

INCORPORATING META-SCIENCE IN THE DEVELOPMENT OF MEDIATION AND MODERATION ANALYSIS

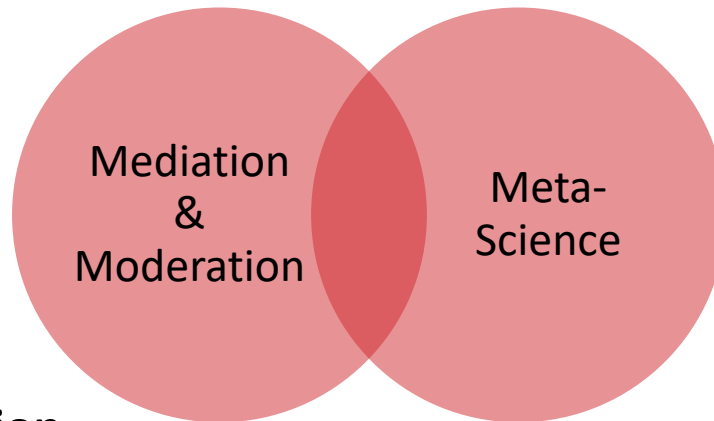
AMANDA KAY MONTOYA

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UNIVERSITY OF CALIFORNIA, LOS ANGELES

WHY AM I A QUANTITATIVE METHODOLOGIST?

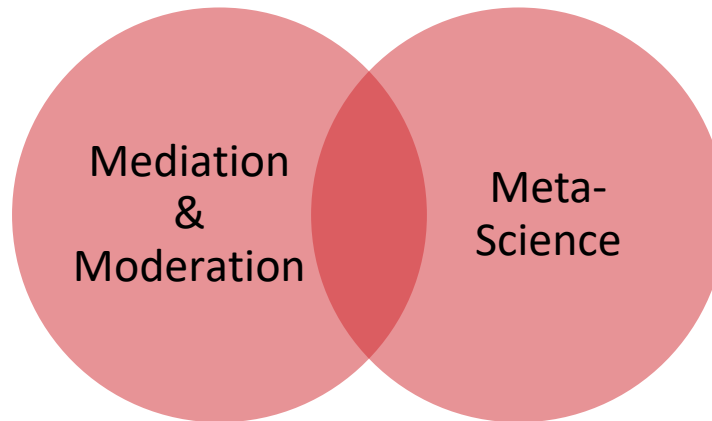
MY RESEARCH AGENDA



Mediation & Moderation

- Two-Instance Repeated-Measures Designs
 - Mediation: Montoya & Hayes (2017)
 - Moderation: Montoya (2019)
 - Comparing to Between-Subject: Montoya (2022)
- Machine Learning Methods for Detecting Treatment Responders
 - Random Forest to Detect Treatment Seekers: Green, Lin, Montoya, Bello, Grodin, Ryu, Ho, Leventhal, Ray, 2022)
 - Grodin, Montoya, Bujarski, & Ray, 2021
 - Grodin, Montoya, Cruz, Donato, Baskerville, Ray, under review
 - NIAAA/NIH R03 Grant
- Inferential Methods for Indirect Effects
 - Bias-Corrected Bootstrap: Tibbe & Montoya (2022)
 - Comparison in Two-Instance Repeated-Measures Designs: Montoya (2022)

MY RESEARCH AGENDA



Meta-Science

- Early implementation of Registered Reports
 - Montoya, Krenzer, Fossum (2022)
 - Montoya, Tibbe, Krenzer (In-principle Acceptance)
 - NSF ER2 Grant
- Power Analysis and Sample Size Planning
 - Two-Instance Repeated-Measures Designs Mediation: Montoya (2022)
 - Inferential Methods for Power Analysis: Fossum & Montoya (Under Review)
- Quality Evaluation and Preregistration in Mediation and Moderated Mediation
 - P-curve of Mediation: Charlton, Montoya, Price, & Hilgard (under review)
 - Planning and Conducting Mediation: Montoya (in press)

TODAY'S TALK

Two-Instance Repeated-Measures Designs

- Mediation Analysis
- Moderation Analysis
- Conditional Process Analysis

Meta-Science

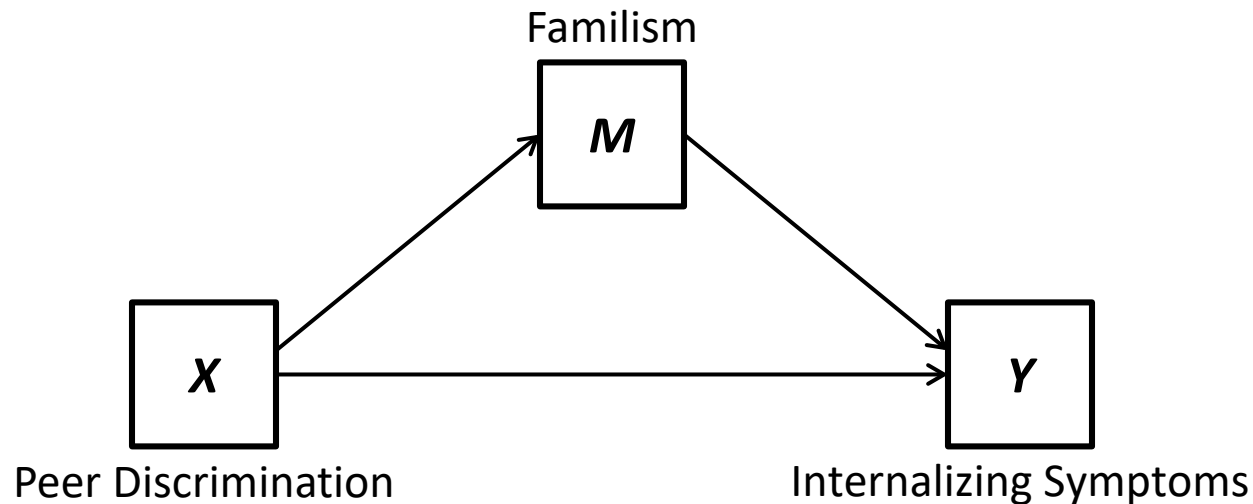
- Quality of Evidence in Mediation Analysis
- Sample Size Planning in Mediation and Moderated Mediation
- Preregistration and Registered Reports

Throughout: Future Directions and Connections

MAJOR THEMES

- **User-focus:** Methodological development and evaluation focuses on usability and appropriateness in real data situations
- **Tool Development:** The work is not done until it's easy for researchers to do these analyses on their own
- **Mentorship:** Incorporating undergraduate researchers into quantitative projects increases the scale at which we are able to work
- **Collaboration:** Working directly with researchers and teams in every area of psychology and behavioral science to implement the complex methods.

MEDIATION: WHAT EXPLAINS AN EFFECT?



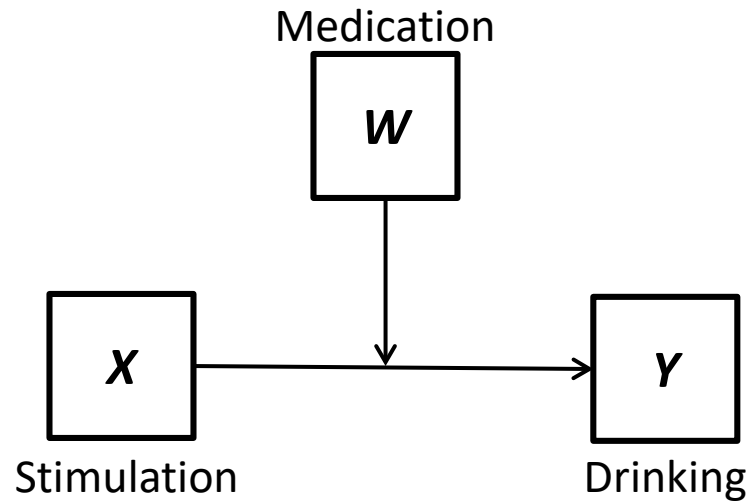
A simple mediation model connects an **assumed** causal variable (X) to an **assumed** outcome variable (Y), through some mechanism (M).

Example: Among a sample of LatinX youth, we examined if peer discrimination (X) affects internalizing symptoms (Y) through a reduction in familism (M).

The goal of statistical mediation analysis is to determine if there is an effect of X on Y through M . This is typically done by estimating the **indirect effect** and testing if it is different than zero.

Causality: Causal order of the variables is an **assumption** of mediation. The term “effect” is used based on this assumption. The quality of causal inference is determined by study design and theory.

MODERATION: WHEN AND FOR WHOM?



The relationship between the focal predictor (X) and an outcome (Y) is said to be moderated when the size or direction of this relationship depends on W .

Example: Can medication (ibudilast vs. placebo, W) alter the effect of stimulation during drinking (X) on future drinking behavior (Y).

Moderation helps us understand **boundary conditions** of effects: for whom or when is the effect large or small, present or absent, positive or negative.

META-SCIENCE: THE SCIENCE OF SCIENCE

Meta-science is the scientific study of the practice of science

Meta-science has increased in popularity about the replicability crisis as a way to reflect on how common practices in our field impact the fidelity of our results.

Meta-scientific methods:

- Large-scale systematic literature reviews
- Monte Carlo Simulation
- (Multi-site) Replication
- Survey Methods
- Experimental Designs

My work blends meta-science methods with quantitative methods to **reflect on research practices** while simultaneously **developing new research practices**.

TWO-INSTANCE REPEATED- MEASURES DESIGNS

TWO-INSTANCE REPEATED-MEASURES DESIGNS

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: A group of participants will all go through same intervention, measure hypothesized mediator and outcome before and after treatment.

FACTORS AFFECTING WOMEN'S INTEREST IN STEM

Developing a strong STEM workforce is a top priority in the US

- NSF INCLUDES: “Transforming education and career pathways to help broaden participation in science and engineering”

Stereotypes of STEM fields can lead women to be opt out

Cultural ideologies communicate ways to select an occupation

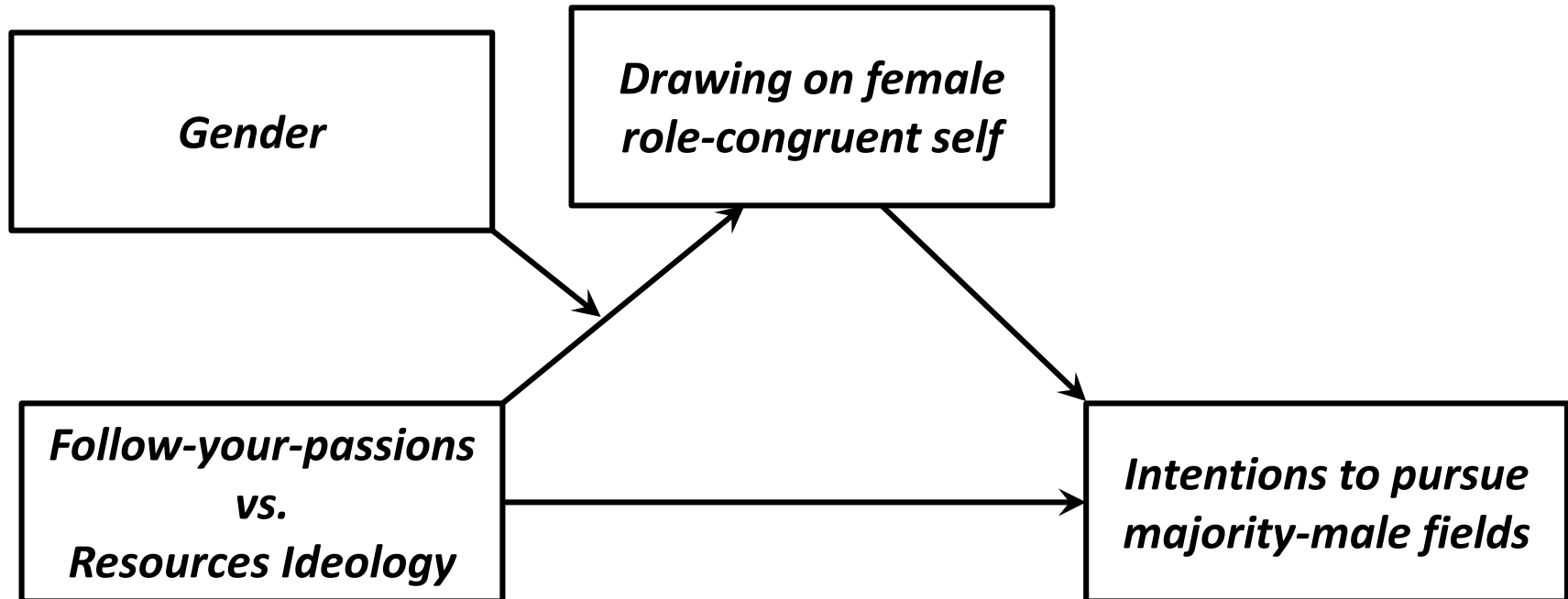
- “Follow your passions” is a common ideology in the US
- “Resource driven” ideology is common in places where individualism is less prominent
 - These places also have greater proportions of women in STEM

Our Question: Why would the follow-your-passions ideology decrease women's interest in STEM?



NEGATIVE IMPACTS OF “FOLLOWING YOUR PASSIONS”

Our theoretical model



THE DATA

A two-instance repeated-measures design was used

Participants responded in each of the two conditions (order counterbalanced)

People are sometimes told to pursue a career that...

allows you to follow your passions

OR

leads to a high income

“List a career that would fit this ideology”

Outcome: 3 questions on 1 (women) – 7 (men) Likert scale, averaged

“To what extent is the career you listed typically associated with females or males in U.S. society?”

Mediator: 3 questions on 1 – 7 Likert scale, averaged

“To what extent does the advice above cause you to draw on aspects of yourself that are feminine or masculine (regardless of your gender)?”

MONTOYA & HAYES, 2017

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Two-Condition Within-Participant Statistical Mediation Analysis: A Path-Analytic Framework

Amanda K. Montoya and Andrew F. Hayes
The Ohio State University

Researchers interested in testing mediation often use designs where participants are measured on a dependent variable Y and a mediator M in both of 2 different circumstances. The dominant approach to assessing mediation in such a design, proposed by Judd, Kenny, and McClelland (2001), relies on a series of hypothesis tests about components of the mediation model and is not based on an estimate of or formal inference about the indirect effect. In this article we recast Judd et al.'s approach in the path-analytic framework that is now commonly used in between-participant mediation analysis. By so doing, it is apparent how to estimate the indirect effect of a within-participant manipulation on some outcome through a mediator as the product of paths of influence. This path-analytic approach eliminates the need for discrete hypothesis tests about components of the model to support a claim of mediation, as Judd et al.'s method requires, because it relies only on an inference about the product of paths—the indirect effect. We generalize methods of inference for the indirect effect widely used in between-participant designs to this within-participant version of mediation analysis, including bootstrap confidence intervals and Monte Carlo confidence intervals. Using this path-analytic approach, we extend the method to models with multiple mediators operating in parallel and serially and discuss the comparison of indirect effects in these more complex models. We offer macros and code for SPSS, SAS, and Mplus that conduct these analyses.

Keywords: mediation, indirect effect, path analysis, within-participant design, resampling methods

Statistical mediation analysis allows an investigator to answer questions about the process by which some presumed causal variable X operates to affect an outcome variable Y . Using simple principles of linear modeling (though other analytical approaches are possible; Imai, Keele, & Tingley, 2010; Pearl, 2010, 2012), mediation analysis is used to quantify and test the pathways of influence from X to Y . In a mediation process, one of those pathways consists of a sequence of causal steps in which X affects a mediator variable M , which in turn causally influences Y . This indirect effect of X —the conjunction of the effect of X on M and the effect of M on Y —quantifies the degree to which M acts as the “mechanism” by which X affects Y . An indirect effect that is different from zero by an inferential test is used to support (but by no means definitively establishes or proves) a claim of mediation of X 's effect on Y by M .

Mediation analysis is commonplace in the social sciences, business, medical research, and many other areas. For example, White,

Abu-Rayya, Blum, and Faulkner (2015) investigated how long-term interaction with a member of the same religion or a different religion (X) influenced intergroup bias (Y) through five different emotions (e.g., anger and sadness; M). Littleton (2015) found that pregnant women who had a history of sexual victimization (X) had higher rates of depression (M), which predicted increased somatic complaints (e.g., back pain; Y). Schuldt, Guillory, and Gay (2016) examined how the weight of a person recommending a recipe (X) influenced the perceived healthiness of the recipe (Y) through the perceived health of the recommender (M).

Discussions of mediation analysis and its application are most typically couched in terms of or conducted using data from research designs that are cross-sectional or “between-participant” in nature. Typically in these designs, participants are measured once on a proposed mediator M and dependent variable Y , as in the examples above. This may occur following random assignment of participants into one of two conditions (X) that vary via some manipulation (e.g., a “treatment” vs. a “control” group) that is presumed to cause differences in M and Y . Alternatively, measurement of M and Y may occur contemporaneously with the observation of X (rather than random assignment). For expositional convenience, we refer to designs of this sort (i.e., with or without random assignment to X) throughout this article as “between-participant” designs.

Less attention in the methodology literature has been dedicated to mediation analysis when the data come from repeated measurement of the same people on variables in the mediation process, even though such designs are common. In this article we address mediation analysis in a specific category of repeated measures designs. Researchers sometimes measure a dependent variable Y and a mediator M in two different situations or circumstances (X),

- Path-analytic approach to mediation in two-instance repeated-measures designs
- Criticisms of stepwise approach (Judd, Kenny, and McClelland, 2001)
- Generalization to multiple mediator models
 - Parallel Mediation
 - Serial Mediation
- Introduces MEMORE, and SPSS and SAS macro for estimation and inference in these models

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We extend our appreciation to Dr. Simone Dohle and Dr. Michael Siegrist for their generosity in providing access to their data and permission for us to reproduce it in this article. This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant DGE-1343012.

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PATH ANALYTIC METHOD FOR MEDIATION

Total Effect c :

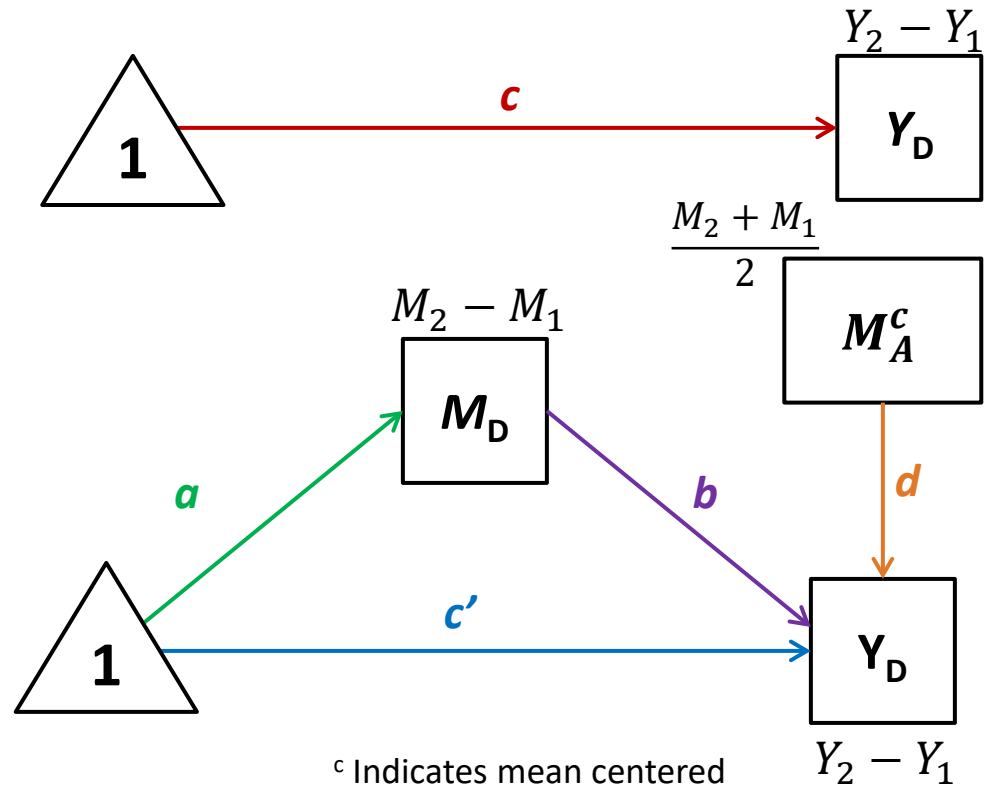
$$Y_{2i} - Y_{1i} = c + \epsilon_{Y_i^*}$$

a path:

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

b path and c' path:

$$Y_{Di} = c' + bM_{Di} + dM_{Ai}^c + \epsilon_{Y_i}$$



Indirect effect of *instance* on Y (through M) = $a \times b$

Direct effect of *instance* on Y (not through M) = c'

Total effect = direct effect + indirect effect

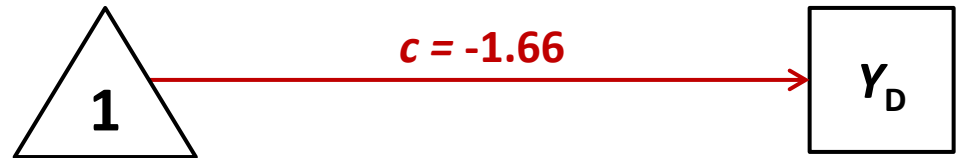
$$c = c' + a \times b$$

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

FOLLOW YOUR PASSIONS (WOMEN ONLY)

Total Effect c :

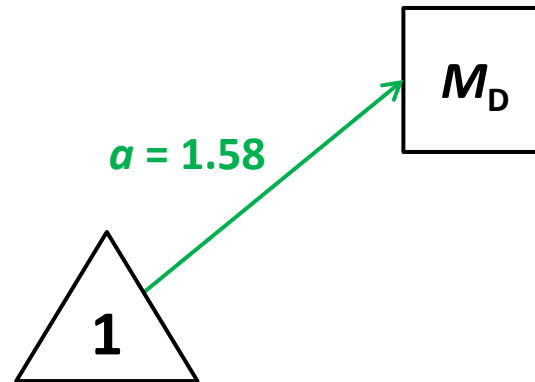
$$Y_{2i} - Y_{1i} = -1.66 + \epsilon_{Y_i^*}$$



Women rated careers generated under the follow-your-passions ideology as **1.66** units less associated with men than careers generated under the resources ideology ($t(374) = 18.80, p < .00001$).

a path:

$$M_{2i} - M_{1i} = 1.58 + \epsilon_{M_i}$$

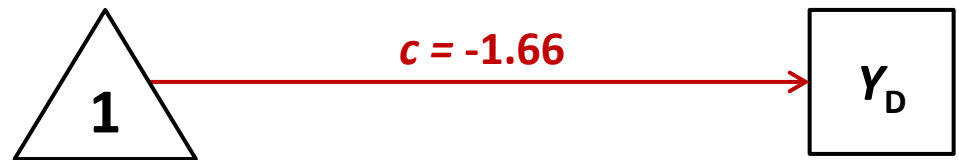


Women drew on their female-role congruent selves **1.58** units more when considering the follow-your-passions ideology than when considering the resources ideology ($t(374) = 18.21, p < .00001$)

FOLLOW YOUR PASSIONS (WOMEN ONLY)

Total Effect c:

$$Y_{2i} - Y_{1i} = -1.66 + \epsilon_{Y_i^*}$$

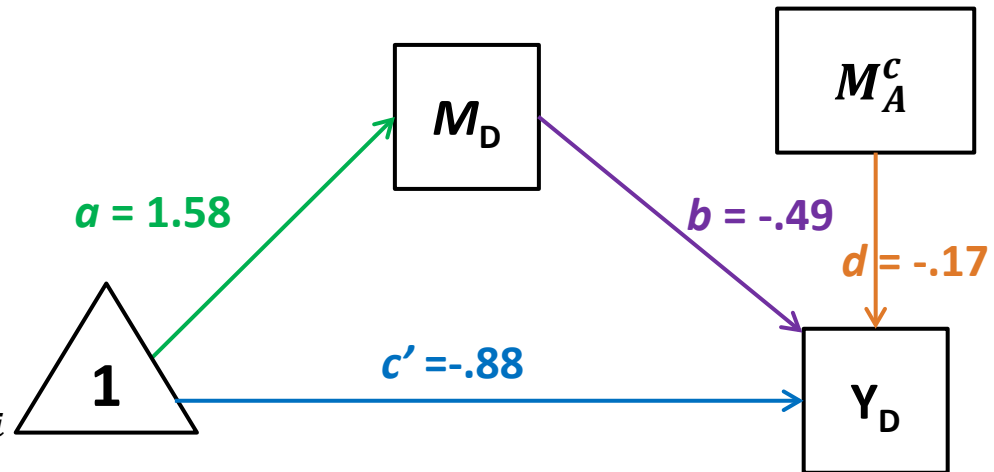


a path:

$$M_{2i} - M_{1i} = 1.58 + \epsilon_{M_i}$$

b path, d path, and c' path:

$$Y_{Di} = -.88 - .49M_{Di} - .17M_{Ai}^c + \epsilon_{Y_i}$$



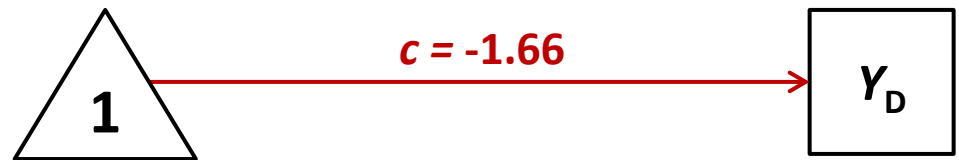
^c Indicates mean centered

Independent of the effect of drawing on your female role congruent self, careers generated in the resources condition are expected to be .88 units less feminine than those generated in the passions condition ($t(372) = -8.29, p < .0001$).

FOLLOW YOUR PASSIONS (WOMEN ONLY)

Total Effect c :

$$Y_{2i} - Y_{1i} = -1.66 + \epsilon_{Y_i^*}$$

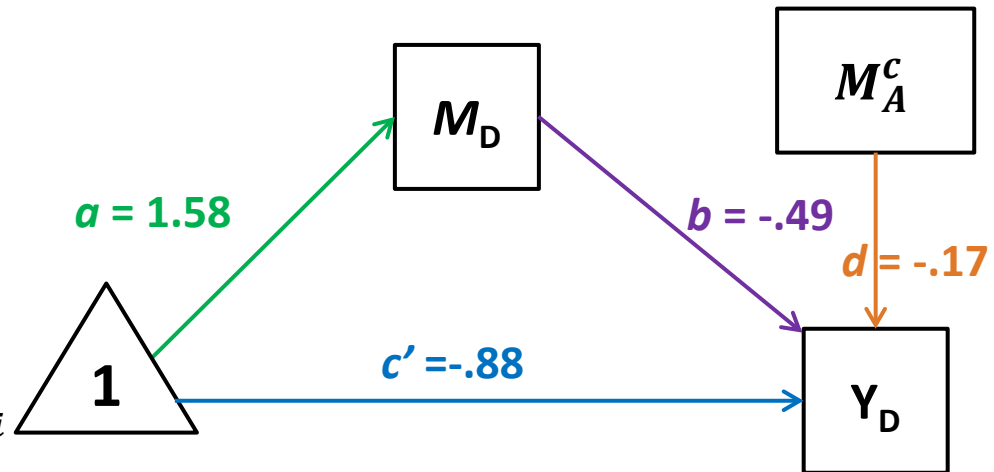


a path:

$$M_{2i} - M_{1i} = 1.58 + \epsilon_{M_i}$$

b path, d path, and c' path:

$$Y_{Di} = -.88 - .49M_{Di} - .17M_{Ai}^c + \epsilon_{Y_i}$$



^c Indicates mean centered

Women who draw on their female role-congruent selves more rated the generated careers as less feminine ($b = -.49$, $t(372) = -10.63$, $p < .0001$)

The negative impact of drawing on their female-role congruent self on interest is stronger (more negative) in the follow-your-passions condition than the resource driven condition ($d = -.17$, $t(372) = -1.72$, $p = .09$)

INTERPRETTING THE COEFFICIENTS

In this model there are two measures of the effect of M on Y : g_{11} and g_{21}

$$E(Y_{1i}) = g_{10} + g_{11}M_{1i}$$

$$E(Y_{2i}) = g_{20} + g_{21}M_{2i}$$

Subtract these equations, to get the effect of the difference in M on the difference in Y .

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

Then apply a rotation to get:

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

$$b = \frac{g_{21} + g_{11}}{2}$$

b is the relationship between M and Y averaged across the two conditions

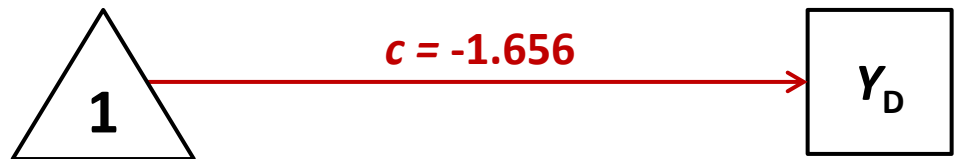
$$d = (g_{11} - g_{21})$$

d is the difference in the relationship between M and Y between the two conditions (XM interaction)

THE INDIRECT EFFECT

Total Effect c :

$$Y_{2i} - Y_{1i} = -1.656 + \epsilon_{Y^*i}$$

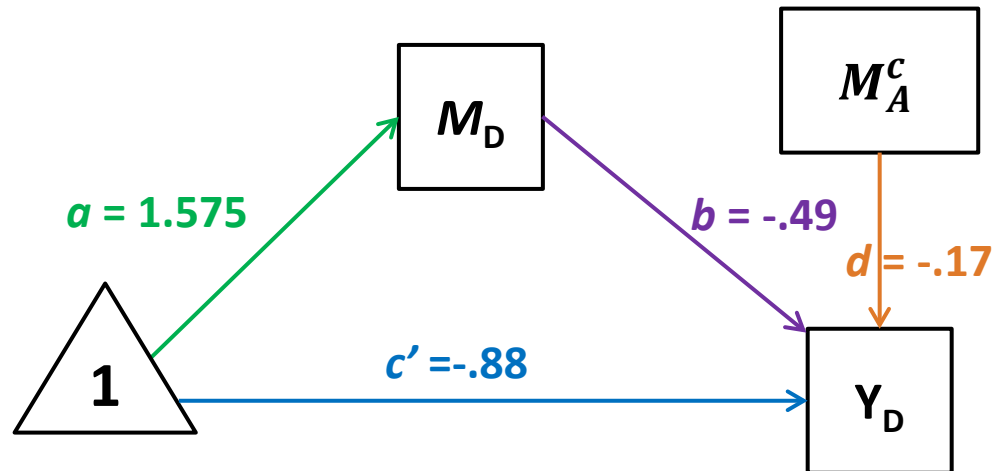


a path:

$$M_{2i} - M_{1i} = 1.575 + \epsilon_{Mi}$$

b path, d path, and c' path:

$$Y_D = -.88 - .49M_D - .17M_A^c + \epsilon_{Yi}$$



^c Indicates mean centered

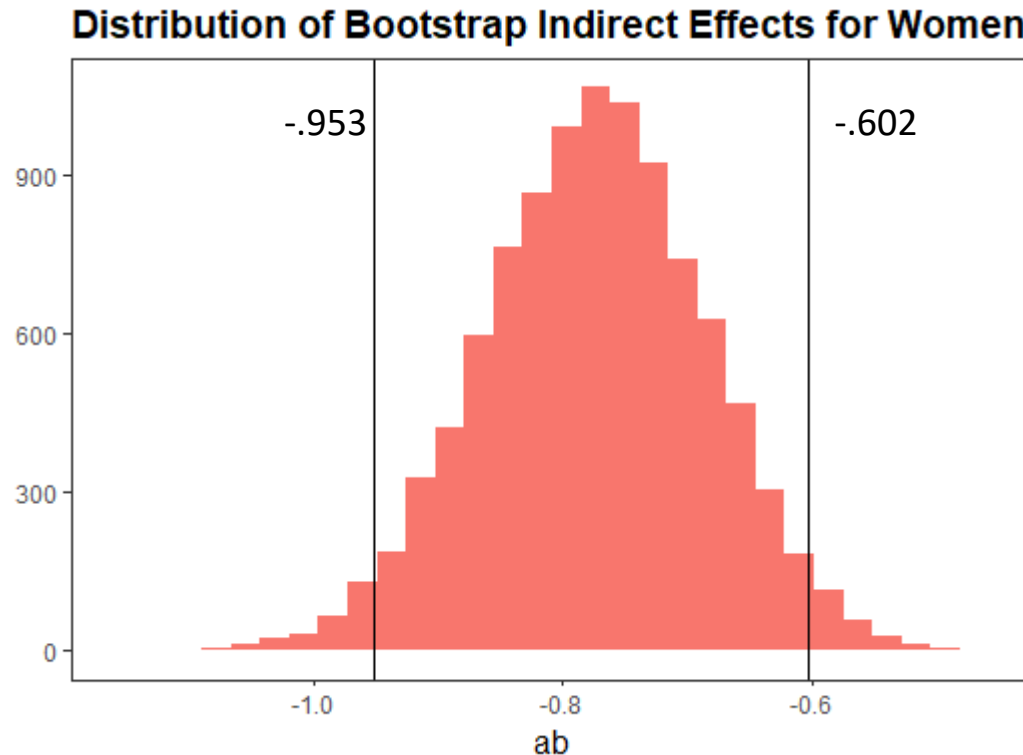
Indirect effect of *instance* on Y (through M) = $1.575 \times -.49 = -.77$

Women expected careers in the follow-your-passions condition to be .77 less associated with men compared to the resources driven condition, due to drawing on female-role congruent selves more in the passions condition which in turn decreased expected masculinity of careers.

Montoya & Hayes, 2017

Siy, Germano, Vianna, Azpeitia, Yan, Montoya, Cheryan, in press, *JPSP*

INFERENCE ABOUT THE INDIRECT EFFECT



Zero is not contained in the confidence interval $[-.953, -.602]$ so we conclude the indirect effect is different from zero with 95% confidence.

Among women, there is a significant indirect effect of the follow-your-passions ideology on intentions to pursue male dominated careers through drawing on the female role-congruent self.

MEMORE

MEMORE is a macro available for SPSS and SAS for conducting (MEdiation and MOderation in REpeated measures designs). Documentation and download at akmontoya.com. Mediation functions described in *Two-Condition Within-Participant Statistical Mediation Analysis: A Path-Analytic Framework*

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MEMORE can estimate a variety of models. Find the model you are interested in in the templates file, then use that model number.

SPSS Syntax:

```
MEMORE Y = Y1 Y2 /M = M1 M2 /model  
= 1.
```

SAS Syntax:

```
MEMORE (data = filename, Y = Y1 Y2,  
M = M1 M2, model = 1);
```

Written by Amanda Montoya

Documentation available at akmontoya.com

Model:

1

Variables:

Y = FMpas FMinc

M = gendSpas gendSinc

Computed Variables:

Ydiff = FMpas - FMinc
 Mdiff = gendSpas - gendSinc
 Mavg = (gendSpas + gendSinc) /2

Centered

Sample Size:

375

Seed:

453078

Outcome: Ydiff = FMpas - FMinc

Model

	Effect	SE	t	p	LLCI	ULCI
constant	-1.65600	.08810	-18.79632	.00000	-1.82924	-1.48276

Degrees of freedom for all regression coefficient estimates:

374

Outcome: Mdiff = gendSpas - gendSinc

Model

	Effect	SE	t	p	LLCI	ULCI
constant	1.57511	.08649	18.21107	.00000	1.40504	1.74518

Degrees of freedom for all regression coefficient estimates:

374

Outcome: Ydiff = FMpas - FMinc

Model Summary

	R	R-sq	MSE	F	df1	df2	p
	.48415	.23440	2.24046	56.94638	2.00000	372.00000	.00000

Model

	coeff	SE	t	p	LLCI	ULCI
constant	-.88079	.10629	-8.28668	.00000	-1.08979	-.67178
Mdiff	-.49216	.04632	-10.62539	.00000	-.58324	-.40108
Mavg	-.17329	.10058	-1.72286	.08574	-.37107	.02449

Degrees of freedom for all regression coefficient estimates:

372

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

Total effect of X on Y

	Effect	SE	t	df	p	LLCI	ULCI
	-1.65600	.08810	-18.79632	374.00000	.00000	-1.82924	-1.48276

Direct effect of X on Y

	Effect	SE	t	df	p	LLCI	ULCI
	-.88079	.10629	-8.28668	372.00000	.00000	-1.08979	-.67178

Indirect Effect of X on Y through M

	Effect	BootSE	BootLLCI	BootULCI
Ind1	-.77521	.08928	-.95259	-.60240

Indirect Key

Ind1 'X' -> Mdiff -> Ydiff

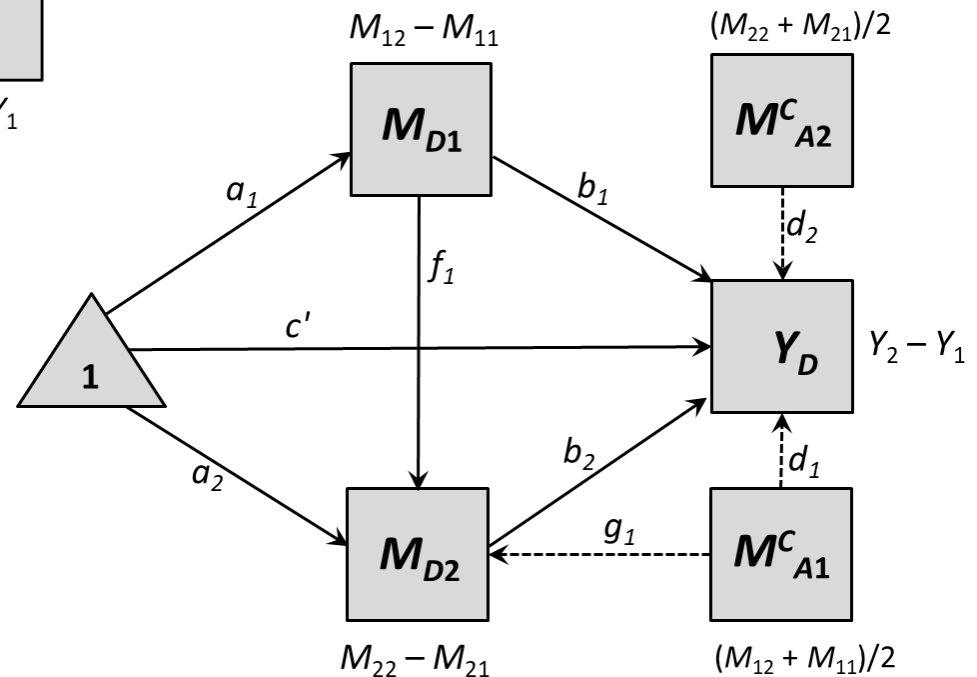
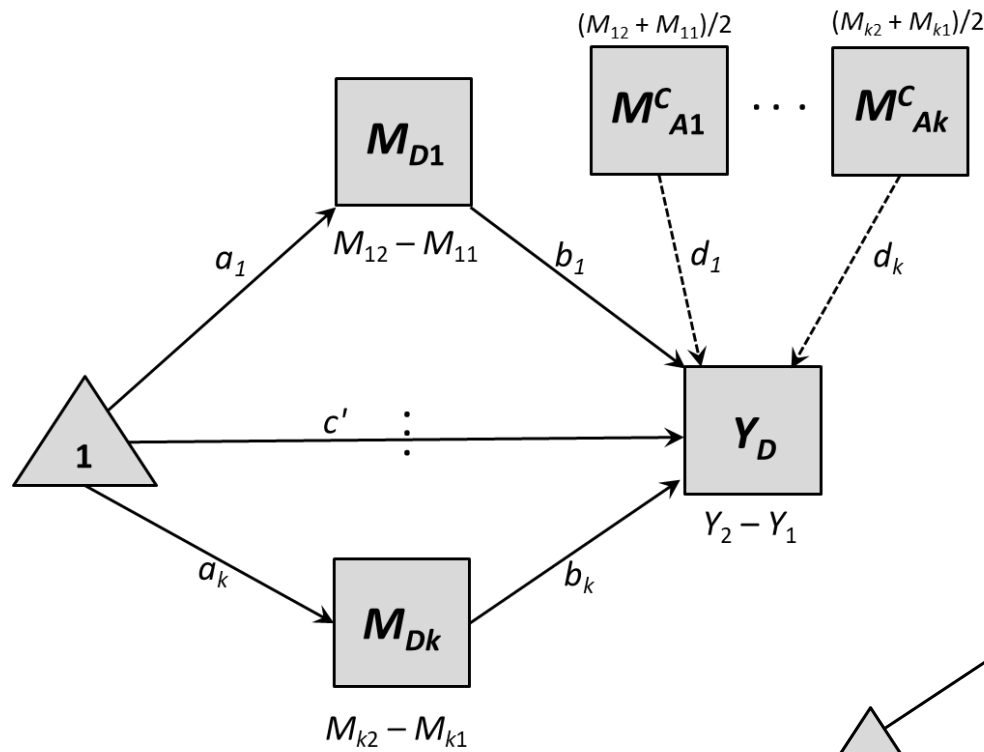
Model Information

Total Effect Model

Model for M_2-M_1 Model for Y_2-Y_1

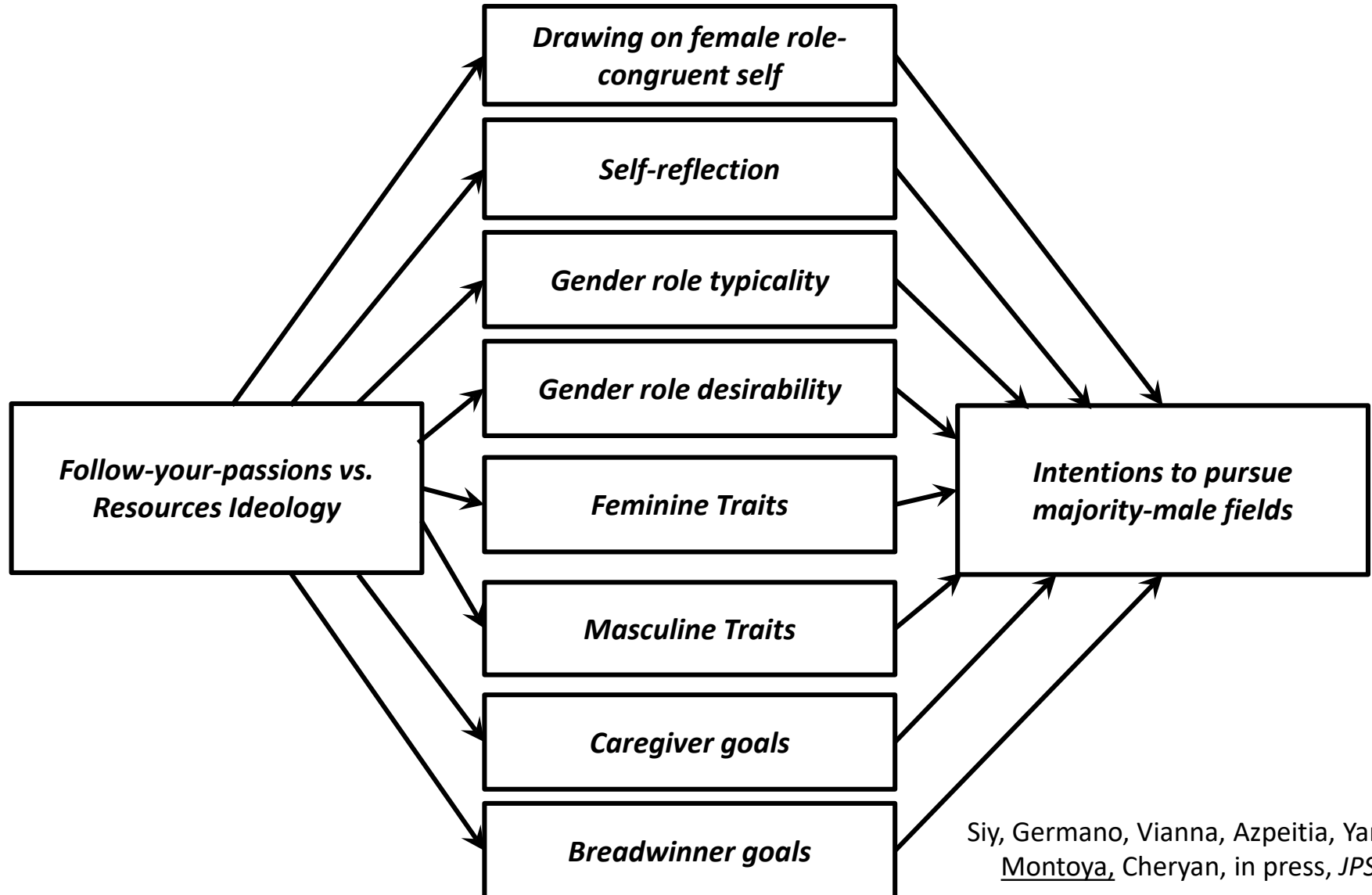
Total, Direct, and Indirect Effects

MULTIPLE MEDIATOR MODELS: PARALLEL & SERIAL



FOLLOW YOUR PASSIONS

We tested parallel mediators in the follow-your-passions research



ADVANCES

Model based approach, rather than piecewise hypotheses

Provides an estimate of the indirect, total, and direct effects

- Allows us to conduct inferential tests directly on an estimate of the indirect effect
- Montoya (2022) Introduced an R script for **power analysis** in these models

Connects researchers understanding of between-subjects mediation to within-subjects mediation

- Reduce misinterpretation of regression coefficients

Using a path analytic framework will help extend to more complicated questions

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

SOME EXTENSIONS (IN THE WORKS)

Dichotomous outcomes (Nickie Yang & Jessica Fossum)

What if, at the end of the study, we asked participants to **choose which career** they preferred?

- ✓ Derived estimates of indirect effects
- ✓ Compared results from a study with continuous and dichotomous outcomes
- ☐ Software implementation
- ☐ Tutorial



More than two conditions (Alondra Cruz)

In one study, we also looked at the *communal ideology*.

- ✓ Derived estimates of *relative indirect effects* (3 conditions)
- ✓ Applied Example
- ☐ General solution for any contrasts
- ☐ Software implementation



MODERATION IN TWO INSTANCE REPEATED MEASURES DESIGNS

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

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

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0893-3200/96/\$08.00

Testing Treatment by Covariate Interactions When Treatment Varies Within Subjects

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Purdue University

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

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

illness. It may be, for instance, that the treatment's effect is greater for patients whose pretreatment symptoms were relatively severe. Equivalently, it may be that posttreatment symptom severity is less well predicted by pretreatment course of illness in the case of patients in the intervention condition than in the case of patients in the control condition.

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

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

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

and

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \beta_3 X_i Z_i + e_i$$

In the first equation, β_2 represents the magnitude of

Does the degree to which W predicts Y depend on instance?

Or

Does effect of instance on Y depend on an individual's W ?

Data should be a two-instance repeated-measures design with a **person level covariate**.

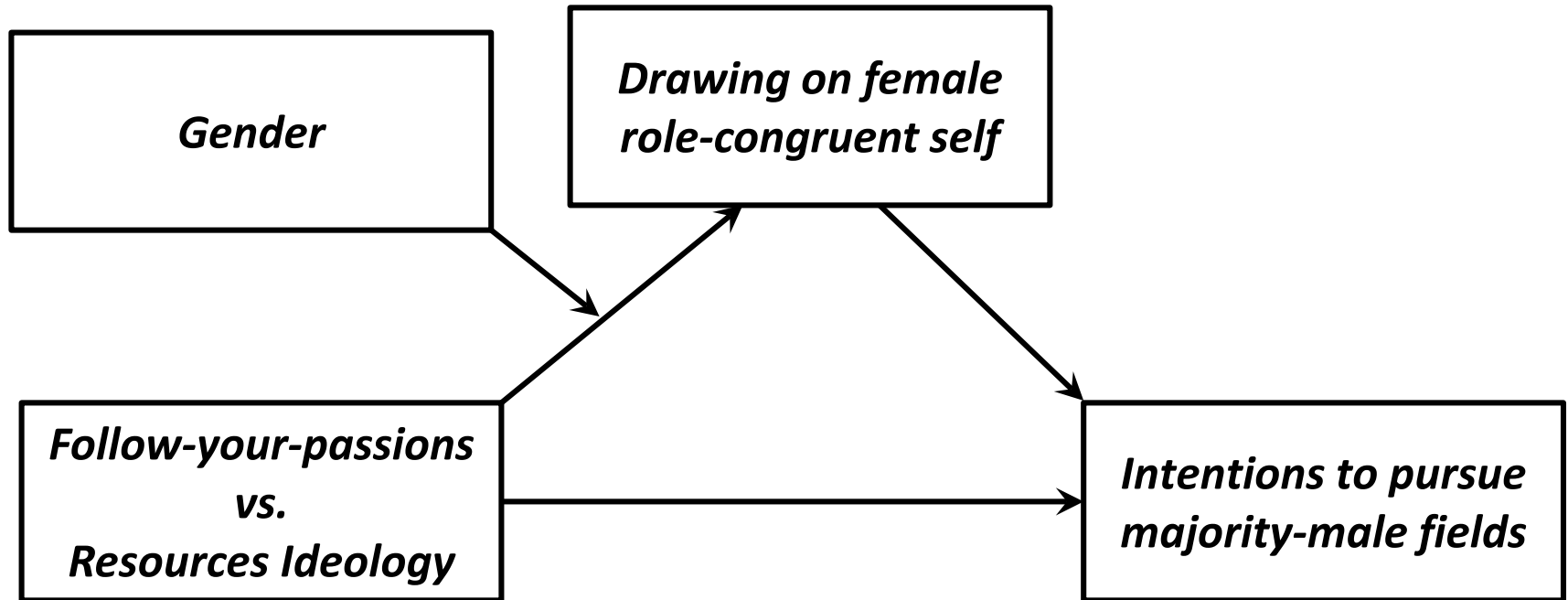
Charles M. Judd and Gary H. McClelland, Department of Psychology, University of Colorado at Boulder; Eliot R. Smith, Department of Psychological Sciences, Purdue University.

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FOLLOW YOUR PASSIONS

Let's consider a specific part of our theoretical model from the follow-your-passions study:



We hypothesize the effect of ideology on drawing on the female role-congruent self is moderated by gender (stronger among women).

How can we test this hypothesis, and how can we estimate the effect of ideology for men and for women separately?

TESTING THE INTERACTION

1. Setup two regression equations, one for each instance

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

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

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

2. Take the difference between those two regression equations

$$Y_{2i} - Y_{1i} = (b_{10} - b_{20}) + (b_{11} - b_{21})W_i + (\epsilon_{1i} - \epsilon_{2i}) = b_0 + b_1W_i + \epsilon_i$$

3. Regression weight for person level covariate in Step 2 tests moderation.

Estimate equation above and test if b_1 is significantly different from zero

FOLLOW YOUR PASSIONS

$$Y_{2i} - Y_{1i} = .62 + .48W_i + \epsilon_i$$

The coefficient $\widehat{b}_1 = .48$ is statistically significant, meaning that gender significantly moderates the effect of ideology on drawing on your female role-congruent self ($t(670) = 3.96, p < .001$).

In many senses, this raises more questions...

- What is the effect of ideology for women? Is it significant?
- What is the effect of ideology for men? Is it significant?

WHAT'S MISSING?

- **Definitions of Conditional Effects**
 - What is the effect of ideology for women, for men?
 - What is the effect of gender in each ideology?
- **Inference about Conditional Effects**
 - **Pick-a-point approach:** Is the effect of ideology significant for women? For men?
 - **Johnson-Neyman:** For what values of my moderator is the effect of ideology significant?
- **How to deal with multiple moderators**
 - **Three-way interactions:** Is the moderation by gender moderated by age?
 - **Multiple two-way interactions:** Is the effect of ideology also moderated by age?

Issues all addressed in Montoya (2019) *Behavioral Research Methods*

CONDITIONAL EFFECTS IN WITHIN-SUBJECT MODERATION

$$Y_{2i} - Y_{1i} = (b_{20} - b_{10}) + (b_{21} - b_{11})W_i + (\epsilon_{1i} - \epsilon_{2i}) = b_0 + b_1W_i + \epsilon_i$$

Given a value of W what is the effect of instance on the outcome?

$Y_{2i} - Y_{1i}$ is a quantification of the effect of instance, which means that the conditional effect of instance $\theta_{X \rightarrow Y}(W) = b_0 + b_1W$

$$\hat{\theta}_{X \rightarrow Y}(W) = .62 + .48W_i$$

Men (Gender = 1)

$$\theta_{X \rightarrow Y}(1) = .62 + .48(1)$$

$$\theta_{X \rightarrow Y}(1) = 1.10$$

Men on average draw on their female role-congruent self 1.10 units more in the passions condition than the resources condition

Women (Gender = 2)

$$\theta_{X \rightarrow Y}(2) = .62 + .48(2)$$

$$\theta_{X \rightarrow Y}(2) = 1.58$$

Women on average draw on their female role-congruent self 1.58 units more in the passions condition than the resources condition

INFERENCE FOR CONDITIONAL EFFECTS

Select a value of the moderator (W)

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

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

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

Squared standard error of b_0

Covariance of b_0 and b_1

Squared standard error of b_1

The ratio of the effect to standard error is t -distributed as $t(df_{residual})$ under the null hypothesis that the effect of instance is zero at that moderator value.

$$\frac{\hat{\theta}_{X \rightarrow Y}(W)}{\hat{s}_{\hat{\theta}_{X \rightarrow Y}(W)}} \sim t_{df}$$

FOLLOW YOUR PASSIONS

This model can be estimated in MEMORE

```
memore y = gendSpas gendSinc /w = gendr /model = 2 /plot = 1.
```

Conditional effect of ideology:

Men on average draw on their female role-congruent self 1.10 units more in the passions condition than the resources condition, **and this effect is statistically significant ($t(670) = 12.15, p < .01$).**

Women on average draw on their female role-congruent self 1.58 units more in the passions condition than the resources condition, **and this effect is statistically significant ($t(670) = 19.61, p < .01$).**

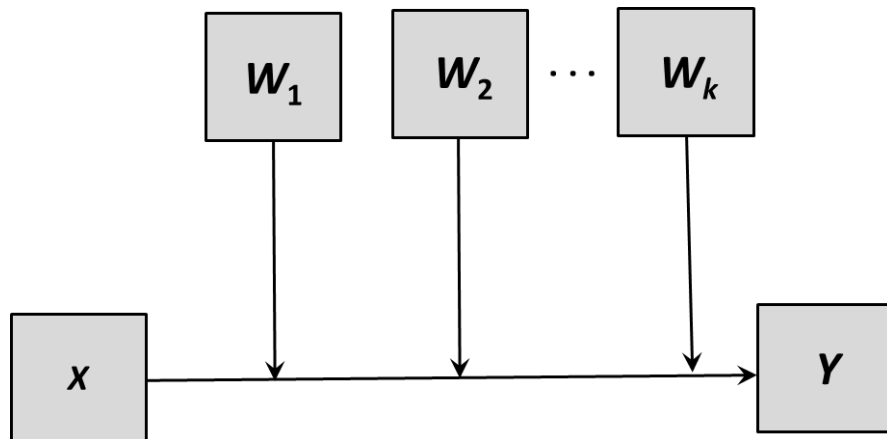


MULTIPLE MODERATOR MODELS

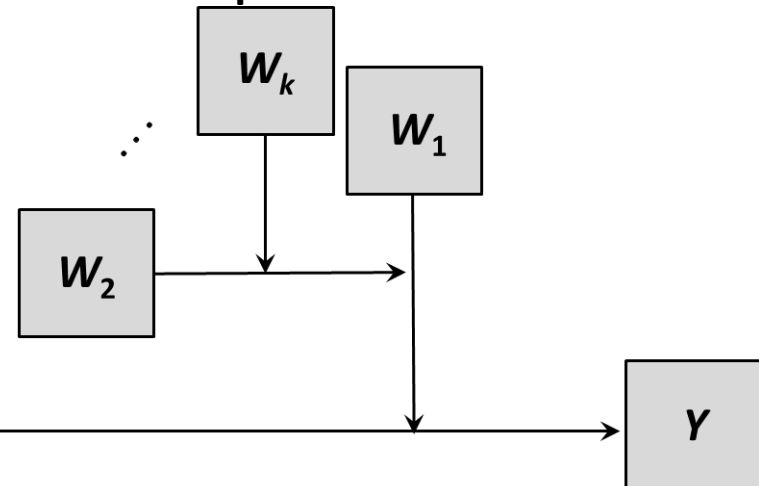
Multiple moderator models are also included!

- Can have up to 5 moderators

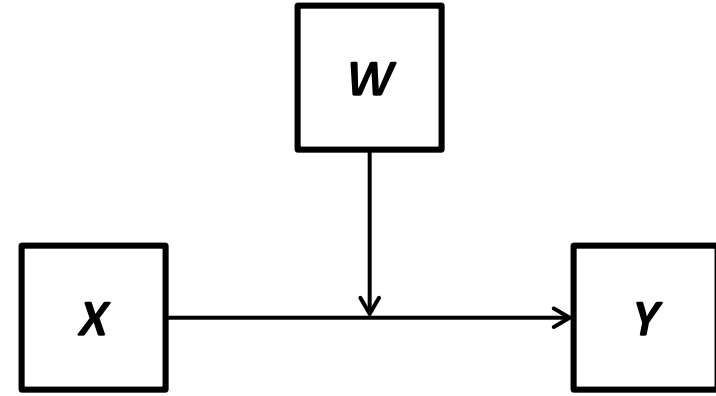
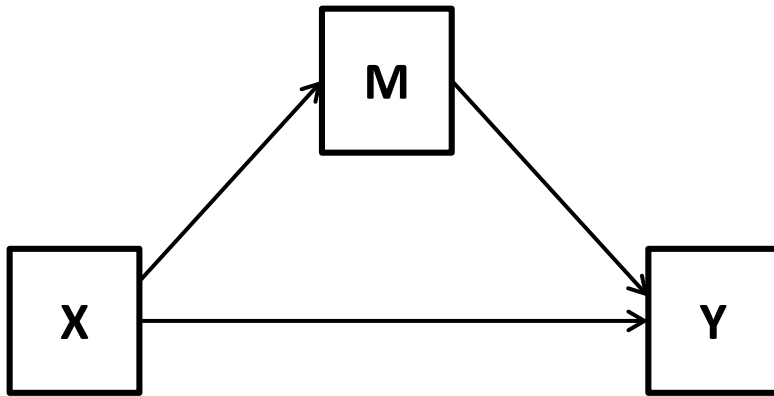
Model 2: Additive Moderation



Model 3: Multiplicative Moderation



COMBINING MEDIATION AND MODERATION: CONDITIONAL PROCESS ANALYSIS



Research questions:

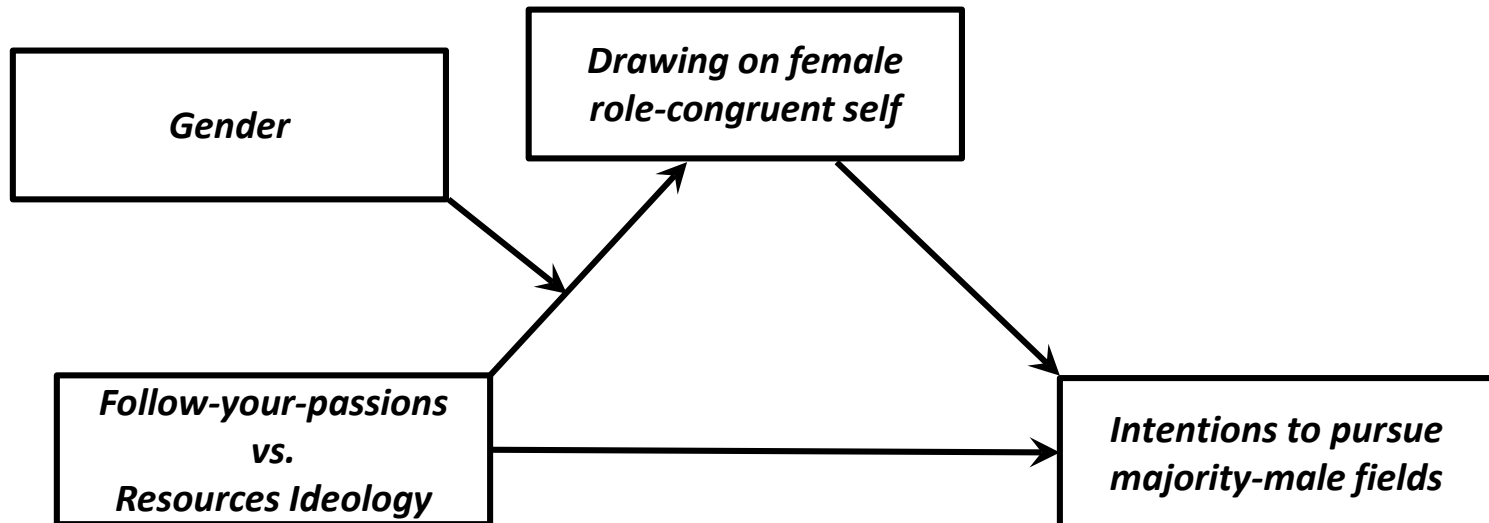
- Does the process through which X affects Y through M depend on W ?
- Are there certain groups where X affects Y through M and certain groups where this process does not occur?

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

CPA IN TWO-INSTANCE REPEATED-MEASURES DESIGNS

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

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



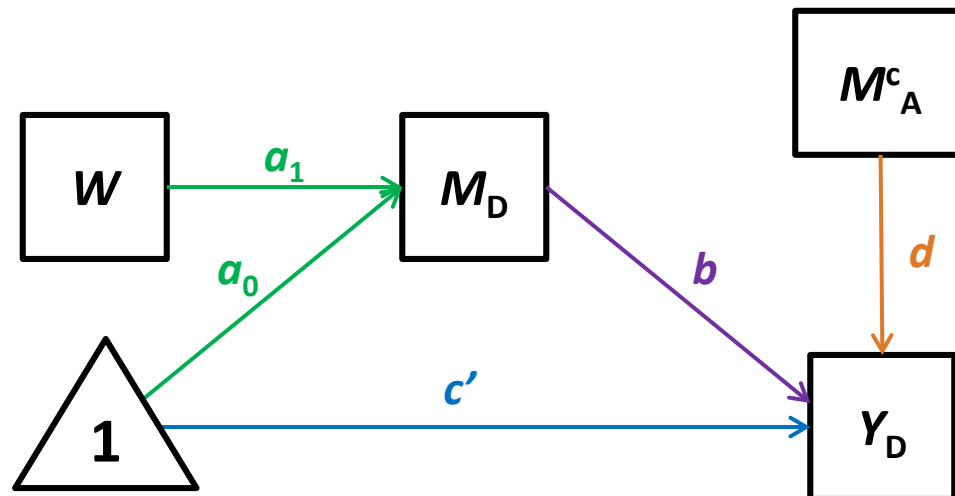
EQUATIONS AND PATH DIAGRAM

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

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

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

$$Y_{Di} = c' + b M_{Di} + d M_{Ai}^c + \epsilon_{Yi}$$



What is the indirect effect?

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

Indirect effect is a *function* of the moderator

MAKING INFERENCE

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

Conditional Indirect Effects

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

Does the indirect effect *depend* on the moderator?

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

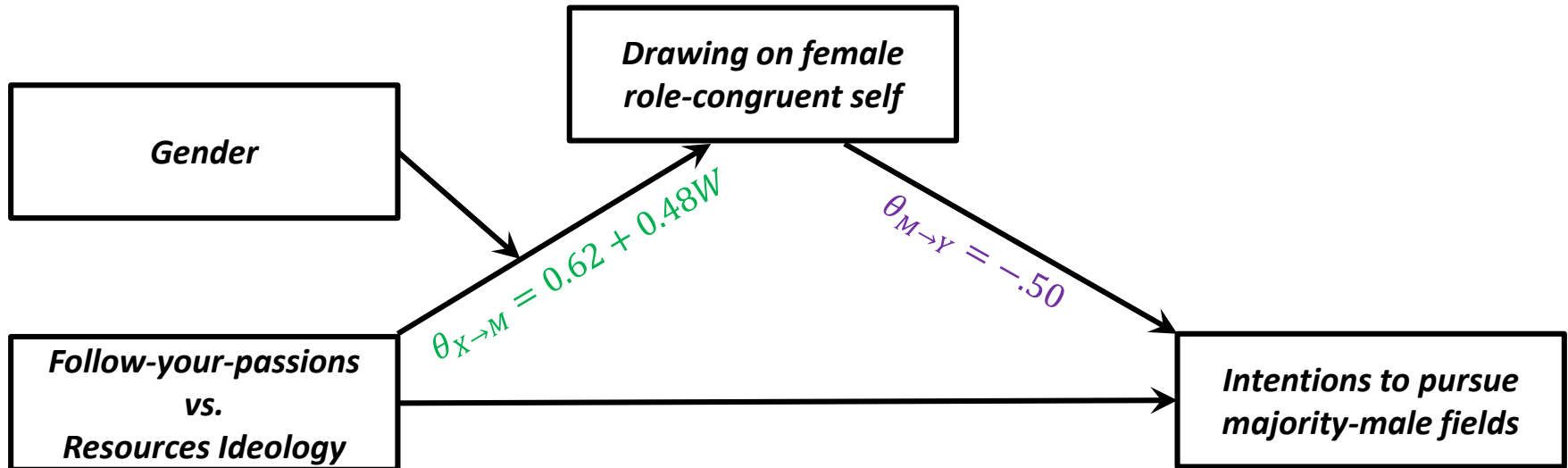
$$\theta_{X \rightarrow M}(W) \times b = a_0 b + 0 * W = a_0 b$$

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

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

FOLLOW YOUR PASSIONS

```
memore y = FMpas FMinc /m = gendSpas gendSinc /w =  
gendr /model = 14.
```

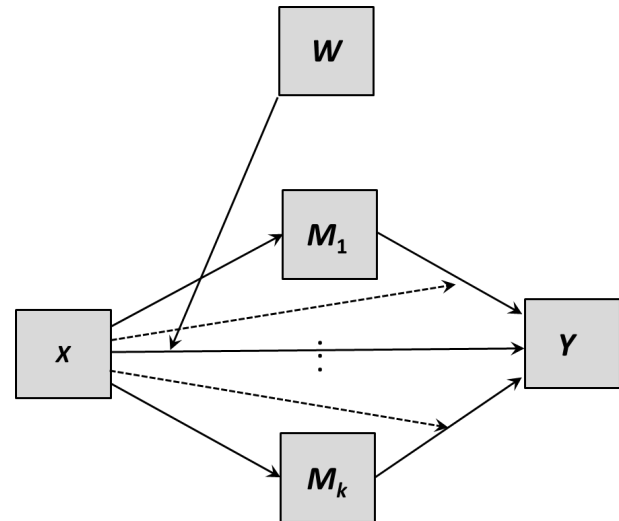
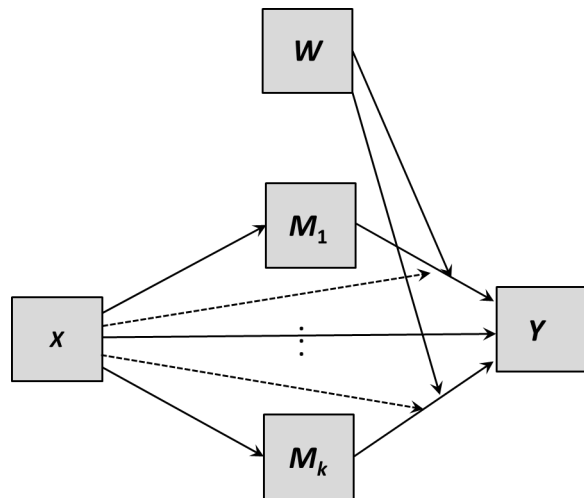
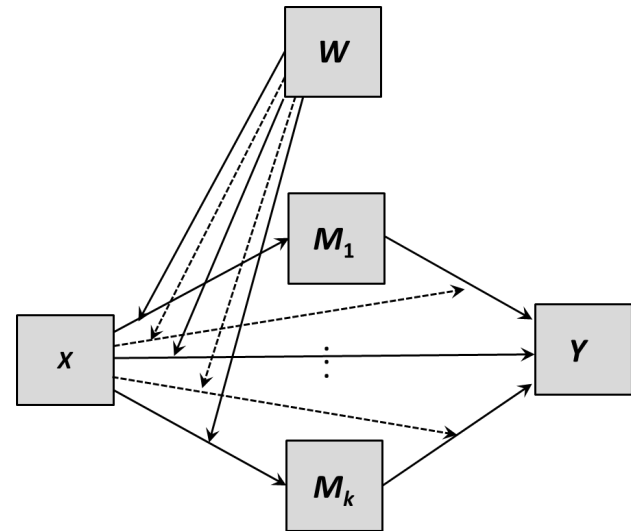
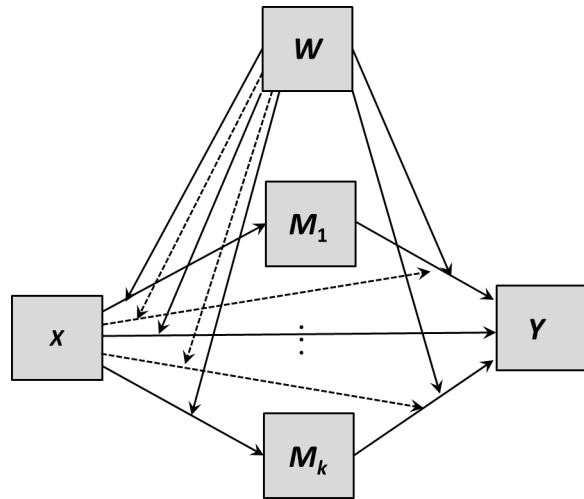


The indirect effect for both men and women was such that **the follow-your-passions ideology decreased interest through drawing on feminine self** (Men: -.55 [-.66, -.44], Women: -.78 [-.94, -.63]).




The *index of moderated mediation* was significantly different from zero (-.24 [-.37, -.12]), meaning the **indirect effect through drawing on the feminine self was stronger for women than for men**.

MEMORE V3: MODELS 4 - 18

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



NEXT STEPS...

- Formal release of MEMORE with final publication
- MEMORE for R  
- Generalizations similar to those described for mediation
 - More than two conditions
 - Dichotomous outcomes (and other GzLMs) 
- Causal inference in moderated mediation (between and within)
- Building bridges to more complex models:
 - Multilevel models
 - Latent growth curve models
 - Latent Difference Score
 - Diff-in-Diff

These areas have had very limited discussion of conditional process analysis

OVERVIEW

Two-Instance Repeated-Measures Designs

- Mediation Analysis
- Moderation Analysis
- Conditional Process Analysis

Meta-Science

- Quality of Evidence in Mediation Analysis
- Sample Size Planning in Mediation and Moderated Mediation
- Preregistration and Registered Reports

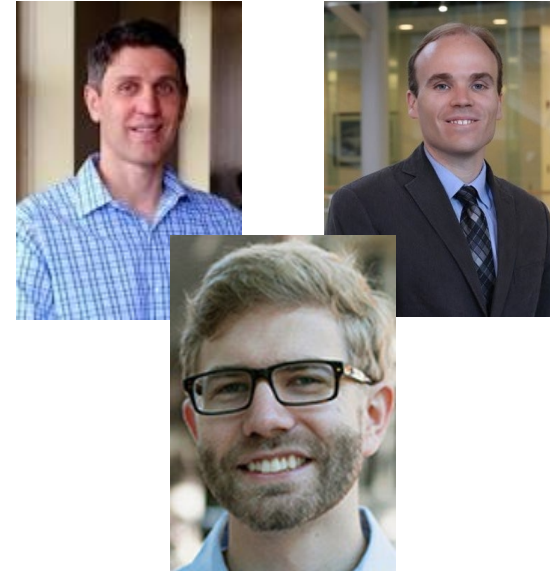
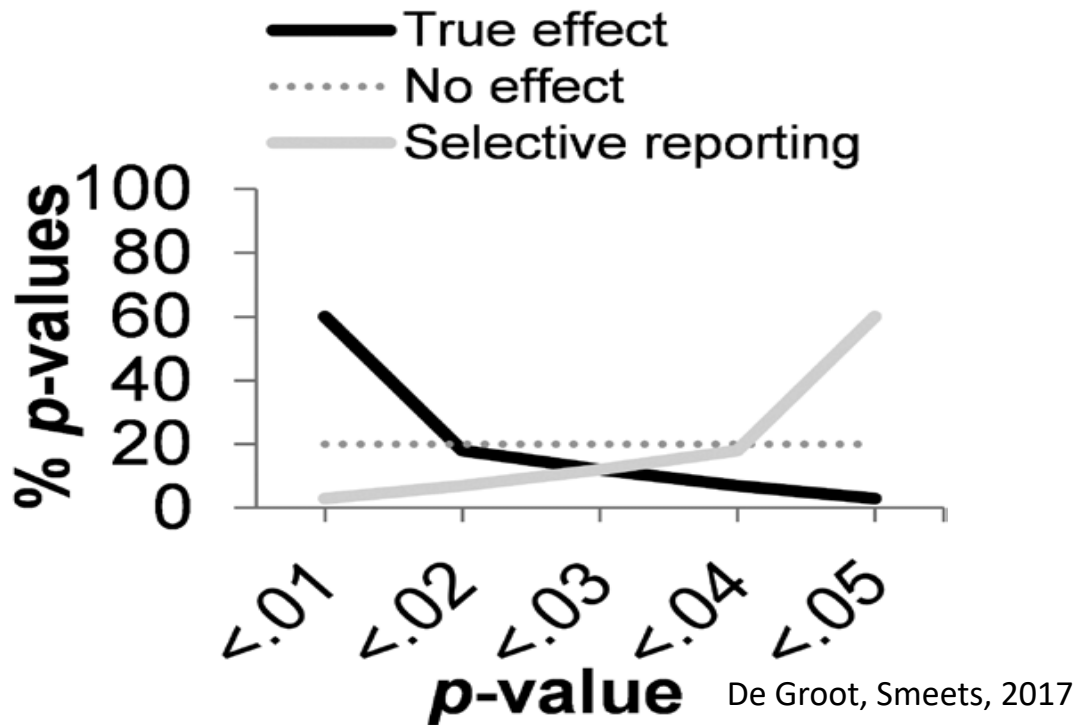
Throughout: Future Directions and Connections

ANALYTICAL FLEXIBILITY IN MEDIATION AND MODERATED MEDIATION

- Easy to swap around variables in different orientations
 - Mediator/Outcome
 - Covariate/Moderator
- Easy to move moderation to different paths
 - First-stage vs. Second-stage, Moderation of Direct Effect
 - Additive or Multiplicative
- Multiple options for inferential methods
- Multiple options of estimation methods
- Exploitation of randomness in resampling procedures

P-CURVE FOR MEDIATION

P-curve is a method of analyzing *p*-values from a set of literature to investigate if there is evidence of *p*-hacking



Mediation analyses are most commonly reported with a bootstrap CI

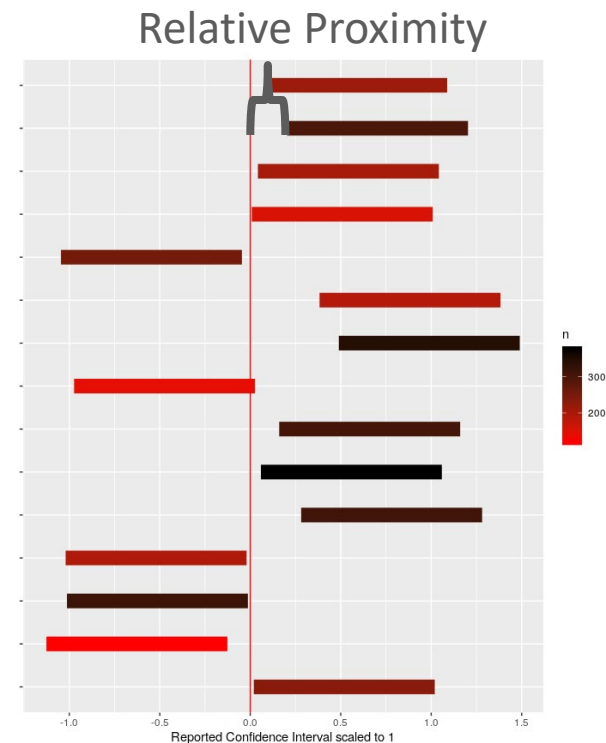
How can we evaluate the presence of *p*-hacking for mediation analyses?

P-CURVE FOR MEDIATION

Relative Proximity:

If CI does not contain zero: $\frac{\min(|CI_{2.5\%}|, |CI_{97.5\%}|)}{|CI_{2.5\%} - CI_{97.5\%}|}$

If CI contains zero: $-1 \frac{\min(|CI_{2.5\%}|, |CI_{97.5\%}|)}{|CI_{2.5\%} - CI_{97.5\%}|}$



Gotz, O'Boyle, Gonzales-Mule, Banks (2021) *Psychological Bulletin*
 Charlton, Montoya, Price, Hilgard (*under review*),
 ...

P-CURVE FOR MEDIATION

Gotz, O'Boyle, Gonzales-Mule, Banks, 2021, *Psychological Bulletin*

Using a sample from APA journals, confidence intervals for mediation analyses

- Small proportion of null results suggests publication bias
- Large piling at zero suggests “CI”-hacking or low power & file drawer

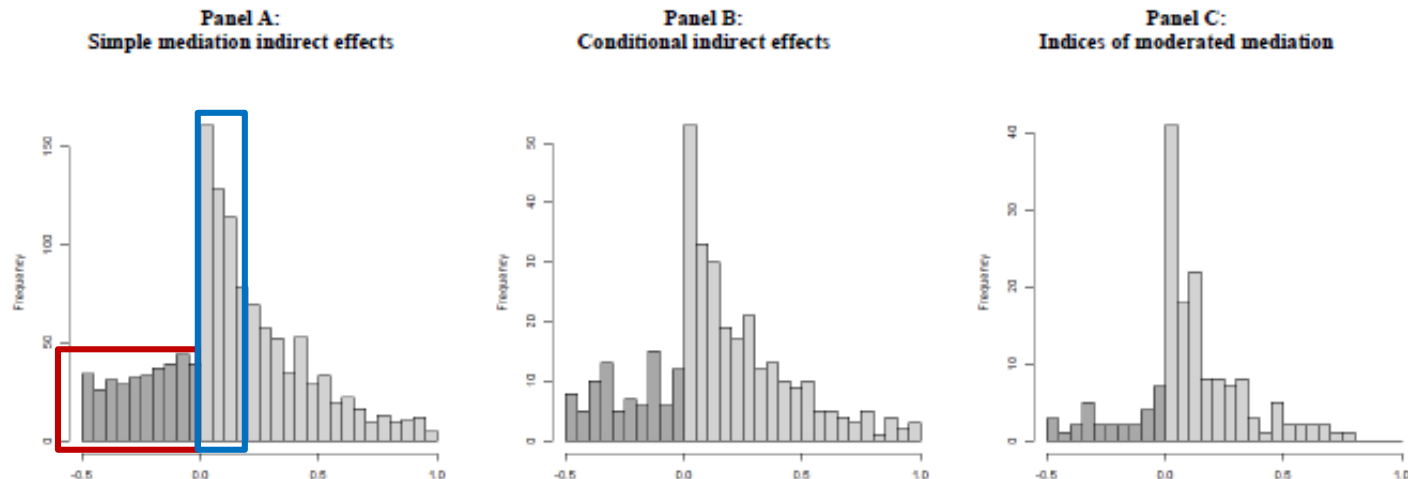


Figure 5. Relative proximities of hypothesized tests of mediation with indirect effects (Panel A, $k = 1,372$), conditional indirect effects (Panel B, $k = 361$), and indices of moderated mediation (Panel C, $k = 161$). Bars in dark grey represent frequencies of non-significant point estimates, whereas bars in light grey frequencies of significant ones.

MARKETING PAPERS (2017 – 2020)

Keywords: mediat*, indirect, Hayes, and *PROCESS*



Journal of Consumer Research
79 papers



Journal of Consumer Psychology
120 papers



Journal of Marketing Research
66 papers



Journal of Marketing
43 papers

SUMMARY OF RESULTS

N = 308

Type of Estimate

- 212 indirect effect (69%)
- 22 conditional indirect (7%)
- 73 index of moderated mediation (24%)

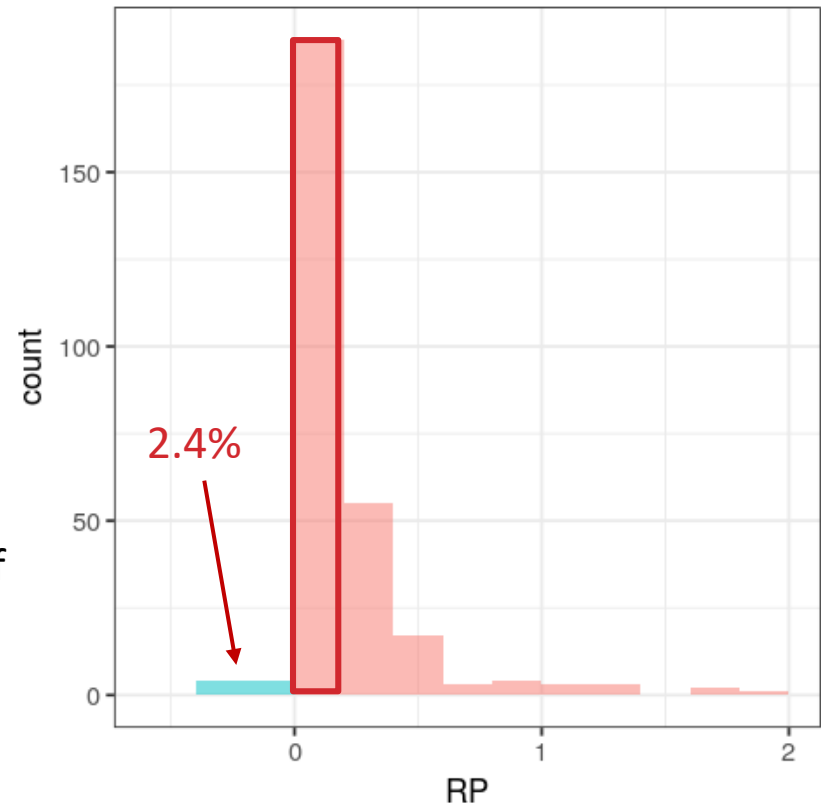
Sample Size

- Min: 56, Max: 61,642
- Mean: 712, Median: 212.5
- Missing: 1

This suggests potential issues with the quality of evidence in mediation analysis.

“CI-hacking” or Low Power and File Drawer

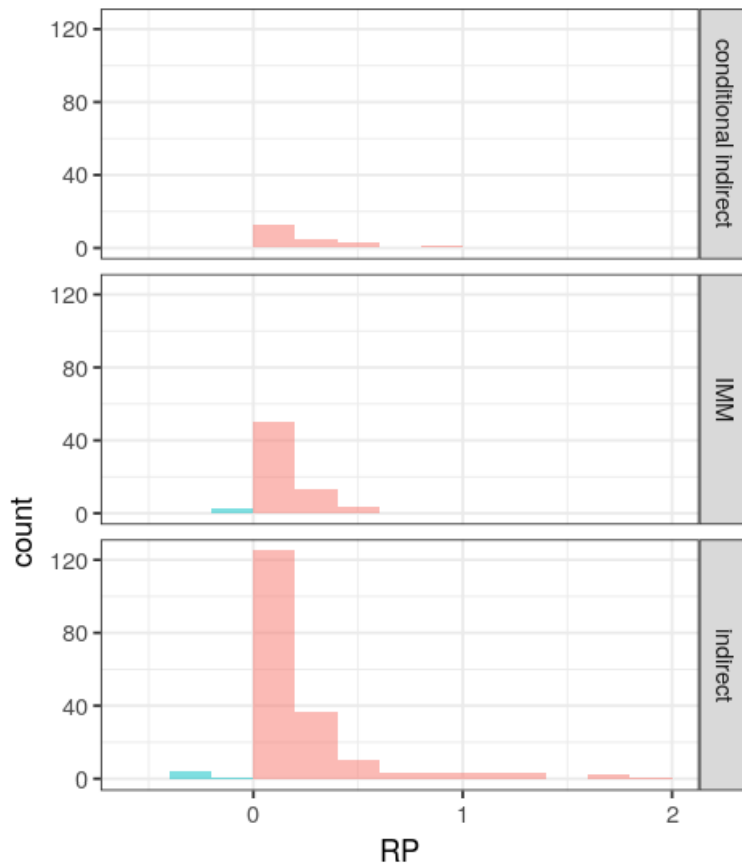
There is an overwhelming stack of results very close to zero



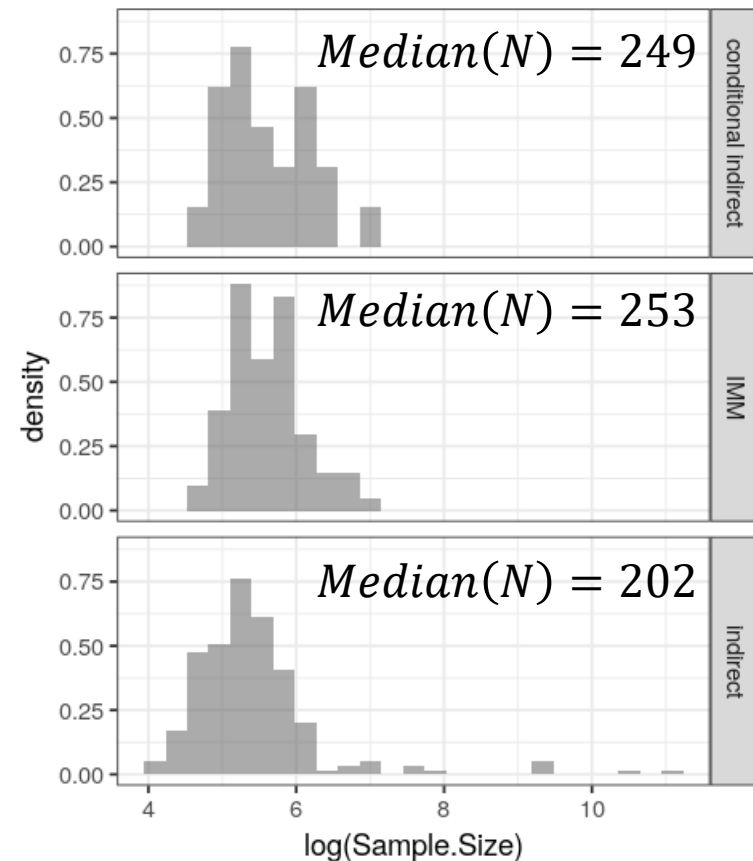
TYPES OF ESTIMATE AND SAMPLE SIZE

Larger samples **should** be needed to detect indices of moderated mediation compared to indirect effects, so the relative proximity distribution should look different or the sample sizes should be different.

RP does not significantly differ across Type of Estimate. $F(2, 281) = 1.24, p = 0.29$



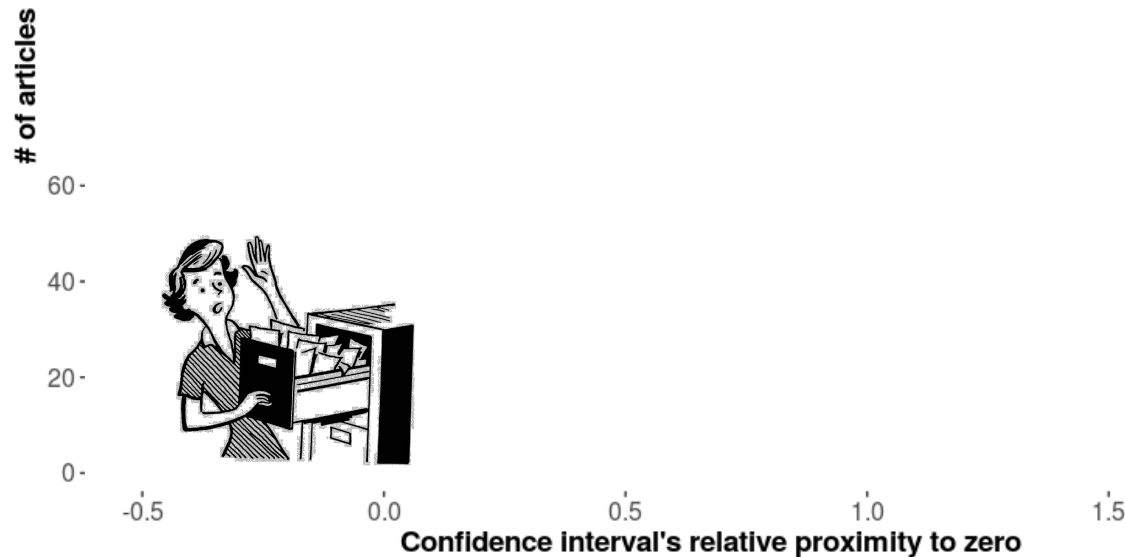
Log(N) does not significantly differ across Type of Estimate $F(2, 291) = 1.14, p = 0.32$



LOW POWER?

We conducted simulations to evaluate what power curves fit the data best.

If the results are due to low power, this indicates another problem: A very large file drawer.



285 mediation tests reported in JM, JMR, JCR and JCP 2018-2020. Only one test per article was collected.

Charlton, Montoya, Price, Hilgard (*under review*), <https://psyarxiv.com/ck2r5/>

P-CURVE WITH MEDIATION: SUMMARY

Evidence from this study and Gotz et al. (2021) in psychology suggest there are potential issues with bias in reporting and/or conduct on mediation analysis

- “CI-hacking” to get confidence intervals just over zero
- Low power & file drawer

Researchers do not seem to be adjusting their sample size to account for complexity of their model.

Solutions?

- **Improve power:** Stronger manipulations, Larger samples, Better measures
- **Preregistration:** Make a record of your planned analyses before data collection
- **Replication:** Most replication attempts have focused on primary hypotheses (main effects), but we also need to replicate the mediation

SAMPLE SIZES FOR MODERATED MEDIATION

Previous research in mediation has suggested $N = 500$ to detect “medium” indirect effects, and now we are looking at moderation of indirect effects (Fritz & MacKinnon, 2007).

Team of 3 Undergraduates + Jessica coded more than 400 published examples of moderated mediation models

Sample Size

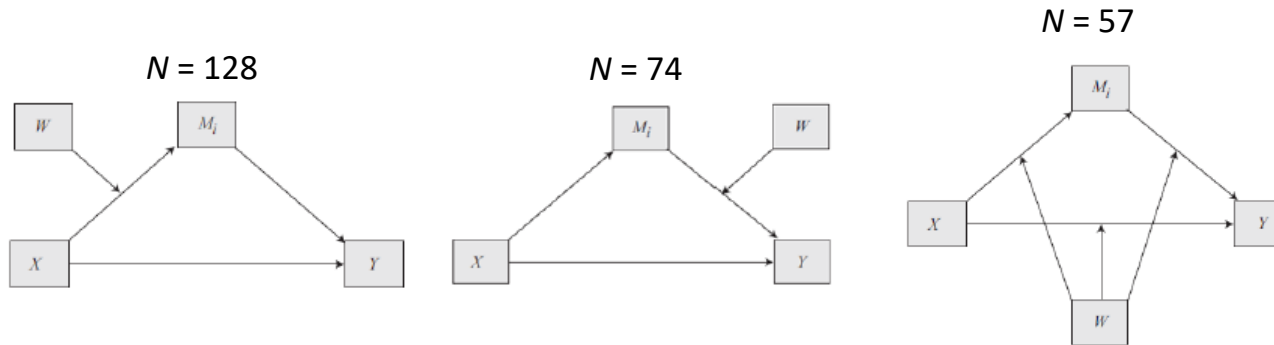
Median sample size: 285



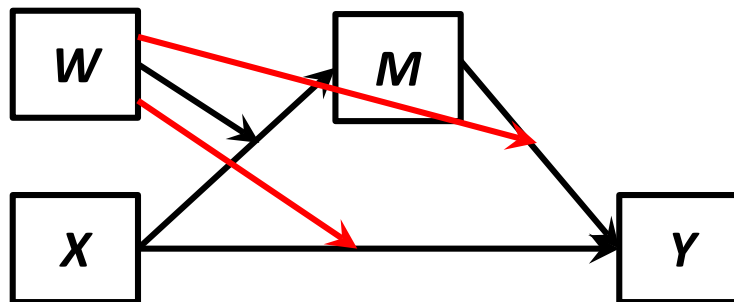
WHAT MODELS ARE PEOPLE USING?

Team of 3 Undergraduates + Jessica coded more than 400 published examples of moderated mediation models

Model Specification



Follow up: How does specification impact power?



A TOOL FOR FINDING EXAMPLES

A common question our lab receives is if we know of an example of a paper that uses Model XX from PROCESS.

Jessica created a database from her literature search, and has continued to add to it through the help of undergrad RAs. You can also submit a form to add your paper to the database if you want others to be able to find it!

<https://www.jlfoosum.com/home/moderated-mediation-article-database>

Model Number	Type of Manipulated Variable	Number of Moderators	Number of Mediators	Year	Estimation Procedure	Research Area	Journal	Number of X Variables	Number of Y Variables	Mediators	Moderators	Covariates
Article	Journal	First Author	Research Area	Model Number	Sample Size	Estimation Procedure	Number of X Variables	Type of X Variable	Number of Y Variables	Mediators	Moderators	Covariates
"They've conspired against us": Understanding the role of social identification and conspiracy beliefs in justification of ingroup collective behavior	EUROPEAN JOURNAL OF SOCIAL PSYCHOLOGY	Chayinska, M	Psychology	7	315	Regression	1		1	1	1	0
A Conditional Process Analysis of the Teacher Confirmation-Student Learning Relationship	COMMUNICATION QUARTERLY	Goldman, ZW	Communication	7	208	Regression	1		1	1	1	1
A Latent Growth Moderated Mediation Model of Math Achievement and Postsecondary Attainment: Focusing on Context-Invariant Predictors	JOURNAL OF EDUCATIONAL PSYCHOLOGY	Guglielmi, RS	Psychology		8791	Regression	1		1	3	2	2
A Longitudinal Study of Inhibited Temperament, Effortful Control, Gender, and Anxiety in Early Childhood	CHILD & YOUTH CARE FORUM	Niditch, LA	Psychology	59	1226	SEM	1		1	1	1	4
A Moderated Mediation Model for Board Diversity and Corporate Performance in ASEAN Countries	SUSTAINABILITY	E-Vahdati, S	Science & Technology - Other Topics	58	264	SEM	2		1	1	1	3
A Social Influence Interpretation of Workplace Ostracism and Counterproductive Work Behavior	JOURNAL OF BUSINESS ETHICS	Yang, J	Business & Economics	21	156	Regression	1		1	1	2	4
A genetic variant brain-derived neurotrophic factor (BDNF) polymorphism interacts with hostile parenting to predict error-related brain activity and thereby risk for internalizing disorders in children	DEVELOPMENT AND PSYCHOPATHOLOGY	Meyer, A	Psychology	7	201	Regression	1		1	1	1	2
A mediant assessment of	TOXIDISM	Tourmalin I	Environmental	0	317	Regression	1		1	1		

PREREGISTRATION OF MEDIATION ANALYSIS

An example of a “preregistered” mediation analysis:

"We plan to conduct mediation tests (including multiple mediation) using the MEMORE macro (Montoya & Hayes, 2017) and the PROCESS macro (Hayes, 2017)."

We need better guidelines for what decisions to include in our preregistrations:

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

IS PREREGISTRATION ENOUGH?

Limitations of preregistration

- A plan is not always a *good* plan
- Review process can conflict with prereg
- Does not address publication bias/file drawer

Registered Reports: An alternative

- Submit an introduction, methods, and analysis plan to a journal (Stage 1)
- Stage 1 submission is peer-reviewed (can be revised)
- In-principle acceptance: journal will publish regardless of the results
- Researchers collect data, write up results and discussion (Stage 2)
- Stage 2 submission is peer-reviewed for adherence to original plan

REGISTERED REPORTS

Implemented in 2013 (*Cortex* and *Perspectives on Psychological Science*)

Benefits

- Reduces publication bias (acceptance is not based on results)
- Reduces questionable research practices (QRPs)
 - Trying analyses many ways to find what “works”
 - Selective study reporting
 - Data Falsification/Fabrication
- (If peer review works), improves implementation
- Incentivizes Open Science Practices
 - Replications
 - Open Data and Materials
 - Preregistration
 - Preprints

IMPLEMENTATION

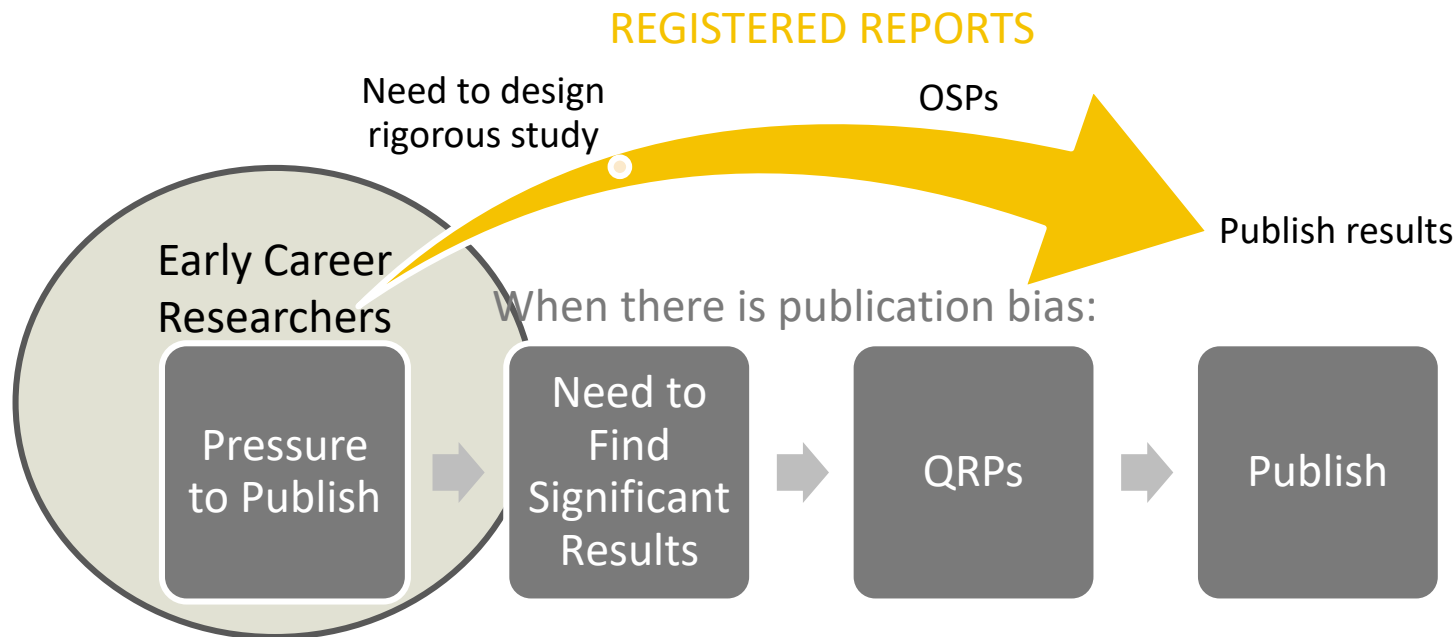
Registered reports are being increasingly adopted across scientific disciplines.



More than 350 journals accept registered reports!

Peer Community In Registered Reports can also allow you to do an RR outside a journal

OUR QUESTION



Can publishing using a registered report mechanism help reduce QRPs and increase OSPs?

Would this be especially true among early career researchers, who experience high levels of pressure to publish?

CORE STUDIES

We focus on two primary goals:

1. Exploring the interaction of RRs with OSPs/QRPs
2. Gathering information about RRs for potential intervention

[illegible]

A NEW DATABASE FOR REGISTERED REPORTS

Being implemented as go-to tool with Open Science Framework

Easy-to-search database with all journals adopting registered reports

Provides information about policies, academic field, etc.

Scientific Discipline	5 Year Range	Registered Replications	Secondary Data Analysis allo...	H-index Range	
Special Issue	Novel studies within RR	Multiple Studies	Word Limits	Research Area	

Journal Hyperlink	Scientific Discipline	Research Area	h-index	Power Requirements	Word Limits	Novel studies within RR	5 year IF	2017 IF (Two Year)	Multiple Studies	Access to Data Required	Access to Material Required	Changes to Introduction Allowed	Deadline after Stage 1 approval	Special Issue	Exploratory Analysis allowed (not in original plan)	External Pre-approval required?	Preliminary Studies allowed?
AAS Open Research	General	null	null	0.9 or high...	No mention	No mention	None	null	Incremental Re...	Yes	No mention	Only minor styl...	Request specifi...	No	Yes, separate section	No mention	Yes
AERA Open	Psychology	Learning, Devel...	null	No mention	8,000 words	Yes	None	null	No mention	No, but encoura...	No, but encoura...	No mention	Date specific	Yes	Yes	No, but enco...	No menti...
AIMS Neuroscie	Psychology	Biopsychology/...	6	0.9 or high...	None	Yes	None	1028	Yes, sequential	Yes	Yes	No	Request specifi...	No	Yes, separate section	No mention	Yes
AMRC Open Re	General	null	null	0.9 or high...	No mention	No mention	None	null	Incremental Re...	Yes	No mention	Only minor styl...	Request specifi...	No	Yes, separate section	No mention	Yes
Academia Jour	Medicine	null	null	No mention	No mention	No mention	None	null	No mention	No mention	No mention	No mention	No mention	No	No mention	No mention	No menti...
Acta Psychologi	Psychology	null	88	0.9 or high...	No mention	Yes	2.258	1632	Incremental Re...	Yes	Yes	Only minor styl...	Request specifi...	No	Yes, separate section	No mention	Yes
Adaptive Huma	Psychology	null	13	No mention	1,500 extended...	Yes	None	3.326	No mention	Encouraged	No mention	No mention	Out of date	Yes	No mention	No mention	No menti...
Addiction Res	Psychology	null	45	0.9 or high...	No mention	Yes	194	2.478	Incremental Re...	Yes	Yes	Only minor styl...	Request specifi...	No	Yes, separate section	Yes	Yes
Advances in Me	Psychology	Research Meth...	null	No	Soft word limits...	Yes	N/A	null	Incremental Re...	Yes	Yes	No	No mention	No	Yes, separate section	Yes	Yes, not m...
Affective Science	Psychology	null	null	No mention	2,000 words (int...	No mention	None	null	No mention	Yes	Yes	No mention	No mention	No	No mention	No mention	No menti...
Alimentary Pha	Medicine (gast...	null	155	No mention	12-20 pages dou...	No mention	None	7.357	No mention	No, but encoura...	No, but encoura...	No mention	No mention	No m...	No mention	No mention	No menti...
American Journ	Political Science	null	136	No mention	10,000 words	Yes	None	5.22	No mention	Yes, data provid...	Yes	No mention	Date specific	Yes	Yes, separate section	Yes	No menti...
American Politi	Political Science	null	148	No mention	12,000 words	Yes	6.224	3.252	No mention	Yes, data provid...	Yes	No mention	Date specific	Yes	Yes, separate section	Yes	No menti...
American Politi	Political Science	null	41	No mention	No mention	Yes	1.444	1.089	No mention	Yes, data provid...	Yes	No mention	Date specific	Yes	Yes, separate section	Yes	No menti...

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Journal	OSF Link 1	OSF Link 2	OSF Link 3
AAS Open Research	Author Guidelines	null	null
AERA Open	Call for submissions	null	null
AIMS Neuroscience	Editorial	Guidelines	null
AMRC Open Research	Author Guidelines	null	null
Academia Journal of Stroke	null	null	null
Acta Psychologica	Guidelines	null	null

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Data Last Updated: 6/21/2020 11:00:53 AM | [Privacy Policy](#)

META-SCIENCE SUMMARY

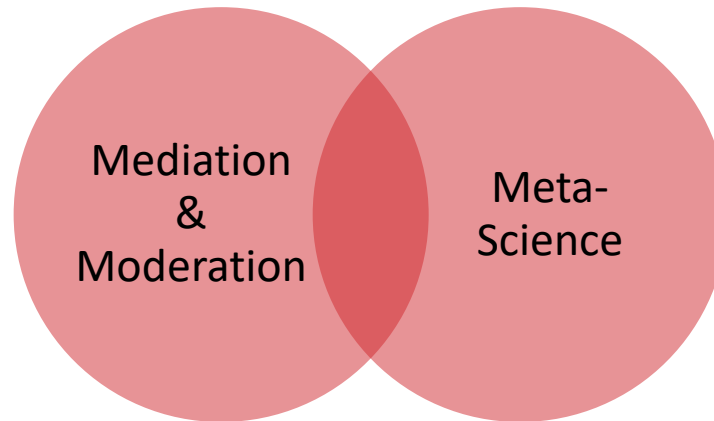
Research in mediation and moderated mediation may have low evidential value.

- Potential evidence of “CI-hacking”
- Low power and a large file drawer
- Undisclosed flexibility in analysis choices

Our team focuses on helping research plan their work better:

- Preregistration (Montoya, in press)
- Power analysis (Montoya, 2022; Fossum & Montoya, under review)
- Registered reports (Montoya, Krenzer, Fossum, 2021)

SUMMARY



Mediation and moderation are very important to answering research questions in psychology

- Repeated-measures designs are common but underexplored in this area
- Extension to complex outcomes are underway

Methods development needs to focus on **replicability related practices**

- Current research suggests that sample sizes for mediation and moderated mediation are too low
- Guidelines for preregistration are underdeveloped
- Registered reports offer benefits above and beyond preregistration

THANK YOU!

I am available for questions now and in the future via email at akmontoya@ucla.edu

MEMORE can be downloaded from akmontoya.com

RR database can be found at bit.ly/RRdatabase

Slides available at
github.com/akmontoya/OSU2023

