MEDIATION, MODERATION, AND CONDITIONAL PROCESS ANALYSIS IN TWO-INSTANCE REPEATED-MEASURES DESIGNS

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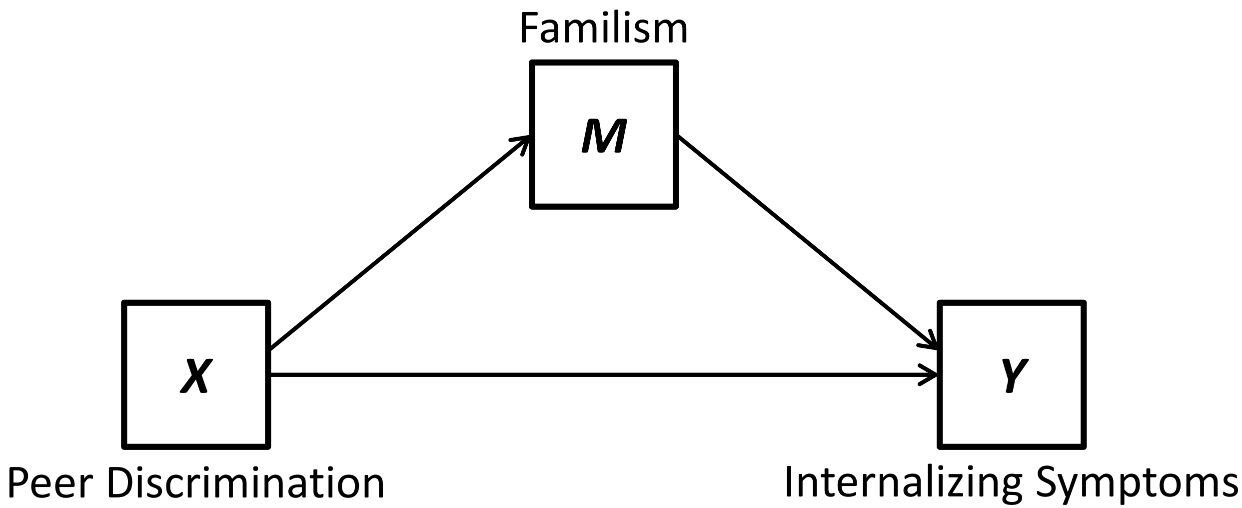
Slides available at github.com/akmontoya/CAIDe2023

TODAY'S TALK

- Two-Instance Repeated-Measures Designs
- A Motivating Example
- Mediation Analysis
- Moderation Analysis
- Conditional Process Analysis
- Comparison with MLM and SEM
- Future Directions

MEDIATION: WHAT EXPLAINS AN EFFECT?



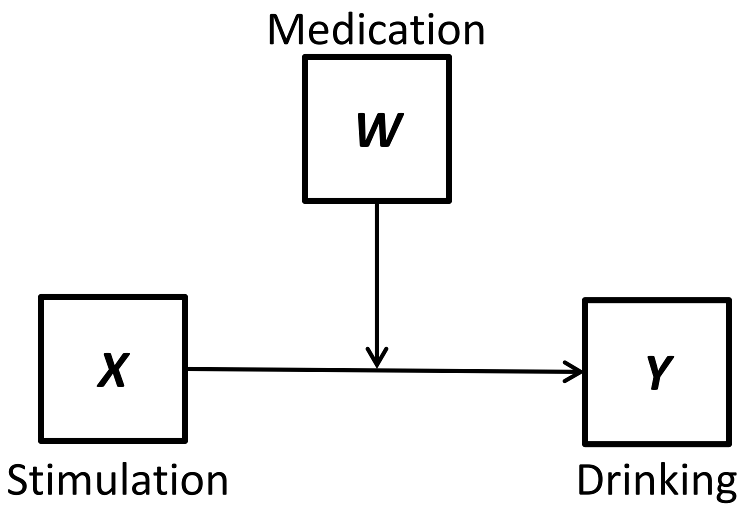
A simple mediation model connects an **assumed** causal variable (*X*) to an **assumed** outcome variable (*Y*), through some mechanism (*M*).

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.

Ramos, Delgadillo, Fossum, Montoya, Thamrin, Rapp, Escovar, Chavira (2021)

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.

Meredith, Grodin, Montoya, Miranda, Squeglia, Towns, Evans, Ray, 2022

TWO-INSTANCE REPEATED-MEASURES DESIGNS

The "paired t-test" design

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

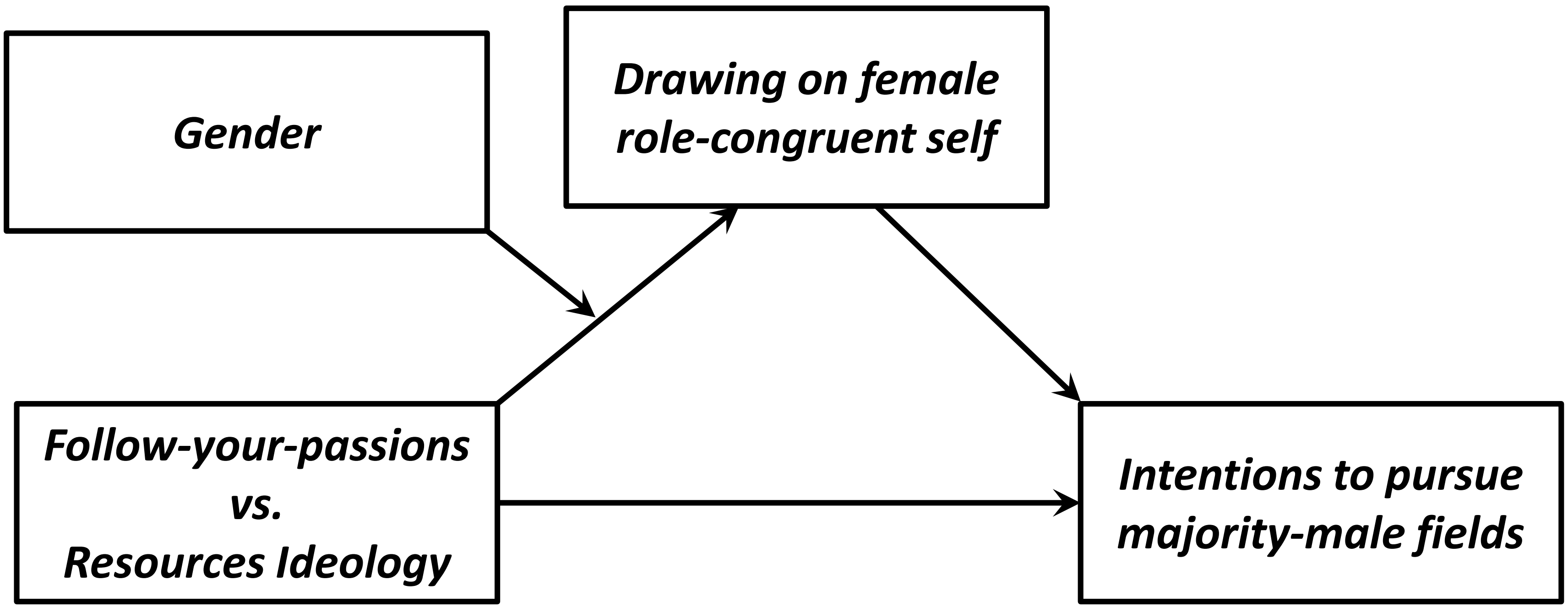
- "Follow your passions" is a common ideology in the US
- "Resource driven" ideology is common in places where individualism is less prominent
    - These places also have greater proportions of women in STEM

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

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

NEGATIVE IMPACTS OF "FOLLOWING YOUR PASSIONS"

Our theoretical model



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

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 (masculine) – 7 (feminine) 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)?"

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

MEDIATION FOR TWO-INSTANCE REPEATED-MEASURES

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

Amanda K. Montoya and Andrew F. Hayes
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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, Bliuc, 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),

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- 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

Montoya & Hayes, 2017

PATH ANALYTIC METHOD FOR MEDIATION

Total Effect *c*:

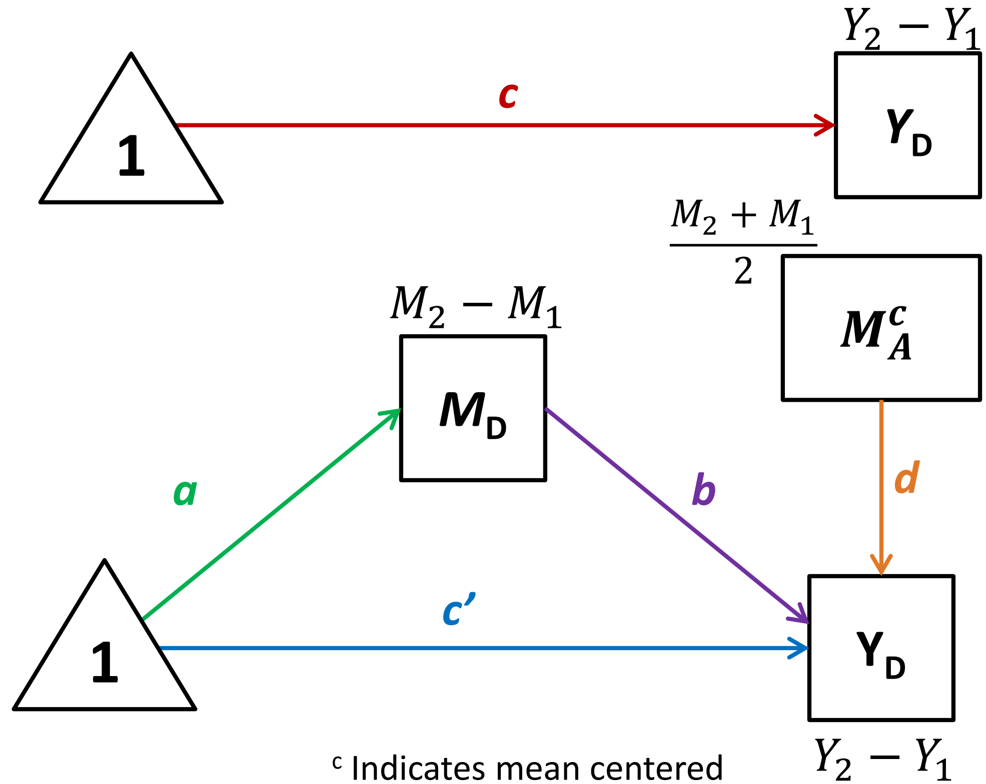
$$Y_{2i} - Y_{1i} = c + \epsilon_{Y_i^*}$$

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* × *b*

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

Total effect = direct effect + indirect effect

c = *c′* + *a* × *b*

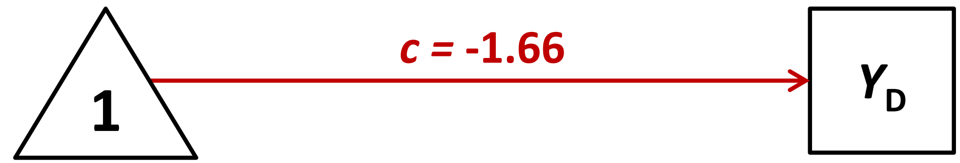
Note: M_A must be mean centered for *c′* to have intended interpretation

Montoya & Hayes, 2017

FOLLOW YOUR PASSIONS (WOMEN ONLY)

Total Effect *c*:

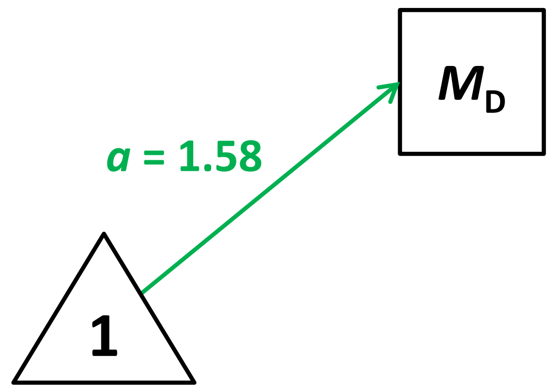
$$Y_{2i} - Y_{1i} = -1.66 + \epsilon_{Y_i^*}$$



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 ($t(374) = 18.21$, $p < .00001$)

Montoya & Hayes, 2017

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

FOLLOW YOUR PASSIONS (WOMEN ONLY)

Total Effect *c*:

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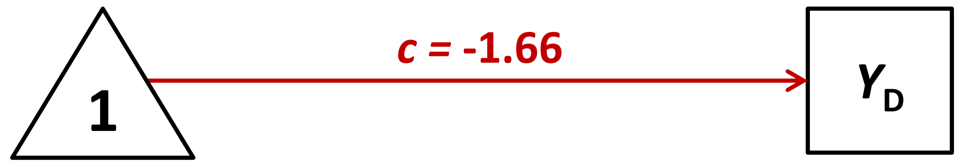
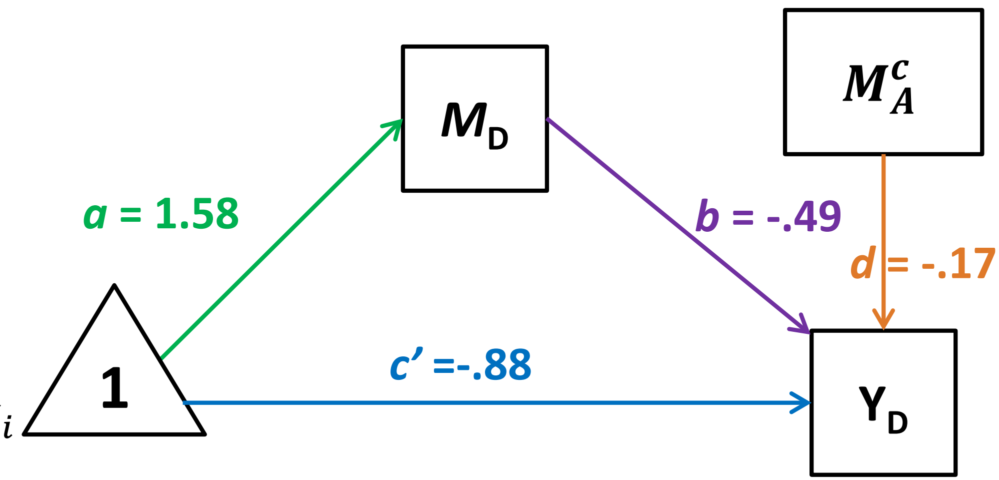


a path:

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

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 ($t(372) = -8.29$, $p < .0001$).

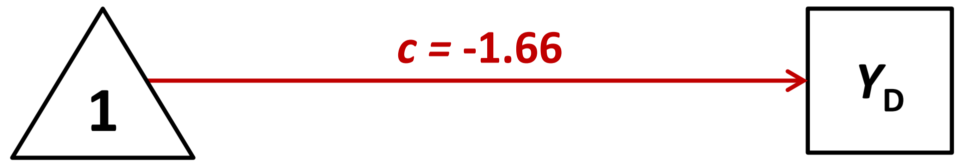
Montoya & Hayes, 2017

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

FOLLOW YOUR PASSIONS (WOMEN ONLY)

Total Effect *c*:

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



a path:

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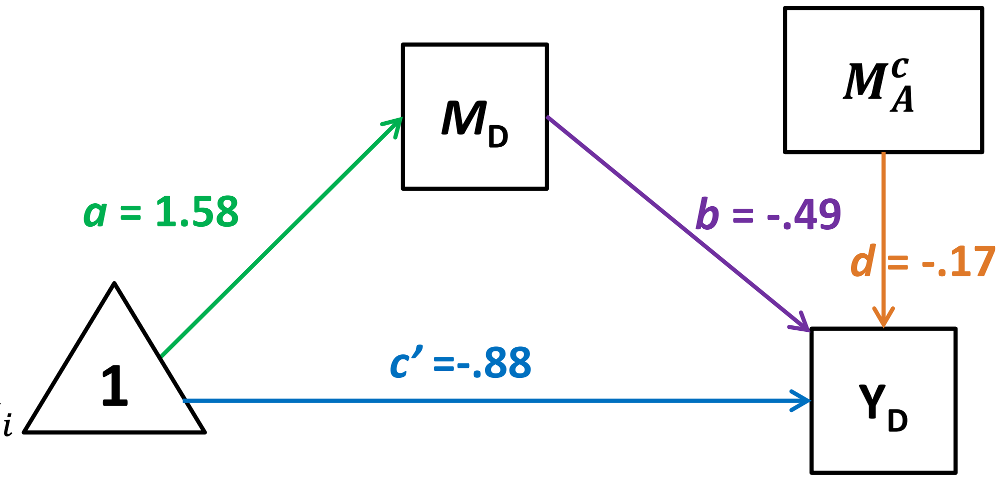


[c] Indicates mean centered

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 ($d = -.17$, $t(372) = -1.72$, $p = .09$)

Montoya & Hayes, 2017

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

INTERPRETTING THE COEFFICIENTS

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

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

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

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

Then apply a rotation to get:

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

$b = \dfrac{g_{21} + g_{11}}{2}$ — *b* is the relationship between *M* and *Y* averaged across the two conditions

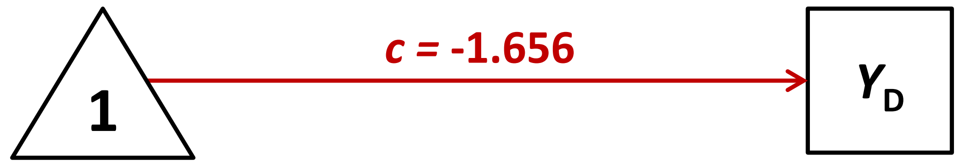
$d = (g_{11} - g_{21})$ — *d* is the difference in the relationship between *M* and *Y* between the two conditions (*XM* interaction)

Montoya & Hayes, 2017

THE INDIRECT EFFECT

Total Effect *c*:

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

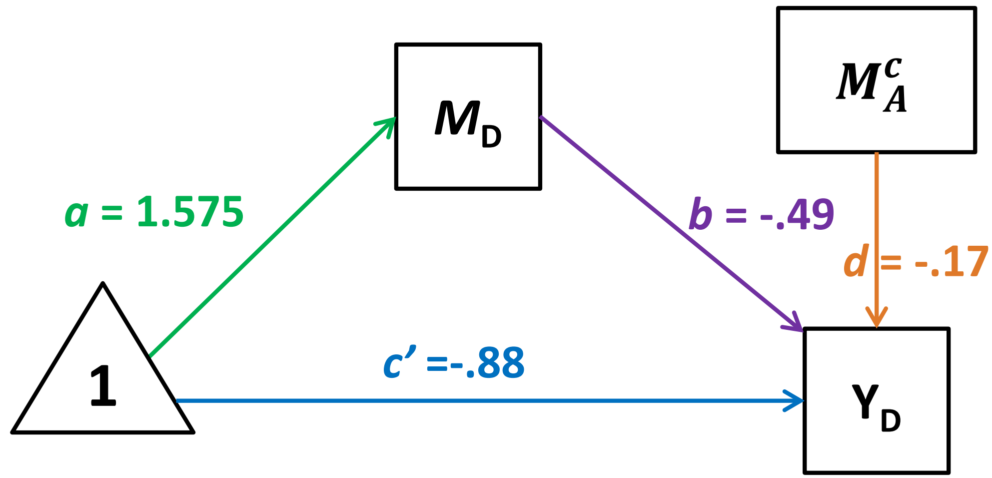


a path:

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

b path, *d* path, and *c'* path:

$$Y_D = -.88 - .49M_{\mathrm{D}} - .17M_{\mathrm{A}}^{c} + \epsilon_{Yi}$$



[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.

<u>Montoya</u> & Hayes, 2017

Siy, Germano, Vianna, Azpeitia, Yan, <u>Montoya</u>, Cheryan, in press, *JPSP*

Evaluating Methods of Inference

RESEARCH QUESTION: Which methods of inference for the indirect effect work best for within-subjects across a variety of situations?

Methods:

- Causal steps (JKM)
- Joint significance
- Sobel Test
- Bootstrapping (Percentile)
- Monte Carlo Confidence Intervals

Population Characteristics:

Sample size: 20, 50, 100, 200
a path: 0, 0.14, 0.39, 0.59
b path: 0, 0.14, 0.39, 0.59
c' path: 0, 0.14, 0.39, 0.59
d path: 0, 0.14, 0.39, 0.59
ρ_m : 0, .3, .6, .9
ρ_y : 0, .3, .6, .9

Estimated models including and excluding moderation (M_A)

Some combination were impossible, which left 11,648 conditions

Generated 1000 data sets per condition

Used each method of inference on each dataset

Recorded rejection rate for each method in each condition ($\alpha = .05$)

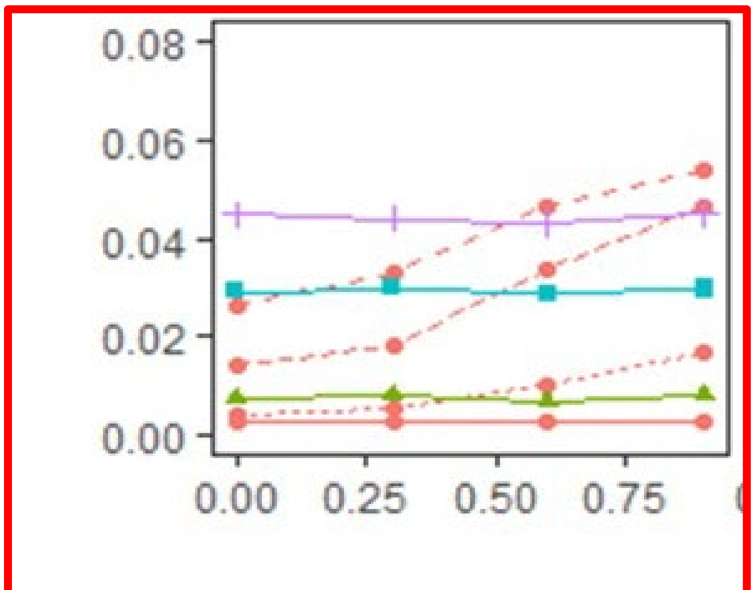
Montoya, 2022

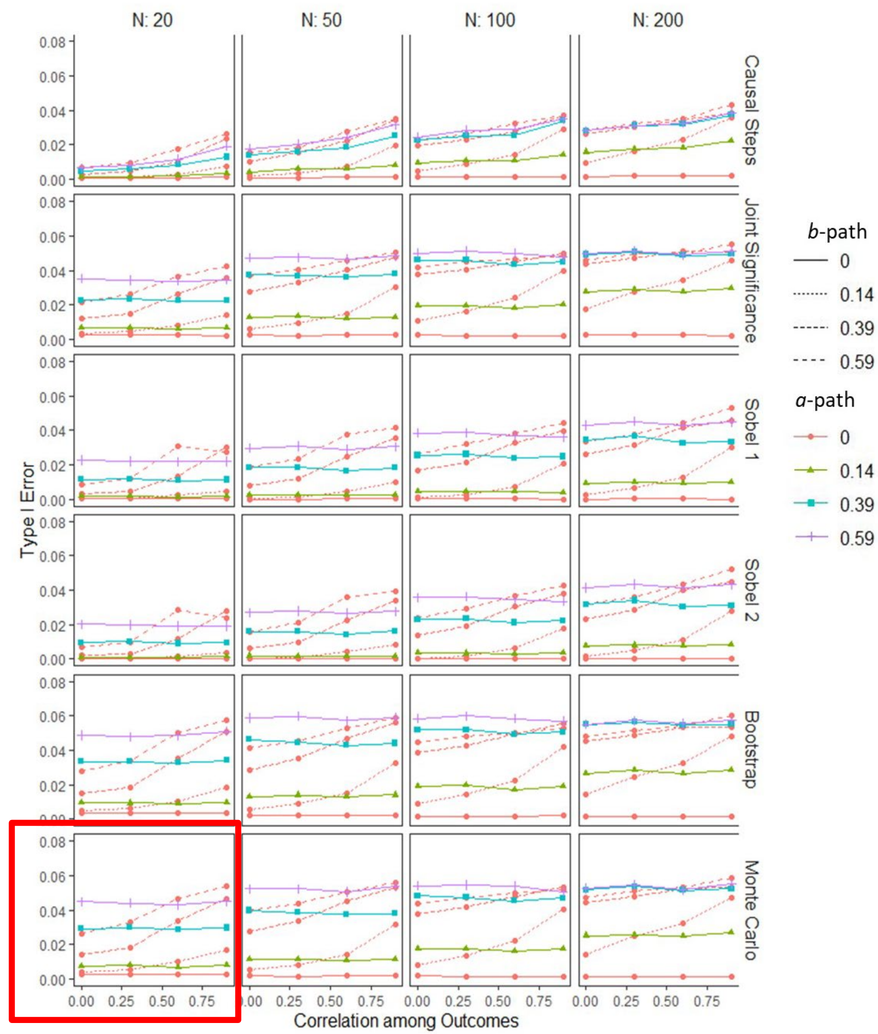
Type I Error: Correlation among the Outcomes

Type I Error tends to be very low

As either *a* or *b* get's large Type I Error approaches .05

Type I Error tends to increase as correlation among outcomes increases, but only when $a = 0$ and $b \neq 0$





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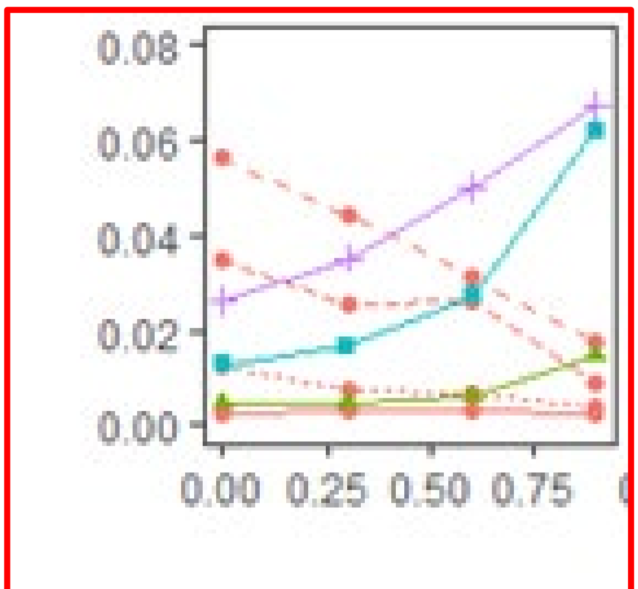
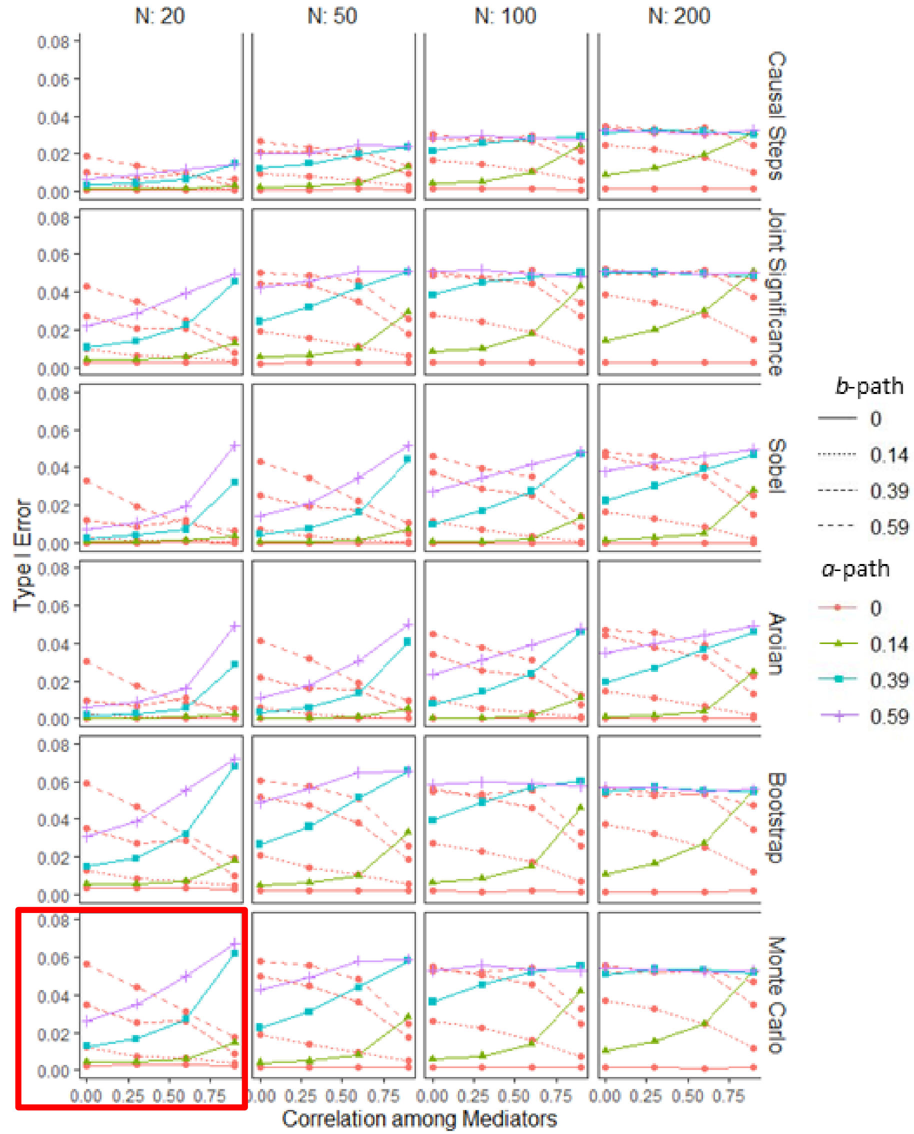
Type I Error: Correlation among the Mediators

As either *a* or *b* get large Type I Error approaches .05

Type I Error tends to decrease as correlation among mediators increases, when *a* = 0 and *b* ≠0

Type I Error tends to increase as correlation among mediators increases, when *a* ≠ 0 and *b* = 0





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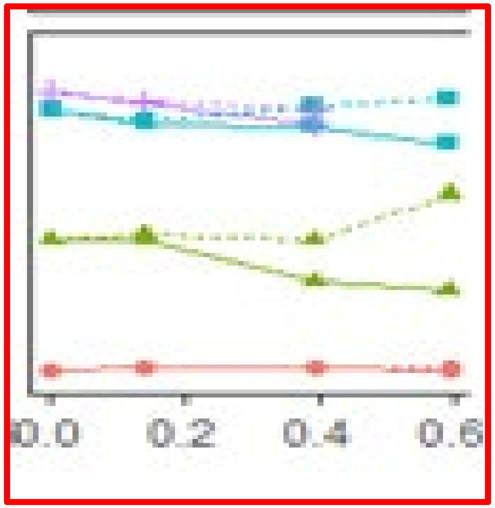
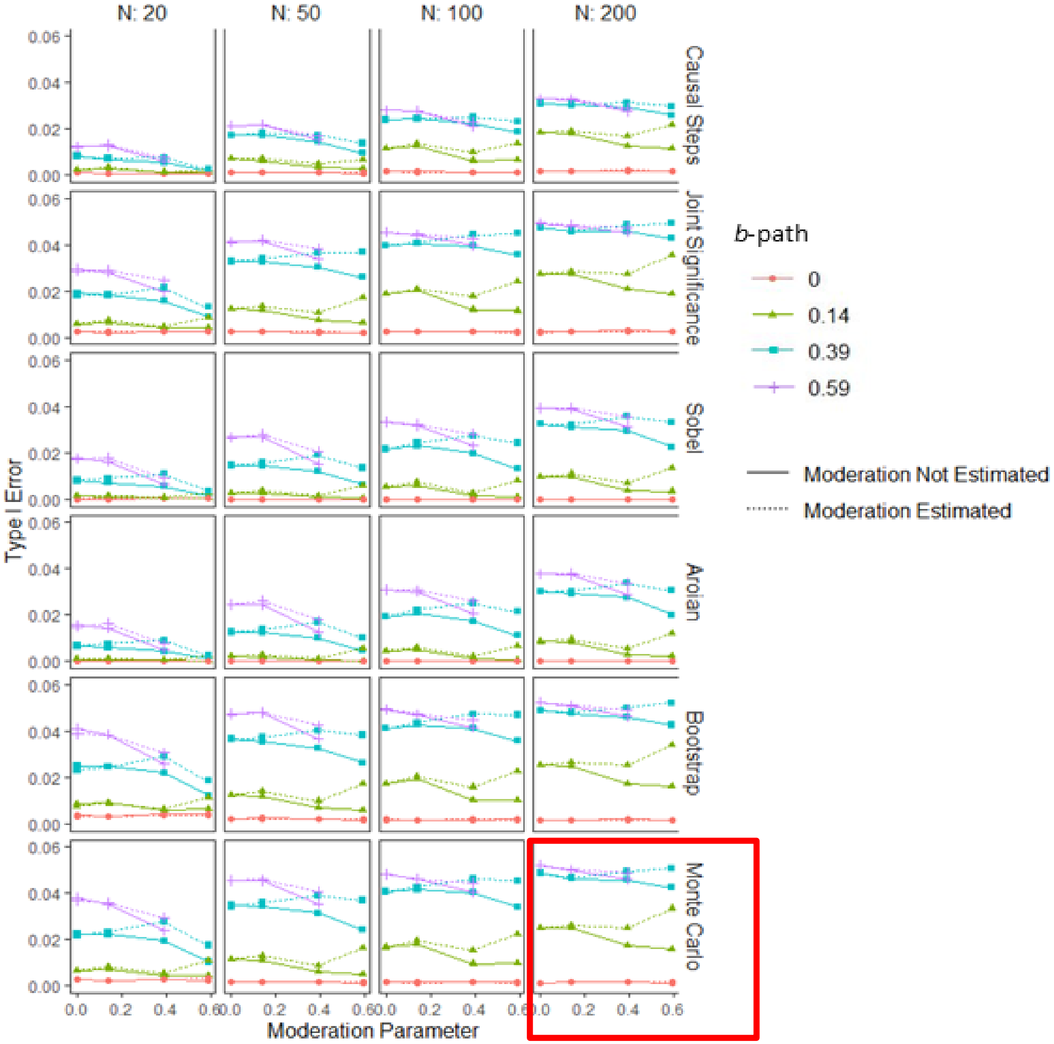
Type I Error: Moderation Parameter

Type I Error is generally stable across moderation parameter.

As b-path gets larger, the difference in Type I error between estimating an not estimating moderation gets larger





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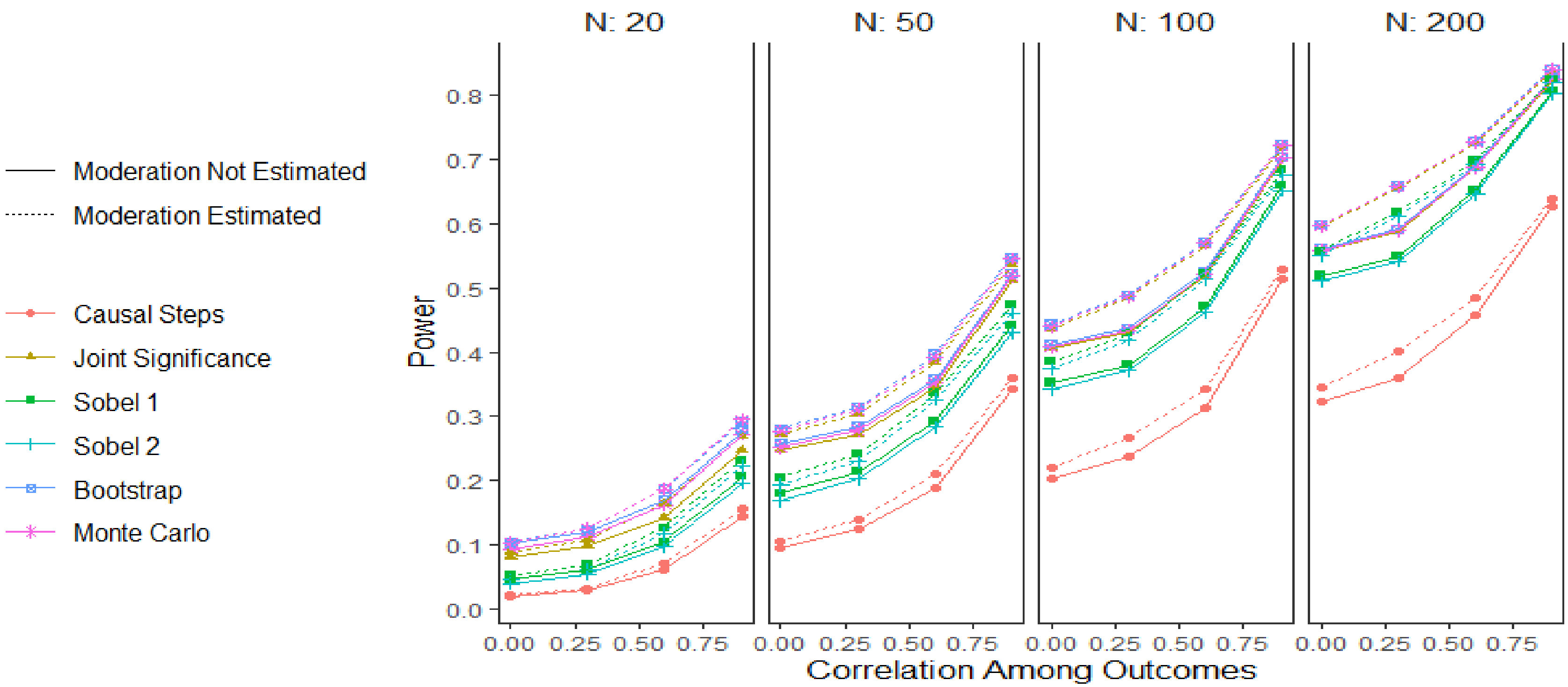
Power: Correlation among the Outcomes

Power increases as correlation among the outcomes increases

Small power advantage of estimating moderation (when it is present)



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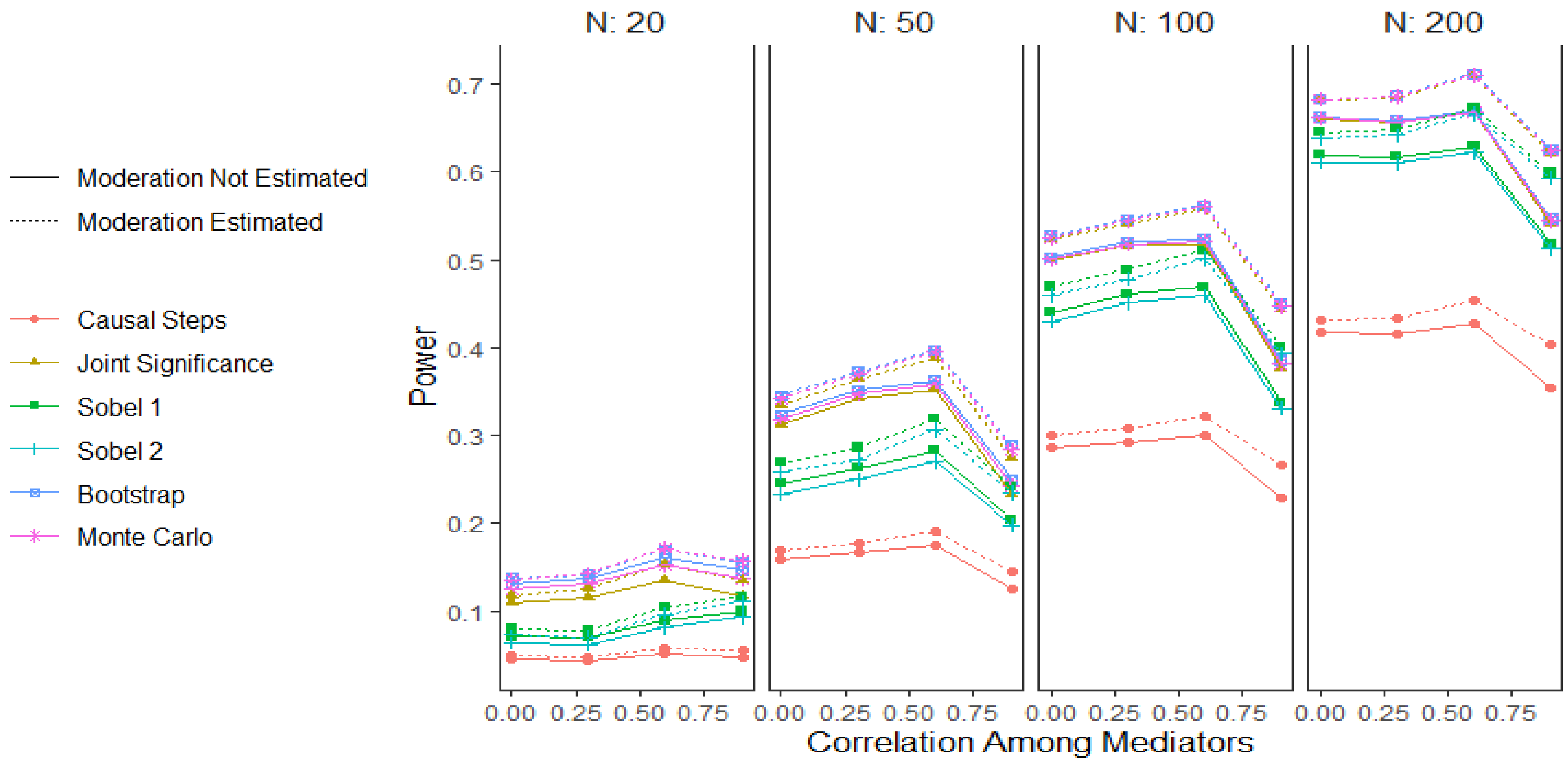
Power: Correlation among the Mediators

Power increases as correlation among the mediators increases (to a point, .75)

Small power advantage of estimating moderation (when it is present)



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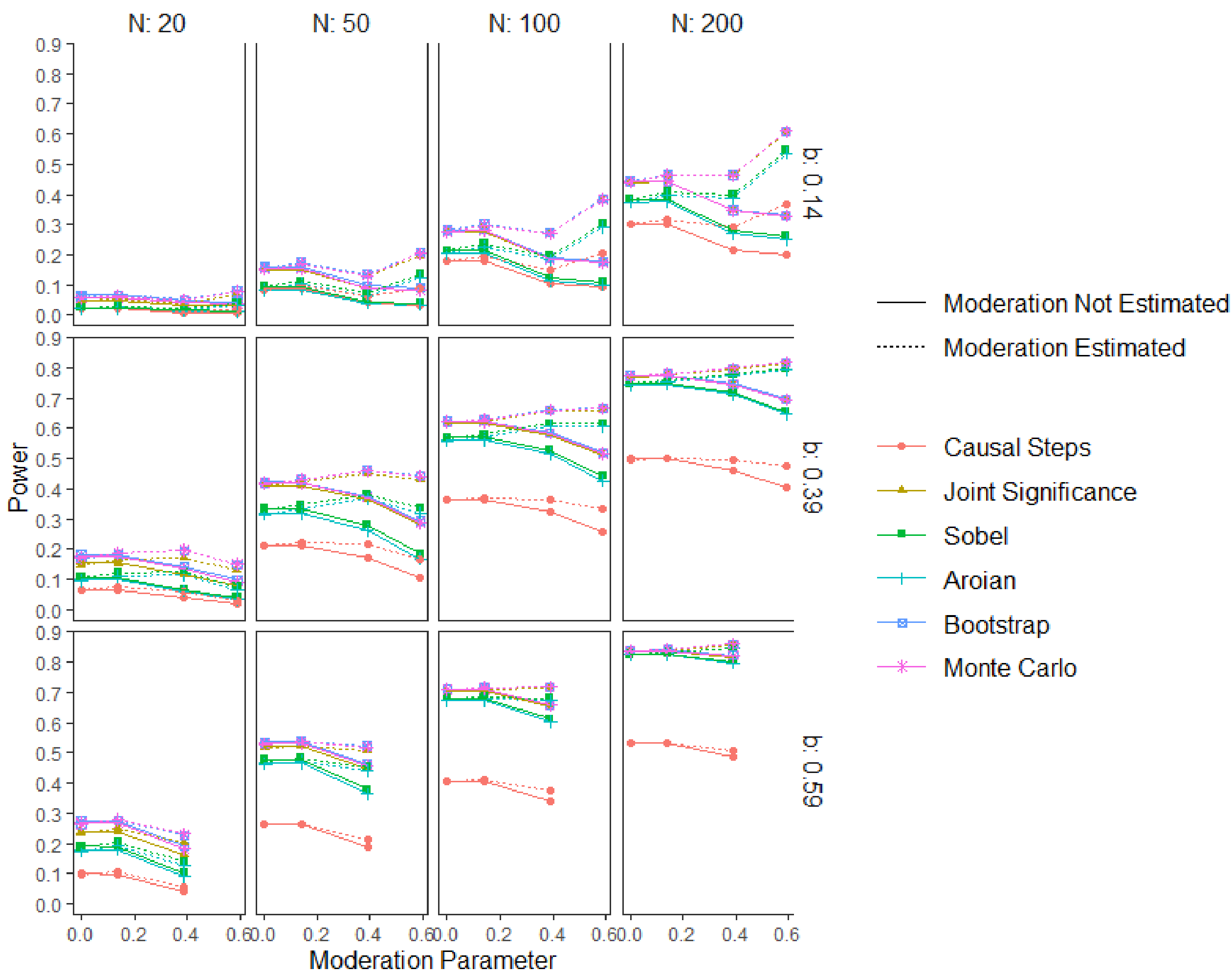
Power: Moderation Parameter

Estimating moderation can result in a large power advantage if the coefficient is large

Otherwise power is mostly unaffected by moderation parameter



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Implications

- Best methods (based on Type I Error and Power)
  - Percentile bootstrap confidence interval
  - Monte Carlo method
  - Joint significance test

provide point estimates and confidence intervals for the indirect effect

- Within-subjects designs buys additional power in mediation analysis when:
  - repeated observations are not independent
  - *M*'s are not too correlated
- *Proximity:* Mediators that are *too correlated* may result in a loss of power due to increases in standard error of *b* path. (Judd & Kenny, 2014; Hoyle & Kenny1999)
- Many findings from the between subjects mediation simulation literature were replicated in this study.

So if bootstrapping is better, how do we do it?

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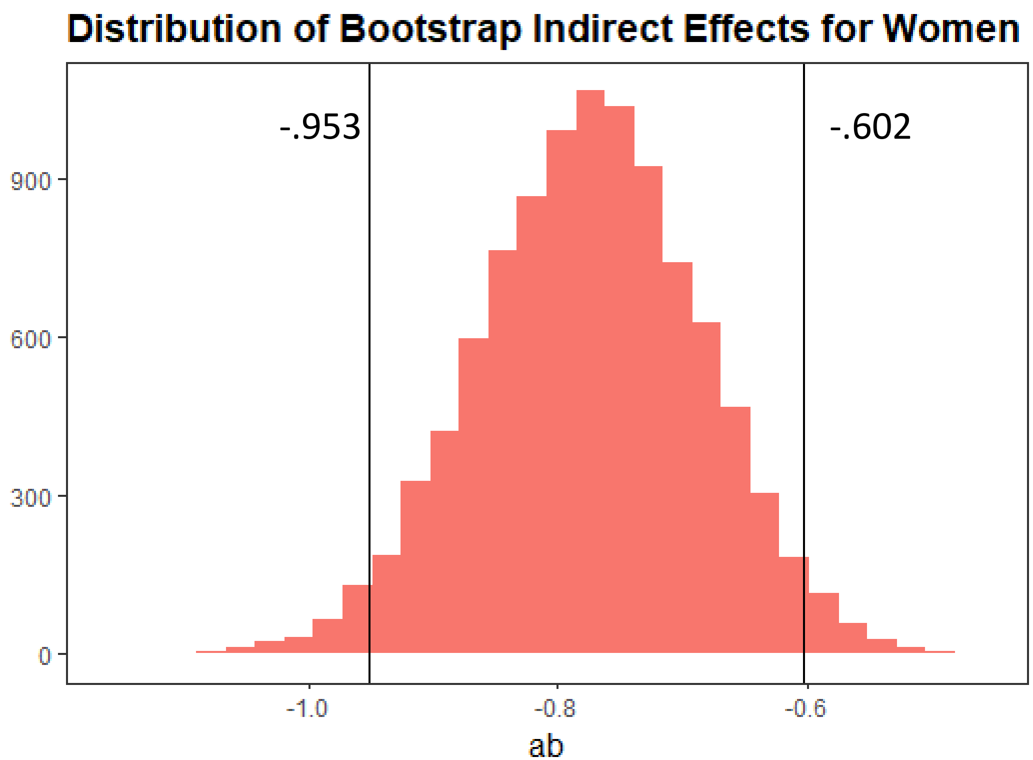
FYP EXAMPLE: INFERENCE



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.

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

MEMORE

MEMORE is a macro available for SPSS and SAS for conducting (<u>ME</u>diation and <u>MO</u>deration in <u>RE</u>peated 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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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, Bliuc, 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*),

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Amanda K. Montoya and Andrew F. Hayes, Department of Psychology, The Ohio State University.

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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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);
```


Montoya & Hayes, 2017

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

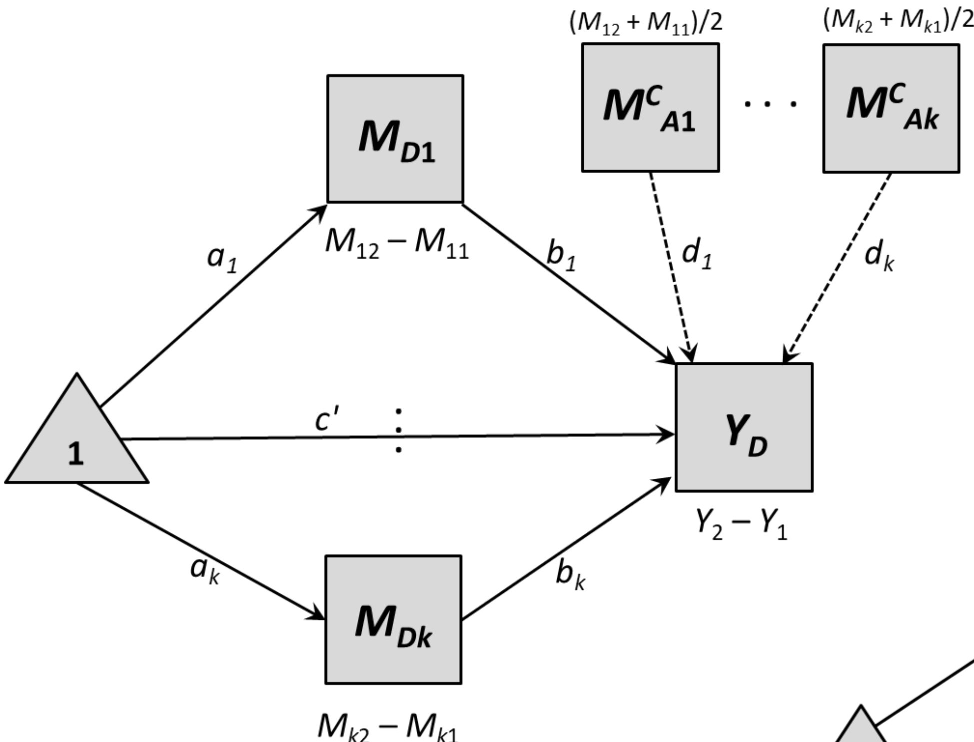
Model for M_2-M_1

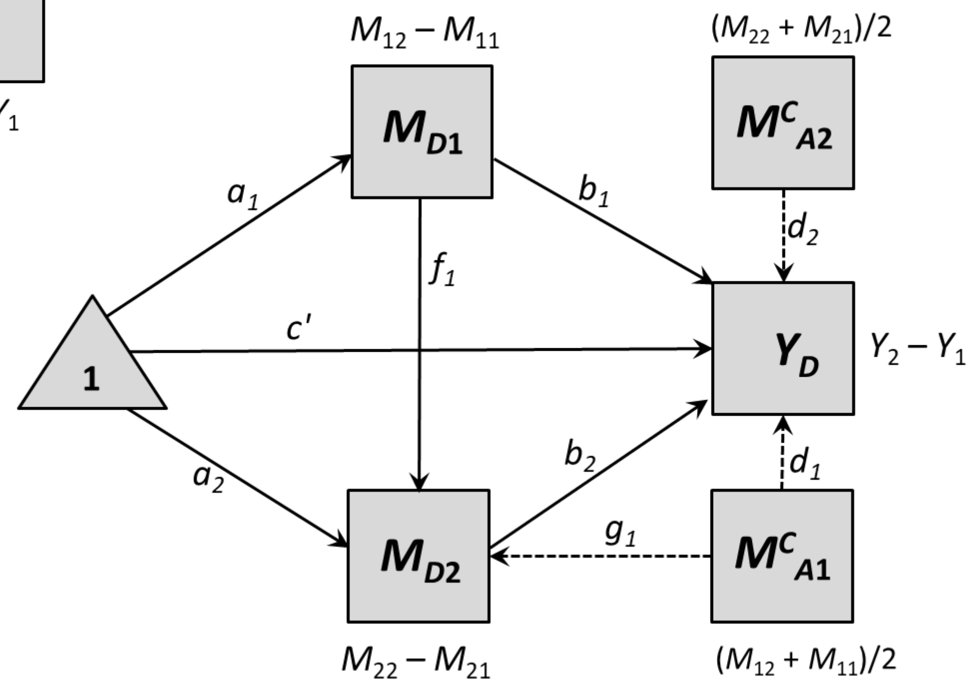
Model for Y_2-Y_1

Total, Direct, and Indirect Effects

Montoya & Hayes, 2017

MULTIPLE MEDIATOR MODELS: PARALLEL & SERIAL

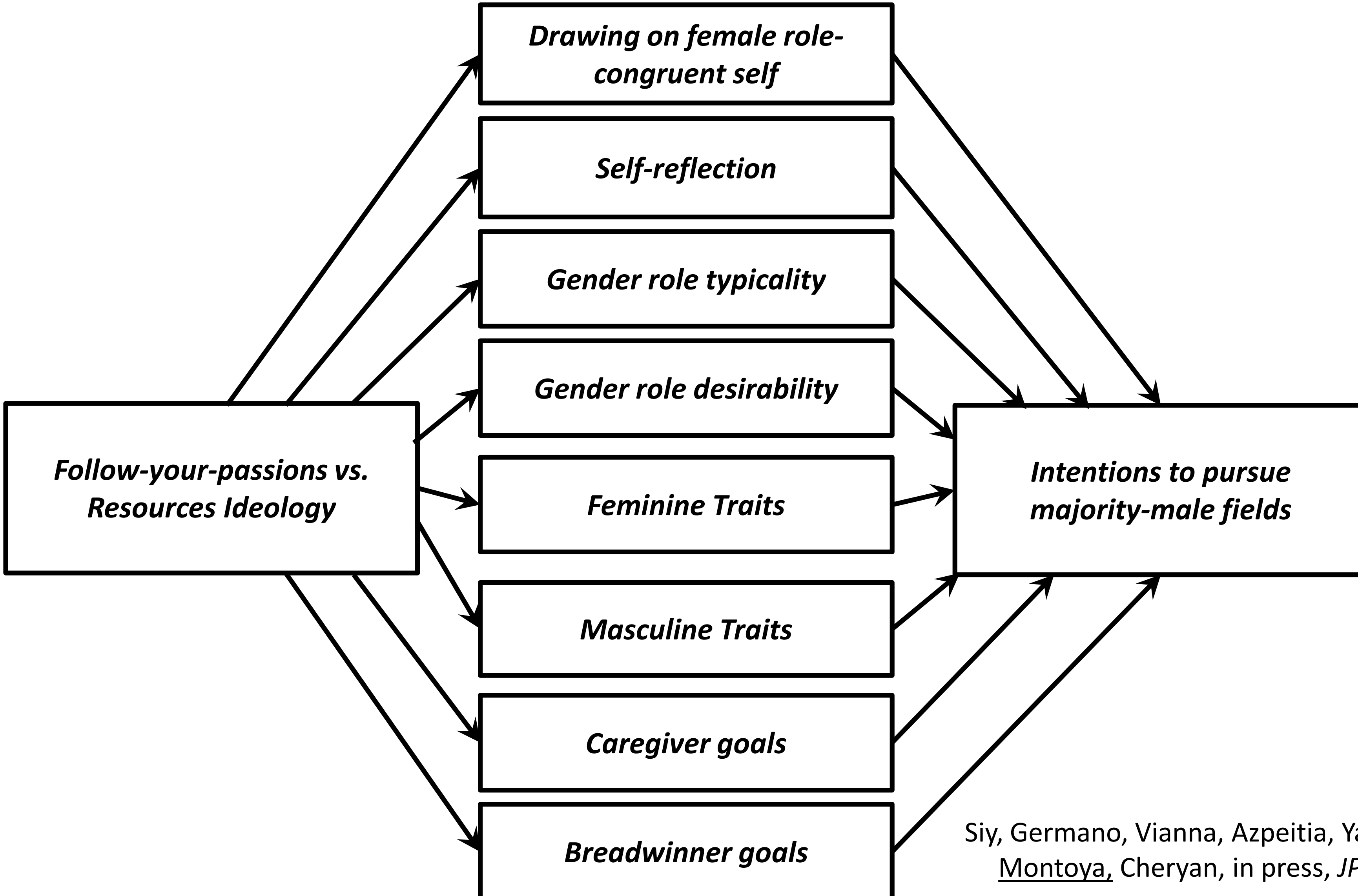




Montoya & Hayes, 2017

FOLLOW YOUR PASSIONS

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



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

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

Montoya, 2022
Montoya & Hayes, 2017

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

1082-989X/96/$3.00

Testing Treatment by Covariate Interactions When Treatment Varies Within Subjects

Charles M. Judd and Gary H. McClelland
University of Colorado at Boulder

Eliot R. Smith
Purdue University

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

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

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

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

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

and

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \beta_3 X_i Z_i + \varepsilon_i.$$

In the first equation, β_1 represents the magnitude of

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

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

Correspondence concerning this article should be addressed to Charles M. Judd, Department of Psychology, University of Colorado, Boulder, Colorado 80309. Electronic mail may be sent via the Internet to charles.judd@colorado.edu.

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

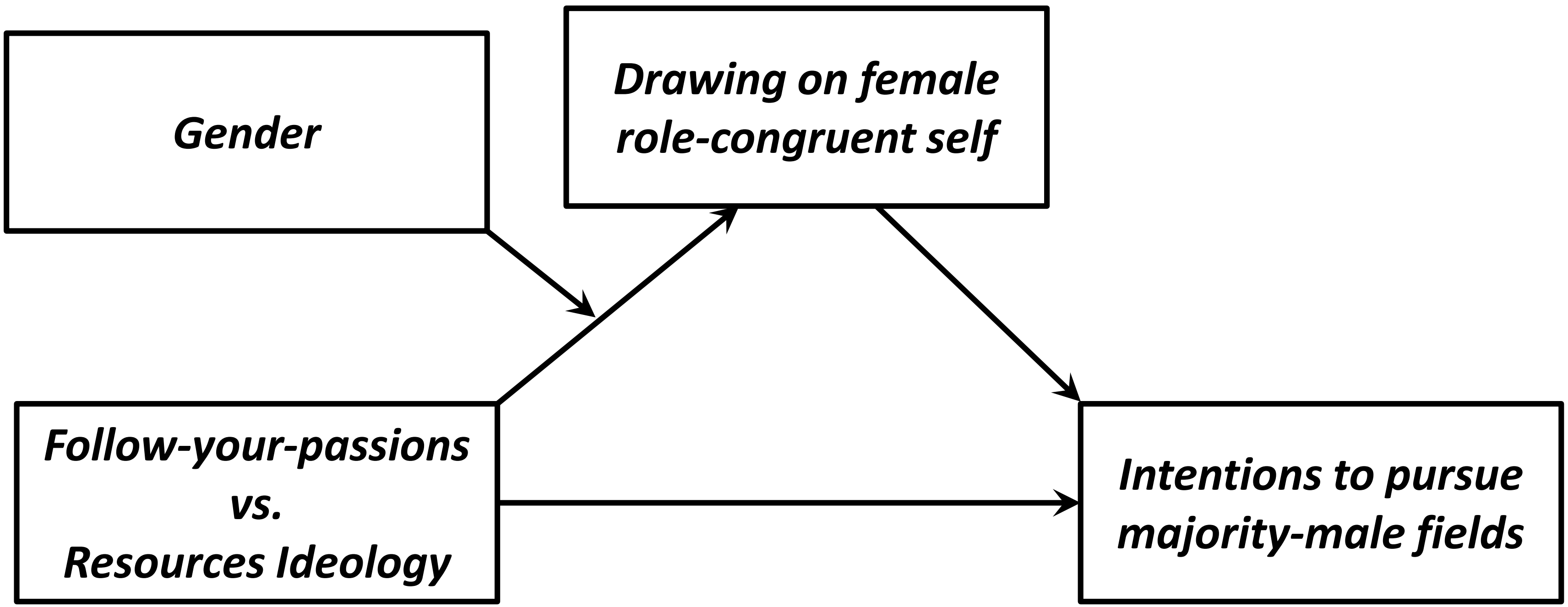
Or

Does effect of <u>instance</u> on *Y* depend on an individual's *W*?

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

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?

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

TESTING THE INTERACTION

1. Setup two regression equations, one for each instance

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

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

Judd, McClelland, and Smith, 1996

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?

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

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*

Montoya, 2019

CONDITIONAL EFFECTS IN WITHIN-SUBJECT MODERATION

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

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

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

Men (Gender = 1)

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

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

Women (Gender = 2)

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

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

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

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

Montoya, 2019

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.

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

Montoya, 2019

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. Moderation functions described in *Moderation analysis in two-instance repeated measures designs: Probing methods and multiple moderator models*

Behavior Research Methods (2019) 51:61–82
https://doi.org/10.3758/s13428-018-1088-6

BRIEF REPORT

Moderation analysis in two-instance repeated measures designs: Probing methods and multiple moderator models

Amanda Kay Montoya[1,2]

Published online: 10 October 2018

Abstract
Moderation hypotheses appear in every area of psychological science, but the methods for testing and probing moderation in two-instance repeated measures designs are incomplete. This article begins with a short overview of testing and probing interactions in between-participant designs. Next I review the methods outlined in Judd, McClelland, and Smith (*Psychological Methods* 1; 366–378, 1996) and Judd, Kenny, and McClelland (*Psychological Methods* 6; 115–134, 2001) for estimating and conducting inference on an interaction between a repeated measures factor and a single between-participant moderator using linear regression. I extend these methods in two ways: First, the article shows how to probe interactions in a two-instance repeated measures design using both the pick-a-point approach and the Johnson–Neyman procedure. Second, I extend the models described by Judd et al. (1996) to multiple-moderator models, including additive and multiplicative moderation. Worked examples with a published dataset are included, to demonstrate the methods described throughout the article. Additionally, I demonstrate how to use Mplus and MEMORE (Mediation and Moderation for Repeated Measures; available at http://akmontoya.com), an easy-to-use tool available for SPSS and SAS, to estimate and probe interactions when the focal predictor is a within-participant factor, reducing the computational burden for researchers. I describe some alternative methods of analysis, including structural equation models and multilevel models. The conclusion touches on some extensions of the methods described in the article and potentially fruitful areas of further research.

Keywords Linear regression · Moderation · Repeated measures · Interaction · Probing · Johnson-Neyman

Across areas of experimental psychology and many other scientific fields, researchers are interested in questions that address the boundaries and contingencies of certain effects they observe. Do women feel more comfortable around men after learning their sexual orientation, or does it depend on whether the man is hetero- or homosexual (Russell, Ickes, & Ta, 2018)? Does fear-based advertisement always work, or will thinking about God make these methods less effective (Wu & Cutright, 2018)? Are all veterans equally likely to experience post-service stress, or will certain psychological characteristics impact the risk of stress (Mobbs & Bonanno, 2018)? These are all questions of *moderation* or *interaction*. Though some differentiate between these two terms, I will use them interchangeably (see VanderWeele, 2009, for a discussion of the differences from a causal modeling perspective). Statistical moderation analysis is used to test whether the relationship between a *focal predictor*, *X*, and an *outcome variable*, *Y*, depends on some *moderator*, *W*. For example, Kraus and Callaghan (2016) found that higher-class individuals were more likely to help than lower-class individuals in public contexts, but the opposite was true when the context was private, where lower-class individuals helped more than higher-class individuals. Here, the relationship between class (*X*) and helping (*Y*) depended on context (*W*). Learning has been shown to improve when adjunct questions are included in a text, but Roelle, Rahimkhani-Sagvand, and Berthold (2017) found that when reading texts with adjunct questions, receiving immediate feedback (*X*) had a detrimental effect on learning (*Y*) for students who felt that answering the questions was highly demanding (*W*). So, how is social class related to helping? Does immediate feedback lead to worse learning outcomes? It depends. Moderation analysis is a statistical method for testing whether these relationships depend on certain proposed variables (i.e., moderators).

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Springer

Model 2 or 3 can be used for single mediator models (no difference in result)

Model 2: Additive Moderation

Model 3: Multiplicative Moderation

SPSS Syntax:

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

SAS Syntax:

```
MEMORE(data = fyp, Y = gendSpas gendSinc, W = gendr, model = 2, plot = 1);
```


Montoya, 2019

```
Run MATRIX procedure:

********************** MEMORE Procedure for SPSS Version 3.0 ***********************
                         Written by Amanda Montoya
                   Documentation available at akmontoya.com
*************************************************************************************
Model:
  2
Variables:
Y = gendSpas gendSinc
W = gendr

Computed Variables:
Ydiff =          gendSpas  -       gendSinc

Sample Size:
  672
*************************************************************************************
Outcome: Ydiff =  gendSpas  -       gendSinc
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .1513      .0229     2.4199    15.6875     1.0000   670.0000      .0001
Model
              coeff         SE          t          p       LLCI       ULCI
constant      .6179      .1976     3.1273      .0018      .2300     1.0059
gendr         .4786      .1208     3.9607      .0001      .2413      .7158
Degrees of freedom for all regression coefficient estimates:
  670
*************************************************************************************
Conditional Effect of 'X' on Y at values of moderator(s)
      gendr     Effect         SE          t          p       LLCI       ULCI
     1.0000     1.0965      .0903    12.1478      .0000      .9193     1.2738
     2.0000     1.5751      .0803    19.6079      .0000     1.4174     1.7328
Degrees of freedom for all conditional effects:
  670
Values for dichotomous moderators are the two values of the moderator.
*************************************************************************************
Conditional Effect of Moderator(s) on Y in each Condition
Condition 1 Outcome:
 gendSpas
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2709      .0734     1.1374    53.0791     1.0000   670.0000      .0000
Model
              coeff         SE          t          p       LLCI       ULCI
constant     3.3538      .1355    24.7575      .0000     3.0878     3.6198
gendr         .6035      .0828     7.2855      .0000      .4409      .7662
Degrees of freedom for all conditional effects:
  670
-------------------------------------------------------------------------------------
Condition 2 Outcome:
 gendSinc
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0553      .0031     1.2610     2.0520     1.0000   670.0000      .1525
Model
              coeff         SE          t          p       LLCI       ULCI
constant     2.7359      .1426    19.1809      .0000     2.4558     3.0160
gendr         .1249      .0872     1.4325      .1525     -.0463      .2962
Degrees of freedom for all conditional effects:
  670
*************************************************************************************
```

Model Information

Regression model for testing moderation

Conditional effects of *X* on *Y* at values of *W*

Conditional Effect of *W* on *Y* in first instance

Conditional Effect of *W* on *Y* in second instance

Montoya & Hayes, 2017

CONDITIONAL EFFECTS

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 **($t(670) = 19.61$, $p < .01$).**

Conditional effect of gender:

In the follow your passions condition, women draw on their female role-congruent selves 0.60 units more than men, and this effect is statistically significant **($t(670) = 7.29$, $p < .01$).**

In the resource driven condition, women drew on their female role-congruent selves 0.12 units more than men, but this effect was not statistically significant **($t(670) = 1.43$, $p = .15$).**

PLOTTING

Plotting option provides output to create plots

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

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

DATA LIST FREE/gendr YdiffHAT gendSpasHAT gendSincHAT.

BEGIN DATA.

     1.0000     1.0965     3.9574     2.8608
     2.0000     1.5751     4.5609     2.9858

END DATA.

GRAPH/SCATTERPLOT = gendr WITH YdiffHAT.
GRAPH/SCATTERPLOT = gendr WITH gendSpasHAT.
GRAPH/SCATTERPLOT = gendr WITH gendSincHAT.
```

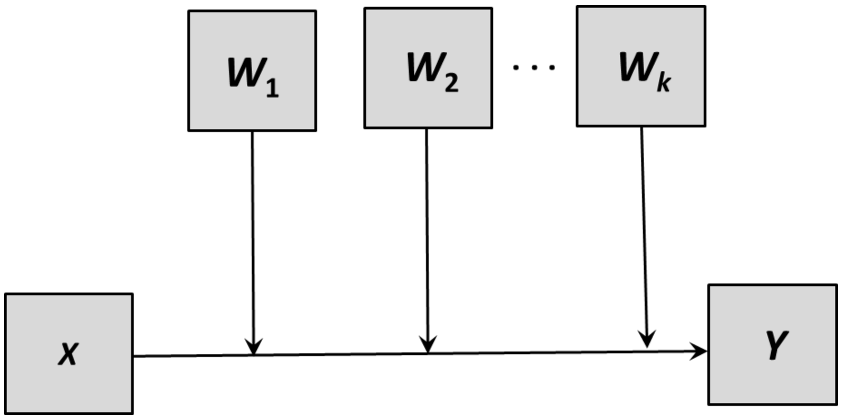
Siy, Germano, Vianna, Azpeitia, Yan, Montoya, Cheryan, in press, *JPSP*

MULTIPLE MODERATOR MODELS

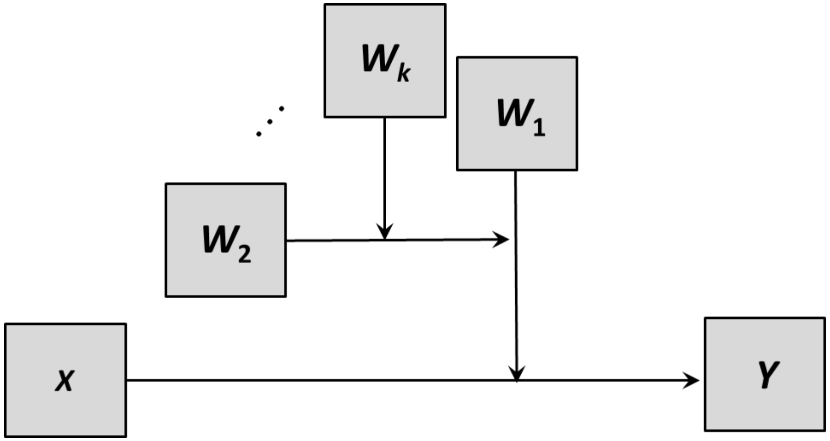
Multiple moderator models are also included!

- Can have up to 5 moderators

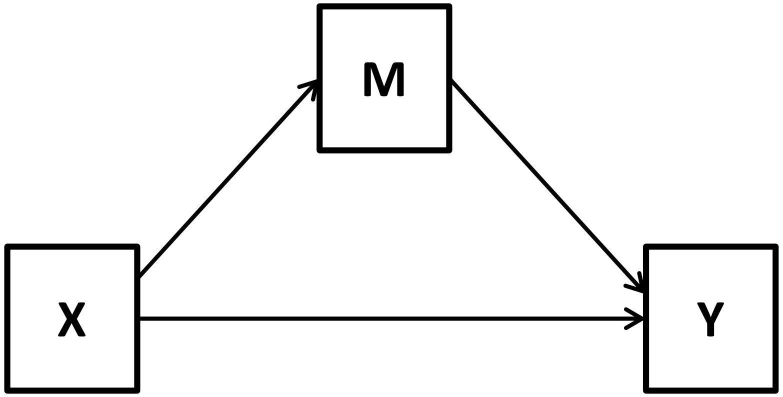
Model 2: Additive Moderation

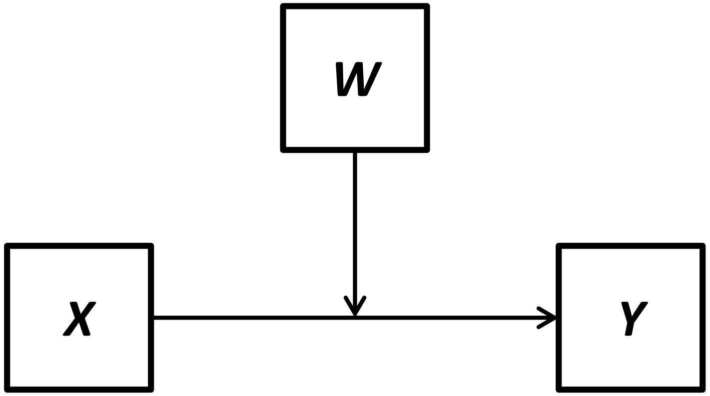


Model 3: Multiplicative Moderation



COMBINING MEDIATION AND MODERATION: CONDITIONAL PROCESS ANALYSIS





Research questions:

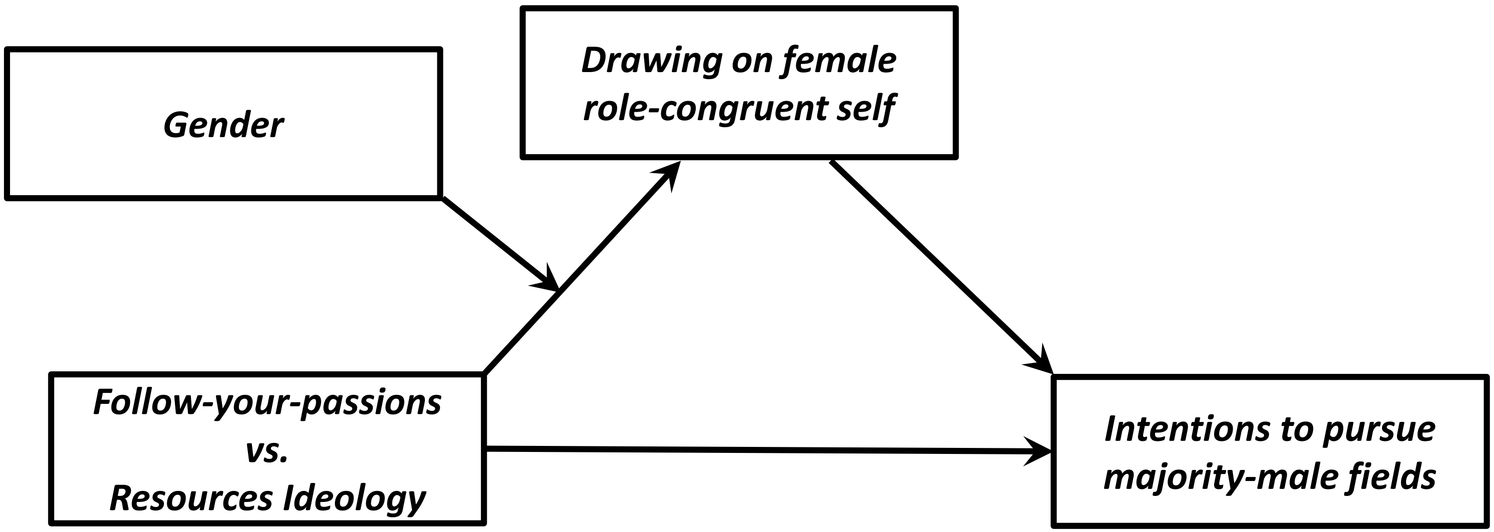
- Does the process through which *X* affects *Y* through *M* depend on *W*?
- Are there certain groups where *X* affects *Y* through *M* and certain groups where this process does not occur?

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.



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

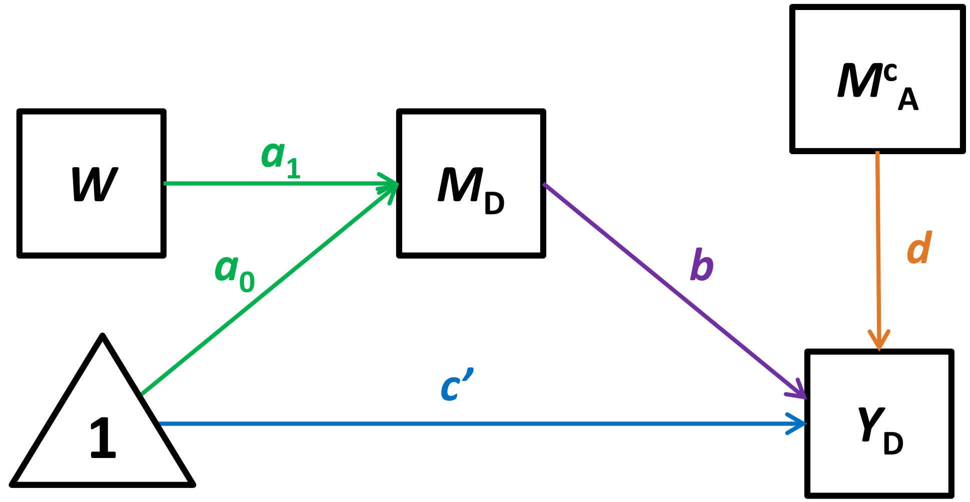
EQUATIONS AND PATH DIAGRAM

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

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

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

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



What is the indirect effect?

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

Indirect effect is a *function* of the moderator

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

MAKING INFERENCE

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

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

Does the indirect effect *depend* on the moderator?

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

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

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

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

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

```
Model:
  15
Variables:
Y = FMpas    FMinc
W = gendr
M = gendSpas gendSinc
Computed Variables:
Ydiff =          FMpas     -       FMinc
Mdiff =          gendSpas  -       gendSinc
Mavg =   (       gendSpas  +       gendSinc )        /2                        Centered
Sample Size:
  672
*******************************************************************************
Outcome: Ydiff =  FMpas     -       FMinc
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2490      .0620     2.6562    44.2691     1.0000   670.0000      .0000
Model
             Effect         SE          t          p       LLCI       ULCI
constant       .0286      .2070      .1382      .8901     -.3779      .4351
W             -.8423      .1266    -6.6535      .0000    -1.0909     -.5937
Degrees of freedom for all regression coefficient estimates:
  670
Conditional Effect of Focal Predictor on Outcome at values of Moderator(s)
 Focal:   'X'      (X)
 Outcome: Ydiff    (Y)
 Mod:     gendr    (W)
      gendr     Effect         SE          t          p       LLCI       ULCI
     1.0000     -.8137      .0946    -8.6042      .0000     -.9994     -.6280
     2.0000    -1.6560      .0842   -19.6764      .0000    -1.8213    -1.4907
     Values for dichotomous moderators are the two values of the moderator.
Degrees of freedom for all conditional effects:
  670
*******************************************************************************
Outcome: Mdiff =  gendSpas  -       gendSinc
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .1513      .0229     2.4199    15.6875     1.0000   670.0000      .0001
Model
             Effect         SE          t          p       LLCI       ULCI
constant       .6179      .1976     3.1273      .0018      .2300     1.0059
W              .4786      .1208     3.9607      .0001      .2413      .7158
Degrees of freedom for all regression coefficient estimates:
  670
Conditional Effect of Focal Predictor on Outcome at values of Moderator(s)
 Focal:   'X'      (X)
 Outcome: Mdiff    (M)
 Mod:     gendr    (W)
      gendr     Effect         SE          t          p       LLCI       ULCI
     1.0000     1.0965      .0903    12.1478      .0000      .9193     1.2738
     2.0000     1.5751      .0803    19.6079      .0000     1.4174     1.7328
     Values for dichotomous moderators are the two values of the moderator.
Degrees of freedom for all conditional effects:
  670
*******************************************************************************
```

Model Information

Model for difference in outcomes (no mediators)

Conditional effects of *X* on *Y* at values of *W*

Model for the difference in mediators

Conditional Effect of *X* on *M* at values of *W*

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

```
Outcome: Ydiff =  FMpas     -       FMinc
Model Summary
         R       R-sq        MSE          F        df1        df2          p
     .4802      .2306     2.1819   100.2607     2.0000   669.0000      .0000
Model
              coeff         SE          t          p       LLCI       ULCI
constant     -.6056      .0754    -8.0268      .0000     -.7538     -.4575
Mdiff        -.4973      .0363   -13.7123      .0000     -.5685     -.4261
Mavg         -.2696      .0721    -3.7399      .0002     -.4111     -.1280
Degrees of freedom for all regression coefficient estimates:
  669
****************** CONDITIONAL TOTAL, DIRECT, AND INDIRECT EFFECTS ******************
Conditional Total Effect of X on Y at values of the Moderator(s)
      gendr     Effect         SE          t         df          p       LLCI       ULCI
     1.0000     -.8137      .0946    -8.6042   670.0000      .0000     -.9994     -.6280
     2.0000    -1.6560      .0842   -19.6764   670.0000      .0000    -1.8213    -1.4907
     Values for dichotomous moderators are the two values of the moderator.
Direct effect of X on Y
     Effect         SE          t         df          p       LLCI       ULCI
     -.6056      .0754    -8.0268   669.0000      .0000     -.7538     -.4575
Conditional Indirect Effect of X on Y through Mediator at values of the Moderator
  Ind:      Ind1
  Med:      Mdiff      (M)
      gendr     Effect     BootSE   BootLLCI   BootULCI
     1.0000     -.5453      .0549     -.6577     -.4411
     2.0000     -.7833      .0801     -.9449     -.6302
     Values for dichotomous moderators are the two values of the moderator.
Indirect Key
Ind1  'X'      ->       Mdiff    ->       Ydiff
******************************** INDICES OF MODERATION ********************************
Test of Moderation of the Total Effect
      Effect         SE          t         df          p       LLCI       ULCI
W     -.8423      .1266    -6.6535   670.0000      .0000    -1.0909     -.5937
Index of Moderated Mediation for each Indirect Effect.
          Effect     BootSE   BootLLCI   BootULCI
Ind1      -.2380      .0651     -.3701     -.1144
*************************** ANALYSIS NOTES AND WARNINGS ****************************
NOTE: Some cases were deleted due to missing data. The number of cases was:
  11
Bootstrap confidence interval method used: Percentile bootstrap.
Number of bootstrap samples for bootstrap confidence intervals:
  5000
The following variables were mean centered prior to analysis:
 (        gendSpas  +       gendSinc )        /2
Level of confidence for all confidence intervals in output:
      95.00
```

Model for difference in outcomes (including mediators)

Conditional total, direct, and indirect effects

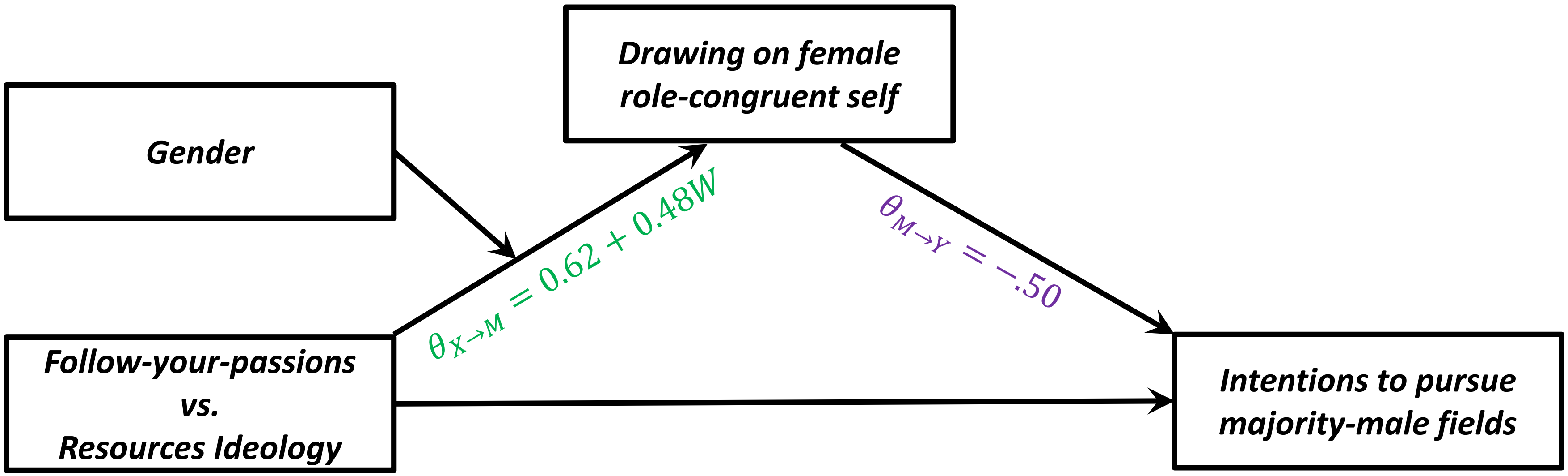
Tests of moderation for the total and indirect effects (direct effect not moderated in this model)

Errors, notes, etc

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

FOLLOW YOUR PASSIONS

```
memore y = FMpas FMinc /m = gendSpas gendSinc /w =
gendr /model = 15.
```



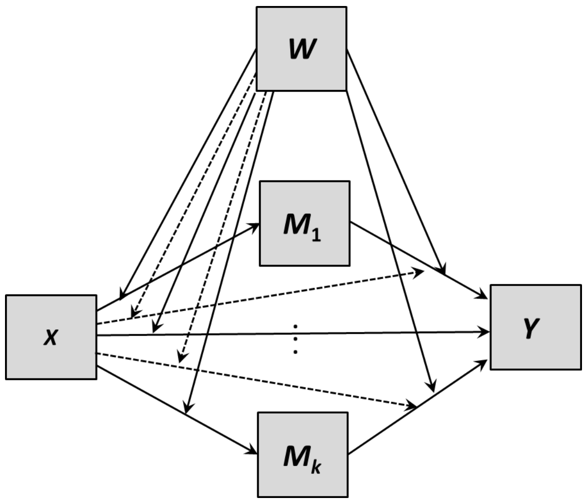
The indirect effect for both men and women was such that **the follow-your-passions ideology decreased interest through drawing on feminine self** (Men: -.55 [-.66, -.44], Women: -.78 [-.94, -.63]).

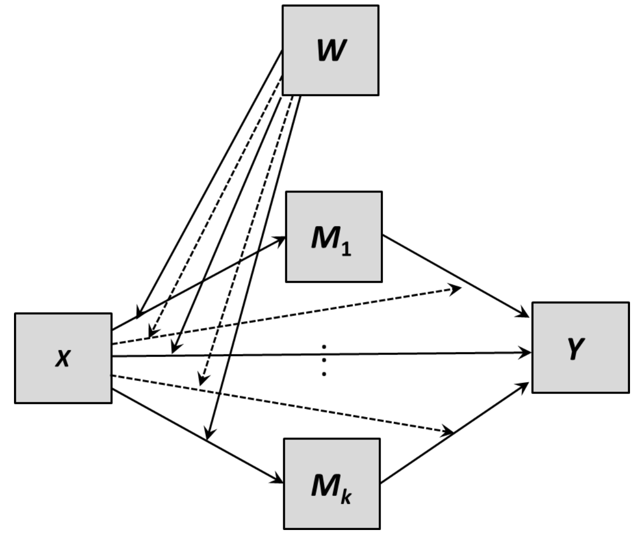
The *index of moderated mediation* was significantly different from zero (-.24 [-.37, -.12]), meaning the **indirect effect through drawing on the feminine self was stronger for women than for men**.

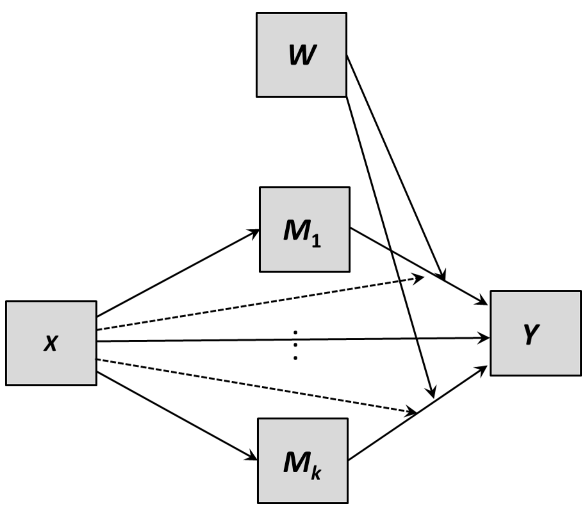
Siy, Germano, Vianna, Azpeitia, Yan, Montoya, Cheryan, in press, *JPSP*

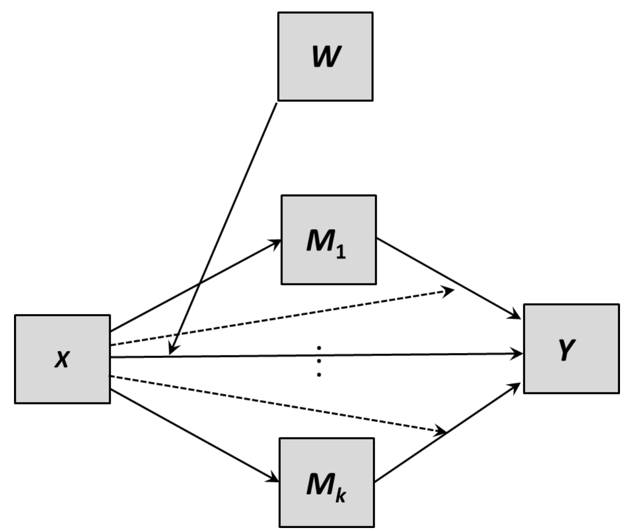
MEMORE V3: MODELS 4 - 18

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









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

COMPARISONS TO OTHER TECHNIQUES

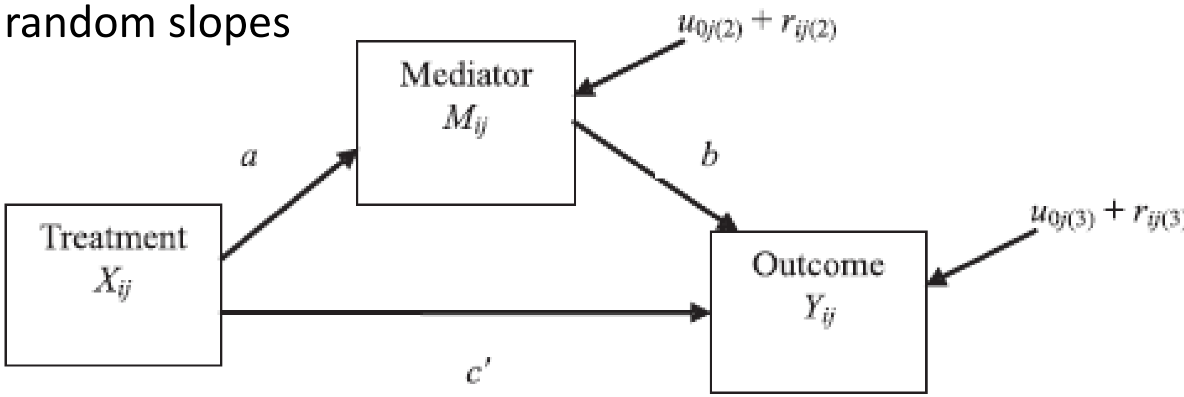
MULTILEVEL MODELING

The model MEMORE fits is equivalent to a random intercept only 1-1-1 mediation model:

- when we have 2 observations per person
- *X* is dichotomous
- each person is observed once for each level of *X*

MLmed is a macro for multilevel mediation

- Syntax is more verbose
- Much more flexible
- Can fit 1-1-1 or 2-1-1 mediations
- Can include covariates, multiple mediators, Level 2 moderators
- Can include random slopes



$$M_{ij} = \gamma_{00(2)} + aX_{ij} + u_{0j(2)} + r_{ij(2)}$$

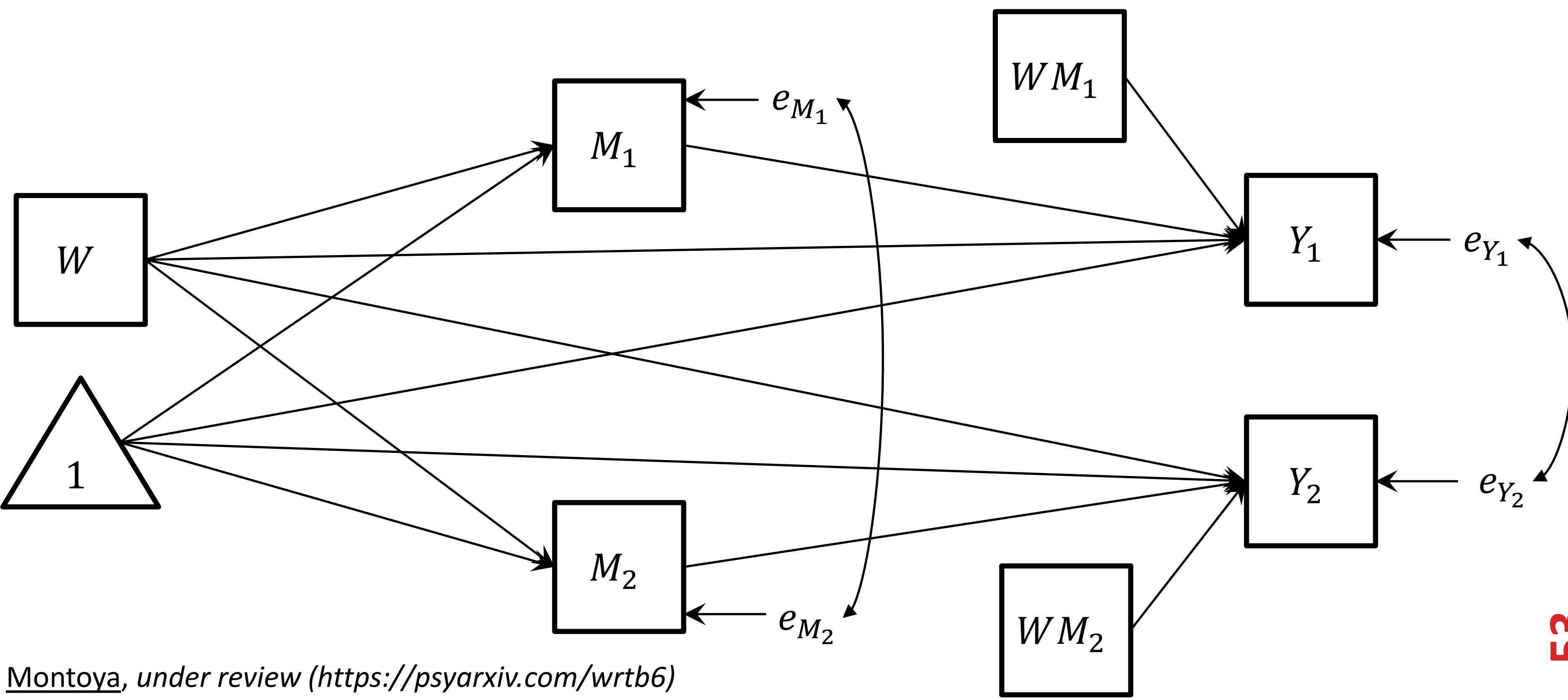
$$Y_{ij} = \gamma_{00(3)} + c'X_{ij} + bM_{ij} + u_{0j(3)} + r_{ij(3)}$$

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

STRUCTURAL EQUATION MODELS

Three SEM approaches which are related to this model:

1. **Simultaneous estimation of equations**
   - Limited advantage over the OLS method
   - Does not scale up well
   - Could incorporate latent variables



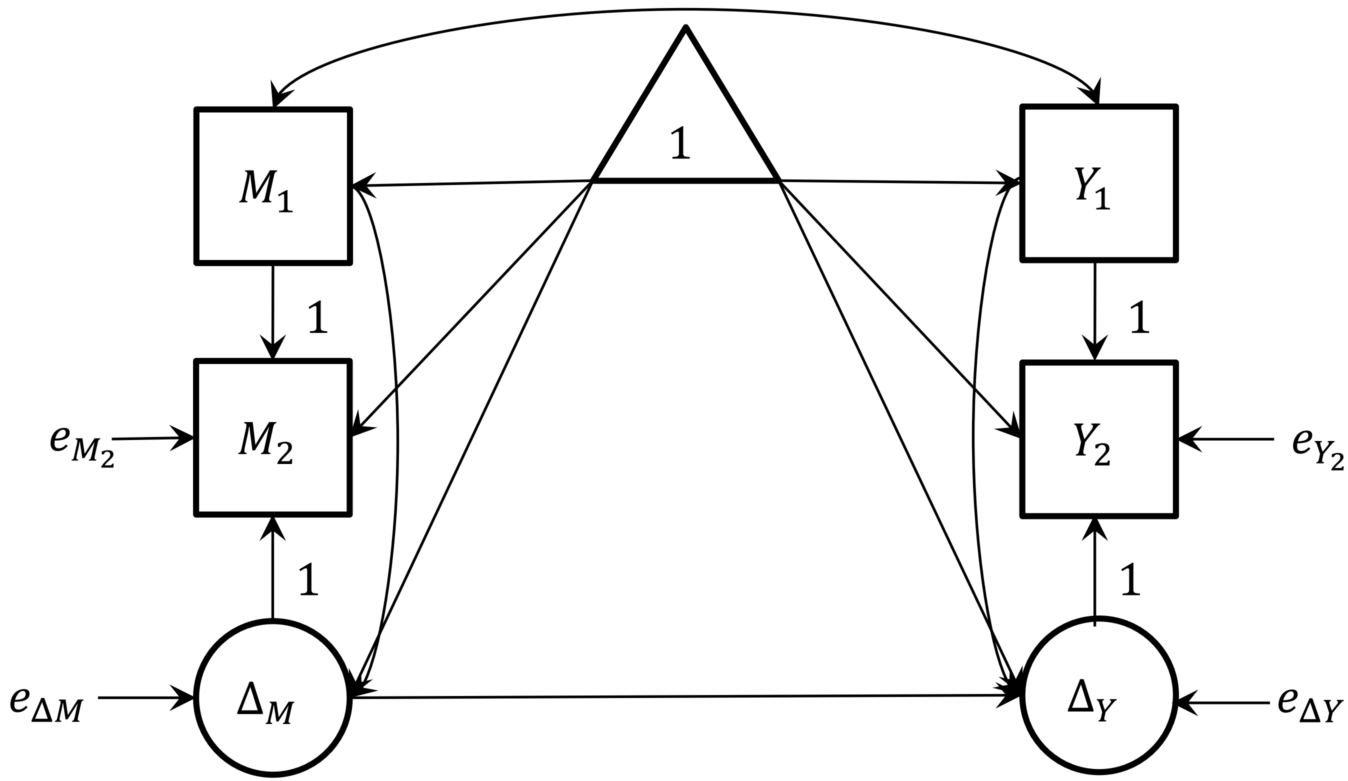
Montoya, *under review (https://psyarxiv.com/wrtb6)*

STRUCTURAL EQUATION MODELS

Three SEM approaches which are related to this model:

2. Latent difference score

- Treats change as latent rather than observed
- Generalizes beyond two-instances (especially repeated-replicates and more timepoints)
- No generalization to conditional process model yet



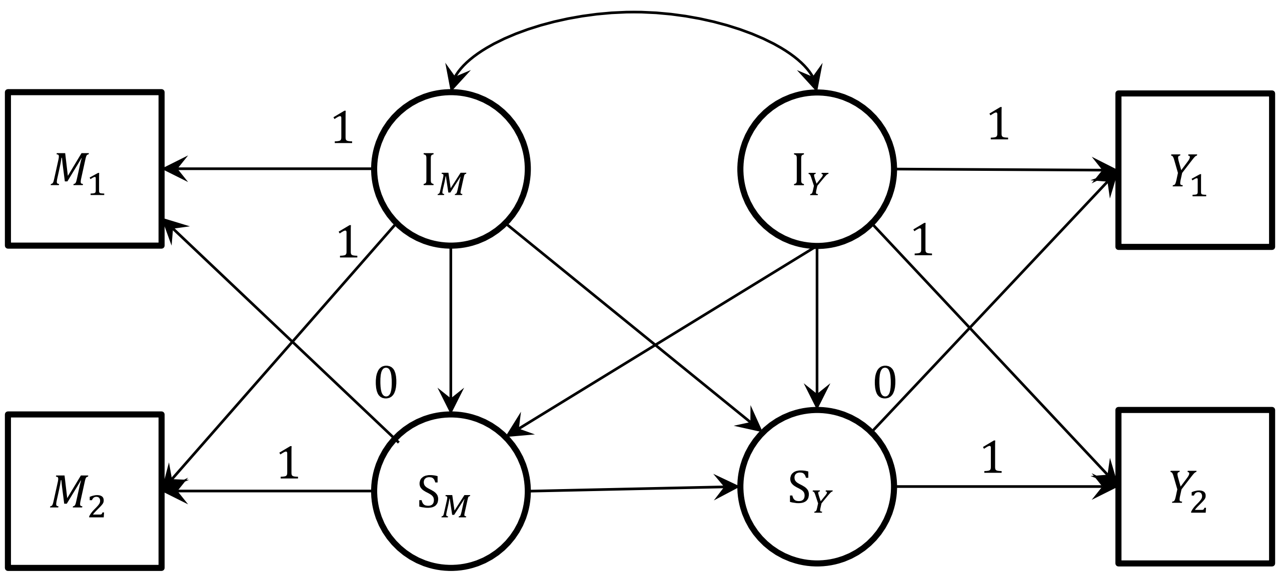
Montoya, *under review (https://psyarxiv.com/wrtb6)*

STRUCTURAL EQUATION MODELS

Three SEM approaches which are related to this model:

3. Latent growth curve model

- Individual differences in intercepts and slopes as latent variables
- Generalizes beyond two time-points (not more conditions)
- No generalization to conditional process model yet



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

FUTURE DIRECTIONS

- 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

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

If you want the beta verion (moderated mediation) email me!

Slides available at
github.com/akmontoya/CAIDe2023