Mediation with Repeated-Measures and Multilevel Data

Amanda K. Montoya & Nicholas J. Rockwood
The Ohio State University

Workshop: 9:00am – 12:50pm

Please go to https://github.com/akmontoya/APS2018.git, download the folder and open SPSS.

Workshop Procedures

Assuming some familiarity with:
- Regression & Multilevel Models
- Mediation
- SPSS

Download files at
https://github.com/akmontoya/APS2018.git

What we will learn:
- Mediation in Between Subjects Designs (~20 min)
- Mediation in Two-Instance Within-Participant Designs (~90 min)
- Introduction to Multilevel Modeling (~20 min)
- Mediation with Multilevel Data (~90 min)
- Q&A at the end

Short breaks throughout

How we will learn:
- Combination of theory and practice
- Follow along with the analysis as we go
  - Use syntax!
  - **Ask questions** about concepts or anything that is confusing
- Make friends, if you have troubles as you go through you can work together.

2

Mediation

- Between Subjects Mediation
  - Path analytic approach
  - Interpretation
  - Estimation
  - Inference
- Repeated Measures Data
- Two-Instance Repeated-Measures Mediation
  - Judd Kenny and McClelland (2001)
  - Path analytic approach
  - Estimation of Indirect Effects
  - MEMORE
  - Reporting (Writing and Figures)
  - Common Questions

John McGraw Photography

3

Running Example: Group Work in Computer Science (BS)

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

Between-Subjects Version (CASC_BS.sav) :
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?
  - 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

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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You must abide by the following rules:

- You may not work with another student on homework assignments.
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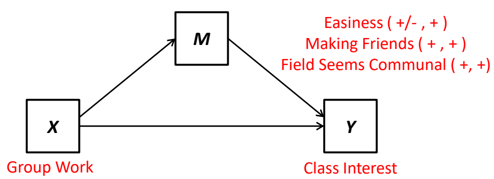
- You may not have anyone describe in detail how to solve an assignment or sit with you as you write it.
- You may not post online about your homework to ask others for help.

Mediation



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

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

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

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

A quick example: Name some possible mediators!

Mediation: Path Analysis

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

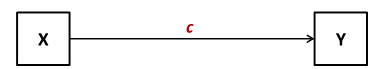
These could be measured using regression coefficients from OLS or path estimates in a structural equation model using maximum likelihood estimation.

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

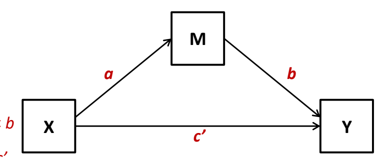
Direct effect of *X* on *Y* (not through *M*) = *c′*

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

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



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



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

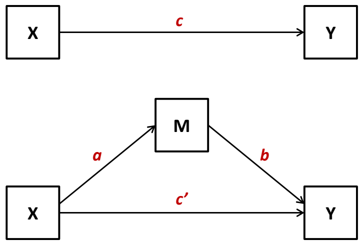
Interpreting the Coefficients

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 <u>same score on *X*</u> but who differ on *M* by one unit).

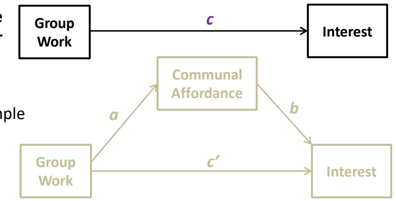
Direct effect (*c'*): The effect of our presumed cause (*X*) on *Y* while controlling for *M*. (i.e. predicted difference in *Y* for two people who differ by one unit on *X* but with the same score on *M*)



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

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

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

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

Coefficients[a]

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

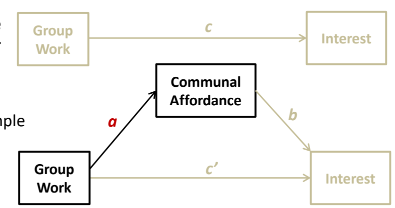
a. Dependent Variable: Interest

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

c = .462

Estimation with CompSci_BS Data

Research Question: Can <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 *a*-path can be estimated in a sample using the regression equation below.

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

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

Coefficients[a]

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

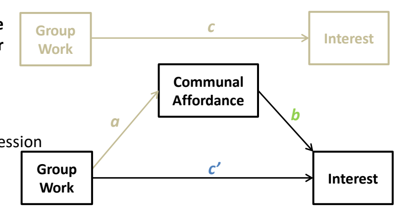
a. Dependent Variable: CSComm

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.

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

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

Coefficients[a]

Model		Unstandardized Coefficients B	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

c' = 0.218

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

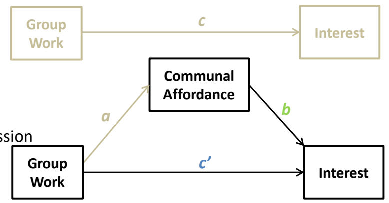
b = .508

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?

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

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




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

c' = 0.218

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

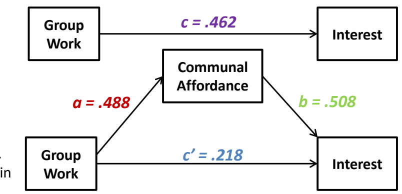
a. Dependent Variable: Interest

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

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).



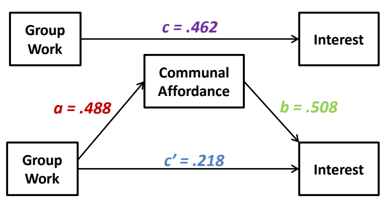
But what about the indirect effect?

Interpreting Indirect, Direct, and Total Effects

Indirect Effect

$a \times b$ = .488 × .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

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?

- Most software does not have this functionality 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

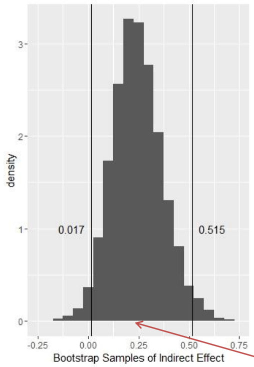
Bootstrap Sample

X	M	Y

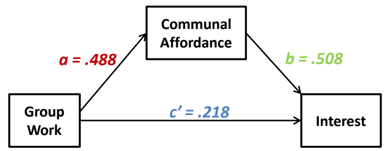
a = -.1035 b = .1495

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 the same as reject the null hypothesis at α = .05.

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.

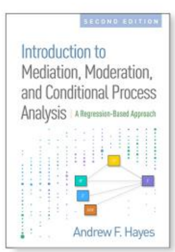
(1) Generate *k* samples from a normal distribution with mean *a* and standard deviation s_a
(2) Generate *k* samples from a normal distribution with mean *b* and standard deviation s_b
(3) Multiply samples together to get a distribution of *k* estimates of *ab.*
(4) Rank order estimates and select estimates 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 2.5th and 97.5th 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

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

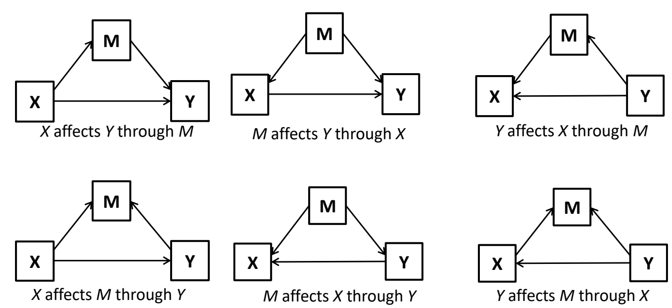


Published in January 2018 and available through The Guilford Press, Amazon.com, and elsewhere.

- PROCESS integrates a variety of macros previously developed by Hayes: SOBEL, INDIRECT, MODMED, MODPROBE, MED3C. If you are using any of these now, switch to PROCESS.
- Current version is 3.0
- PROCESS can assess a variety of models. Find the model you are interested in in the templates file, then use that model number.
- Appendix A of IMMCPA provides complete documentation of options in PROCESS and how to use them.
- Version 3 allows for specifying your own models (not from templates)

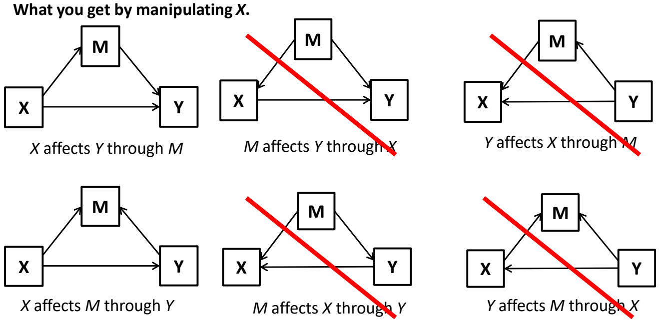
A Brief Caution on Causality

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



A Brief Caution on Causality

What you get by manipulating *X*.



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

Repeated Measures Data

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

Types of *Repeated Measurements:*

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

What is measured repeatedly?

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

Repeated Measures Data

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

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

Examples:

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

Non-Examples:

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

Running Example: Group Work in Computer Science (WS)

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

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

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

Measured Variables:

- Interest in each the class (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.

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

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Analysis using Judd et al. (2001)

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

Setup a model of the outcome in each condition:

$$Y_{1i} = c_1 + \epsilon_{Y_{1i}^*}$$
$$Y_{2i} = c_2 + \epsilon_{Y_{2i}^*}$$

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 $c_2 - c_1$):

$$Y_{2i} - Y_{1i} = (c_2 - c_1) + \left(\epsilon_{Y_{2i}^*} - \epsilon_{Y_{1i}^*}\right) = c + \epsilon_{Y_i^*}$$

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

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

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

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					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

31

Analysis using Judd et al. (2001)

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

Setup a model of the mediator in each condition:

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

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 $a_2 - a_1$):

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

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

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

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

Paired Samples Test

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

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Analysis using Judd et al. (2001)

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

Setup a model of the outcome in each condition:

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

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 $\frac{1}{2}(g_{21} + g_{11})$):

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

Optional board work

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

33

Analysis using Judd et al. (2001)

3. Does *M* predict *Y* controlling for condition?

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

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

Coefficients[a]

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

a. Dependent Variable: int_diff

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Analysis using Judd et al. (2001)

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

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

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.

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

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

Intercept is predicted *outcome* when all regressers 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*.

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

Coefficients[a]

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

a. Dependent Variable: int_diff

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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:

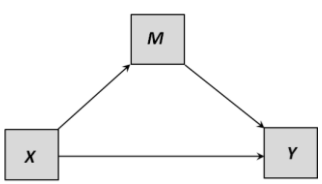
- There is no explicit quantification of the indirect effect
  - Inference about an indirect effect should be the result of a test on a *quantification* of the indirect effect
- Requiring that there must be a total effect is too restrictive
  - The direct and indirect effect could be of opposite sign
  - 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 300 citing papers, with around 140 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

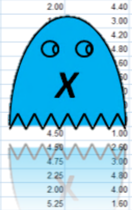
Can we think about it like a path analysis?

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



Where is X in the data?

Y_1 int_I	Y_2 int_G	M_1 comm_I	M_2 comm_G
1.50	4.00	1.00	6.80
2.75	3.25	2.00	5.40
5.75	2.50	3.20	3.60
3.50	5.75	1.60	5.20
2.25	2.00	4.40	4.60
1.50	[illegible]	3.00	5.00
2.50	[illegible]	4.20	4.40
6.00	[illegible]	4.80	2.40
3.00	[illegible]	[illegible]	5.80
4.00	[illegible]	[illegible]	5.00
5.00	[illegible]	[illegible]	6.20
2.00	[illegible]	[illegible]	4.20
1.00	[illegible]	[illegible]	3.20
1.25	4.50	1.00	6.00
5.75	4.50	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

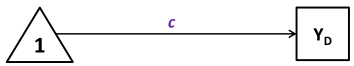
Using a path analytic framework will help extend the simple mediation model to more complicated questions

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

Path-Analytic Approach

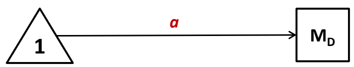
Total Effect (*c*): The effect of our presumed cause (*X*) on our outcome (*Y*), without controlling for any other variables. (i.e. mean difference in outcome between the two conditions).

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



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

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

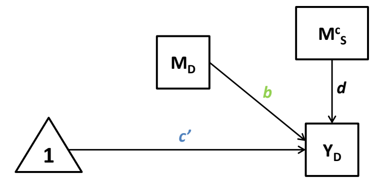


Path-Analytic Approach

***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 <u>same score on *X*</u> but who differ on *M* by one unit).

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

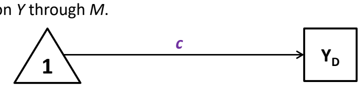
$$Y_{2i} - Y_{1i} = c' + b(M_{2i} - M_{1i}) + d(M_{2i} + M_{1i} - (\overline{M_2 + M_1})) + \epsilon_{Y_i}$$



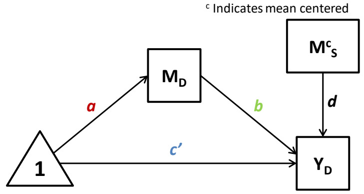
^{c} Indicates mean centered

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*.



^{c} Indicates mean centered

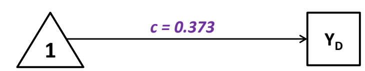


Within Subjects: Path Estimates

Total Effect c: (Regress Y_D on a constant)

$\widehat{Y_D} = c$

$\widehat{Y_D} = .373$

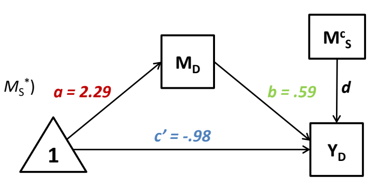


a path: (Regress M_D on a constant)

$\widehat{M_D} = a$

$\widehat{M_D} = 2.29$

^{c} Indicates mean centered



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

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

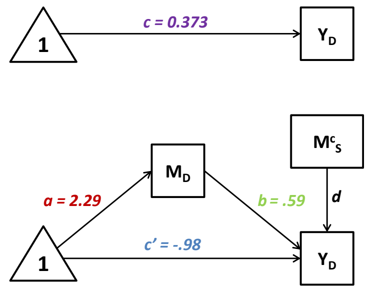
A one unit increase in the difference in communal goal affordance is expected to result in a .59 unit increase in the difference in interest.
People with no difference in communal goal affordance perceptions are expected to be .98 units more interested in the individual class than the group work class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

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	x	b
.373	=	-.98	+	2.29	x	.59
.373	=	-.98	+	1.35		

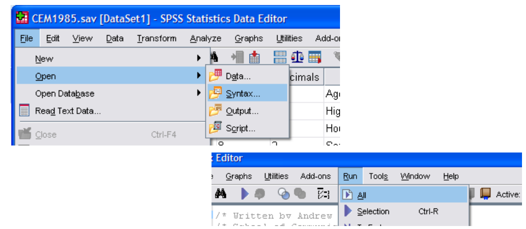


We can conduct inferential tests on the estimate of the indirect effect as in any other mediation analysis.

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

Teaching your package MEMORE

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



SPSS now knows a new command called MEMORE

Writing MEMORE Syntax

MEMORE has 2 required arguments: `Y` and `M`

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

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

Some other arguments:

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

Using MEMORE for CASC WS data

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

```
********************* 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 CASC WS data

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

```
**************************************************************************
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 CASC WS data

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

```
**************************************************************************
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 CASC WS data

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

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

Writing up a Repeated Measures Mediation Analysis

Tips:

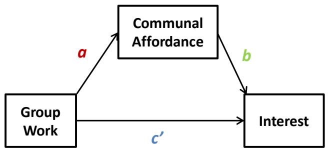
- Walk the reader through the steps of the mediation in a way that is intuitive.
  - Include interpretations of the results: b.e.g. "The total effect was significant, $p < .05$"
- Use equations and numbers *where helpful*.
- Avoid using computational variable names (e.g. RESPAPPR)
- Avoid causal language 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?

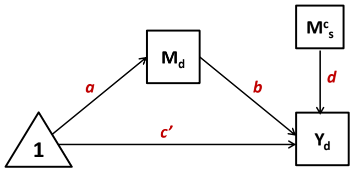
Overall there was no evidence of a total effect of group work on interest in computer science classes, we estimate that individuals were .37 units higher on interest in group work than individual work classes ($p = .19$). The class with group work was rated 2.29 units higher on communal goal affordance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

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!

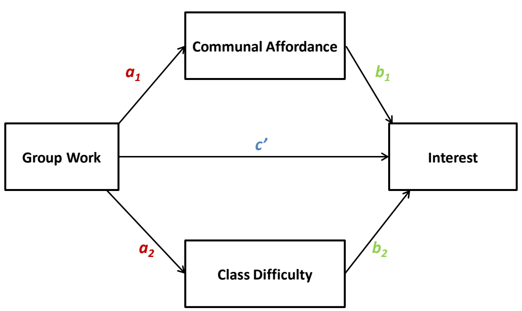
Common Questions

- 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, in press for instructions).
- Can we do conditional process models?
  VERY SOON!
- How do I control for covariates?
  All of MEMORE's mediation analyses are within-person models, so you do not need to control for any between subjects variables such as age, gender, big-5.
  Sometimes there are covariates which change within a person across conditions that you want to account for, this can be done by treating this additional variable as another set of mediators.

Using MEMORE for CASC WS data

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



Using MEMORE for CASC WS data

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

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

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

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

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

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

Using MEMORE for CASC WS data

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

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

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

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

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

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

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

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

57

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?

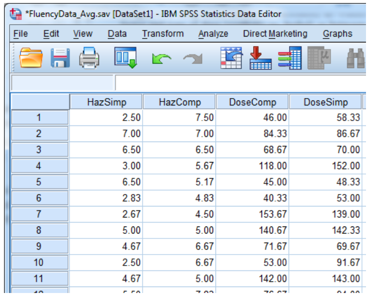
Example: Drug Name Fluency

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
    - Dangerousness



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

File Edit View Data Transform Analyze Direct Marketing Graphs

	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. Find estimates of the following paths: a, b, c, c'
3. Of the following inferential methods, which support the hypothesized mediation model (use $\alpha = 0.05$ or 95% confidence intervals):
   Percentile bootstrap CIs, bias corrected CIs, Monte Carlo CIs, Sobel Test / Normal Theory, JKM Causal Steps

5. Practice writing up some of the results explored above.

Raise your hand with Questions!

Using MEMORE for Drug Fluency data

```
MEMORE m= HazSimp HazComp /y = DoseSimp DoseComp.
```

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

Model
          Effect         SE          t          p       LLCI       ULCI
'X'      11.0476     1.5770     7.0055      .0000     7.9016    14.1937

Degrees of freedom for all regression coefficient estimates:
  69

**************************************************************************
Outcome: Mdiff =  HazSimp   -       HazComp

Model
          Effect         SE          t          p       LLCI       ULCI
'X'      -2.1048      .1848   -11.3893      .0000    -2.4734    -1.7361

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

c = 11.05

Interpretation?

a = -2.10

Interpretation?

On average, participants dosed 11.05 mL more of the simply named drug than the complex named drug ($t(69) = 7.06$, $p < .001$).

Participants thought the complex drug was 2.10 points more hazardous than the simply named drug, on average ($t(69) = 11.39$, $p < .001$).

Using MEMORE for Drug Fluency data

```
MEMORE m= HazSimp HazComp /y = DoseSimp DoseComp.
```

```
Outcome: Ydiff =  DoseSimp  -       DoseComp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4029      .1623   150.1860     6.4899     2.0000    67.0000      .0027

Model
          coeff         SE          t          p       LLCI       ULCI
'X'      3.8061     2.4874     1.5301      .1307    -1.1589     8.7711
Mdiff   -3.4405      .9552    -3.6020      .0006    -5.3471    -1.5340
Mavg      .3474     1.4566      .2385      .8122    -2.5601     3.2549

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

c′ = 3.81   *Interpretation?*

b = -3.44   *Interpretation?*

After controlling for hazardousness, participants were expected to dose 3.8 mL more of the simple drug. This effect was not significantly different than zero ($t(67) = 1.53$, $p = .13$).

A one unit increase in the difference in perceived hazardousness between conditions results in a 3.44 unit decrease in the difference in dosage ($t(67) = 3.60$, $p < .001$).

A one unit increase in perceived hazardousness results in a 3.44 unit decrease in dosage, averaged across fluency conditions ($t(67) = 3.60$, $p < .001$).

Using MEMORE for Drug Fluency data

```
MEMORE m= HazSimp HazComp /y = DoseSimp DoseComp.
```

```
************************* 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
     3.8061     2.4874     1.5301    67.0000      .1307    -1.1589     8.7711

Indirect Effect of X on Y through M
          Effect     BootSE   BootLLCI   BootULCI
Ind1      7.2415     1.9243     3.7813    11.3817

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

ab = 7.24   *Interpretation?*

Participants were dosed simple drugs 7.24 mL more, through the effect of simple drugs on hazardousness and the subsequent effect of hazardousness on dosage (Percentile CI = [3.78, 11.38]).

Drug name fluency increased dosage by 7.24 mL through it's indirect effect through hazardousness (Percentile CI = [3.78, 11.38]).

Simple names were perceived as less hazardous, which then increased dosage, resulting in an indirect effect of 7.24 mL on dosage (Percentile CI = [3.78, 11.38]).

Using MEMORE for Drug Fluency data

Methods of Inference

Percentile Bootstrap CI

```
MEMORE m= HazSimp HazComp /y = DoseSimp DoseComp.
```

```
Indirect Effect of X on Y through M
          Effect     BootSE   BootLLCI   BootULCI
Ind1      7.2415     1.9243     3.7813    11.3817
```

Bias Corrected Bootstrap CI

```
MEMORE m= HazSimp HazComp /y = DoseSimp DoseComp /bc = 1.
```

```
Indirect Effect of X on Y through M
          Effect     BootSE   BootLLCI   BootULCI
Ind1      7.2415     1.9390     3.6371    11.2256
```

Monte Carlo CI

```
MEMORE m= HazSimp HazComp /y = DoseSimp DoseComp /mc = 1.
```

```
Indirect Effect of X on Y through M
          Effect       MCSE     MCLLCI     MCULCI
Ind1      7.2415     2.1195     3.2620    11.5534
```

Using MEMORE for Drug Fluency data

Methods of Inference

Sobel Test / Normal Theory

```
MEMORE m= HazSimp HazComp /y = DoseSimp DoseComp /normal = 1.
```

```
     Normal Theory Tests for Indirect Effect
                 Effect         SE          Z          p
     Ind1        7.2415     2.1086     3.4343      .0006
```

JKM Causal Steps

```
MEMORE m= HazSimp HazComp /y = DoseSimp DoseComp.
```

```
Outcome: Ydiff =  DoseSimp  -      DoseComp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4029      .1623   150.1860     6.4899     2.0000    67.0000      .0027

Model
          coeff         SE          t          p       LLCI       ULCI
'X'      3.8061     2.4874     1.5301      .1307    -1.1589     8.7711
Mdiff   -3.4405      .9552    -3.6020      .0006    -5.3471    -1.5340
Mavg      .3474     1.4566      .2385      .8122    -2.5601     3.2549

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


Mediation

- Between Subjects Mediation
  - Path analytic approach
  - Interpretation
  - Estimation
  - Inference
- Repeated Measures Data
- Two-Instance Repeated-Measures Mediation
  - Judd Kenny and McClelland (2001)
  - Path analytic approach
  - Estimation of Indirect Effects
  - MEMORE
  - Reporting (Writing and Figures)
  - Common Questions

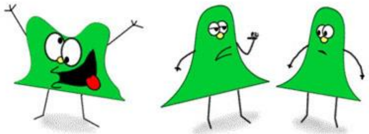
New York Elegance

Thank you!

I am available for questions after the workshop and via email at montoya.29@osu.edu

Things to look forward to:

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



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

Other Kinds of Bootstrap Confidence Intervals

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

Bias-Corrected Confidence Interval

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

Bias-Corrected and Accelerated

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

Other Types of Repeated Measures Mediation

- Multilevel Models
  - Bauer, Preacher, Gil (2006) *Psychological Methods*
    Covers Mediation and Moderated Mediation for 1-1-1 multilevel mediation
  - Kenny, Korchmaros, Bolger (2003) *Psychological Methods*
    Covers mediation for 1-1-1 multilevel models
  - **COMING SOON**: Nick Rockwood's MLMediation Macro (see afhayes.com for updates)
- Latent Growth Curve Models (Longitudinal Processes M-Y measured over time)
  - Choeng, MacKinnon, Khoo (2003) *Structural Equation Modeling*
- Structural Equation Modeling (Can be used for a variety of data types)
  - Cole & Maxwell (2003) *Journal of Abnormal Psychology*
    X, M, and Y all measured over time
  - Newsom (2009) *Structural Equation Modeling*
    Dyadic data using LGMs
  - Selig & Little (2012) *Handbook of Developmental Research Methods*
    Autoregressive models and cross-lagged panel models for longitudinal data X, M, and Y all measured over time.
- **Selig & Preacher (2009) *Research in Human Development***
  - **Longitudinal Models X, M, and Y measured across time. Cross-lagged panel models, latent growth models, latent difference score models**
- Multilevel SEM
  - Preacher, Zyphyr, Zhang, 2010
  - Preacher, Zhang, Zyphur, 2011

Ordinary least squares (OLS) regression is not directly applicable when the data are nested.

- Students nested within classrooms
- Employees nested within organizations
- Repeated measurements nested within individuals

Responses from students (employees) within the same classroom (organization) tend to be more related than responses from students (employees) in different classrooms (organizations).

This violates the assumption of independence.

Several methods are available for accounting for the dependence.

Here, we will used multilevel/mixed modeling.

Basic Multilevel Model

Multilevel models are often expressed either as separate equations for the different levels of the model, or as one combined model.

The lower-level equation for a two-level *unconditional* model with 1 level-1 predictor can be expressed as:

$$Y_{ij} = d_{0j} + b_{1j}X_{ij} + e_{ij} \tag{1}$$

- Y_{ij} and X_{ij} represent the responses for the ith person in group j
- d_{0j} is the intercept for group j
- b_{1j} is the slope for group j
- $e_{ij} \sim N(0, \sigma^2)$ is the error

Equivalent to a single-level model except for the j subscript for the intercept and slope indicating that these values are allowed to randomly vary across groups, and are therefore termed *random effects*.

Basic Multilevel Model

Multilevel models are often expressed either as separate equations for the different levels of the model, or as one combined model.

The lower-level equation for a two-level *unconditional* model with 1 level-1 predictor can be expressed as:

$$Y_{ij} = d_{0j} + b_{1j}X_{ij} + e_{ij} \tag{2}$$

Interpretation:

- d_{0j} is the expected value of Y for for someone in group j with $X_{ij} = 0$
- b_{1j} is the expected difference in Y for two people in the same group j that differ by 1 unit on X_{ij}

Basic Multilevel Model

The slope and intercepts themselves can be modeled. An unconditional model means that there are no level-2 predictors. The unconditional level-2 models are:

$$d_{0j} = d_0 + u_{0j} \tag{3}$$

$$b_{1j} = b_1 + u_{1j} \tag{4}$$

- d_0 and b_1 represent the grand mean intercept and slope values, respectively
- u_{0j} and u_{1j} represent group j's deviations from the grand means

The variances of the deviations, notated as τ_{00} and τ_{11} respectively, as well as their covariance τ_{10}, are estimated rather than the specific deviations.

The random effects are assumed to be multivariate normal, with mean $\mathbf{0}$ and covariance matrix $\mathbf{T}$.

Basic Multilevel Model

Not all coefficients must be specified as random effects.

A common model is the random intercepts model in which the intercept is a random effect but the slope is fixed across groups:

$$d_{0j} = d_0 + u_{0j} \tag{5}$$

$$b_{1j} = b_1 \tag{6}$$

This can be viewed as a special case of the previous model (found when $Var(u_{1j} = 0)$).

Throughout, I will use the more general model with all random coefficients, knowing we can simplify the model if necessary or desired.

Multilevel Model

The combined form of the two-level model can be formulated by plugging the intercept and slope equations into their respective spots in the lower-level model:

$$Y_{ij} = (d_0 + u_{0j}) + (b_1 + u_{1j})X_{ij} + e_{ij} \tag{7}$$

Expanding and rearranging the terms to separate the fixed and random components yields:

$$Y_{ij} = \underbrace{d_0 + b_1 X_{ij}}_{\text{fixed}} + \underbrace{u_{0j} + u_{1j}X_{ij} + e_{ij}}_{\text{random}} \tag{8}$$

which demonstrates that the response for the ith person in group j is a function of the grand mean intercept and slope, the deviations from the grand mean intercept and slope for group j, and an individual-specific residual.

Multilevel Model

Level-2 predictors may be added to explain variability in the intercept or slope.
Adding one level-2 predictor, W_j, for the intercept and slope results in the following level-2 equations:

$$d_{0j} = d_0 + g_{01}W_j + u_{0j} \tag{9}$$

$$b_{1j} = b_1 + g_{11}W_j + u_{1j} \tag{10}$$

- d_0 and b_1 now represent the expected intercept and slope values for a group whose value for $W_j = 0$.
- The systematic change in expected group intercept and slope values as a function of W_j is represented by the level-2 regression coefficients g_{01} and g_{11}.
- The covariance matrix of random effects u_{0j} and u_{1j}, $\mathbf{T}$, contains residual variances and covariances of the random effects, after removal of variance explained by W_j.

Multilevel Model

The combined model for this conditional two-level model with one level-1 predictor and one level-2 predictor becomes:

$$Y_{ij} = (d_0 + g_{01}W_j + u_{0j}) + (b_1 + g_{11}W_j + u_{1j})X_{ij} + e_{ij} \tag{11}$$

Expanding and rearranging the terms yields:

$$Y_{ij} = \underbrace{d_0 + g_{01}W_j + b_1 X_{ij} + g_{11}W_j X_{ij}}_{\text{fixed}} + \underbrace{u_{0j} + u_{1j}X_{ij} + e_{ij}}_{\text{random}} \tag{12}$$

- The addition of W_j as a predictor of b_{1j} acts as a moderator, in that the effect of X_{ij} on Y_{ij} changes as a function of W_j.

Fluency Data

The Fluency data (`FluencyData_Raw.sav`) is in wide-form and must be converted to long-form (`FluencyData_Raw_Long.sav`).

In SPSS, we can convert the data to long-form using:

```
VARSTOCASES
  /ID=id
  /MAKE Hazard FROM HazFas HazCyt HazNxu HazTon HazRib HazCal
  /MAKE Dose FROM DoseFas DoseCyt DoseNxu DoseTon DoseRib DoseCal
  /INDEX=Drug(6)
  /KEEP=
  /NULL=KEEP.

RECODE Drug (1=1) (2=0) (3=0) (4=1) (5=0) (6=1) INTO Simple.
EXECUTE.
```


Fluency Data

The SPSS MIXED procedure can be used to fit a multilevel model.

Here, we regress Dosage on Hazardousness using a model with a random intercept and slope (and estimated covariance):

```
MIXED Dose WITH Hazard
  /FIXED=Hazard | SSTYPE(3)
  /METHOD=REML
  /PRINT=G  SOLUTION TESTCOV
  /RANDOM=INTERCEPT Hazard | SUBJECT(id) COVTYPE(UN).
```


Fixed Effects

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	105.925690	4.629519	56.250	22.880	.000	96.652557	115.198824
Hazard	-4.172617	.548167	43.028	-7.612	.000	-5.278080	-3.067153

a. Dependent Variable: Dose.

For the average individual, the dose administration of drugs given a hazardousness rating of $X_{ij} = 0$ is expected to be $d_0 = 105.93$.

Averaged across individuals, the dosages of two drugs that differ by 1 unit on the hazardousness rating are expected to differ by $b_1 = -4.17$ units, with smaller doses corresponding to more hazardous drugs.

Random Effects

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		248.139405	20.503660	12.102	.000	211.038305	291.762976
Intercept + Hazard [subject = id]	UN (1,1)	964.361439	262.211119	3.678	.000	565.974728	1643.17052
	UN (2,1)	-18.259864	26.037836	-.701	.483	-69.293086	32.773357
	UN (2,2)	3.630624	3.390303	1.071	.284	.582268	22.638079

a. Dependent Variable: Dose.

There is substantial between-person variability ($\tau_{00} = 964.36$) in dosage for drugs with a hazardousness rating of $X_{ij} = 0$.
The relationship between hazardousness and dosage varies across individuals ($\tau_{11} = 3.63$).
Those that have higher-than-average dosage values when $X_{ij} = 0$ tend to have lower-than-average slopes for the relationship between hazardousness and dosage ($\tau_{10} = -18.26$).

Centering Predictors

In the previous example, a Hazardousness score of 0 was not possible, so the intercept (and possibly its variance*) are meaningless.

Centering the predictor variable(s) can help with the interpretation of the coefficients.

For multilevel models, there are two common centering approaches (grand mean centering; group mean centering).

The choice of centering can have a big impact on the parameter estimates and their substantive meaning.

Enders, C. K., & Tofighi, D. (2007). Centering predictor variables in cross-sectional multilevel models: a new look at an old issue. *Psychological Methods, 12*(2), 121-138.

Centering Predictors

Grand mean centering:

Subtract the overall mean of a level-1 predictor from each individual's score on that predictor

$$Y_{ij} = d_{0j} + b_{1j}(X_{ij} - \overline{X}_{..}) + e_{ij} \quad (13)$$

- The intercept for group j in an unconditional model can now be interpreted as the expected value for a person in group j who has a value equal to the grand-mean on that variable.
- The interpretation of the slope b_{1j} remains as before.

Centering Predictors

Grand mean centering:

- Grand-mean centering is a linear transformation, so the ordering between two individuals' scores remains the same, regardless of what group they are in.
- The variance of the random intercepts, τ_{00}, is the intercept variance after adjusting for differences on the Level-1 predictor.
- Enders and Tofighi (2007) recommend grand-mean centering level-1 predictors when the focus of the analysis is on a level-2 predictor, but the researcher wants to control for individual differences on the level-1 predictors.

Grand mean centering in SPSS

```
DESCRIPTIVES VARIABLES=Hazard
  /STATISTICS=MEAN.

COMPUTE Hazard_grand = Hazard - 5.3048.
EXECUTE.

MIXED Dose WITH Hazard_grand
  /FIXED=Hazard_grand | SSTYPE(3)
  /METHOD=REML
  /PRINT=G  SOLUTION TESTCOV
  /RANDOM=INTERCEPT Hazard_grand | SUBJECT(id) COVTYPE(UN).
```

Grand mean centering in SPSS

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	83.790792	3.620127	68.730	23.146	.000	76.568330	91.013255
Hazard_grand	-4.172617	.548167	43.028	-7.612	.000	-5.278080	-3.067153

a. Dependent Variable: Dose.

For the average individual, the dose administration of drugs given a hazardousness rating of $X_{ij} = 5.30$ is expected to be $d_0 = 83.79$.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		248.139405	20.503660	12.102	.000	211.038305	291.762976
Intercept + Hazard_grand [subject = id]	UN (1,1)	872.800618	156.497654	5.577	.000	614.172288	1240.33750
	UN (2,1)	.999869	17.923026	.056	.956	-34.128616	36.128354
	UN (2,2)	3.630624	3.390303	1.071	.284	.582268	22.638079

a. Dependent Variable: Dose.

Decomposing a Predictor

Usually*, a level-1 variable will contain within-group and between-group variability.

We can decompose the predictor into separate pieces: one that only contains within-group variability and one that only contains between group variability.

$$X_{ij} = \underbrace{X_{ij} - \overline{X}_{.j}}_{within} + \underbrace{\overline{X}_{.j}}_{between} \tag{14}$$

where $\overline{X}_{.j}$ is the mean of X_{ij} for group j.

Note that $(X_{ij} - \overline{X}_{.j})$ and $\overline{X}_{.j}$ are uncorrelated.

Centering Predictors

When no centering (or grand mean centering) is used, we are restricting the within-group relationship of X_{ij} on Y_{ij} to be equivalent to the between-group relationship:

$$\begin{aligned} Y_{ij} &= d_{0j} + b_1 X_{ij} + e_{ij} && (15)\\ &= d_{0j} + b_1(X_{ij} - \overline{X}_{.j} + \overline{X}_{.j}) + e_{ij} && (16)\\ &= d_{0j} + b_1(X_{ij} - \overline{X}_{.j}) + b_1(\overline{X}_{.j}) + e_{ij} && (17) \end{aligned}$$

Consequently, b_1 ends up being an uninterpretable blend of the within-group and between-group effects of X_{ij} on Y_{ij} (Raudenbush & Bryk, 2002).

Centering Predictors

If we are interested in the within-group effect of X_{ij}, we can use group-mean centering:

Subtract the group mean of a level-1 predictor from each individuals' score on that predictor

$$Y_{ij} = d_{0j} + b_{1j}(X_{ij} - \overline{X}_{.j}) + e_{ij} \tag{18}$$

- This centers each group's mean at 0 and the intercept for group j in an unconditional model is now interpreted as the expected response for individuals in group j who have their average group response on the level-1 predictors.
- The coefficients for the level-1 predictors now represent the within-group relationship between the predictor and the outcome.

In SPSS

```
AGGREGATE
  /OUTFILE=* MODE=ADDVARIABLES
  /BREAK=id
  /Hazard_m=MEAN(Hazard).

COMPUTE Hazard_groupc = Hazard - Hazard_m.
EXECUTE.

MIXED Dose WITH Hazard_groupc
  /FIXED=Hazard_groupc | SSTYPE(3)
  /METHOD=REML
  /PRINT=G  SOLUTION TESTCOV
  /RANDOM=INTERCEPT Hazard_groupc | SUBJECT(id) COVTYPE(UN).
```


In SPSS

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	83.757143	3.673043	69.000	22.803	.000	76.429623	91.084663
Hazard_groupc	-4.095374	.565015	40.218	-7.248	.000	-5.237119	-2.953628

a. Dependent Variable: Dose.

For the average individual, the dose administration of drugs given a hazardousness rating that equals the individual's mean hazardousness rating across conditions, is expected to be $d_0 = 83.76$.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		246.440042	20.428978	12.063	.000	209.483480	289.916389
Intercept + Hazard_groupc [subject = id]	UN (1,1)	903.313685	160.819172	5.617	.000	637.231259	1280.50155
	UN (2,1)	7.559687	18.902010	.400	.689	-29.487571	44.606946
	UN (2,2)	4.372548	3.713800	1.177	.239	.827506	23.104577

a. Dependent Variable: Dose.

In SPSS

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	83.757143	3.673043	69.000	22.803	.000	76.429623	91.084663
Hazard_groupc	-4.095374	.565015	40.218	-7.248	.000	-5.237119	-2.953628

a. Dependent Variable: Dose.

For the average individual, the dosages of two drugs that differ by 1 unit on the hazardousness rating are expected to differ by $b_1 = -4.10$ units, with smaller doses corresponding to more hazardous drugs.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		246.440042	20.428978	12.063	.000	209.483480	289.916389
Intercept + Hazard_groupc [subject = id]	UN (1,1)	903.313685	160.819172	5.617	.000	637.231259	1280.50155
	UN (2,1)	7.559687	18.902010	.400	.689	-29.487571	44.606946
	UN (2,2)	4.372548	3.713800	1.177	.239	.827506	23.104577

a. Dependent Variable: Dose.

Centering Predictors

Contextual effect:

- Sometimes a researcher is interested in the within-group relationship between a level-1 predictor and an outcome as well as the between-group relationship.
- Scenarios in which the between-group effect differs from the within-group effect are labeled contextual effects (Raudenbush & Bryk, 2002).
- The between-group relationship can be tested by adding the group mean of the level-1 predictor as a level-2 predictor for the random intercept.

Centering Predictors

A two-level model with one within-group centered level-1 predictor and the group mean on the predictor added as a level-2 predictor of the intercept is:

$$Y_{ij} = b_{0j} + b_{1j}(X_{ij} - \overline{X}_{.j}) + e_{ij} \quad (19)$$

$$d_{0j} = d_0 + g_{01}\overline{X}_{.j} + u_{0j} \quad (20)$$

$$b_{1j} = b_1 + u_{1j} \quad (21)$$

where $\overline{X}_{.j}$ is the mean of X_{ij} for group j.

The combined model is:

$$Y_{ij} = (d_0 + g_{01}\overline{X}_{.j} + u_{0j}) + (b_1 + u_{1j})(X_{ij} - \overline{X}_{.j}) + e_{ij} \quad (22)$$

Centering Predictors

The combined model is:

$$Y_{ij} = (d_0 + g_{01}\overline{X}_{.j} + u_{0j}) + (b_1 + u_{1j})(X_{ij} - \overline{X}_{.j}) + e_{ij} \quad (23)$$

which can be expanded and rearranged as:

$$Y_{ij} = \underbrace{d_0 + g_{01}\overline{X}_{.j} + b_1(X_{ij} - \overline{X}_{.j})}_{\text{fixed}} + \underbrace{u_{0j} + u_{1j}(X_{ij} - \overline{X}_{.j}) + e_{ij}}_{\text{random}} \quad (24)$$

The average within-group effect of X_{ij} on Y_{ij} is represented as b_1 with variance $\text{Var}(b_{1j}) = \text{Var}(u_{1j}) = \tau_{11}$, and the between group-effect is represented as g_{01}.

Differences between b_1 and g_{01} indicate the presence of a contextual effect.

In SPSS

```
MIXED Dose WITH Hazard_groupc Hazard_m
  /FIXED=Hazard_groupc Hazard_m | SSTYPE(3)
  /METHOD=REML
  /PRINT=G  SOLUTION TESTCOV
  /RANDOM=INTERCEPT Hazard_groupc | SUBJECT(id) COVTYPE(UN).
```


In SPSS

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	115.154269	19.445544	68.041	5.922	.000	76.351710	153.956828
Hazard_groupc	-4.100481	.565042	40.331	-7.257	.000	-5.242182	-2.958780
Hazard_m	-5.918668	3.601331	68.037	-1.643	.105	-13.104941	1.267605

a. Dependent Variable: Dose.

For the average individual, the dosages of two drugs that differ by 1 unit on the hazardousness rating are expected to differ by $b_1 = -4.10$ units, with smaller doses corresponding to more hazardous drugs.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		246.439899	20.424317	12.066	.000	209.491105	289.905502
Intercept + Hazard_groupc [subject = id]	UN (1,1)	880.025923	158.001384	5.570	.000	618.969516	1251.18541
	UN (2,1)	6.079377	18.206131	.334	.738	-29.603985	41.762739
	UN (2,2)	4.367985	3.707268	1.178	.239	.827628	23.052975

a. Dependent Variable: Dose.

In SPSS

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	115.154269	19.445544	68.041	5.922	.000	76.351710	153.956828
Hazard_groupc	-4.100481	.565042	40.331	-7.257	.000	-5.242182	-2.958780
Hazard_m	-5.918668	3.601331	68.037	-1.643	.105	-13.104941	1.267605

a. Dependent Variable: Dose.

Two individuals that differ in their average (across conditions) hazardousness ratings by 1 unit are estimated to differ by $g_{01} = -5.92$ units on their average dosage, where individuals that tend to perceive drugs as more hazardous tend to administer small dosages.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		246.439899	20.424317	12.066	.000	209.491105	289.905502
Intercept + Hazard_groupc [subject = id]	UN (1,1)	880.025923	158.001384	5.570	.000	618.969516	1251.18541
	UN (2,1)	6.079377	18.206131	.334	.738	-29.603985	41.762739
	UN (2,2)	4.367985	3.707268	1.178	.239	.827628	23.052975

a. Dependent Variable: Dose.

General 1-1-1 Mediation Model

Multilevel mediation processes are often labeled by the level at which each variable varies.

- 2-1-1 implies X is a level-2 variable and M and Y are level-1 variables
- 2-2-1 implies X and M are level-2 variables and Y is a level-1 variable.

The most general three-variable multilevel mediation model exists when X, M, and Y are level-1 variables that contain both within-group and between-group variability*.

In this scenario, a mediation process can exist at both levels.

We will start with this general model and later discuss simplifications.

General 1-1-1 Mediation Model

Recall the basic single-level mediation model:

$$M_i = d_M + aX_i + e_i$$

$$Y_i = d_Y + c'X_i + bM_i + e_i$$

We can easily convert this to multilevel form (using group centered predictors):

$$M_{ij} = d_{Mj} + a_j(X_{ij} - \overline{X}_{.j}) + e_{ij}$$

$$Y_{ij} = d_{Yj} + c'_j(X_{ij} - \overline{X}_{.j}) + b_j(M_{ij} - \overline{M}_{.j}) + e_{ij}$$

where $\overline{X}_{.j}$ and $\overline{M}_{.j}$ represent the observed group means of X and M, respectively.

Within-group effects

$$M_{ij} = d_{Mj} + a_j(X_{ij} - \overline{X}_{.j}) + e_{ij}$$
$$Y_{ij} = d_{Yj} + c'_j(X_{ij} - \overline{X}_{.j}) + b_j(M_{ij} - \overline{M}_{.j}) + e_{ij}$$

$$a_j = a_W + u_{aj}$$
$$b_j = b_W + u_{bj}$$
$$c'_j = c'_W + u_{c'j}$$

- a_j is the within-group effect of X on M for group j
- b_j is the within-group effect of M on Y, controlling for X, for group j
- c'_j is the within-group effect of X on Y, controlling for M, for group j
- a_W, b_W, and c'_W are the average within-group effects

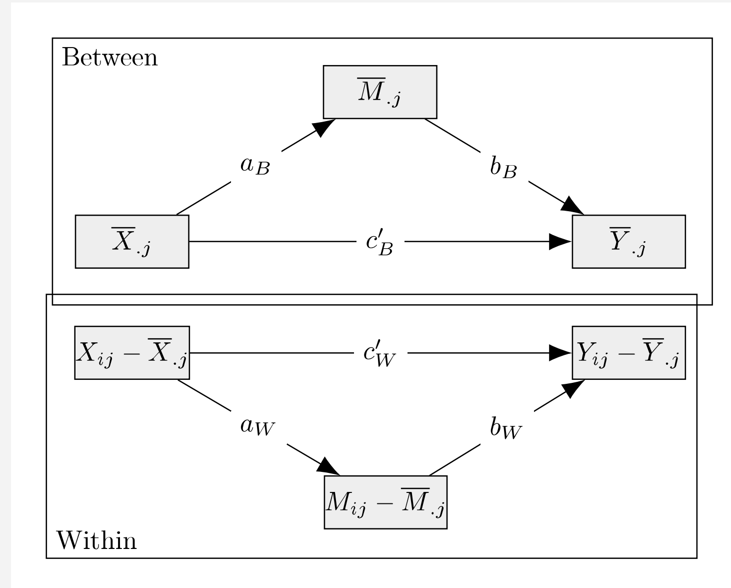
Between-group effects

$$M_{ij} = d_{Mj} + a_j(X_{ij} - \overline{X}_{.j}) + e_{ij}$$
$$Y_{ij} = d_{Yj} + c'_j(X_{ij} - \overline{X}_{.j}) + b_j(M_{ij} - \overline{M}_{.j}) + e_{ij}$$

$$d_{Mj} = d_M + a_B\overline{X}_{.j} + u_{Mj}$$
$$d_{Yj} = d_Y + c'_B\overline{X}_{.j} + b_B\overline{M}_{.j} + u_{Yj}$$

- a_B is the between-group effect of X on M
- b_B is the between-group effect of M on Y, controlling for X
- c'_B is the between-group effect of X on Y, controlling for M

Conceptual Diagram



Full Model

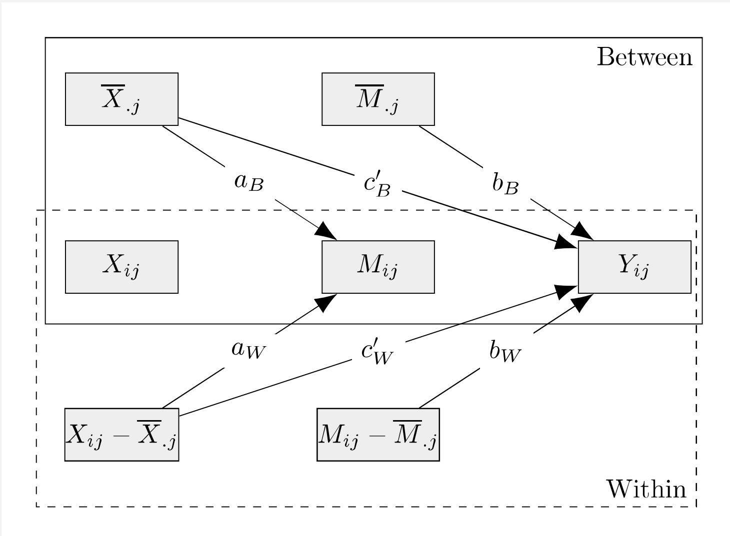
$$M_{ij} = d_{Mj} + a_j(X_{ij} - \overline{X}_{.j}) + e_{ij}$$
$$Y_{ij} = d_{Yj} + c'_j(X_{ij} - \overline{X}_{.j}) + b_j(M_{ij} - \overline{M}_{.j}) + e_{ij}$$
$$d_{Mj} = d_M + a_B\overline{X}_{.j} + u_{Mj}$$
$$d_{Yj} = d_Y + c'_B\overline{X}_{.j} + b_B\overline{M}_{.j} + u_{Yj}$$
$$a_j = a_W + u_{aj}$$
$$b_j = b_W + u_{bj}$$
$$c'_j = c'_W + u_{c'j}$$

Combined Equations

$$\begin{aligned} M_{ij} =& (d_M + a_B\overline{X}_{.j} + u_{Mj}) + (a_W + u_{aj})(X_{ij} - \overline{X}_{.j}) + e_{ij} \\ =& \underbrace{d_M + a_B\overline{X}_{.j} + a_W(X_{ij} - \overline{X}_{.j})}_{fixed} + \underbrace{u_{Mj} + u_{aj}(X_{ij} - \overline{X}_{.j}) + e_{ij}}_{random} \end{aligned}$$

$$\begin{aligned} Y_{ij} =& (d_Y + c'_B\overline{X}_{.j} + b_B\overline{M}_{.j} + u_{Yj}) \\ &+ (c'_W + u_{c'j})(X_{ij} - \overline{X}_{.j}) + (b_W + u_{bj})(M_{ij} - \overline{M}_{.j}) + e_{ij} \\ =& \underbrace{d_Y + c'_B\overline{X}_{.j} + b_B\overline{M}_{.j} + c'_W(X_{ij} - \overline{X}_{.j}) + b_W(M_{ij} - \overline{M}_{.j})}_{fixed} \\ &+ \underbrace{u_{Yj} + u_{c'j}(X_{ij} - \overline{X}_{.j}) + u_{bj}(M_{ij} - \overline{M}_{.j}) + e_{ij}}_{random} \end{aligned}$$

Statistical Diagram



In SPSS - M Equation

We need to group mean center `Simple` and predict `Hazard` from the group mean centered `Simple` and the group means of `Simple`:

```
AGGREGATE
  /OUTFILE=* MODE=ADDVARIABLES
  /BREAK=id
  /Simple_m=MEAN(Simple).

COMPUTE Simple_groupc = Simple - Simple_m.
EXECUTE.

MIXED Hazard WITH Simple_groupc Simple_m
  /FIXED=Simple_groupc Simple_m | SSTYPE(3)
  /METHOD=REML
  /PRINT=G  SOLUTION TESTCOV
  /RANDOM=INTERCEPT | SUBJECT(id) COVTYPE(VC).
```


Error in Fixed Effects

SPSS alerts about an error:

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	5.304762	.121182	69	43.775	.000	5.063010	5.546513
Simple_groupc	-2.104762	.130990	349	-16.068	.000	-2.362390	-1.847134
Simple_m	0[b]	0	.	.	.	.	.

a. Dependent Variable: Hazard.

b. This parameter is set to zero because it is redundant.

Error in Fixed Effects

SPSS alerts about an error:

What does it mean?

- Because each participant completed all of the `Simple` conditions (coded 0 and 1), all participants have a person-level mean of 0.5 (see `Simple_m` in the dataset).
- Thus, there is no between-person variability on `Simple`, so the group means and the intercept are linear combinations of one another (i.e., the model is not identified).
- We must remove the between-person effect of X from the model.
- Now there can no longer be a between-person indirect effect.

In SPSS - M Equation

The new syntax is:

```
MIXED Hazard WITH Simple_groupc
  /FIXED=Simple_groupc | SSTYPE(3)
  /METHOD=REML
  /PRINT=G  SOLUTION TESTCOV
  /RANDOM=INTERCEPT | SUBJECT(id) COVTYPE(VC).
```


In SPSS - M Equation

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	5.304762	.121182	69	43.775	.000	5.063010	5.546513
Simple_groupc	-2.104762	.130990	349	-16.068	.000	-2.362390	-1.847134

a. Dependent Variable: Hazard.

Within a given individual, Simple drugs tend to be rated as less hazardous, on average, than non-Simple drugs ($a_W = -2.10$).

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		1.801617	.136384	13.210	.000	1.553193	2.089774
Intercept [subject = id]	Variance	.727687	.176481	4.123	.000	.452385	1.170524

a. Dependent Variable: Hazard.

In SPSS - Y Equation

Now, we want to predict Dose from the group mean centered Hazard variable, the group means of Hazard, and the group mean centered Simple variable*. We have already created the group mean centered Hazard and Simple variables.

```
MIXED Dose WITH Hazard_groupc Hazard_m Simple_groupc
  /FIXED=Hazard_groupc Hazard_m Simple_groupc | SSTYPE(3)
  /METHOD=REML
  /PRINT=G  SOLUTION TESTCOV
  /RANDOM=INTERCEPT | SUBJECT(id) COVTYPE(VC).
```


In SPSS - Y Equation

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	115.420197	19.457732	68	5.932	.000	76.592897	154.247498
Hazard_groupc	-3.196311	.639284	348.000	-5.000	.000	-4.453657	-1.938965
Hazard_m	-5.968798	3.603669	68	-1.656	.102	-13.159807	1.222211
Simple_groupc	4.320145	2.063436	348.000	2.094	.037	.261770	8.378521

a. Dependent Variable: Dose.

Holding Simple constant, within an individual, more hazardous drugs tend to be administered smaller dosages than less hazardous drugs ($b_W = -3.20$).

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		256.965667	19.480517	13.191	.000	221.485693	298.129206
Intercept [subject = id]	Variance	878.286359	158.003104	5.559	.000	617.313213	1249.58759

a. Dependent Variable: Dose.

In SPSS - Y Equation

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	115.420197	19.457732	68	5.932	.000	76.592897	154.247498
Hazard_groupc	-3.196311	.639284	348.000	-5.000	.000	-4.453657	-1.938965
Hazard_m	-5.968798	3.603669	68	-1.656	.102	-13.159807	1.222211
Simple_groupc	4.320145	2.063436	348.000	2.094	.037	.261770	8.378521

a. Dependent Variable: Dose.

Holding Hazard constant, within an individual, Simple drugs tend to be administered at higher dosages than non-Simple drugs ($c'_W = 4.32$).

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		256.965667	19.480517	13.191	.000	221.485693	298.129206
Intercept [subject = id]	Variance	878.286359	158.003104	5.559	.000	617.313213	1249.58759

a. Dependent Variable: Dose.

In SPSS - Y Equation

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	115.420197	19.457732	68	5.932	.000	76.592897	154.247498
Hazard_groupc	-3.196311	.639284	348.000	-5.000	.000	-4.453657	-1.938965
Hazard_m	-5.968798	3.603669	68	-1.656	.102	-13.159807	1.222211
Simple_groupc	4.320145	2.063436	348.000	2.094	.037	.261770	8.378521

a. Dependent Variable: Dose.

Two individuals that differ in their average (across conditions) hazardousness ratings by 1 unit are estimated to differ by $b_B = -5.97$ units on their average dosage, where individuals that tend to perceive drugs as more hazardous tend to administer smaller dosages.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		256.965667	19.480517	13.191	.000	221.485693	298.129206
Intercept [subject = id]	Variance	878.286359	158.003104	5.559	.000	617.313213	1249.58759

a. Dependent Variable: Dose.

Within- Indirect Effect

What is the meaning of the within-group indirect effect?

A within-group indirect effect quantifies the expected difference in Y through M for two level-1 units in the *same* level-2 unit who differ by one unit on X.

It is the effect of X on Y through M within a given level-2 unit.

Within- Indirect Effect

How do we compute the within-group indirect effect?

Because a_j and b_j may randomly vary across groups, we are often interested in the average (across groups) within-group indirect effect, and possibly the variance of this indirect effect.

We can define the average within-group indirect effect as the expected value of $a_j b_j$, which equals:

$$E(a_j b_j) = a_W b_W + \sigma_{a_j,b_j}$$

Note that, if a_j and b_j covary, there can be a non-zero indirect effect even if a_W or b_W equal 0.

This formula holds under simplifications to the multilevel mediation equations (e.g., if one of the slopes is fixed).

Example

For our example, $a_W = -2.10$, $b_W = -3.20$, and $\sigma_{a_j,b_j} = 0$, so $E(a_j b_j) = (-2.10)(-3.20) + 0 = 6.73$.

Thus, within a given individual, the expected difference in dosage between Simple and non-Simple names, by way of Hazardousness, is estimated to be 6.73, with Simple drugs being administered in higher dosages.

Independent of Hazardousness, within a given individual, higher dosages tend to be administered for Simple drugs relative to non-Simple drugs ($c'_W = 4.32$).

Within- Indirect Effect

If a_j and/or b_j is random, the within-group indirect effect is also random.

We can calculate the variance of the within-group indirect effect across groups as:

$$Var(a_j b_j) = b^2\sigma^2_{a_j} + a^2\sigma^2_{b_j} + \sigma^2_{a_j}\sigma^2_{b_j} + 2ab\sigma_{a_j,b_j} + \sigma^2_{a_j,b_j}$$

Again, this formula is for the general model and holds under simplifications to the mediation equations.

In our current example, a_j and b_j are fixed, so the variance is 0.

Between- Indirect Effect

What is the meaning of the between-group indirect effect?

When the between-group effect of X is a result of the group aggregate of X, the between-group indirect effect quantifies the expected difference in the group aggregate of Y through the group-aggregate of M for two level-2 units that differ by one-unit in the group-aggregate of X.

Between- Indirect Effect

Often, the between-group indirect effect in this situation can be difficult to interpret, as the meaning of the group aggregate of a variable may differ from the meaning of the variable at the individual level.

Example by Preacher et al. (2010) on differentiating individual efficacy and the collective efficacy of a group:

- The aggregated individual efficacy for a given group is a group-level variable (in that it only varies between groups).
- But the focus is still at the individual level and the meaning of such a variable is likely to differ from the meaning of a variable characterizing the dynamics of the self efficacy of the group as a collective.

Between- Indirect Effect

The between-group indirect effect is:

$$E(a_B b_B) = a_B b_B$$

The between-group indirect effect cannot be estimated to vary across groups, so there is no covariance term.

In our current example, X contains no between-group variability, so there is no between-group effect of X on M (i.e., $a_B = 0$), so $a_B b_B = 0$.

Inference about the indirect effect(s)

As with single-level mediation, p-values and/or confidence intervals for the indirect effect(s) constructed using the Sobel/normal theory method are not appropriate, due to the non-normal sampling distribution of the indirect effect(s).

Bootstrapping, which is popular for single-level mediation can be quite complex for multilevel models.

Instead, Monte Carlo confidence intervals (MCCIs) are usually recommended.

MCCIs are constructed by simulating data from the estimated sampling distribution of the model parameters and constructing an estimate of the sampling distribution of the indirect effect(s) using the simulated values.

MCCIs

Simulate $k \times p$ values from the multivariate distribution:

$$\begin{bmatrix} \mathbf{f}^* \\ \mathbf{r}^* \end{bmatrix} \sim MVN\left(\begin{bmatrix} \hat{\mathbf{f}} \\ \hat{\mathbf{r}} \end{bmatrix}, \begin{bmatrix} \hat{\boldsymbol{\Sigma}}_{\hat{f}} & \mathbf{0} \\ \mathbf{0} & \hat{\boldsymbol{\Sigma}}_{\hat{r}} \end{bmatrix} \right),$$

- k is an arbitrarily large number
- p is the total number of fixed and random parameters
- $\hat{\mathbf{f}}$ is a vector containing all of the fixed effect estimates with estimated asymptotic sampling covariance matrix $\hat{\boldsymbol{\Sigma}}_{\hat{f}}$
- $\hat{\mathbf{r}}$ is a vector containing all of the variance/covariance parameter estimates with estimated asymptotic sampling covariance matrix $\hat{\boldsymbol{\Sigma}}_{\hat{r}}$

MCCIs

Simulate $k \times p$ values from the multivariate distribution:

$$\begin{bmatrix} \mathbf{f}^* \\ \mathbf{r}^* \end{bmatrix} \sim MVN\left(\begin{bmatrix} \hat{\mathbf{f}} \\ \hat{\mathbf{r}} \end{bmatrix}, \begin{bmatrix} \hat{\boldsymbol{\Sigma}}_{\hat{f}} & \mathbf{0} \\ \mathbf{0} & \hat{\boldsymbol{\Sigma}}_{\hat{r}} \end{bmatrix} \right),$$

Calculate $a_W^* b_W^* + \sigma^*_{a_j,b_j}$ and $a_B^* b_B^*$ in each of the k vectors of simulated values to obtain empirical sampling distributions of the within-group and between-group indirect effects, respectively.

$100(1-\alpha)\%$ CIs can be calculated using the $100(\frac{\alpha}{2})$ and $100(1-\frac{\alpha}{2})$ percentiles.

Simultaneous Estimation

When the M and Y equations are fit separately and a_j and b_j covary, their covariance σ_{a_j,b_j} is not estimated.

In such circumstances, it is not possible to obtain an estimate of the average within-group indirect effect.

Instead, the equations need to be estimated simultaneously.

Some SEM software packages (e.g., Mplus) can estimate multilevel models simultaneously.

Bauer, Preacher, and Gil (2006) demonstrate how the equations can be estimated simultaneously using traditional (univariate) multilevel modeling software.

Simultaneous Estimation

All parameters can be estimated as one equation using the following formulation:

$$\begin{aligned} Z_{ij} = S_{M_{ij}}[d_M + a_B\overline{X}_{.j} + u_{Mj} + (a_W + u_{aj})(X_{ij} - \overline{X}_{.j})] \\ +S_{Y_{ij}}[d_Y + c'_B\overline{X}_{.j} + b_B\overline{M}_{.j} + u_{Yj} + (b_W + u_{bj})(M_{ij} - \overline{M}_{.j}) \\ +(c'_W + u_{c'j})(X_{ij} - \overline{X}_{.j})] + e_{Zij} \end{aligned}$$

Expanding terms yields:

$$\begin{aligned} Z_{ij} = d_M[S_{M_{ij}}] + d_Y[S_{Y_{ij}}] + a_B[S_{M_{ij}}\overline{X}_{.j}] + c'_B[S_{Y_{ij}}\overline{X}_{.j}] + b_B[S_{Y_{ij}}\overline{M}_{.j}] \\ +a_W[S_{M_{ij}}(X_{ij} - \overline{X}_{.j})] + c'_W[S_{Y_{ij}}(X_{ij} - \overline{X}_{.j})] + b_W[S_{Y_{ij}}(M_{ij} - \overline{M}_{.j})] \\ +u_{aj}S_{M_{ij}}(X_{ij} - \overline{X}_{.j}) + u_{c'j}S_{Y_{ij}}(X_{ij} - \overline{X}_{.j}) + u_{bj}S_{Y_{ij}}(M_{ij} - \overline{M}_{.j}) \\ +u_{Mj}S_{M_{ij}} + u_{Yj}S_{Y_{ij}} + e_{Zij} \end{aligned}$$

MLmed

The `MLmed` macro for SPSS (available at *njrockwood.com*) simplifies the procedure.

`MLmed` automatically:

- Decomposes level-1 predictors into within-group and between-group components.
- Stacks the data and fits the model using the MIXED procedure in SPSS.
- Organizes the output by equation and within-group and between-group effects.
- Constructs MCCIs for the indirect effects.

Currently, `MLmed` can handle up to 3 (parallel, level-1) mediators and the indirect effects through the first mediator can be moderated by a level-2 variable.

MLmed

The `MLmed` macro can be loaded into SPSS by highlighting and running the entire syntax file that defines the macro.

Then, models can be fit using the `MLmed` command.

Full descriptions of the available commands and their meaning can be found in the User Guide, which accompanies the macro.

Commands relevant to this workshop will be explained as needed.

Fitting the dosage data with MLmed

```
MLmed data = DataSet2
/x = Simple
/xB = 0
/m1 = Hazard
/y = Dose
/cluster = id
/folder = /Users/username/Desktop/.
```


Fitting the dosage data with MLmed

```
 Outcome: Hazard

Within- Effects
         Estimate     S.E.       df        t        p       LL       UL
constant   5.3048    .1212  69.0000  43.7751    .0000   5.0630   5.5465
Simple    -2.1048    .1310 349.0000 -16.0682    .0000  -2.3624  -1.8471

Note: No Between- Effect(s) Specified.

************************************************************************
 Outcome: Dose

Within- Effects
         Estimate     S.E.       df        t        p       LL       UL
constant 115.4202  19.4577  68.0000   5.9318    .0000  76.5929 154.2475
Simple     4.3201   2.0634 348.0000   2.0937    .0370    .2618   8.3785
Hazard    -3.1963    .6393 348.0000  -4.9998    .0000  -4.4537  -1.9390

Between- Effects
       Estimate     S.E.       df        t        p       LL       UL
Hazard  -5.9688   3.6037  68.0000  -1.6563    .1023 -13.1598   1.2222
```


Fitting the dosage data with MLmed

```
**************************  RANDOM EFFECTS  ***************************

Level-1 Residual Estimates
       Estimate     S.E.   Wald Z        p       LL       UL
Dose   256.9657  19.4805  13.1909    .0000 221.4857 298.1292
Hazard   1.8016    .1364  13.2098    .0000   1.5532   2.0898

Random Effect Estimates
   Estimate     S.E.   Wald Z        p       LL       UL
1     .7277    .1765   4.1233    .0000    .4524   1.1705
2  878.2864 158.0031   5.5587    .0000 617.3132 1249.588

Random Effect Key
1    Int        Hazard
2    Int        Dose

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


Fitting the dosage data with MLmed

```
***********************  INDIRECT EFFECT(S)  ************************

Within- Indirect Effect(s)
          E(ab)  Var(ab)    SD(ab)
Hazard   6.7275    .0000     .0000

Within- Indirect Effect(s)
         Effect       SE        Z        p     MCLL     MCUL
Hazard   6.7275   1.4117   4.7656    .0000   4.0088   9.6106

Note: No Between- Indirect Effect(s) Specified.
```

Within an individual, the difference in dosage between Simple drugs and non-Simple drugs that operates indirectly through perceived hazardousness is estimated to be 6.73 (MCCI = [4.01, 9.61]), where Simple drugs are administered at higher dosages than non-Simple drugs.

Adding random slopes and their covariance

Suppose that we expect the within-person $X \to M$ and $M \to Y$ effects to randomly vary (and covary) across people.

We can add these random effects and their covariance in `MLmed`:

```
MLmed data = DataSet6
/x = Simple
/xB = 0
/randx = 01
/m1 = Hazard
/randm = 1
/y = dose
/covmat = UN
/cluster = id
/folder = /Users/username/Desktop/.
```


Adding random slopes and their covariance

```
Level-1 Residual Estimates
        Estimate     S.E.   Wald Z        p       LL       UL
dose    245.4574  20.2443  12.1247    .0000 208.8202 288.5225
Hazard    1.3619    .1151  11.8322    .0000   1.1540   1.6073

Random Effect Estimates
       Estimate     S.E.   Wald Z        p       LL       UL
(1,1)     .8010    .1761   4.5494    .0000    .5206   1.2323
(2,2)  880.2044 158.0058   5.7707    .0000 619.1332 1251.362
(3,3)    1.4827    .4142   3.5799    .0003    .8576   2.5635
(4,3)     .6696    .8673    .7720    .4401  -1.0303   2.3695
(4,4)    3.9093   3.5234   1.1095    .2672    .6682  22.8701

Random Effect Covariance Matrix
          1         2         3         4
1     .8010     .0000     .0000     .0000
2     .0000  880.2044     .0000     .0000
3     .0000     .0000    1.4827     .6696
4     .0000     .0000     .6696    3.9093

Random Effect Correlation Matrix
          1         2         3         4
1    1.0000     .0000     .0000     .0000
2     .0000    1.0000     .0000     .0000
3     .0000     .0000    1.0000     .2781
4     .0000     .0000     .2781    1.0000

Random Effect Key
1    Int      Hazard
2    Int      dose
3    Slope    Simple     ->     Hazard
4    Slope    Hazard     ->     dose
```


Adding random slopes and their covariance

```
*********************** INDIRECT EFFECT(S) ************************

Within- Indirect Effect(s)
         E(ab)  Var(ab)   SD(ab)
Hazard  7.1626  46.3690   6.8095

Within- Indirect Effect(s)
        Effect       SE        Z        p     MCLL     MCUL
Hazard  7.1626   1.8403   3.8921    .0001   3.6467  10.9003

Note: No Between- Indirect Effect(s) Specified.
```

On average, within an individual, the difference in dosage between Simple drugs and non-Simple drugs that operates indirectly through perceived hazardousness is estimated to be 7.16 (MCCI = [3.65, 10.90]), where Simple drugs are administered at higher dosages than non-Simple drugs. However, there is substantial between-person variability in this indirect effect (SD = 6.81).

Another example

This example uses a simulated dataset (`tutor_data.sav`) based on an education experiment.

Suppose 48 classrooms were randomly sampled within a particular state, where each classroom is from a different school.

Next, students within each classroom were randomly sampled to participate in an after-school tutoring program throughout the school year.

The total number of students sampled is 450, where 223 students are assigned to the after-school tutoring program and 227 students are assigned to the control condition.

Another example

This example uses a simulated dataset (`tutor_data.sav`) based on an education experiment.

The `tutor` variable in the dataset codes the assignment of each student (0 = control, 1 = tutoring).

Before completing an end-of-year mathematics post-test (`post`), the students' academic motivation (`motiv`) was measured.

There is also data on the students' test scores from the previous year (`pre`).

Another example

We are interested in testing whether there is evidence that participation in the after-school tutoring program ($X =$ `tutor`) results in higher mathematics post-test scores ($Y =$ `post`), on average, than not participating in after-school tutoring due to an increase in student motivation ($M =$ `motiv`).

Further, we are interested in whether this effect is consistent across classrooms, or whether there is between-classroom variability in the effect.

Throughout, we will use the previous year's mathematics test score ($Q =$ `pre`) as a covariate.

Another example

All variables are level-1 variables.

The proportion of students assigned to tutoring within each class is not equivalent, so there is also between-class variability for X.

Since the class-aggregate of student motivation and pre and post test scores differ across classrooms, there is also between-class variability on M, Q, and Y.

Thus we group-mean center X, M, and Q to remove between-class variability and add this variability back into the model using the classroom means as predictors of the random intercepts so that within-class and between-class effects can be estimated separately.

Another example

We start with a random intercepts model:

$$\begin{aligned} MOTIV_{ij} &= d_{Mj} + a_j(TUTOR_{ij} - \overline{TUTOR}_{.j}) \\ &\quad + g_{1_j}(PRE_{ij} - \overline{PRE}_{.j}) + e_{M_{ij}} \end{aligned}$$

$$\begin{aligned} POST_{ij} &= d_{Yj} + c'_j(TUTOR_{ij} - \overline{TUTOR}_{.j}) \\ &\quad + b_j(MOTIV_{ij} - \overline{MOTIV}_{.j}) \\ &\quad + g_{2_j}(PRE_{ij} - \overline{PRE}_{.j}) + e_{Y_{ij}} \end{aligned}$$

$$\begin{aligned} d_{M_j} &= d_M + a_B\overline{TUTOR}_{.j} + g_{1_B}\overline{PRE}_{.j} + u_{M_j} \\ d_{Y_j} &= d_Y + c'_B\overline{TUTOR}_{.j} + b_B\overline{MOTIV}_{.j} + g_{2_B}\overline{PRE}_{.j} + u_{Y_j} \end{aligned}$$

$$a_j = a_W,\;\; b_j = b_W,\;\; c'_j = c'_W,\;\; g_{1_j} = g_{1_W},\;\; g_{2_j} = g_{2_W}.$$

Using MLmed

```
MLmed data = DataSet9
/x = tutor
/m1 = motiv
/y = post
/cov1 = pre
/cluster = classid
/folder = /Users/username/Desktop/.
```


Fixed Effects

Outcome: motiv

Within- Effects

	Estimate	S.E.	df	t	p	LL	UL
constant	1.2844	.5128	46.8208	2.5049	.0158	.2528	2.3160
tutor	1.3517	.0462	398.0015	29.2783	.0000	1.2610	1.4425
pre	.0194	.0022	398.0015	8.7609	.0000	.0151	.0238

Between- Effects

	Estimate	S.E.	df	t	p	LL	UL
tutor	.8443	.5654	47.1328	1.4933	.1420	-.2930	1.9817
pre	.0039	.0058	45.9489	.6771	.5017	-.0077	.0156

****

Outcome: post

Within- Effects

	Estimate	S.E.	df	t	p	LL	UL
constant	50.3689	7.2512	43.9803	6.9463	.0000	35.7548	64.9830
tutor	-3.2913	1.4885	394.8792	-2.2112	.0276	-6.2176	-.3649
motiv	4.4675	.9097	394.8792	4.9112	.0000	2.6791	6.2559
pre	.3746	.0440	394.8792	8.5215	.0000	.2882	.4611

Between- Effects

	Estimate	S.E.	df	t	p	LL	UL
tutor	-24.6103	7.7505	48.0227	-3.1753	.0026	-40.1935	-9.0271
motiv	12.3961	1.9524	43.5166	6.3490	.0000	8.4600	16.3323
pre	.0119	.0775	44.9123	.1532	.8789	-.1443	.1680

Indirect Effects

************************ INDIRECT EFFECT(S) ************************

Within- Indirect Effect(s)

	E(ab)	Var(ab)	SD(ab)
motiv	6.0388	.0000	.0000

Within- Indirect Effect(s)

	Effect	SE	Z	p	MCLL	MCUL
motiv	6.0388	1.2475	4.8408	.0000	3.5295	8.4957

Between- Indirect Effect(s)

	Effect	SE	Z	p	MCLL	MCUL
motiv	10.4665	7.2843	1.4368	.1508	-3.4180	25.3210

Within a given classroom, there is a significant indirect effect of tutoring on posttest through motivation ($E(a_j b_j) = 6.04$, MCCI = [3.53, 8.50]), where students who participated in tutoring performed better on the posttest.

Adding random slopes

In addition to being interested in the average within-class indirect effect, we are also interested in determining if the within-class indirect effect varies across classrooms.

Exercise:

- Using `MLmed`, expand the model to include random a_j and b_j paths, as well as the covariance between these paths.
- Interpret the individual coefficients (and possibly the variance of the coefficients) that make up the mediation model.
- Interpret the average and variance of the within-class indirect effect in the context of the specific example.

Alternative Data Designs

The 1-1-1 model is for the general data design in which X, M, and Y contain within-group and between-group variability.

Using the dosage dataset, we also fit a model in which X only contained within-group variability.

`MLmed` can also be used to fit models in which X only contains between-group variability* (i.e., a 2-1-1 model) which is useful, for example, for cluster-randomized designs.

2-2-1 models cannot be fit using `MLmed`, but could be fit piecewise, where $X \to M$ is fit using OLS regression and the Y equation is fit using a MLM.

Models containing "upward effect" (e.g., a 1-2-1 model) cannot be fit using MLM software. Instead multilevel structural equation modeling (MSEM) should be used.

A 2-1-1 Example

Suppose that, rather than students being assigned to tutoring, teachers completed a training program designed to teach a number of skills focused on engaging their students through the use of interactive real-world applications.

It is thought that students who are exposed to the interactive real-world applications will see the utility of the content being taught so they will be more motivated, leading to an increase in their post-test performance, where the post-test is completed at the end of the academic year.

The variable `train` is a teacher-level (level-2) training identifier (1 = completed raining, 0 = control)

A 2-1-1 Example

We are interested in testing if the average amount of student motivation mediates the relationship between the teachers' completion of the training program and the average post-test score of their students.

This is a 2-1-1 model since training (X) is a level-2 variable, motivation (M) is a level-1 variable, and post-test (Y) is a level-1 variable.

Therefore, there can only be a between-group indirect effect of X on Y.

In MLmed

We can fit the model in `MLmed` using the code:

```
MLmed data = DataSet9
/x = train
/xW = 0
/m1 = motiv
/y = post
/cov1 = pre
/cluster = classid
/folder = /Users/username/Desktop/.
```

In MLmed

```
 Outcome: motiv

Within- Effects
         Estimate      S.E.        df         t         p        LL        UL
constant   2.2615     .4840   56.7024    4.6724     .0000    1.2921    3.2308
pre         .0295     .0039  398.6255    7.6001     .0000     .0219     .0372

Between- Effects
      Estimate      S.E.        df         t         p        LL        UL
train    .3489     .1743   46.2330    2.0014     .0512    -.0019     .6997
pre     -.0065     .0078   55.2377    -.8368     .4063    -.0220     .0090

*****************************************************************************
 Outcome: post

Within- Effects
         Estimate      S.E.        df         t         p        LL        UL
constant  48.8441    8.4186   45.1925    5.8019     .0000   31.8902   65.7980
motiv      2.8059     .5150  396.2348    5.4481     .0000    1.7934    3.8185
pre         .3991     .0427  396.2348    9.3352     .0000     .3150     .4831

Between- Effects
      Estimate      S.E.        df         t         p        LL        UL
train   5.2720    2.6375   43.0894    1.9989     .0520    -.0467   10.5907
motiv   9.8785    2.1110   43.3758    4.6796     .0000    5.6224   14.1346
pre     -.0992     .1109   47.9342    -.8953     .3751    -.3221     .1236
```


In MLmed

```
**************************  RANDOM EFFECTS  **************************

Level-1 Residual Estimates
      Estimate      S.E.    Wald Z         p        LL        UL
post   75.1677    5.3404   14.0754     .0000   65.3968   86.3983
motiv    .7104     .0503   14.1178     .0000     .6184     .8162

Random Effect Estimates
   Estimate      S.E.    Wald Z         p        LL        UL
1     .0818     .0358    2.2833     .0224     .0347     .1931
2   26.8186    7.9874    3.3576     .0008   14.9596   48.0784

Random Effect Key
1     Int         motiv
2     Int         post

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


In MLmed

```
************************  INDIRECT EFFECT(S)  ************************

Note: No Within- Indirect Effect(s) Specified.

Between- Indirect Effect(s)
        Effect        SE         Z         p      MCLL      MCUL
motiv   3.4462    1.9085    1.8057     .0710     .0534    7.4738
```

There is a significant between-group indirect effect of teacher training on student posttest, by way of student motivation ($a_B b_B = 3.45$, MCCI = [.05, 7.47]). Specifically, the students of teachers who participated in the training had higher motivation, on average, than the students of teachers who did not participate in the training, and higher average motivation led to higher average posttest scores.

Conclusion

The general multilevel mediation framework can be extended to include multiple mediators.

Further, level-2 moderators of the within-group and/or between-group indirect effects can be included to test for multilevel moderated mediation.

`MLmed` can handle up to three mediators, where the indirect effect(s) through the first mediator can be moderated.

Further extensions beyond the capabilities of `MLmed` can be formulated using the general steps we have discussed here.

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