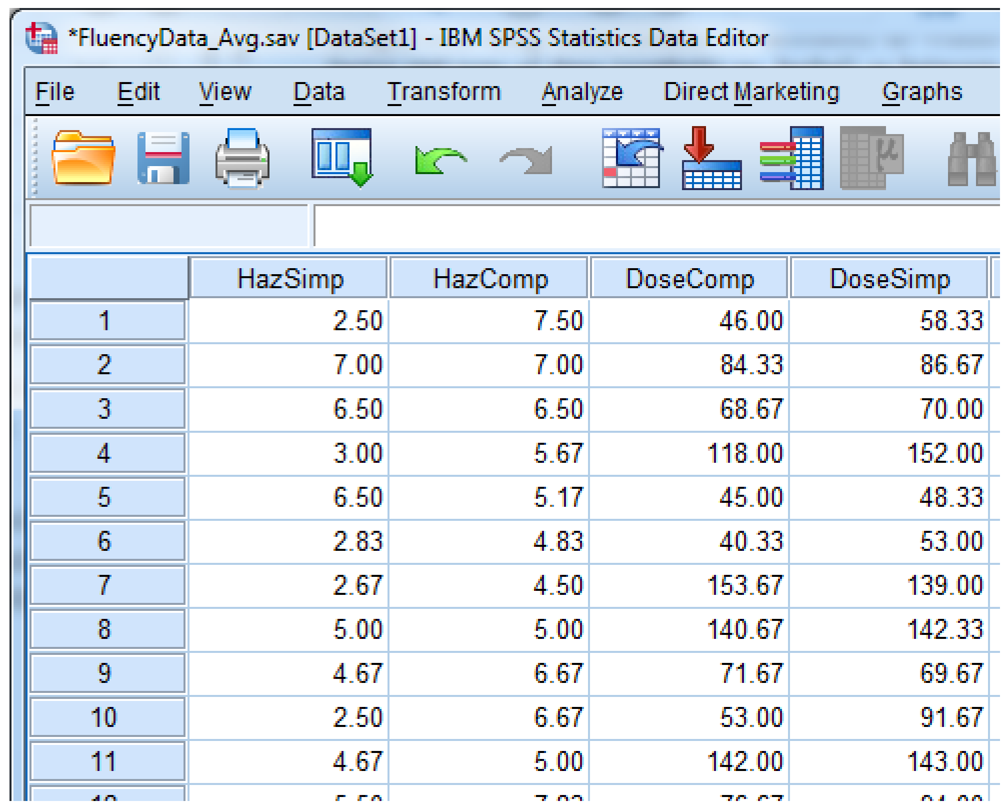
Example: Drug Name Fluency

Dohle, S., & Montoya, A. K. (2017). The dark side of fluency: Fluent names increase drug dosing. *Journal of Experimental Psychology: Applied*, *23*(3), 231 – 239.

Participants (N = 70) were asked to imagine they had the flu, and 6 different drugs were provided to treat the drug. Participants poured the dose they would feel comfortable taking at maximum into a plastic cup. Each person judged drugs with simple or complex names (3 of each). Responses on the measured variables were averaged across the 3 drugs (but later we'll look at what happens when we treat these separately).

Measured Variables:

- Dosage in mL
  - Variable name: `Dose`
  - 0 mL – 200mL
- Hazardousness of drug
  - Variable name: `Haz`
  - Average of two questions:
    - Hazardousness (1-7)
    - Dangerousness (1-7)



	HazSimp	HazComp	DoseComp	DoseSimp
1	2.50	7.50	46.00	58.33
2	7.00	7.00	84.33	86.67
3	6.50	6.50	68.67	70.00
4	3.00	5.67	118.00	152.00
5	6.50	5.17	45.00	48.33
6	2.83	4.83	40.33	53.00
7	2.67	4.50	153.67	139.00
8	5.00	5.00	140.67	142.33
9	4.67	6.67	71.67	69.67
10	2.50	6.67	53.00	91.67
11	4.67	5.00	142.00	143.00

Example: Drug Name Fluency

Dohle, S., & Montoya, A. K. (2017). The dark side of fluency: Fluent names increase drug dosing. *Journal of Experimental Psychology: Applied*, *23*(3), 231 – 239.

1. Estimate the proposed model (Fluency -> Hazardousness -> Dosage) using MEMORE
2. Turn off the *XM* interaction
3. Find estimates of the following paths: *a*, *b*, *c*, *c'*
4. Of the following inferential methods, which support the hypothesized mediation model (use $\alpha = 0.05$ or 95% confidence intervals):
   Percentile bootstrap CIs, Monte Carlo CIs, Sobel Test / Normal Theory
5. Practice writing up some of the results explored above.

Activity for Break

Causality

Mediation hypotheses and indirect effects are inherently causal.

Even when there is no an experiment or random assignment, if your interest is in mediation/indirect effects you’re interest is in causal effects.

There are important assumptions to consider which would allow our estimate of an indirect effect to be an **unbiased estimate of a causal effect** even without random assignment.

Temporal Precedence

The assumption of temporal precedence assumes that the **cause precedes the effect**.

This issue is often of concern with mediators and outcomes measured at the same time points.

Study design elements can be used to improve temporal precedence:

- Measure mediators before outcomes in single sitting surveys (but there are some reasons not to)
- Measure mediators at a time point earlier than outcomes (e.g., Mediator at baseline and 3 months, Outcome at baseline and 6 months)

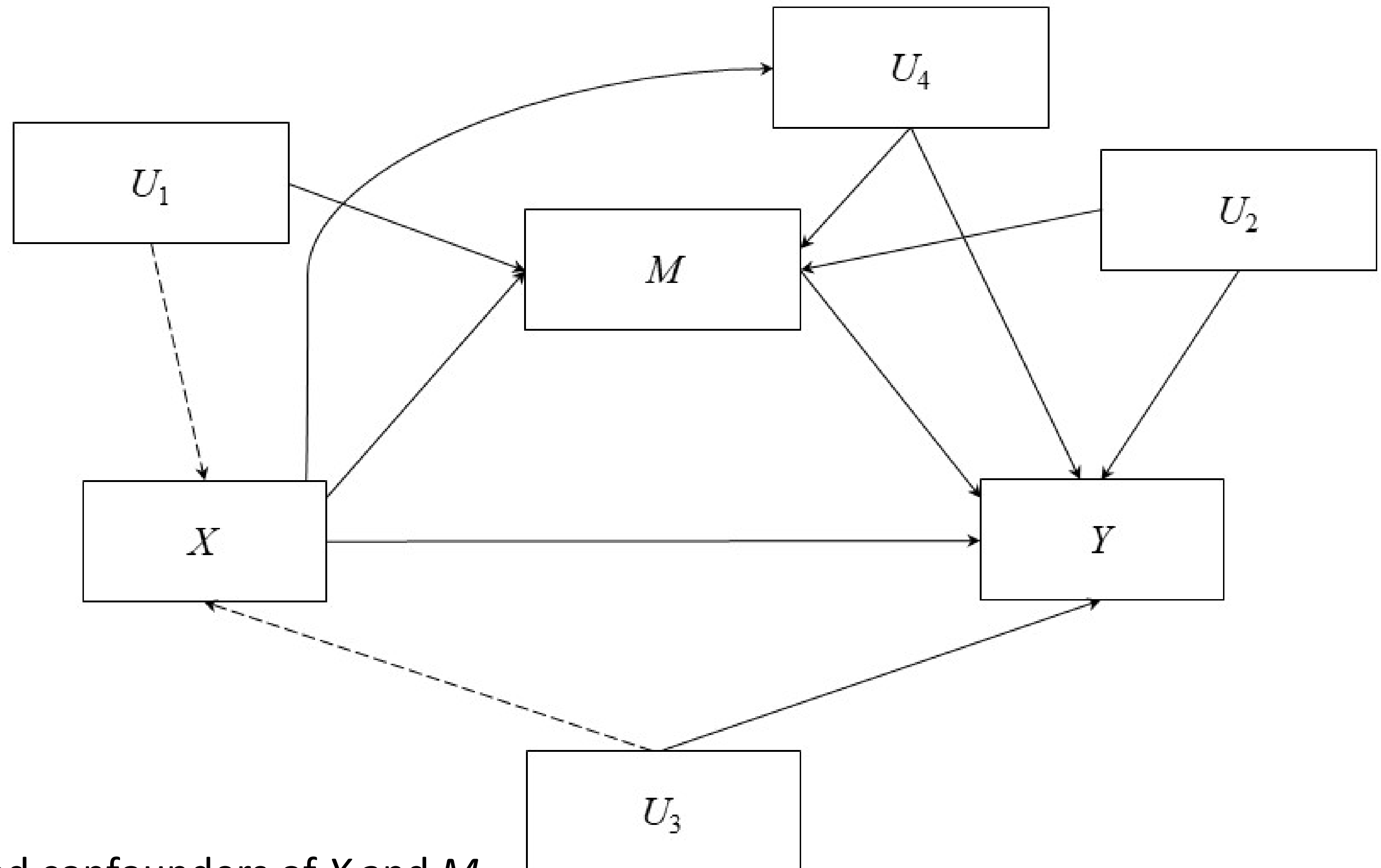
Omitted Confounder Assumptions

What's an "omitted confounder"?
It is any variable that is not included in the model (omitted) that causally affects two variables in the model

These are the classic assumptions for mediation:

1. No omitted confounders of X and M
2. No omitted confounders of M and Y
3. No omitted confounders of X and Y
4. No omitted or measured confounders of M and Y that are affected by X

Omitted Confounders DAG



1. No omitted confounders of *X* and *M*
2. No omitted confounders of *M* and *Y*
3. No omitted confounders of *X* and *Y*
4. No omitted or measured confounders of *M* and *Y* that are affected by *X*

Confounder Levels

In within-subject designs confounders can exist at two different levels:

1. Person level: Constant across instances, but varies across subjects

    Academic year, Gender, Personality

2. Instance level: Varies across instances within subjects

    Expected teacher gender, perceived difficulty of the course

Good news: If upper-level confounders of *M-Y* relationship are additive (no interaction) then they do not affect causal identification (Josephy et al., 2015)

Carry-Over Effects

Carry-over effects are when measures from one instance affect measures from another instance.

Assumed models:

$$M_{1\mathrm{i}} = a_1 + \epsilon_{M_{1i}}$$ M_2 or Y_2 are **not** in this model

$$M_{2\mathrm{i}} = a_2 + \epsilon_{M_{2i}}$$ M_1 or Y_1 are **not** in this model

$$Y_{1\mathrm{i}} = g_{10} + g_{11}M_{1i} + \epsilon_{Y_{1i}}$$ M_2 or Y_2 are **not** in this model

$$Y_{2\mathrm{i}} = g_{20} + g_{21}M_{2i} + \epsilon_{Y_{2i}}$$ M_1 or Y_1 are **not** in this model

If the TRUE data generating model includes these predictors, then our estimates of the indirect effect will be biased.

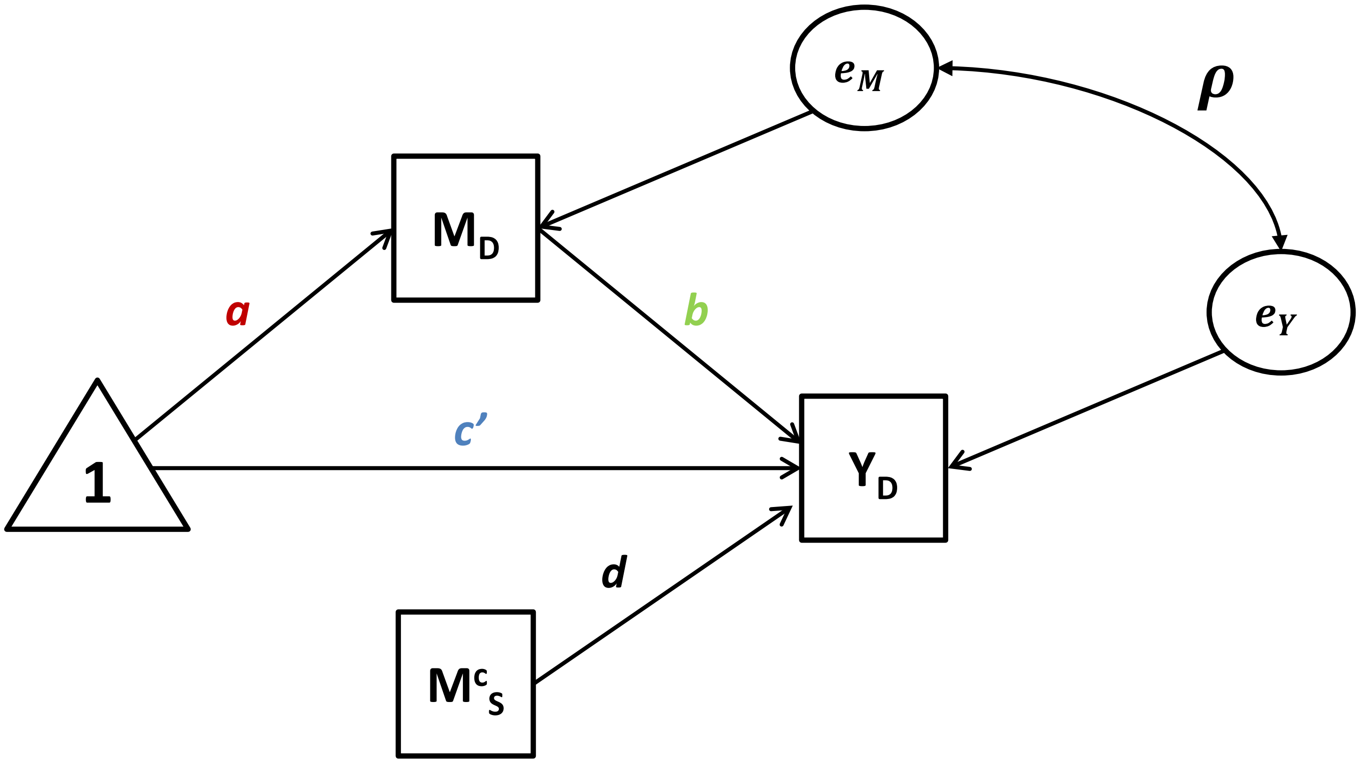
Sensitivity Analysis

An analytical approach for evaluating *how much confounding* would need to be present to reduce indirect effect.

Focus is typically on *M*-*Y* confounders since these can be so problematic for mediation analysis.

When *M*-*Y* is confounded, they have correlated residuals, focus is on the size of that correlation.

Sensitivity Analysis

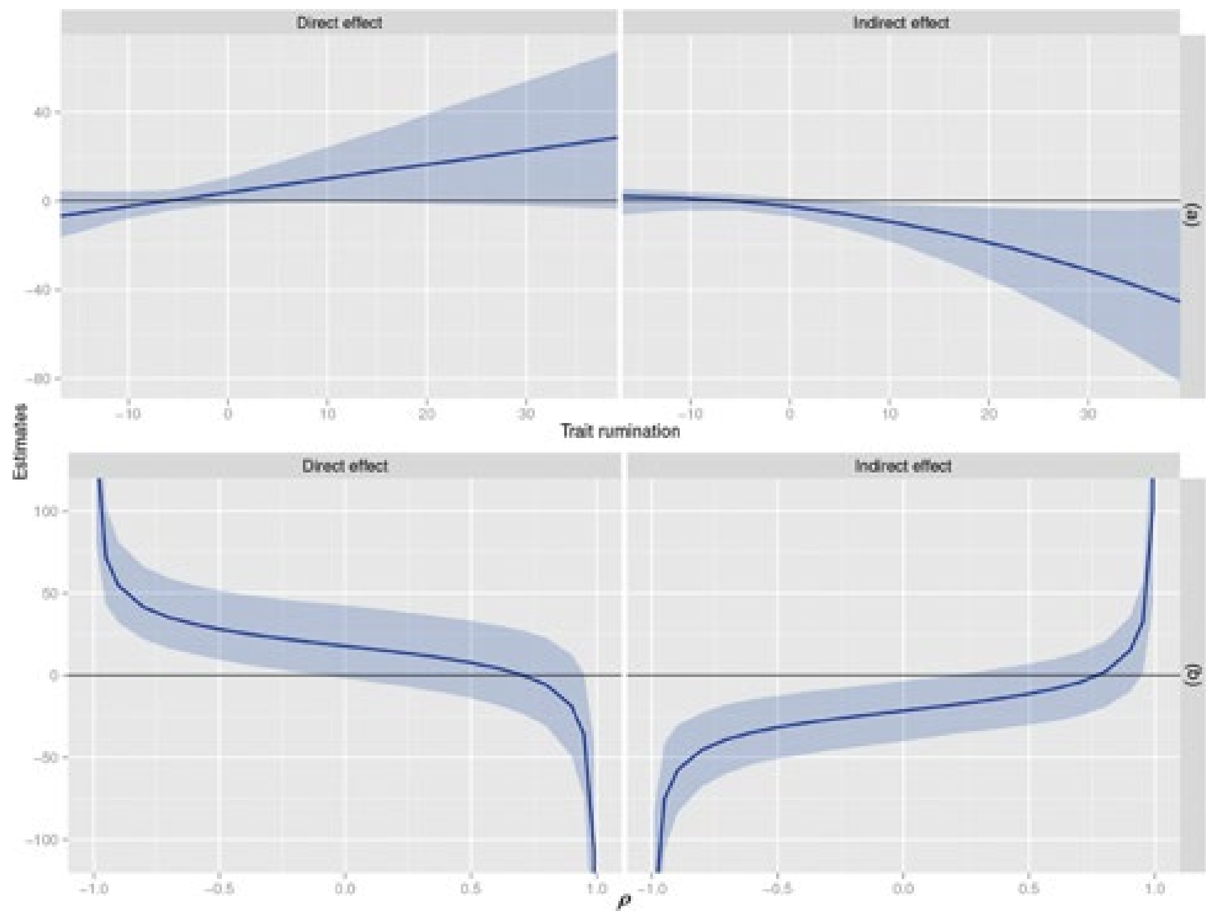


Estimate the size of ρ that would…

- Make the indirect effect non-significant
- Make the indirect effect zero

Sensitivity Analysis

No existing tools for conducting sensitivity analyses in these designs (but can do with *mediation* package in R for multilevel mediation).



Josephy et al. (2015)

STUDY PLANNING

Power Analysis & Preregistration

Power Analysis

R script is available for power analysis for within-subject mediation at this GitHub Page.

Run script in R, then revise the following code for analysis:

```
WSmedpower(nsims = 5000, boots = 0, MCsamples = 0,
alpha = 0.05, N = 100, corm = .22, cory = .32, aest
= -.44, best = -.34, cest = .39, dest = 0)
```

Can set boots and MCsamples to zero to get close with Joint Significance method, run time is long when non-zero

```
 JointSig  Bootstrap MonteCarlo
    0.895         NA         NA
```

Power Analysis

Arguments

- nsims: number of simulations to run (default is 1000)
- boots: number of bootstrap samples (default is 0, which
- doesn't run bootstrap analysis)
- MCsamples: number of monte carlo samples (default is 0, which
- does run Monte Carlo analysis)
- alpha: level of test, acceptable type I error rate (default is
- 0.05)
- N: sample size to test
- corm: correlation among repeated measurements of mediator
- cory: correlation among repeated measurements of outcome
- aest: a-path estimates standardized by SD(M)
- best: b-path estimate standardized by SD(M) and SD(Y)
- cest: c-path estimate standardized by SD(Y)
- dest: d-path estimate standardized by SD(M) and SD(Y)

Preregistration

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

Current preregistrations of mediation analysis are light on the details:
"We plan to conduct mediation tests (including multiple mediation) using the MEMORE macro (Montoya & Hayes, 2017) and the PROCESS macro (Hayes, 2017).“

- ❑ Planned sample size
- ❑ α-level/CI-level for each test
- ❑ Role of different variables in the analysis (e.g., independent variable, mediator, outcome, covariate), and how they are computed
- ❑ Estimation Method
- ❑ Inferential method and any important specifications for that method (e.g., how many bootstraps, seed number)
- ❑ Plans for sensitivity analysis: Benchmarks for acceptable correlations for evaluating confounding
- ❑ *Plans for XM interaction*
- ❑ **Tools and specifications**

Example Preregistration

We will estimate a simple mediation analysis where protest condition (X) affects liking (Y) through response appropriateness (M) using a sample of 500 participants. Protest condition is assigned in a random order where 50% will be assigned to the protest condition first and 50% to the no protest condition first. Liking is measured using 4 Likert type items evaluating the lawyers positive characteristics. We will check the reliability of our scale prior to analysis and if the reliability (alpha) is greater than 0.7, we will proceed. If it is not we may consider dropping items. Similarly, response appropriateness is measured using 5 Likert type items. We will use the same procedure for measurement evaluation as with liking. In our analysis we will not control for any covariates.

We will use the **MEMORE for SPSS (version 3.0)** to estimate our model, which uses ordinary least squares regression and generates percentile bootstrap confidence intervals for the indirect effect. We will use 5,000 bootstraps. *We plan to test whether the XM interaction is statistically significant at alpha = 0.10, if it is, we will use the xmint=1 option in MEMORE to estimate the indirect effect (using 232714). If the XM interaction is not statistically significant, we will use xmint = 0, to estimate the indirect effect. We will test hypothesis 1 by examining the 95% bootstrap confidence interval for the indirect effect includes zero.*

After our analysis we will use the mediation package in R to conduct sensitivity analysis, specifically for the relationship between response appropriateness and liking. Correlations greater than .5 would suggest robustness to reasonable levels of confounding.

Finding Examples

DataStudio for finding examples

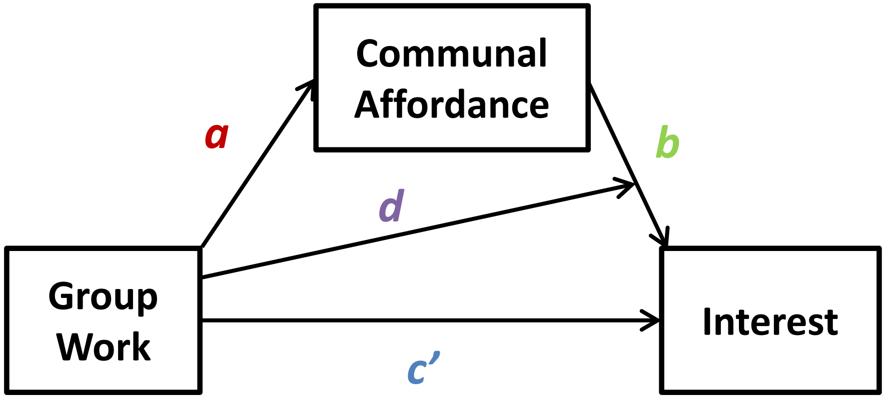
https://lookerstudio.google.com/s/gFgefAkOjKA

Publication Year
Research Areas
ModelNumb... (1)
Xtype
levelsX
numYvars
Journal Title
Covariates
Sample Size
Article Count
50

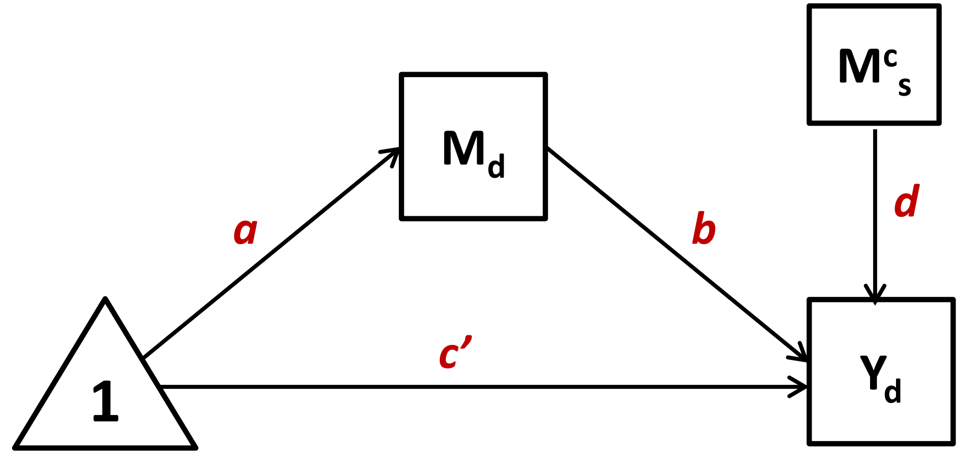
Article Title (link)	Authors	Journal Title	Publication...	Research Areas	Study Num...	SampleSize	ModelNumb...	numXvars	Xtype	levelsX	numYvars
When should retail...	Jeong, H; Ye,...	JOURNAL O...	2021	Business & Economics	1	271	1 (Mediation)	1	Pre-post	2	1
What hinders resi...	Dong, XJ	TOURISM A...	2022	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

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!

Visualization Examples

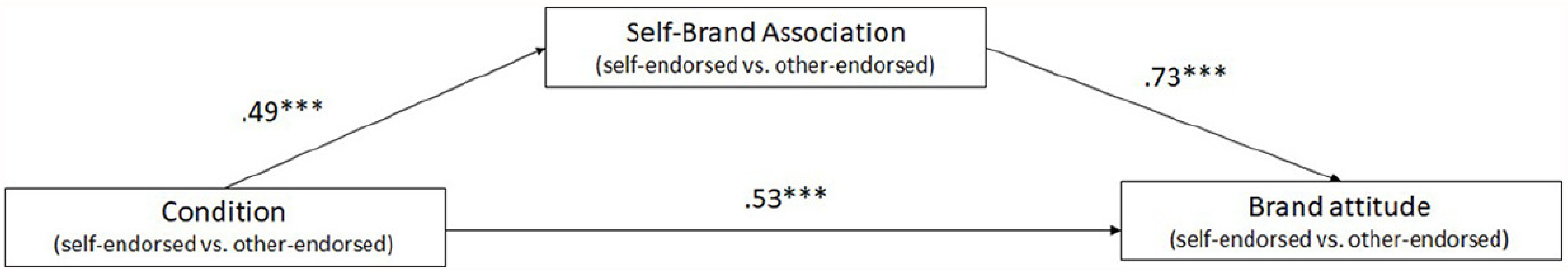
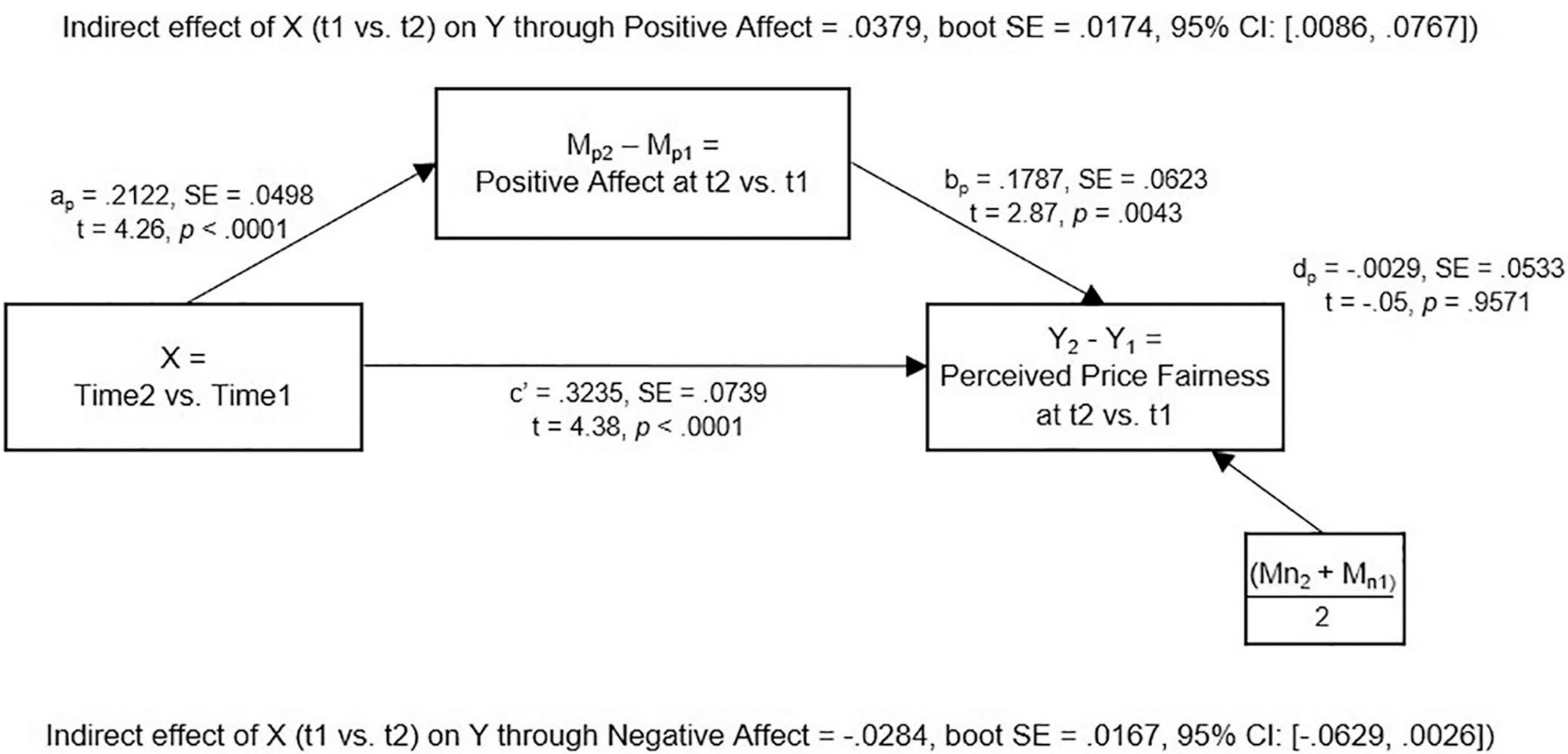


Figure 1. Self-brand association as a mediator of the relationship between condition (self-endorsed vs other-endorsed) and brand attitude (n = 119). *Indirect Effect* = 0.35 CI = [0.23, 0.51]. Used 5000 sample bootstraps to calculate indirect effect. ***p < .001.

https://journals.sagepub.com/doi/10.1177/1461444820912197

Visualization Examples



https://onlinelibrary.wiley.com/doi/10.1002/cb.1934

Visualization Examples

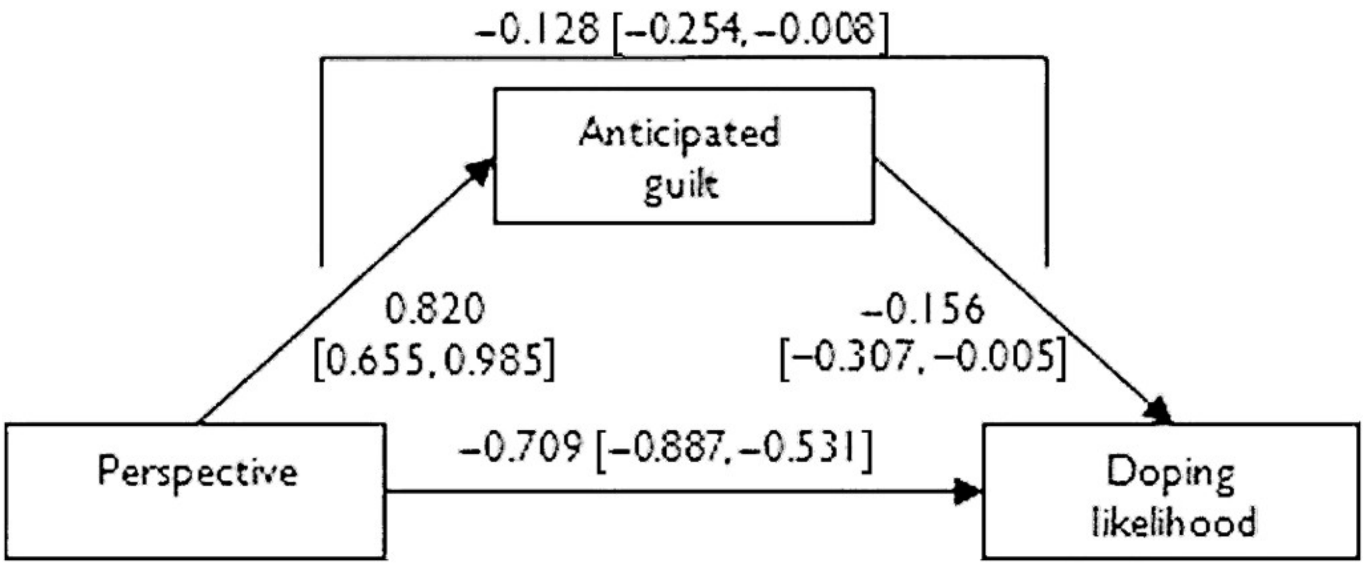
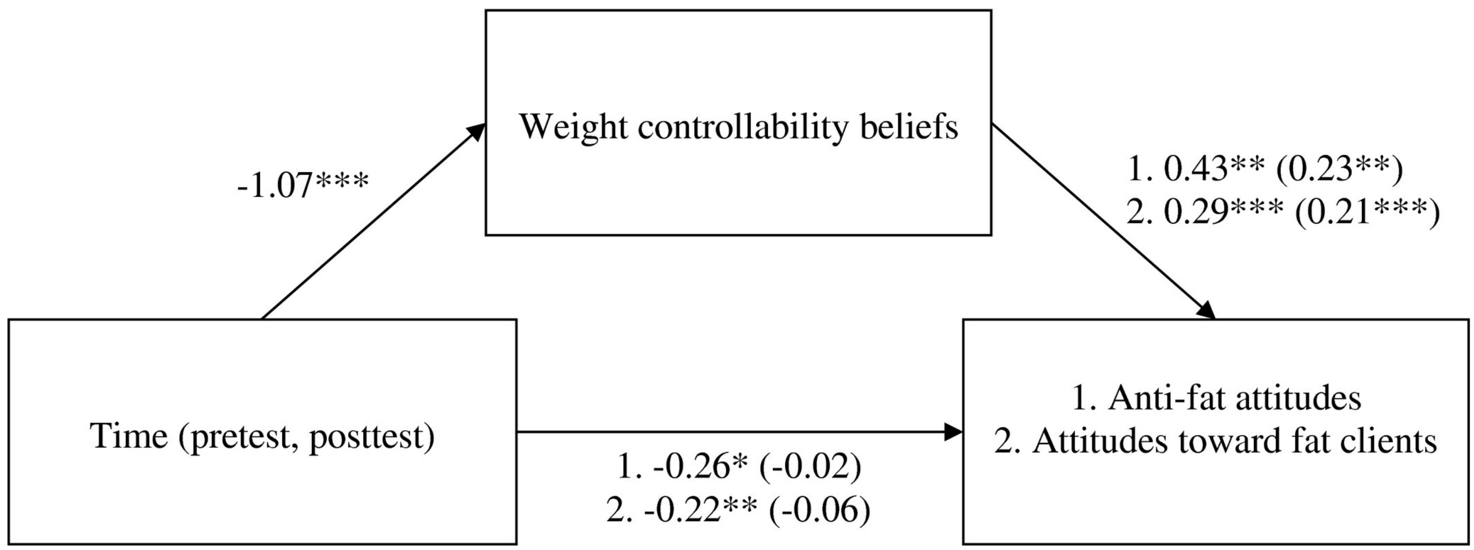


Figure 1—The direct effects of perspective (self minus other) on doping likelihood and guilt, and the indirect effect of perspective on doping likelihood via guilt. Unstandardized coefficients are reported, with 95% confidence intervals in brackets. Solid lines indicate significant paths.

https://journals.humankinetics.com/view/journals/jsep/42/5/article-p417.xml

Visualization Examples



Weight controllability beliefs mediate the effect of the weight bias seminar (time: pretest, posttest) on (1) anti-fat attitudes and (2) attitudes toward fat clients. *Note*. Unstandardized betas are presented on figure paths. Numbers in parentheses represent betas when the mediator and all model variables were included. *p < .05. **p < .01. ***p < .001

https://onlinelibrary.wiley.com/doi/10.1111/jasp.12653

Visualization Examples

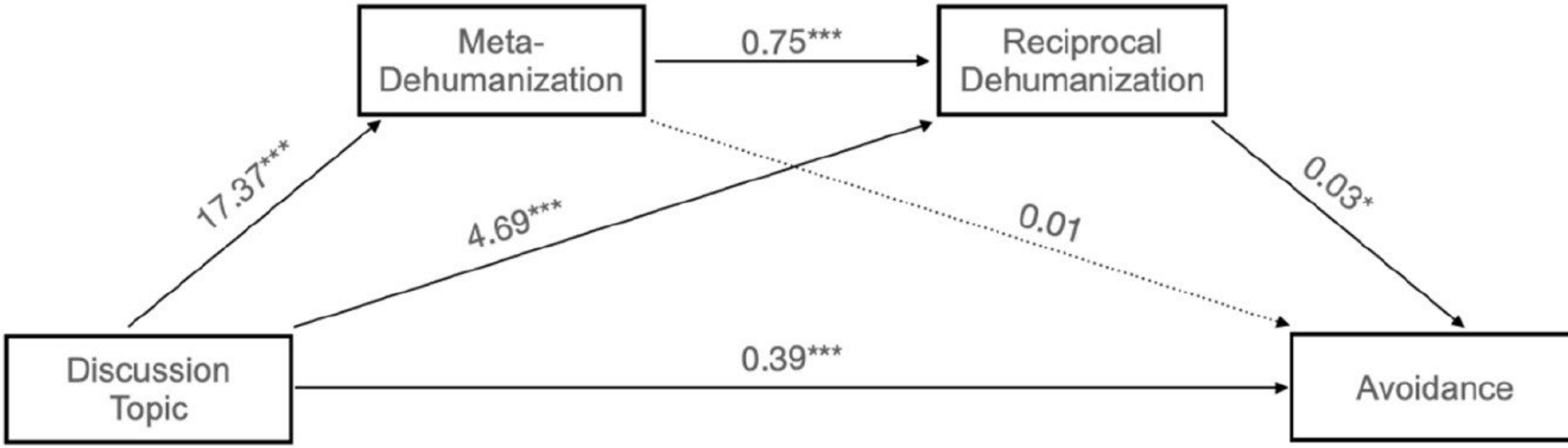


Figure 6. Within-person serial mediation: Study 3.
Note. All reported coefficients are unstandardized effect sizes because standardized betas could not be computed using this analysis.

https://journals.sagepub.com/doi/10.1177/13684302221099449

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 **five** sets of mediators (See Montoya & Hayes 2017 for instructions).

Can we do conditional process models?

YES! We'll review this briefly on the second day, after covering moderation

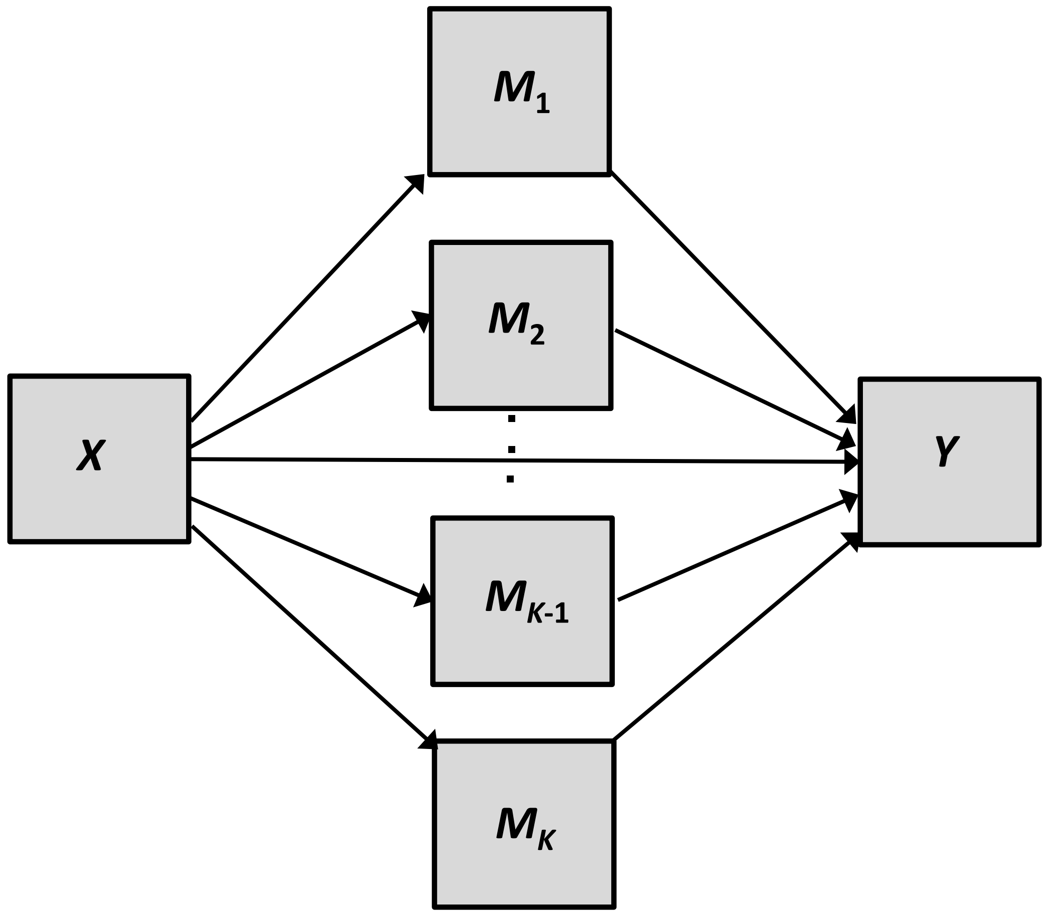
How do I control for covariates?

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.

Models with More Than One Mediator

A parallel multiple mediator model



Why estimate such a model?

- Many causal effects probably operate through multiple mechanisms simultaneously. Better to estimate a model **consistent with such real-world** complexities.
- If your proposed mediator is correlated with the real mediator but not caused by the independent variable, a model with only your proposed mediator in it will be a **misspecification** and will potentially misattribute the process to your proposed mediator rather than the real mediator—"epiphenomenality."
- Different theories may postulate different mediators as mechanisms. Including them all in a model simultaneously allows for a formal statistical comparison of indirect effects **representing different theoretical mechanisms**.

A Note on Notation

Thus far all measures have had 2 subscripts:

M_{ji} is the mediator *M* measured at time *j* for person *i*

Now we will have 3 subscripts:

M_{kji} is the k^{th} mediator measured at time *j* for person *i*

If you ever get confused by these, feel free to pipe up!

Two Mediator Case

The Total Effect model is **unchanged** because it doesn't involve the mediators

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

Each mediator (pair) gets it's own model

$$M_{12i} - M_{11i} = a_1 + \boxed{e_{M_{1i}}}$$
$$M_{22i} - M_{21i} = a_2 + \boxed{e_{M_{2i}}}$$

These residuals are NOT assumed to be independent, and may be correlated

Model for outcome incorporates both pairs of mediators

$$\begin{aligned} Y_{2i} - Y_{1i} = c' &+ b_1(M_{12i} - M_{11i}) + b_2(M_{22i} - M_{21i}) \\ &+ d_1\left(M_{12i} + M_{11i} - (\overline{M_{12} + M_{11}})\right) + d_2\left(M_{22i} + M_{21i} - (\overline{M_{22} + M_{21}})\right) \\ &+ e_{Y_i} \end{aligned}$$

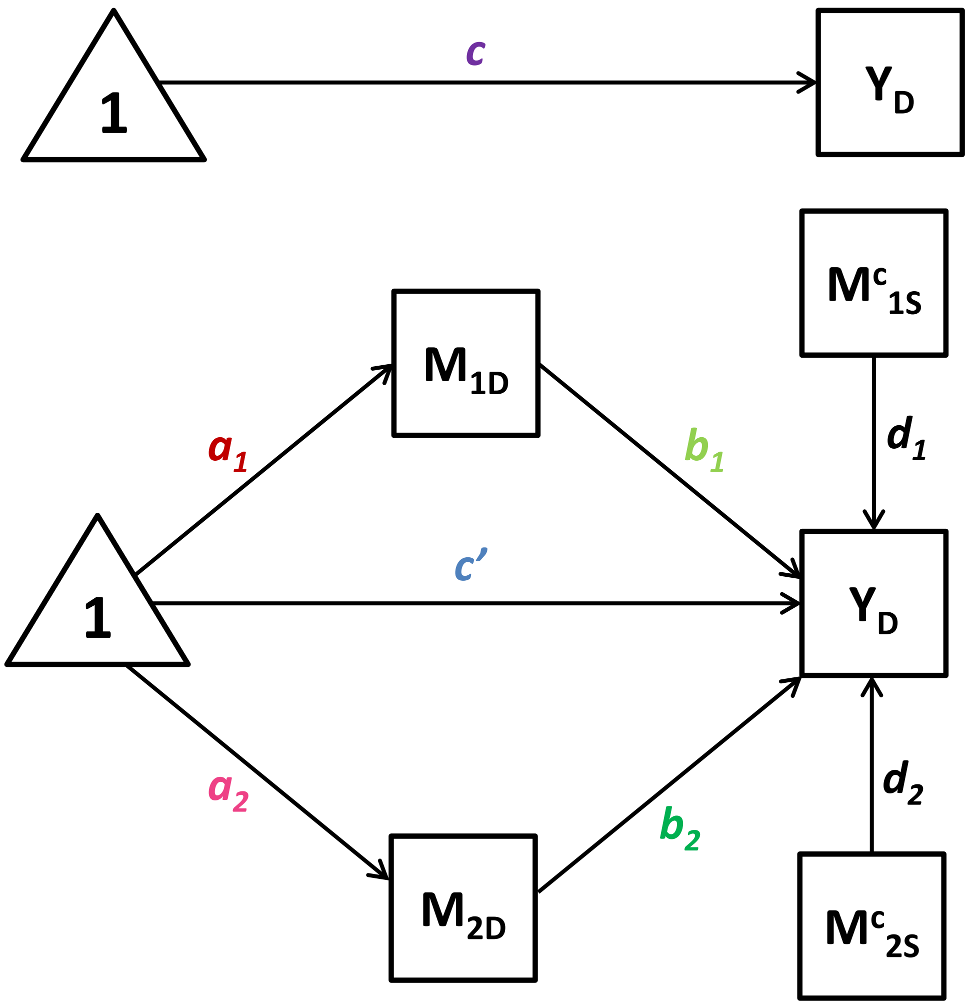
c = "total effect" of X on Y

$a_k \times b_k$ = "specific indirect effect" of X on Y through M_k

$\Sigma\,(a_k \times b_k)$= "total indirect effect" of X on Y

c' = "direct effect" of X on Y

Path Diagram: Total, Direct, and Indirect Effects



^{c} Indicates mean centered

K Mediator Case

The Total Effect model is **unchanged** because it doesn't involve the mediators

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

Each mediator (pair) gets it's own model

$$M_{k2i} - M_{k1i} = a_k + e_{M_{ki}}$$

Model for outcome incorporates all pairs of mediators

$$Y_{2i} - Y_{1i} = c' + \sum_{k=1}^{K} b_k (M_{k2i} - M_{k1i}) + \sum_{k=1}^{K} d_k \left(M_{k2i} + M_{k1i} - (\overline{M_{k2} + M_{k1}})\right) + e_{Y_i}$$

c = "total effect" of X on Y

$a_k \times b_k$ = "specific indirect effect" of X on Y through M_k

$\Sigma (a_k \times b_k)$= "total indirect effect" of X on Y

c' = "direct effect" of X on Y

total effect = direct effect + total indirect effect

$$c = c' + \Sigma (a_k \times b_k)$$

Example: Group work in Computer Science

Participants read two syllabi for computer science classes. The syllabi had of two policies: **procollaboration** or **no collaboration**. Participants were randomly assigned read each syllabus in a random order

Participants completed questionnaire (Higher = greater):

(1) interest in the class (this is the primary DV).
(2) how much they felt the class would help them in achieving **communal goals** (helping others, working with others)
(3) how **difficult** they expected the class to be.

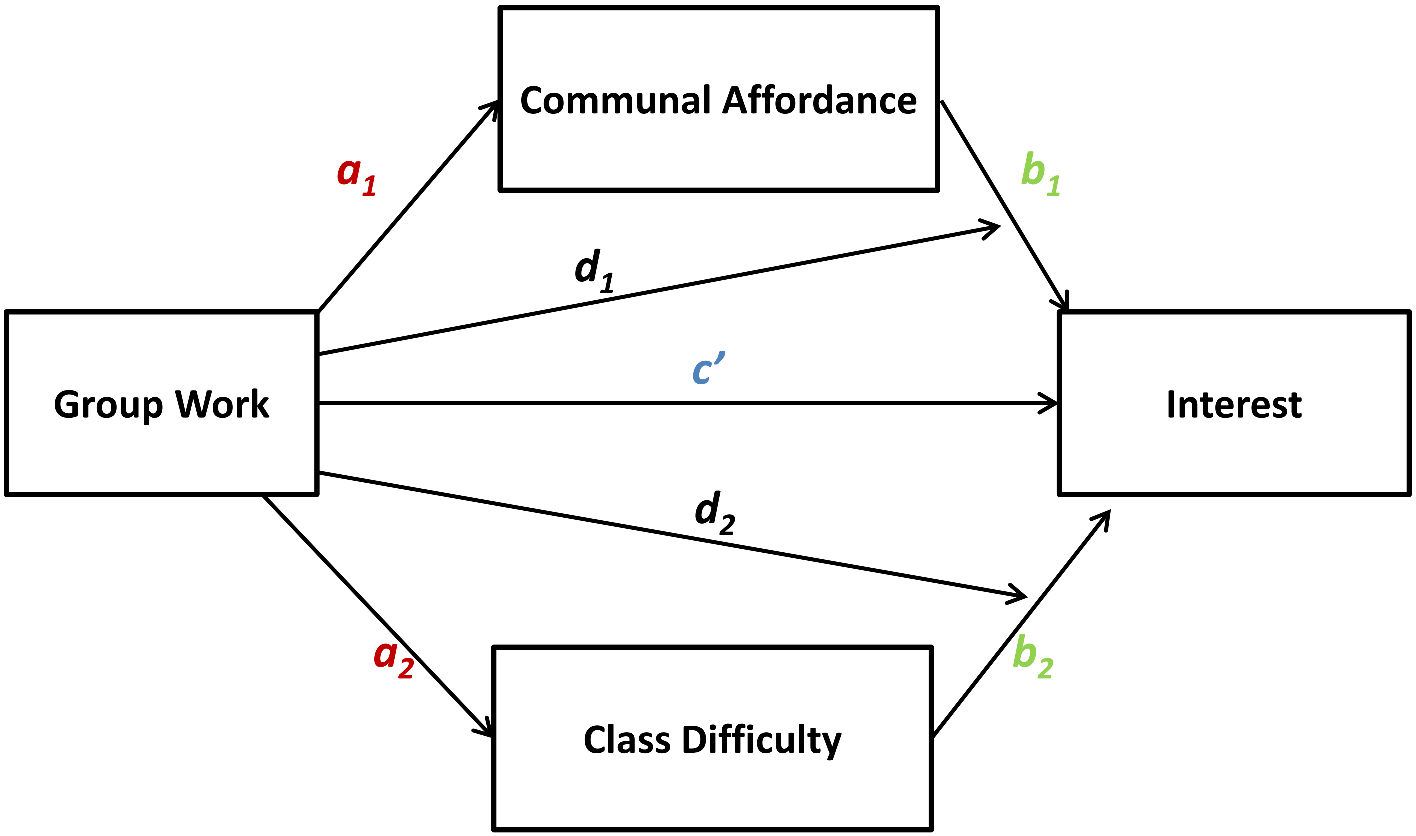
Girls who Code

Question: Does group work in computer science classes increase interest in the class indirectly through perceived communal goal fulfillment, through class difficulty, or both?

Would people who read about the procollaboration policy think the class is more communal and would that communality then predict greater interest? Would the procollaboration policy make students think the course is easier, and this would increase interest?

Using MEMORE for CompSci WS data

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



Multiple Parallel Mediators

To add mediator pairs list them in the m= list, in the same order as the other pair and outcome variables

```
MEMORE m = comm_G comm_I diff_G diff_I /y = int_G int_I /model = 1 /seed =
74572.
```

```
%memore(m = comm_G comm_I diff_G diff_I, y = int_G int_I, model = 1, seed =
74572, data = CompSci_WS);
```

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

                          Written by Amanda Montoya

                   Documentation available at akmontoya.com

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

Model:
  1

Variables:
Y =   int_G    int_I
M1 =  comm_G   comm_I
M2 =  diff_G   diff_I

Computed Variables:
Ydiff =             int_G     -      int_I
M1diff =            comm_G    -      comm_I
M2diff =            diff_G    -      diff_I
M1avg  = (          comm_G    +      comm_I    )        /2                         Centered
M2avg  = (          diff_G    +      diff_I    )        /2                         Centered

Sample Size:
  51
```

Check that variables are in correct pairs and in correct order

Multiple Parallel Mediators

```
MEMORE m = comm_G comm_I diff_G diff_I /y = int_G int_I /model = 1 /seed =
74572.
```

```
%memore(m = comm_G comm_I diff_G diff_I, y = int_G int_I, model = 1, seed =
74572, data = CompSci_WS);
```

Results for Total Effect and Model of M1 (Communal Goals) unchanged

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

Model
             Effect         SE          t          p       LLCI       ULCI
constant      .3725      .2795     1.3330      .1886     -.1888      .9339

Degrees of freedom for all regression coefficient estimates:
  50

**************************************************************************************
Outcome: M1diff = comm_G    -       comm_I

Model
             Effect         SE          t          p       LLCI       ULCI
constant     2.2941      .2491     9.2108      .0000     1.7938     2.7944

Degrees of freedom for all regression coefficient estimates:
  50
```

Multiple Parallel Mediators

```
MEMORE m = comm_G comm_I diff_G diff_I /y = int_G int_I /model = 1 /seed =
74572.
```

```
%memore(m = comm_G comm_I diff_G diff_I, y = int_G int_I, model = 1, seed =
74572, data = CompSci_WS);
```

Model of Difficulty

```
**************************************************************************
Outcome: M2diff = diff_G     -       diff_I

Model
              Effect         SE          t          p       LLCI       ULCI
constant      -.4314      .1905    -2.2648      .0279     -.8139     -.0488

Degrees of freedom for all regression coefficient estimates:
  50
```

Negative coefficient means diff_I > diff_G

The individual work class is perceived as 0.43 units more difficult than the group work class, and this effect is statistically significant ($p < .05$).

Multiple Parallel Mediators

The model of interest now includes both communal goals and difficulty variables

```
MEMORE m = comm_G comm_I diff_G diff_I /y = int_G int_I /model = 1 /seed =
74572.
```

```
%memore(m = comm_G comm_I diff_G diff_I, y = int_G int_I, model = 1, seed =
74572, data = CompSci_WS);
```

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

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          p       LLCI       ULCI
constant     -.9172      .3815    -2.4042      .0203    -1.6851     -.1493
M1diff        .4847      .1448     3.3460      .0016      .1931      .7762
M2diff       -.4123      .1878    -2.1952      .0332     -.7904     -.0342
M1avg        -.5160      .4157    -1.2411      .2209    -1.3528      .3209
M2avg         .3781      .2879     1.3133      .1956     -.2014      .9577

Degrees of freedom for all regression coefficient estimates:
  46
```

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

The effect is still significant and positive

Multiple Parallel Mediators

The model of interest now includes both communal goals and difficulty variables

```
MEMORE m = comm_G comm_I diff_G diff_I /y = int_G int_I /model = 1 /seed =
74572.
```

```
%memore(m = comm_G comm_I diff_G diff_I, y = int_G int_I, model = 1, seed =
74572, data = CompSci_WS);
```

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

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          p       LLCI       ULCI
constant     -.9172      .3815    -2.4042      .0203    -1.6851     -.1493
M1diff        .4847      .1448     3.3460      .0016      .1931      .7762
M2diff       -.4123      .1878    -2.1952      .0332     -.7904     -.0342
M1avg        -.5160      .4157    -1.2411      .2209    -1.3528      .3209
M2avg         .3781      .2879     1.3133      .1956     -.2014      .9577

Degrees of freedom for all regression coefficient estimates:
  46
```

Higher levels of difficulty correspond lower levels of interest in the course.

The effect is statistically significant

Multiple Parallel Mediators

The model of interest now includes both communal goals and difficulty variables

```
MEMORE m = comm_G comm_I diff_G diff_I /y = int_G int_I /model = 1 /seed =
74572.
```

```
%memore(m = comm_G comm_I diff_G diff_I, y = int_G int_I, model = 1, seed =
74572, data = CompSci_WS);
```

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

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          p       LLCI       ULCI
constant     -.9172      .3815    -2.4042      .0203    -1.6851     -.1493
M1diff        .4847      .1448     3.3460      .0016      .1931      .7762
M2diff       -.4123      .1878    -2.1952      .0332     -.7904     -.0342
M1avg        -.5160      .4157    -1.2411      .2209    -1.3528      .3209
M2avg         .3781      .2879     1.3133      .1956     -.2014      .9577

Degrees of freedom for all regression coefficient estimates:
  46
```

Direct effect is significant and negative

After controlling for communal goals and difficulty, students are significantly more interested in the individual work class compared to group work.

Multiple Parallel Mediators

```
MEMORE m = comm_G comm_I diff_G diff_I /y = int_G int_I /model = 1 /seed =
74572.
```

```
%memore(m = comm_G comm_I diff_G diff_I, y = int_G int_I, model = 1, seed =
74572, data = CompSci_WS);
```

```
************************** 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
     -.9172      .3815    -2.4042    46.0000      .0203    -1.6851     -.1493

Indirect Effect of X on Y through M
          Effect     BootSE   BootLLCI   BootULCI
Ind1      1.1119      .3871      .3597     1.8710
Ind2       .1779      .1148      .0000      .4347
Total     1.2897      .3567      .5690     1.9766

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

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

Controlling for communal goals, there is still a significant indirect effect through difficulty. (Just barely)

Total *Indirect* Effect

```
MEMORE m = comm_G comm_I diff_G diff_I /y = int_G int_I /model = 1 /seed =
74572.
```

```
%memore(m = comm_G comm_I diff_G diff_I, y = int_G int_I, model = 1, seed =
74572, data = CompSci_WS);
```

```
************************** 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
     -.9172      .3815    -2.4042    46.0000      .0203    -1.6851     -.1493

Indirect Effect of X on Y through M
          Effect     BootSE   BootLLCI   BootULCI
Ind1      1.1119      .3871      .3597     1.8710
Ind2       .1779      .1148      .0000      .4347
Total     1.2897      .3567      .5690     1.9766

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

Total indirect effect can be useful when mediators are conceptually similar, and you want to estimate their combined effect.

For example, communal goals and agentic goals could both be mediators, and total indirect effect would reflect the indirect effect of "goals"

Summary of Results

Is the effect of group work on class interest mediated by communal goal affordance of the class, difficulty or the class, both or neither?

Overall there was no 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). The class with group work was rated 0.4314 units lower on difficulty (p = 0.027). Controlling for difficulty, a one unit increase in perception of communal goal affordance increased interest in the class by 0.48 units (p = .002), and the relationship between communal goal affordance and interest in a class did not depend on condition (d_1 = -0.5160, p = .22). Controlling for communal goal affordance, a one unit difference in difficulty corresponds to lower interest in the class by 0.41 units (p = .03), and the relationship between difficulty and interest in a class did not significantly depend on condition (d_2 = 0.3781, p = .19). The indirect effect of group work on interest through communal goal fulfillment, controlling for difficulty, was significantly different from zero (a_1b_1 = 1.11, 95% Bootstrap CI [0.36, 1.87]). This means that we expect women to be 1.11 units more interested in a computer science class with group work compared to one without group work that is equally difficult, through the effect of group work on communal goal affordance, and the subsequent effect of communal goal affordance on interest. The indirect effect of group work on interest through difficulty, controlling for communal goal affordance, was significantly different from zero (a_2b_2 = 0.18, 95% Bootstrap CI [0.00, 0.43]). This means that we expect women to be 0.18 units more interested in a computer science class with group work compared to one without group work that is equally affording of communal goals, through the effect of group work on difficulty, and the subsequent effect of difficulty on interest. There was a significant direct effect between group work and interest (c' = -.92, p = .02). This indicates that there may be some other process, separate from communal goal affordance and difficulty, which is actually deterring women from computer science classes with group work.

A note on the d-paths

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

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          p       LLCI       ULCI
constant     -.9172      .3815    -2.4042      .0203    -1.6851     -.1493
M1diff        .4847      .1448     3.3460      .0016      .1931      .7762
M2diff       -.4123      .1878    -2.1952      .0332     -.7904     -.0342
M1avg        -.5160      .4157    -1.2411      .2209    -1.3528      .3209
M2avg         .3781      .2879     1.3133      .1956     -.2014      .9577
```

This model provides a good opportunity to discuss the interpretation of the *d*-paths, because we have one in each direction.

Interpretation depends on the order of subtraction: $M_2 - M_1$

- Positive: Effect of M on Y is more positive in condition 2 than condition 1
- Negative: Effect of M on Y is more positive in condition 1 than condition 2

$d_1 = -0.52$: The effect of communal goal affordance on interest is 0.52 higher in the individual work class than the group work class.

$$\frac{g_{21} + g_{11}}{2} = b_1 = 0.4847$$

$$g_{21} - g_{11} = d_1 = -0.5160$$

A note on the d-paths

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

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          p       LLCI       ULCI
constant     -.9172      .3815    -2.4042      .0203    -1.6851     -.1493
M1diff        .4847      .1448     3.3460      .0016      .1931      .7762
M2diff       -.4123      .1878    -2.1952      .0332     -.7904     -.0342
M1avg        -.5160      .4157    -1.2411      .2209    -1.3528      .3209
M2avg         .3781      .2879     1.3133      .1956     -.2014      .9577
```

g_{21}: Effect of communal goals on interest in group work class
g_{11}: Effect of communal goals on interest in individual work class

$$\frac{g_{21} + g_{11}}{2} = b_1 = 0.4847$$

$$g_{21} - g_{11} = d_1 = -0.5160$$

$$g_{21} = 0.2267$$

$$g_{11} = 0.7427$$

A note on the d-paths

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

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          p       LLCI       ULCI
constant     -.9172      .3815    -2.4042      .0203    -1.6851     -.1493
M1diff        .4847      .1448     3.3460      .0016      .1931      .7762
M2diff       -.4123      .1878    -2.1952      .0332     -.7904     -.0342
M1avg        -.5160      .4157    -1.2411      .2209    -1.3528      .3209
M2avg         .3781      .2879     1.3133      .1956     -.2014      .9577
```

$d_2 = 0.38$: The effect of difficulty on interest is 0.38 *more positive* in the group work class than the individual work class. (NOTE: this does not necessarily mean stronger)

$$\frac{g_{21} + g_{11}}{2} = b_1 = -0.4123 \qquad g_{21} - g_{11} = d_1 = 0.3781$$

$$g_{21} = -0.223 \qquad g_{11} = -0.601$$

CIs that seem too close to zero

The CI for the indirect effect of difficulty seems very very close to zero. Could be hard to tell if it's significant.

Indirect Effect of X on Y through M

	Effect	BootSE	BootLLCI	BootULCI
Ind1	1.1119	.3871	.3597	1.8710
Ind2	.1779	.1148	.0000	.4347
Total	1.2897	.3567	.5690	1.9766

Indirect Effect of X on Y through M

	Effect	BootSE	BootLLCI	BootULCI
Ind1	1.1119	.3795	.3692	1.8557
Ind2	.1779	.1159	-.0014	.4459
Total	1.2897	.3488	.5942	1.9772

Indirect Effect of X on Y through M

	Effect	BootSE	BootLLCI	BootULCI
Ind1	1.1119	.3801	.3483	1.8516
Ind2	.1779	.1134	.0001	.4368
Total	1.2897	.3481	.5789	1.9500

CIs that seem too close to zero

Confidence intervals will vary from run to run if you do not set the seed in your analysis.

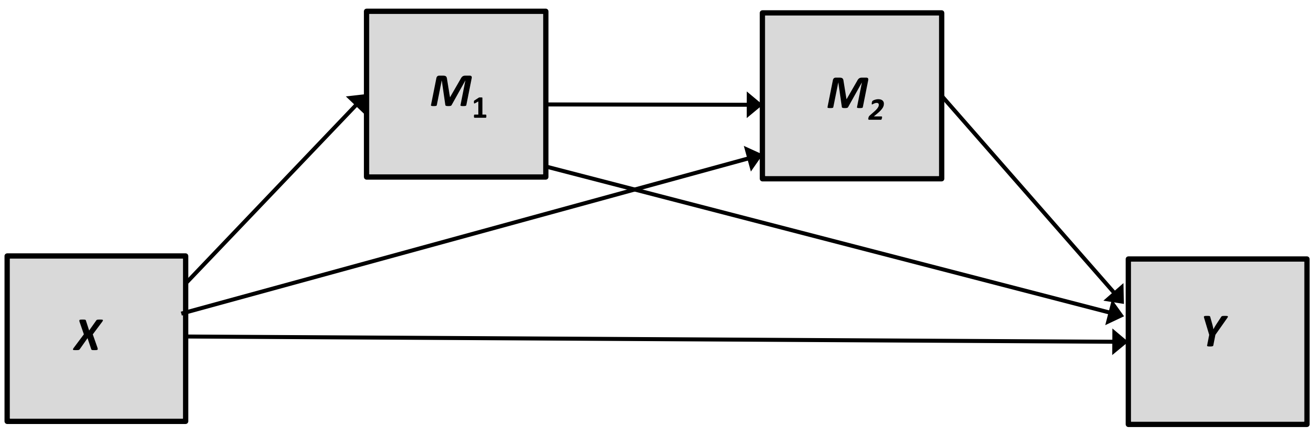
Recommendations:

1. Preregister your seed and rely on the result that you get `seed = 74572`
2. Increase the number of bootstraps until the CI is reliably on one side of zero `samples = 10000`
3. Increase the number of decimal points to see more exact results `decimals = F10.8`

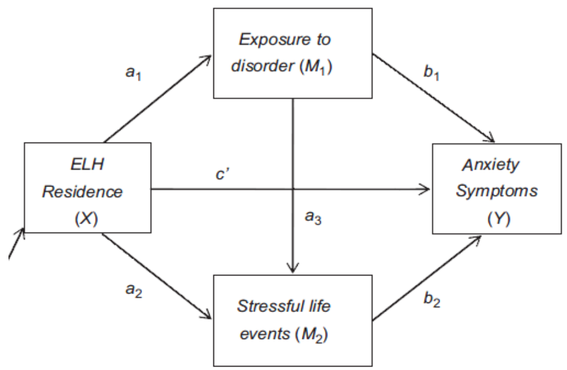
It may seem like overkill to preregister a seed but it can make a big difference especially when results are so borderline

Serial Mediation Models

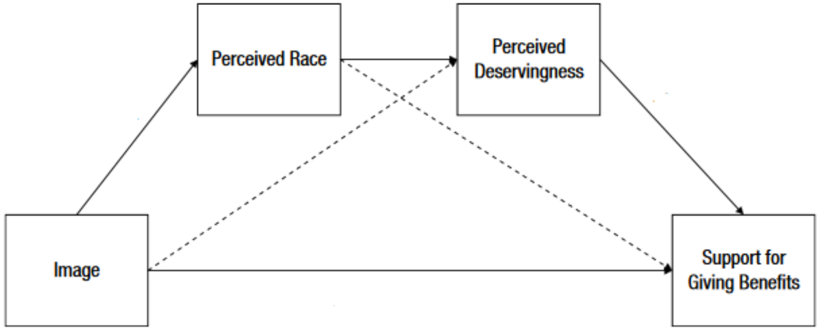
A serial multiple mediator model with two mediators and all possible direct and indirect effects freely estimated.



Some examples in the literature:



Casciano, R., & Massey, D. S. (2012). Neighborhood disorder and anxiety symptoms: New evidence from a quasiexperimental study. ***Health and Place,*** *18*, 180-190.



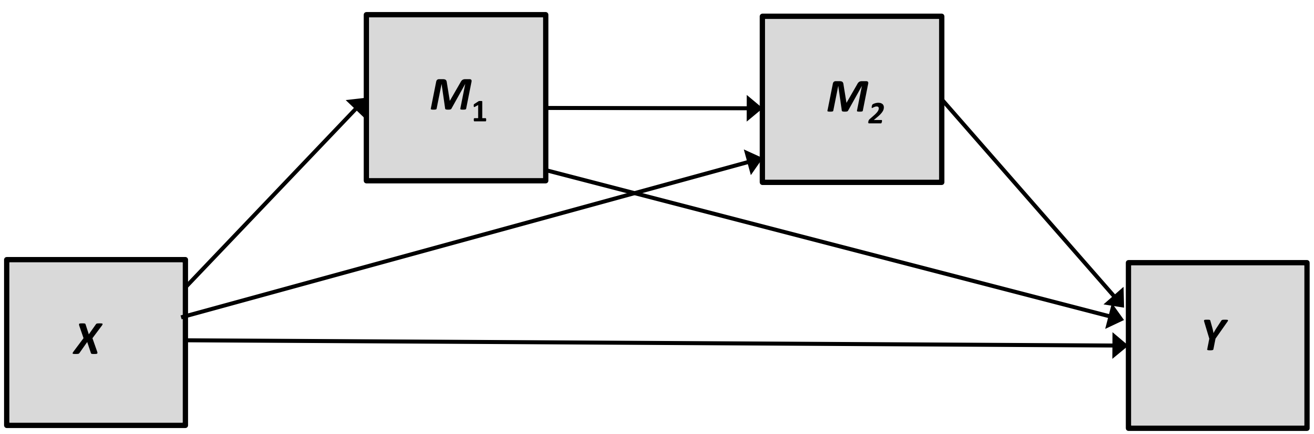
Brown-Iannuzzi, J. L., Dotsch, R., Cooley, E., & Payne, B. K. (2017). The relationship between mental representations of welfare recipients and attitudes toward welfare. ***Psychological Science, 28***, 92-103.

Why estimate such a model?

- Many causal effects probably operate through multiple steps. Estimation of a model that is **aligned with the real world** is ideal.

- Existence of serial mediators is a **violation of the causal assumptions** of a simple mediation, **biasing** the estimate of the indirect effect.
  - M_1 is also a confounder of the effect of M_2 on Y
  - Controlling for M_1 would bias the effect of X on M_2

- Many theories postulate a set of mediators acting in series. Fitting a model consistent with these theories is one way to test them.



Two Mediator Case

The Total Effect model is **unchanged** because it doesn't involve the mediators

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

Each mediator (pair) gets it's own model, all mediators predict downstream mediators

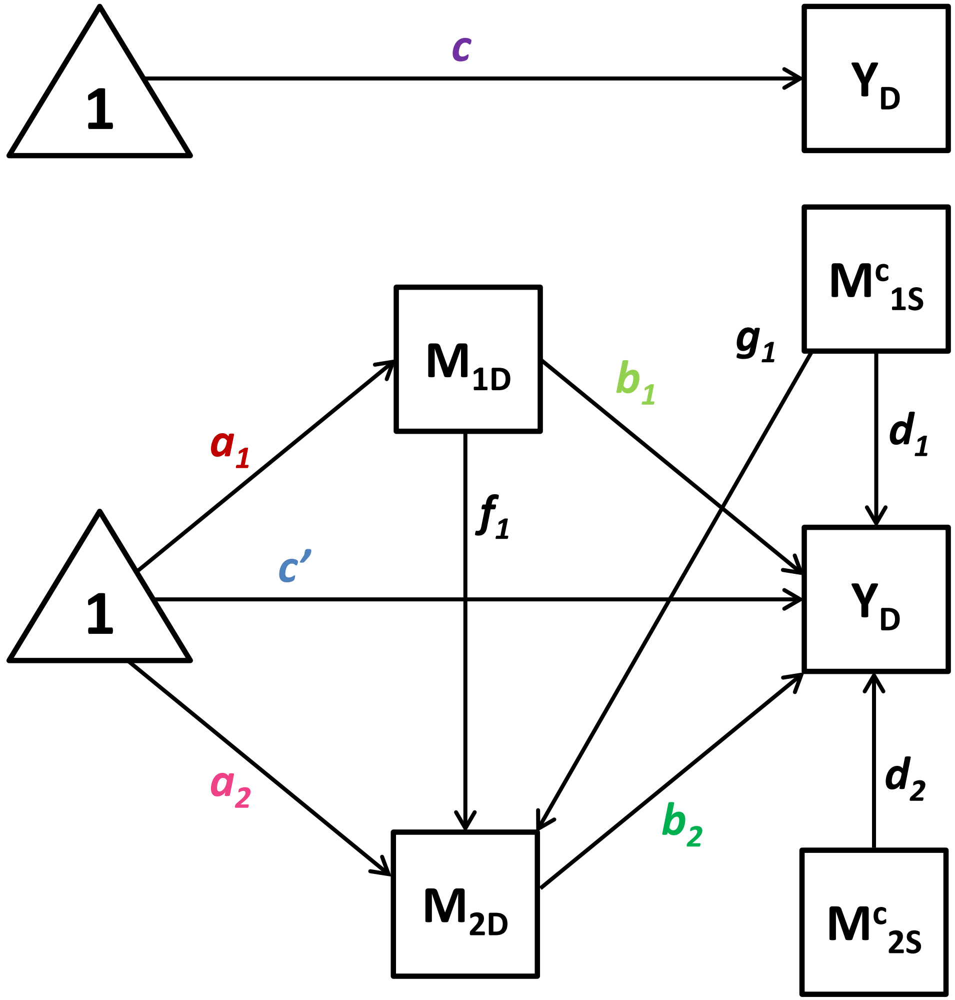
$$M_{12i} - M_{11i} = a_1 + e_{M_{1i}}$$

$$M_{22i} - M_{21i} = a_2 + f_1(M_{12i} - M_{11i}) + g_1\left(M_{12i} + M_{11i} - (\overline{M_{12} + M_{11}})\right) + e_{M_{2i}}$$

Model for outcome incorporates both pairs of mediators, is identical to parallel model

$$\begin{aligned} Y_{2i} - Y_{1i} = c' &+ b_1(M_{12i} - M_{11i}) + b_2(M_{22i} - M_{21i}) \\ &+ d_1\left(M_{12i} + M_{11i} - (\overline{M_{12} + M_{11}})\right) \\ &+ d_2\left(M_{22i} + M_{21i} - (\overline{M_{22} + M_{21}})\right) + e_{Y_i} \end{aligned}$$

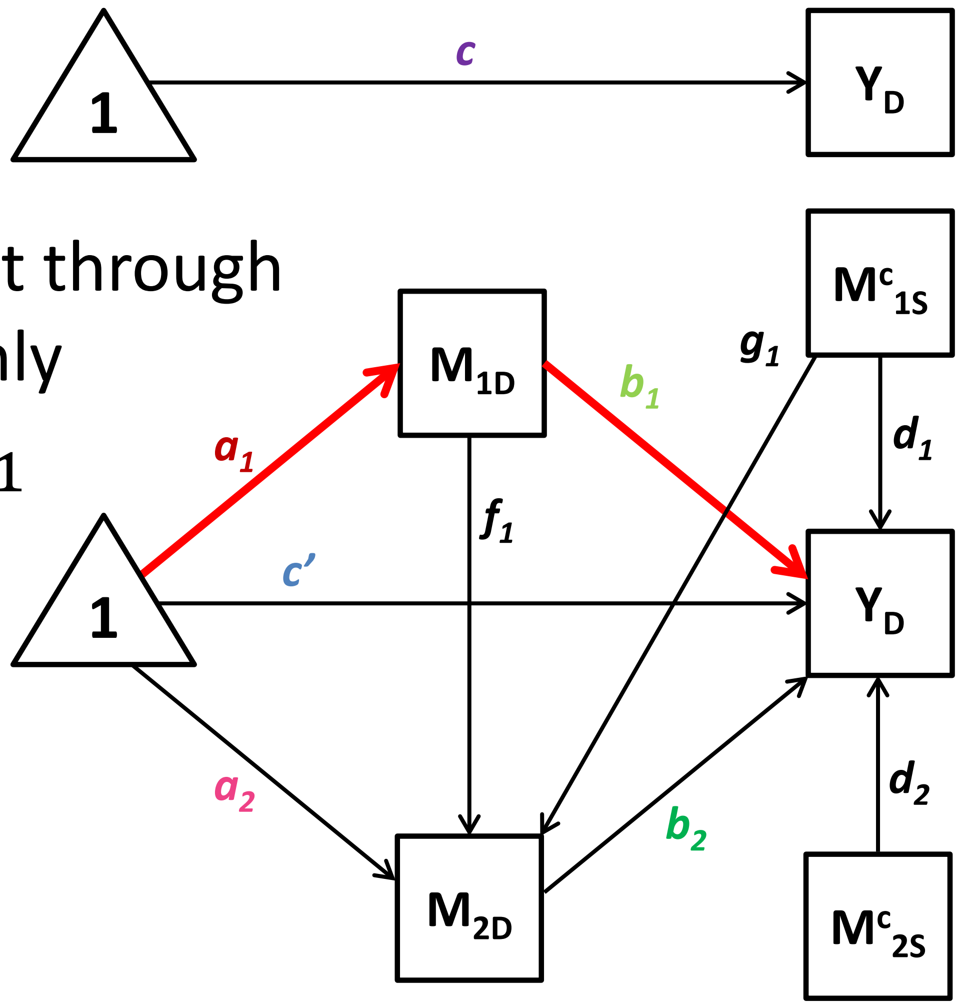
Path Diagram: Total, Direct, and Indirect Effects



^{c} Indicates mean centered

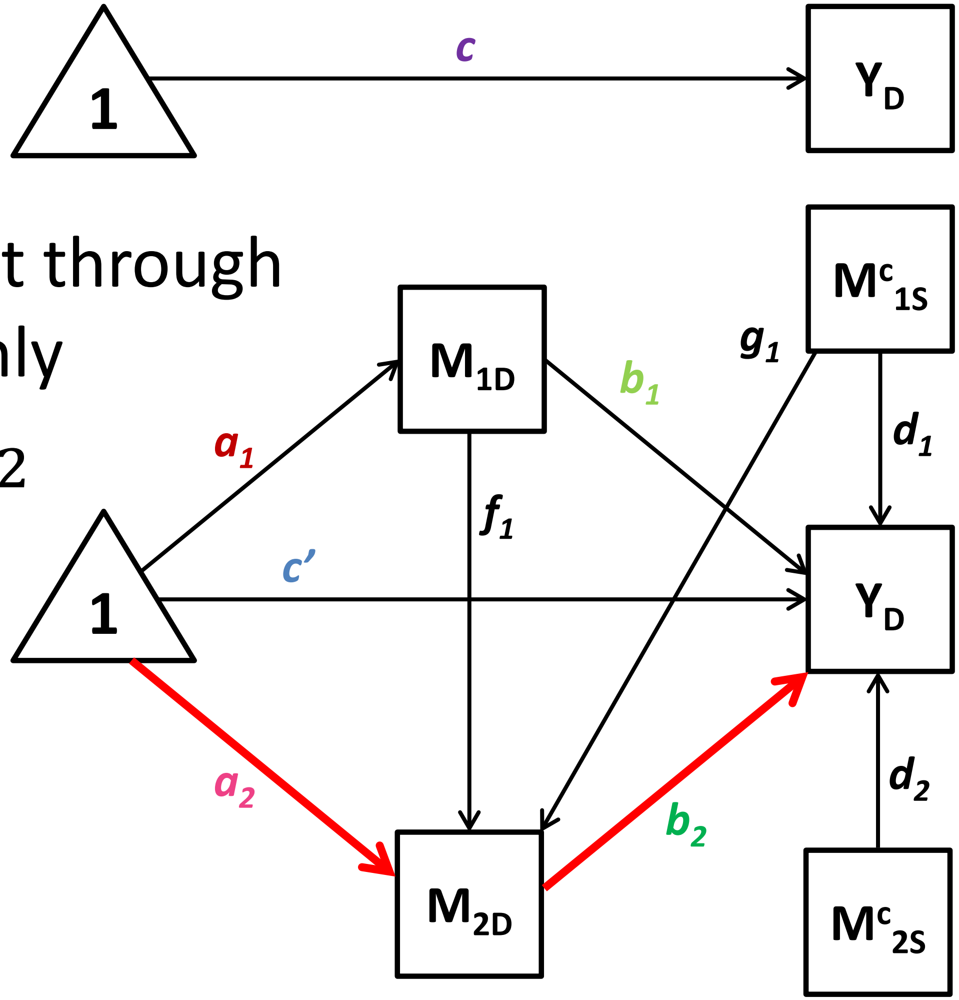
Indirect Effects

Indirect effect through M_1 only $a_1 b_1$



[c] Indicates mean centered

Indirect Effects



Indirect effect through

M_2 only

$a_2 b_2$

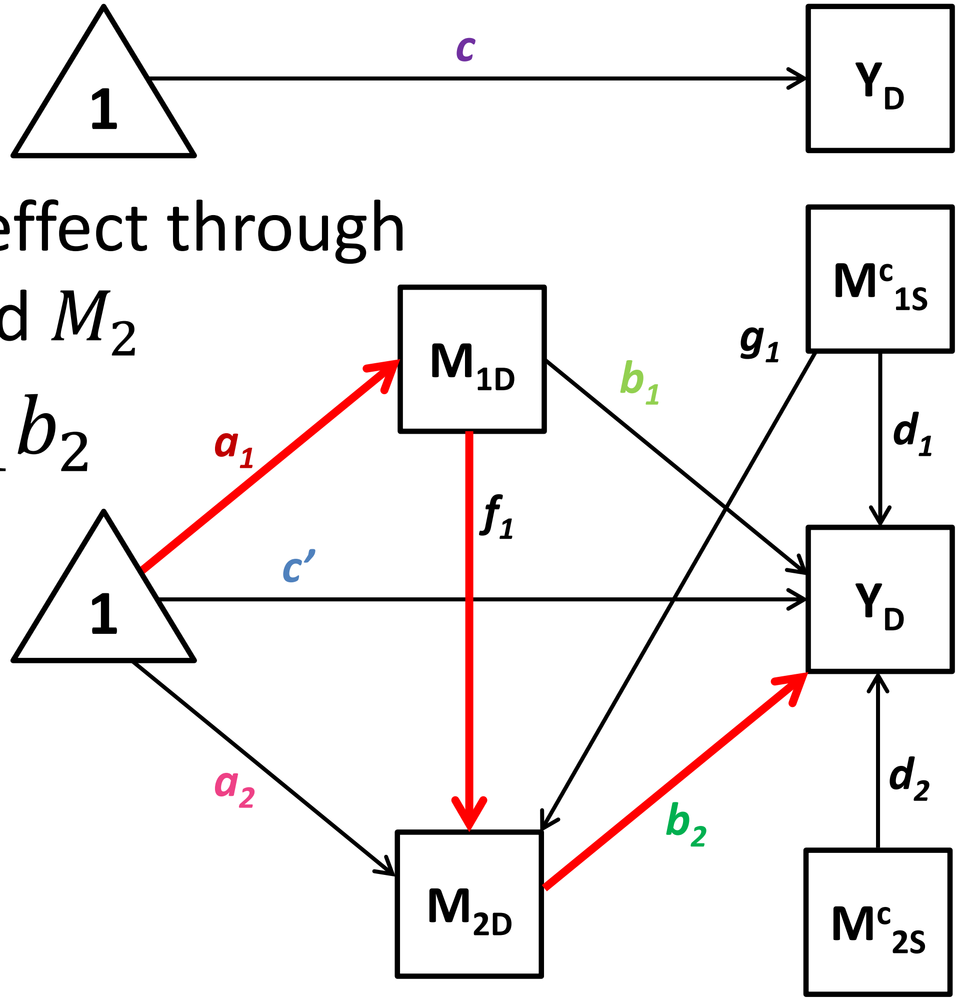
[c] Indicates mean centered

Indirect Effects

Serial indirect effect through

M_1 and M_2

$a_1 f_1 b_2$



[c] Indicates mean centered

Path Analysis Algebra

c = "total effect" of *X* on *Y*

$a_1 b_1$= "specific indirect effect" of *X* on *Y* through M_1

$a_2 b_2$= "specific indirect effect" of *X* on *Y* through M_2

$a_1 f_1 b_2$= "serial indirect effect" of *X* on *Y* through M_1 and M_2

$a_1 b_1 + a_2 b_2 + a_1 f_1 b_2$= "total indirect effect" of *X* on *Y*

c' = "direct effect" of *X* on *Y*

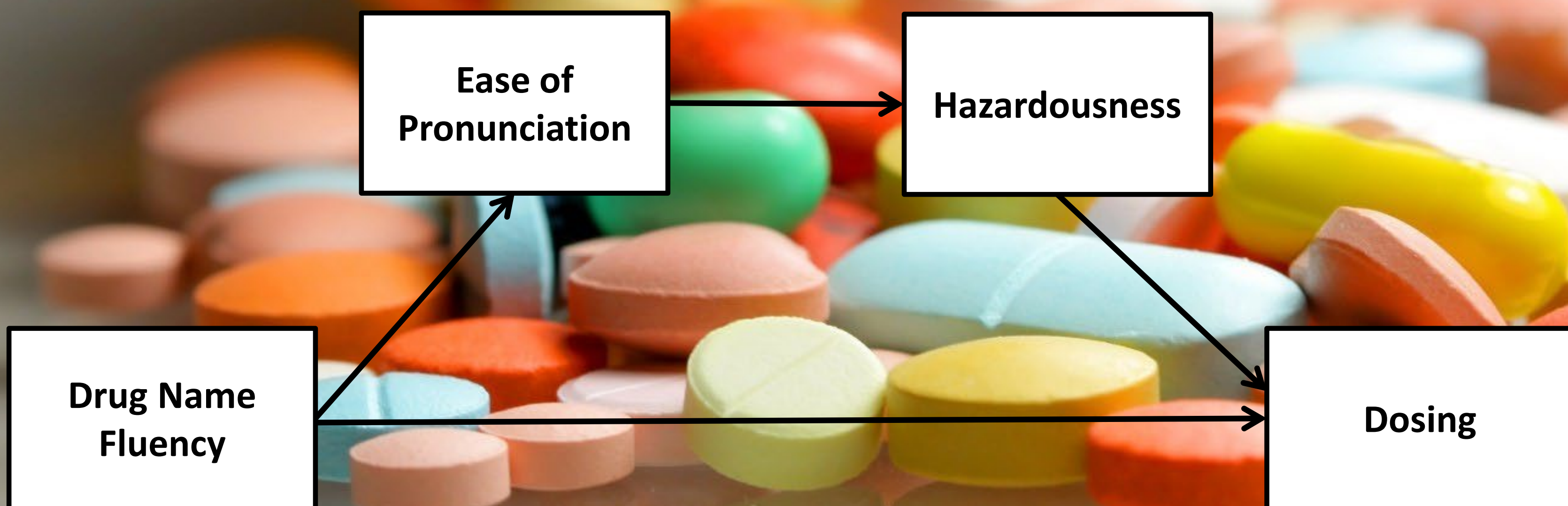
total effect = direct effect + total indirect effect

Example: Drug Name Fluency

Dohle, S., & Montoya, A. K. (2017). The dark side of fluency: Fluent names increase drug dosing. *Journal of Experimental Psychology: Applied*, *23*(3), 231 – 239.

Research Question: Can the name of drugs impact ease of pronunciation which effects how hazardous they seem and how much people are willing to dose the drugs?

Imagine you have a cold, and there are a variety of medications available including (a) Fastinorbine and (b) Cytrigmcmium. Which is easier to pronounce? Which seems more hazardous? Which are you willing to dose more of?



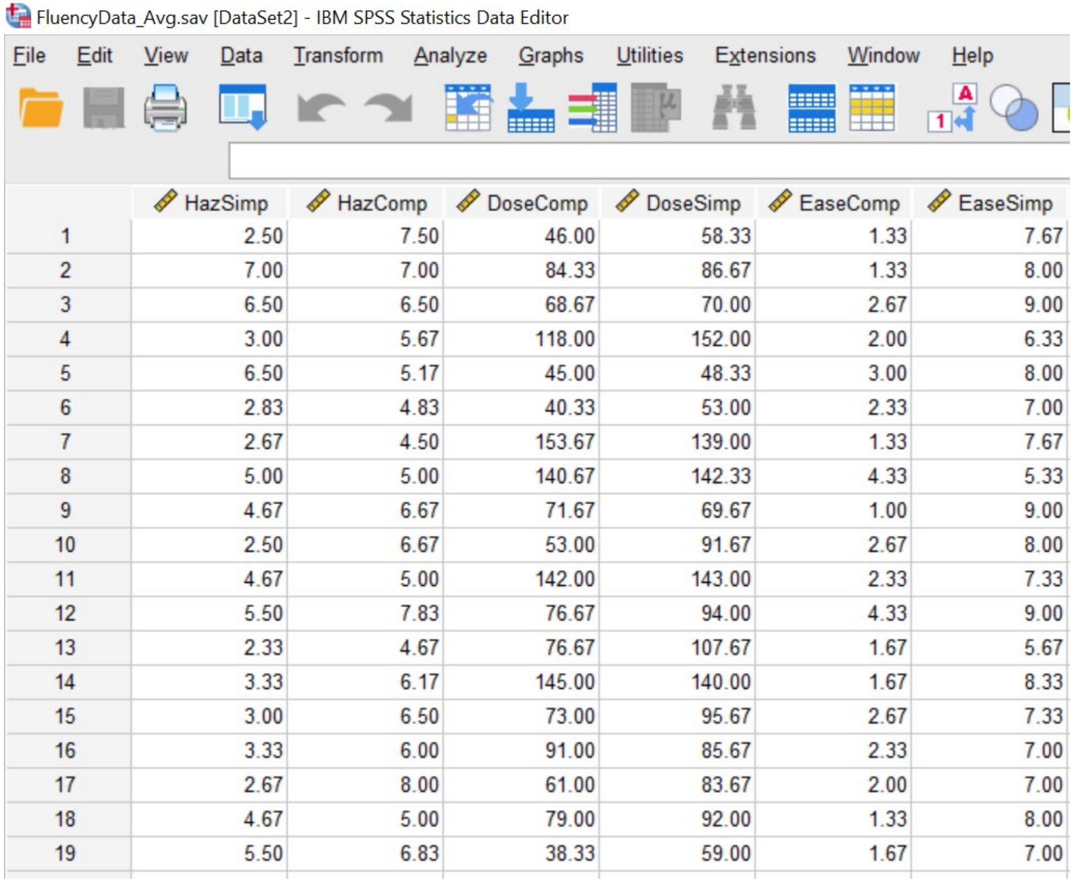
Example: Drug Name Fluency

Dohle, S., & Montoya, A. K. (2017). The dark side of fluency: Fluent names increase drug dosing. *Journal of Experimental Psychology: Applied*, *23*(3), 231 – 239.

N = 70

Measured Variables:

- Dosage in mL
    - Variable name: `Dose`
    - 0 mL – 200mL
- Hazardousness of drug
    - Variable name: `Haz`
    - Average of two questions:
        - Hazardousness (1-7)
        - Dangerousness (1-7)
- Ease of Pronunciation
    - Variable name: `Ease`
    - Single item per drug



	HazSimp	HazComp	DoseComp	DoseSimp	EaseComp	EaseSimp
1	2.50	7.50	46.00	58.33	1.33	7.67
2	7.00	7.00	84.33	86.67	1.33	8.00
3	6.50	6.50	68.67	70.00	2.67	9.00
4	3.00	5.67	118.00	152.00	2.00	6.33
5	6.50	5.17	45.00	48.33	3.00	8.00
6	2.83	4.83	40.33	53.00	2.33	7.00
7	2.67	4.50	153.67	139.00	1.33	7.67
8	5.00	5.00	140.67	142.33	4.33	5.33
9	4.67	6.67	71.67	69.67	1.00	9.00
10	2.50	6.67	53.00	91.67	2.67	8.00
11	4.67	5.00	142.00	143.00	2.33	7.33
12	5.50	7.83	76.67	94.00	4.33	9.00
13	2.33	4.67	76.67	107.67	1.67	5.67
14	3.33	6.17	145.00	140.00	1.67	8.33
15	3.00	6.50	73.00	95.67	2.67	7.33
16	3.33	6.00	91.00	85.67	2.33	7.00
17	2.67	8.00	61.00	83.67	2.00	7.00
18	4.67	5.00	79.00	92.00	1.33	8.00
19	5.50	6.83	38.33	59.00	1.67	7.00

Serial Mediators

To add mediator pairs list them in the m= list, in the same order as the other pair and outcome variables

```
MEMORE m= EaseSimp EaseComp HazSimp HazComp /y = DoseSimp DoseComp /model = 1
/serial = 1.
```

```
%MEMORE(m= EaseSimp EaseComp HazSimp HazComp, y = DoseSimp DoseComp, model =
1, serial = 1, data = Fluency).
```

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

                          Written by Amanda Montoya

                   Documentation available at akmontoya.com

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

Model:
  1

Variables:
Y =    DoseSimp DoseComp
M1 =   EaseSimp EaseComp
M2 =   HazSimp  HazComp

Computed Variables:
Ydiff =           DoseSimp  -        DoseComp
M1diff =          EaseSimp  -        EaseComp
M2diff =          HazSimp   -        HazComp
M1avg   = (       EaseSimp  +        EaseComp )        /2                        Centered
M2avg   = (       HazSimp   +        HazComp  )        /2                        Centered

Sample Size:
  70
```

Check that variables are in correct pairs and in correct order

Serial Mediators

```
MEMORE m= EaseSimp EaseComp HazSimp HazComp /y = DoseSimp DoseComp /model = 1
/serial = 1.
```

```
%MEMORE(m= EaseSimp EaseComp HazSimp HazComp, y = DoseSimp DoseComp, model =
1, serial = 1, data = Fluency).
```

```
**************************************************************************************
Outcome: Ydiff =  DoseSimp  -      DoseComp

Model
             Effect         SE          t          p       LLCI       ULCI
constant    11.0476     1.5770     7.0055      .0000     7.9016    14.1937

Degrees of freedom for all regression coefficient estimates:
  69
```

Positive coefficient means DoseSimp > DoseComp

Participants dosed the simple drugs 11.05 mL more on average than the drugs with complex names, and this is a statistically significant difference ($t(69) = 7.01$, $p < .001$).

Serial Mediators

```
MEMORE m= EaseSimp EaseComp HazSimp HazComp /y = DoseSimp DoseComp /model = 1
/serial = 1.
```

```
%MEMORE(m= EaseSimp EaseComp HazSimp HazComp, y = DoseSimp DoseComp, model =
1, serial = 1, data = Fluency).
```

```
**************************************************************************
Outcome: M1diff = EaseSimp  -      EaseComp

Model
             Effect         SE          t          p       LLCI       ULCI
constant     5.1143      .1679    30.4562      .0000     4.7793     5.4493

Degrees of freedom for all regression coefficient estimates:
  69
```

Positive coefficient means EaseSimp > EaseComp

Participants perceived simple drugs 5.11 units more on easy to pronounce than the drugs with complex names, and this is a statistically significant difference ($t(69) = 30.46$, $p < .001$).

Serial Mediators

```
MEMORE m= EaseSimp EaseComp HazSimp HazComp /y = DoseSimp DoseComp /model = 1
/serial = 1.
```

```
%MEMORE(m= EaseSimp EaseComp HazSimp HazComp, y = DoseSimp DoseComp, model =
1, serial = 1, data = Fluency).
```

```
**************************************************************************************
Outcome: M2diff = HazSimp    -      HazComp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2380      .0566     2.3226     2.0109     2.0000    67.0000      .1419

Model
              coeff         SE          t          p       LLCI       ULCI
constant     -.7642      .6934    -1.1021      .2744    -2.1482      .6199
M1diff       -.2621      .1308    -2.0037      .0491     -.5232     -.0010
M1avg         .0084      .2296      .0367      .9708     -.4499      .4668

Degrees of freedom for all regression coefficient estimates:
  67
```

Negative intercept means HazSimp < HazComp after controlling for Ease

No significant impact of drug name on hazardousness after controlling for ease of pronunciation. (Could be a red flag if this was significant)

Higher ease of pronunciation corresponds to lower hazardousness (f_1= -.26, p = .05)

No significant difference in effect of ease on hazardousness across conditions ($g_1 = 0.01$, p = .97)

Serial Mediators

```
MEMORE m= EaseSimp EaseComp HazSimp HazComp /y = DoseSimp DoseComp /model = 1
/serial = 1.
```

```
%MEMORE(m= EaseSimp EaseComp HazSimp HazComp, y = DoseSimp DoseComp, model =
1, serial = 1, data = Fluency).
```

```
**************************************************************************************
Outcome: Ydiff =  DoseSimp  -      DoseComp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4170      .1739   152.6672     3.4200     4.0000    65.0000      .0134

Model
              coeff         SE          t          p       LLCI       ULCI
constant     4.7395     5.6984      .8317      .4086    -6.6410    16.1200
M1diff       -.2158     1.1011     -.1960      .8452    -2.4149     1.9832
M2diff      -3.5215      .9943    -3.5418      .0007    -5.5072    -1.5358
M1avg       -1.9940     2.1296     -.9363      .3526    -6.2472     2.2592
M2avg        1.1574     1.6968      .6821      .4976    -2.2313     4.5462

Degrees of freedom for all regression coefficient estimates:
  65
```

Intercept is positive meaning DoseSimp > DoseComp after controlling for ease of pronunciation and hazardousness, but the effect is not statistically significant.

Serial Mediators

```
MEMORE m= EaseSimp EaseComp HazSimp HazComp /y = DoseSimp DoseComp /model = 1
/serial = 1.
```

```
%MEMORE(m= EaseSimp EaseComp HazSimp HazComp, y = DoseSimp DoseComp, model =
1, serial = 1, data = Fluency).
```

```
**************************************************************************************
Outcome: Ydiff =  DoseSimp  -      DoseComp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4170      .1739   152.6672     3.4200     4.0000    65.0000      .0134

Model
              coeff         SE          t          p       LLCI       ULCI
constant     4.7395     5.6984      .8317      .4086    -6.6410    16.1200
M1diff       -.2158     1.1011     -.1960      .8452    -2.4149     1.9832
M2diff      -3.5215      .9943    -3.5418      .0007    -5.5072    -1.5358
M1avg       -1.9940     2.1296     -.9363      .3526    -6.2472     2.2592
M2avg        1.1574     1.6968      .6821      .4976    -2.2313     4.5462

Degrees of freedom for all regression coefficient estimates:
  65
```

Higher ease corresponds with lower dosage after controlling for hazardousness, but this is not a statistically significant effect ($b_1 = -.22$, p = .85)

Serial Mediators

```
MEMORE m= EaseSimp EaseComp HazSimp HazComp /y = DoseSimp DoseComp /model = 1
/serial = 1.
```

```
%MEMORE(m= EaseSimp EaseComp HazSimp HazComp, y = DoseSimp DoseComp, model =
1, serial = 1, data = Fluency).
```

```
*****************************************************************************************
Outcome: Ydiff =  DoseSimp  -       DoseComp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4170      .1739   152.6672     3.4200     4.0000    65.0000      .0134

Model
              coeff         SE          t          p       LLCI       ULCI
constant     4.7395     5.6984      .8317      .4086    -6.6410    16.1200
M1diff       -.2158     1.1011     -.1960      .8452    -2.4149     1.9832
M2diff      -3.5215      .9943    -3.5418      .0007    -5.5072    -1.5358
M1avg       -1.9940     2.1296     -.9363      .3526    -6.2472     2.2592
M2avg        1.1574     1.6968      .6821      .4976    -2.2313     4.5462

Degrees of freedom for all regression coefficient estimates:
  65
```

Higher hazardousness corresponds with lower dosage after controlling for ease of pronunciation, but this is not a statistically significant effect ($b_2 = -3.52$, p < .001)

Serial Mediators

```
MEMORE m= EaseSimp EaseComp HazSimp HazComp /y = DoseSimp DoseComp /model = 1
/serial = 1.
```

```
%MEMORE(m= EaseSimp EaseComp HazSimp HazComp, y = DoseSimp DoseComp, model =
1, serial = 1, data = Fluency).
```

```
**************************************************************************************
Outcome: Ydiff =  DoseSimp  -       DoseComp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4170      .1739   152.6672     3.4200     4.0000    65.0000      .0134

Model
              coeff         SE          t          p       LLCI       ULCI
constant     4.7395     5.6984      .8317      .4086    -6.6410    16.1200
M1diff       -.2158     1.1011     -.1960      .8452    -2.4149     1.9832
M2diff      -3.5215      .9943    -3.5418      .0007    -5.5072    -1.5358
M1avg       -1.9940     2.1296     -.9363      .3526    -6.2472     2.2592
M2avg        1.1574     1.6968      .6821      .4976    -2.2313     4.5462

Degrees of freedom for all regression coefficient estimates:
  65
```

Neither the relationship between ease of pronunciation and dosage or hazardousness and dosage seems to differ between the two conditions (d_1=-1.99, *p* = .35; $d_2 = 1.16$, *p* = .50)

Serial Mediators

```
MEMORE m= EaseSimp EaseComp HazSimp HazComp /y = DoseSimp DoseComp /model = 1
/serial = 1.
```

```
%MEMORE(m= EaseSimp EaseComp HazSimp HazComp, y = DoseSimp DoseComp, model =
1, serial = 1, data = Fluency).
```

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

Total effect of X on Y
     Effect         SE          t         df          p       LLCI       ULCI
    11.0476     1.5770     7.0055    69.0000      .0000     7.9016    14.1937

Direct effect of X on Y
     Effect         SE          t         df          p       LLCI       ULCI
     4.7395     5.6984      .8317    65.0000      .4086    -6.6410    16.1200

Indirect Effect of X on Y through M
          Effect    BootSE  BootLLCI  BootULCI
Ind1     -1.1039    5.4275  -12.0719    9.1937
Ind2      2.6911    2.1809   -1.2069    7.4292
Ind3      4.7210    2.5278     .3695   10.2421
Total     6.3081    5.5363   -5.0427   17.2221

Indirect Key
Ind1   'X'      ->       M1diff   ->       Ydiff
Ind2   'X'      ->       M2diff   ->       Ydiff
Ind3   'X'      ->       M1diff   ->       M2diff   ->       YDiff
```

Neither specific indirect effects are statistically significant

Serial indirect effect is positive meaning dosage is higher for simple (vs. complex) drugs through effect on ease of pronunciation then hazardousness

Other Types of Within-Subject Mediation

Mediation Analysis with Multilevel Models

- MEMORE method is equivalent for two repeated-measurements
- Can accommodate multiple trials per condition, longitudinal data, continuous *X*, random slopes
- MLMED is an SPSS macro for multilevel mediation
- Kris Preacher's MLM courses cover mediation for multilevel models.

Resources:
Bauer, Preacher, & Gil (2006)
Hayes & Rockwood (2020)
Rockwood & Hayes (2022)

Other Types of Within-Subject Mediation

Latent Growth Curve models

- MEMORE is equivalent for two time points
- Model trajectories over time
- Accommodate measurement models, longitudinal data, between-subject treatment variables
- Mplus or lavaan in R tend to be the best tools
- Statistical Horizons courses on Longitudinal Data Analysis may cover

Resources:
Cheong, MacKinnon, and Khoo, 2003
Cole & Maxwell (2003)

Mediation Summary

- Estimation with Regression Equations
- Path analysis approach
- Inference for indirect effects
- Visualizations
- Study Planning
- Parallel & Serial Mediator Models
- Next Steps: MLM and SEM