MEDIATION AND MODERATION IN REPEATED MEASURES DESIGNS:

RECENT DEVELOPMENTS AND FUTURE DIRECTIONS

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Slides available at github.com/akmontoya/UCLA2017

Overview

- Personal History and Philosophy
- Introduction to Mediation
- Two-Instance Repeated Measures Designs
    - Mediation
    - Moderation
    - Conditional Process Analysis (AKA Moderated Mediation)
- New Designs & New Questions

Philosophical Approach to Statistics

Quantitative Psychologist (A personal definition)

Evaluate, develop, and improve statistical methods that:

1. are relevant to the types of research questions, and
2. use the types of data collected

in substantive psychology.

- Clinical
- Developmental
- Health
- Personality
- Social
- Cognitive
- Neuroscience
- and more…

Evaluating Methods

- Comparing the performance of multiple methods which are available for the same type of research question and data
- Explore how one type of analysis, traditionally used to answer a different research question, might be useful for a new research question

Examples:

- When assessing conditional moderated mediation, should we use regression based approaches or structural equation modeling approaches?

  Hayes, A. F., **Montoya, A. K.**, & Rockwood, N. J. (2017). The analysis of mechanisms and their contingencies: PROCESS versus structural equation modeling. Australasian Marketing Journal, 25 (1), 76 - 81.

- Can measures of model fit be used to select number of factors in an exploratory factor analysis?

  Montoya, A. K., & Edwards, M. C. (2017, Apr) Cautions on using model t to choose number of factors in EFA. Presented at the 2017 Annual Meeting of the National Council on Measurement in Education, San Antonio, TX.

- Can models like mediation and moderated-mediation be used to better understand and predict differential item functioning in item response theory?

  Montoya, A. K. & Jeon, M. (in prep) MIMIC models for testing uniform and non-uniform differential item functioning as moderated mediation models.

Developing New Methods

Research Question
- Comparing means?
- Relationship between variables?
- Explaining a process?

Properties of the Data
- Independent vs. Paired Data
- Level of measurement
- Multilevel / Longitudinal

Identify combination where researchers **want** to be able to answer the research question with this specific type of data

Question: How does a treatment condition compare to a control?

Data: Multiple control conditions collected

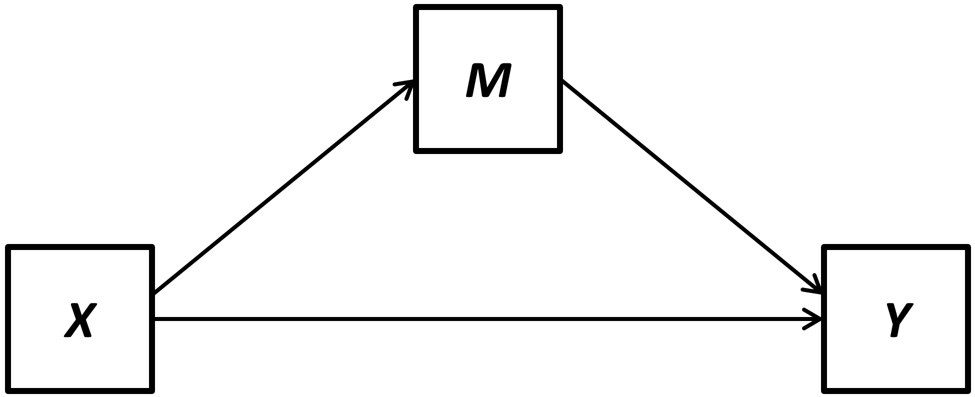
Montoya, A. K., Flaherty, B., & Cheryan, S. (2015, Feb) Collapsing conditions increasing type I error: Changing analysis of multiple control conditions. Presented at the Annual Meeting of the Society for Personality and Social Psychology, Long Beach, CA.

Question: For what levels of a moderating variable do groups differ on some outcome?

Data: More than two groups

Hayes, A. F., & **Montoya, A. K.** (2017). A tutorial on testing, visualizing, and probing an interaction involving a multicategorical variable in linear regression. Communication Methods and Measures, 11 (1), 1-30.

Question: What Explains an Effect?



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

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

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.

<u>Causality: </u>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.

Examples of Mediation in Psychology

Developmental Psychobiology

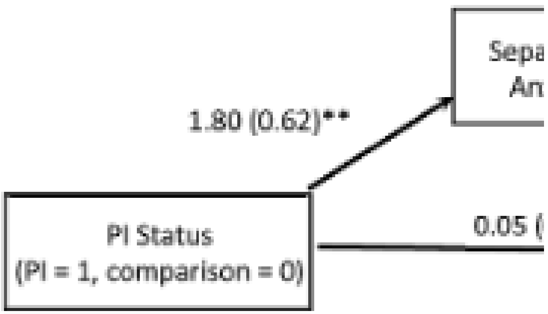


FIGURE 4 Mediation model anxiety, and exploitation. Note: coefficients (SE). PI = previous
** $p < .01$.

ann. behav. med. (2017) 51:683-
DOI 10.1007/s12160-017-9892-

ORIGINAL ARTICLE

Helping Yours
Helping in Sur

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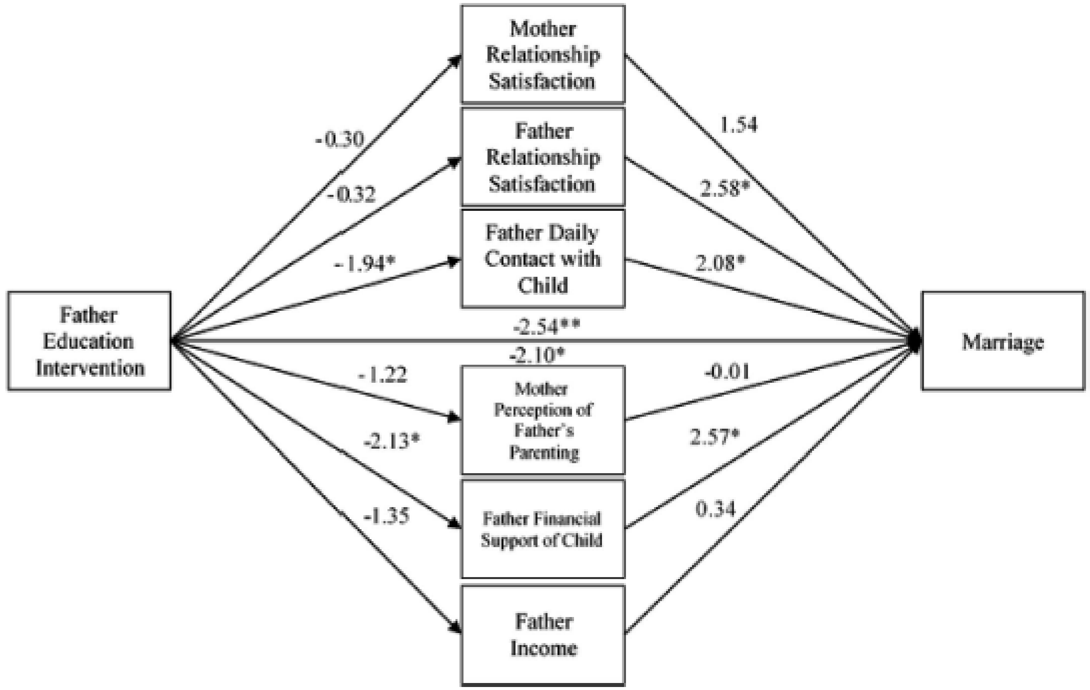
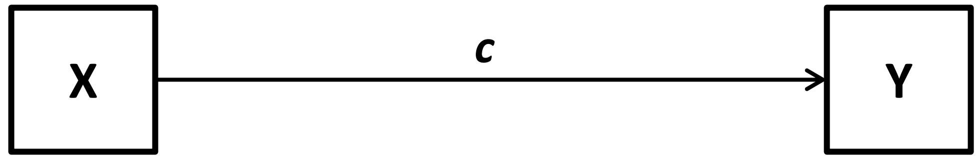


Figure 2. The negative association between educational interventions and 36-month marriage rates is mediated by reductions in fathers' daily contact with the child and fathers' financial support of the child after 15 months. Values shown are standardized regression coefficients. * $p < .05$; ** $p < .01$.

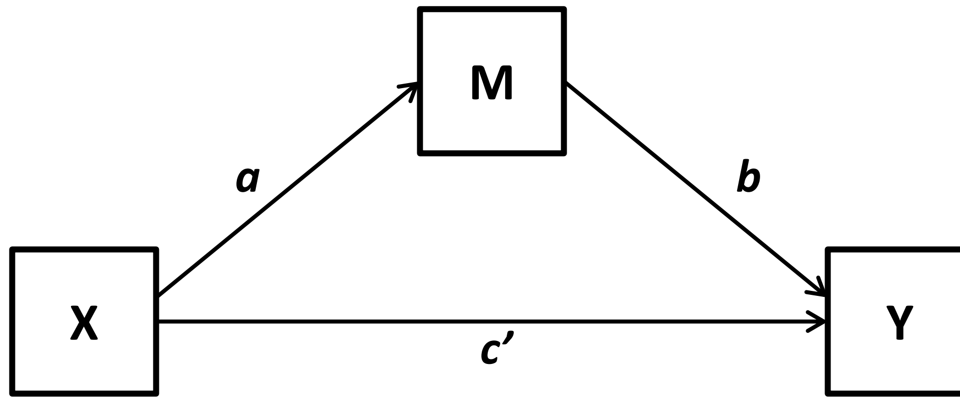
Mediation: Path Analysis

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

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



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



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

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

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

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

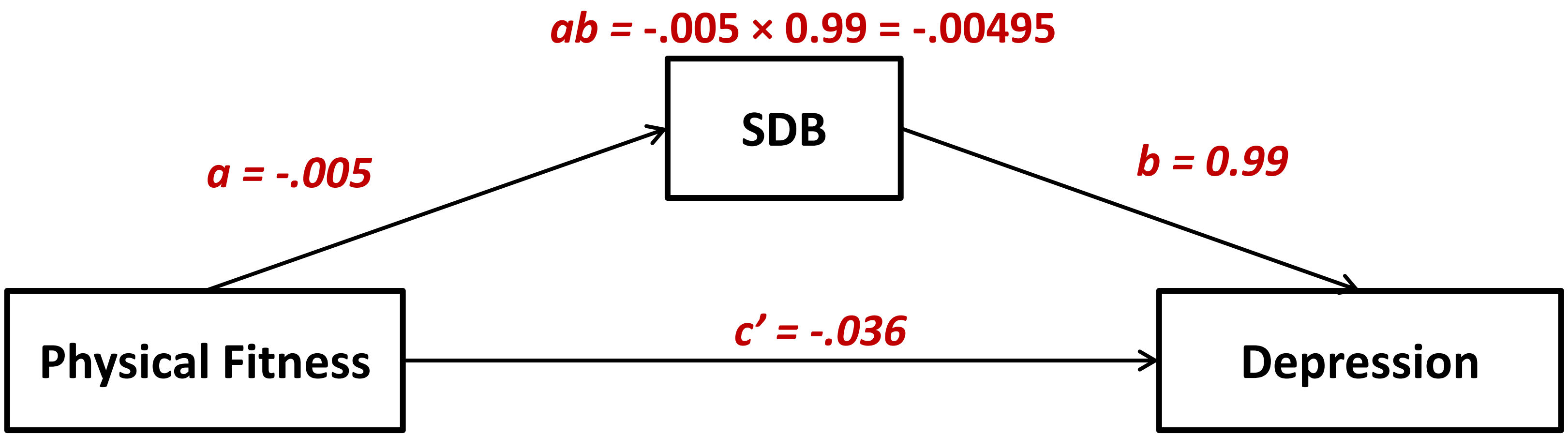
Indirect effect = total effect - direct effect

$a \times b \quad = \quad c \quad - \quad c'$

Total effect = direct effect + indirect effect

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

Does Physical Fitness Impact Depression Through Sleep Disordered Breathing (SDB)?



Increase in physical fitness results in a *reduction* in sleep disordered breathing.

Controlling for physical fitness, increase in sleep disordered breathing results in an *increase* in depression

Indirect Effect: We estimate increase in physical fitness leads to a decrease in depression *through sleep disordered breathing*.

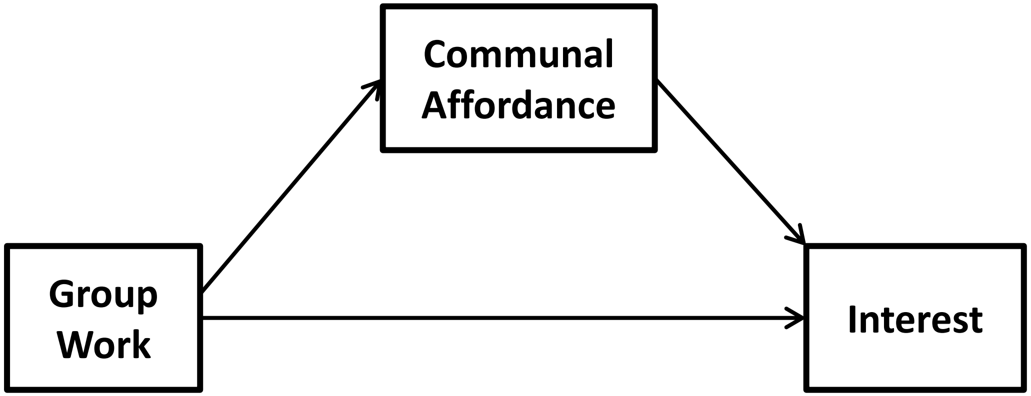
Direct Effect: Controlling for sleep disordered breathing, increase in physical fitness lead to a *decrease* in depression

Stojek, M. K., **Montoya, A. K.**, Drescher, C., Newberry, A., Sultan, Z., Williams, C. F., Pollock, N. K., & Davis, C. L. (in press) Fitness, sleep-disordered breathing, depression symptoms, and cognitive outcomes in overweight inactive children: A mediation model. *Public Health Reports. SHAPE Special Issue.*

What if I Use a Within-Subjects Design?

What if *X* is something we manipulate within-subjects instead of a between-subjects variable?

Study examining how group work in computer science classes might impact women's interest in computer science.



Study 1: Randomly assign individuals to read a computer science syllabus with group work or without group work

Study 2: Everyone reads two syllabi, one with group work and one without.

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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: Therapist measures certain symptoms and various outcomes before administering some intervention, and after administering the intervention.

Non-Examples:

- Levels of *X* are measured, not manipulated.
- Any instance where repeated-measure factor is a “nuisance” (e.g. studying schools, but not interested in comparing schools directly).

Judd, Kenny, and McClelland (2001)

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

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

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

   Paired *t*-test on *Y*'s

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

   Paired *t*-test on *M*'s

3. Does difference in *M* predict a difference in *Y*?

$$\widehat{Y_{1i} - Y_{2i}} = \widehat{c'} + \boxed{\hat{b}}(M_{1i} - M_{2i}) + \hat{d}\left(M_{1i} + M_{2i} - \frac{1}{n}\sum_{i=1}^{n}(M_{1i} + M_{2i})\right)$$

4. Does the difference in *M* account for all the difference in *Y*?

$$\widehat{Y_{1i} - Y_{2i}} = \boxed{\widehat{c'}} + \hat{b}(M_{1i} - M_{2i}) + \hat{d}\left(M_{1i} + M_{2i} - \frac{1}{n}\sum_{i=1}^{n}(M_{1i} + M_{2i})\right)$$

Montoya & Hayes, 2017

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

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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

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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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- Criticisms of approach outlined by Judd, Kenny, and McClelland
- Path-analytic approach to mediation in two-instance repeated-measures designs
- Generalization to multiple mediator models
    - Parallel Mediation
    - Serial Mediation

Montoya & Hayes, *2017*

Judd Criticisms and Misuses

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

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

This method has been used by a variety of researchers:

- Approximately 300 citing papers, with around 140 using this method
- Many researchers do not report or estimate the partial regression coefficient for the sum of the mediators
- Because the estimate of the indirect effect is not made explicit, researchers often misinterpret the coefficients
  - b path is often interpreted as indirect effect
- Extensions to more complicated models have been poorly implemented

Advantages of the Path-Analytic Approach

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

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 & Hayes, 2017

Path-Analytic Method for Two-Instance Repeated-Measures Design

Total Effect c:

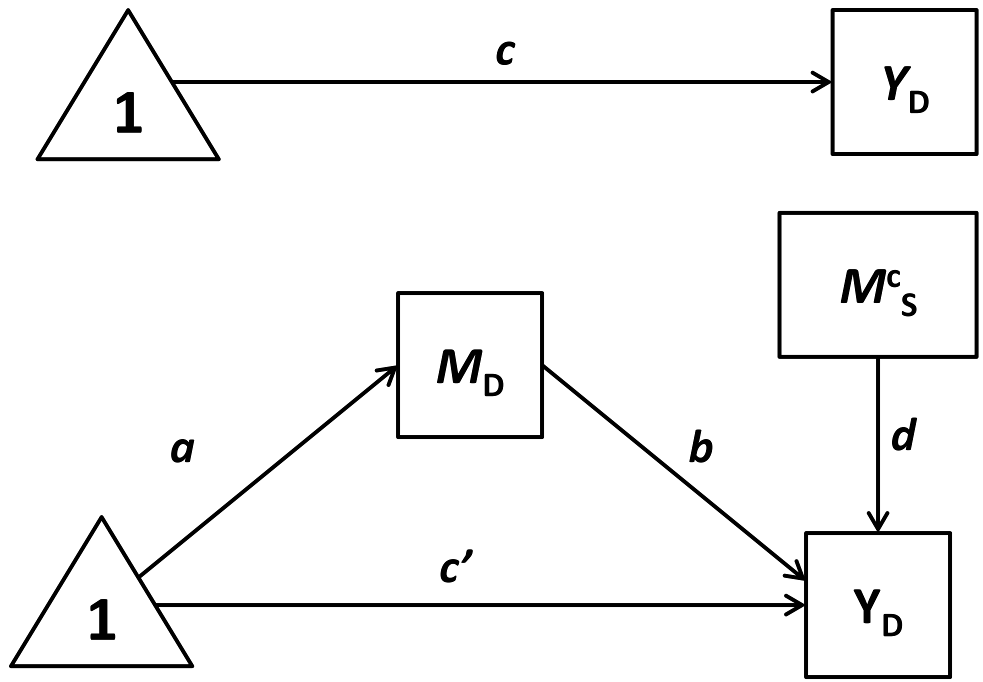
$$Y_{2i} - Y_{1i} = c + \epsilon_{Y^*i}$$

a path:

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

b path and c' path:

$$Y_D = c' + bM_\mathrm{D} + dM_\mathrm{S}^c + \epsilon_{Yi}$$



[c] Indicates mean centered

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

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

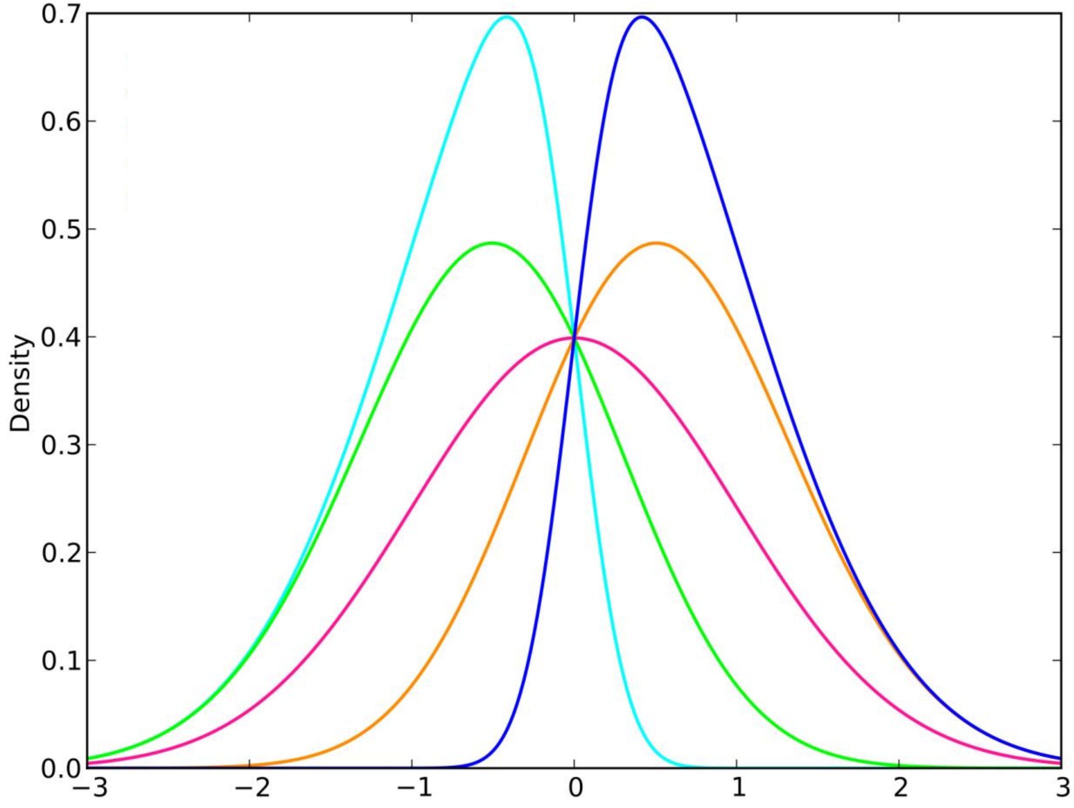
Note: M_s must be mean centered for c' to have intended interpretation

Montoya & Hayes, 2017

Inference about the Indirect Effect

Why is this so hard?

- The product of two normal distributions is not necessarily normal. The shape of the distribution of the indirect effect depends on the true indirect effect.
- There are many instances where the null hypothesis (*ab* = 0) could be true



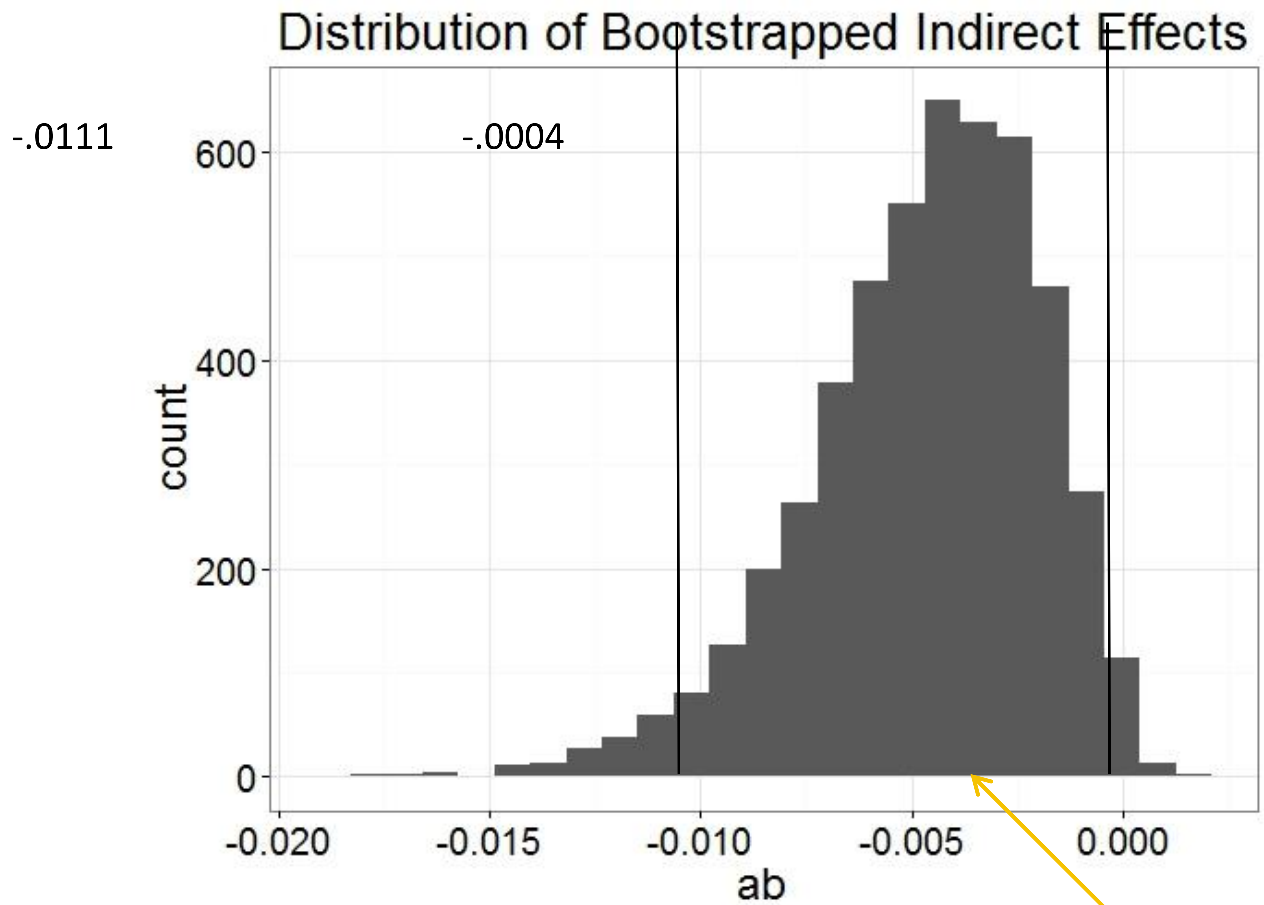
Bootstrap Confidence Intervals (Percentile)

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

Method

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

Bootstrap Confidence Intervals



ab = -.0047

Zero is not contained in the confidence interval [-.0111, -.0004] so we conclude the indirect effect is different from zero with 95% confidence.

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Appeal

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

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

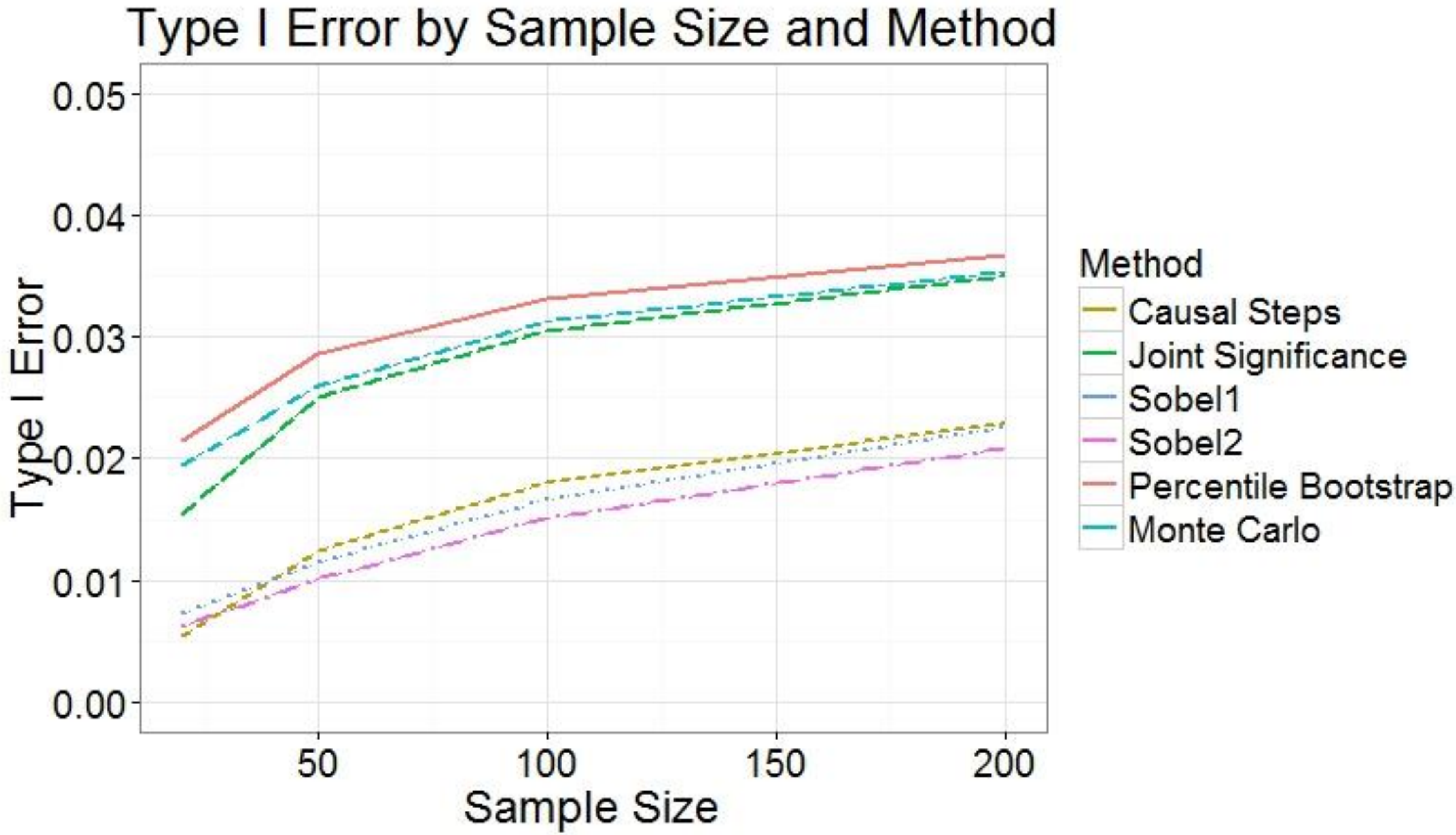
Some combination were impossible, which left 6848 conditions

Generated 1000 data sets per condition

Used each method of inference on each dataset

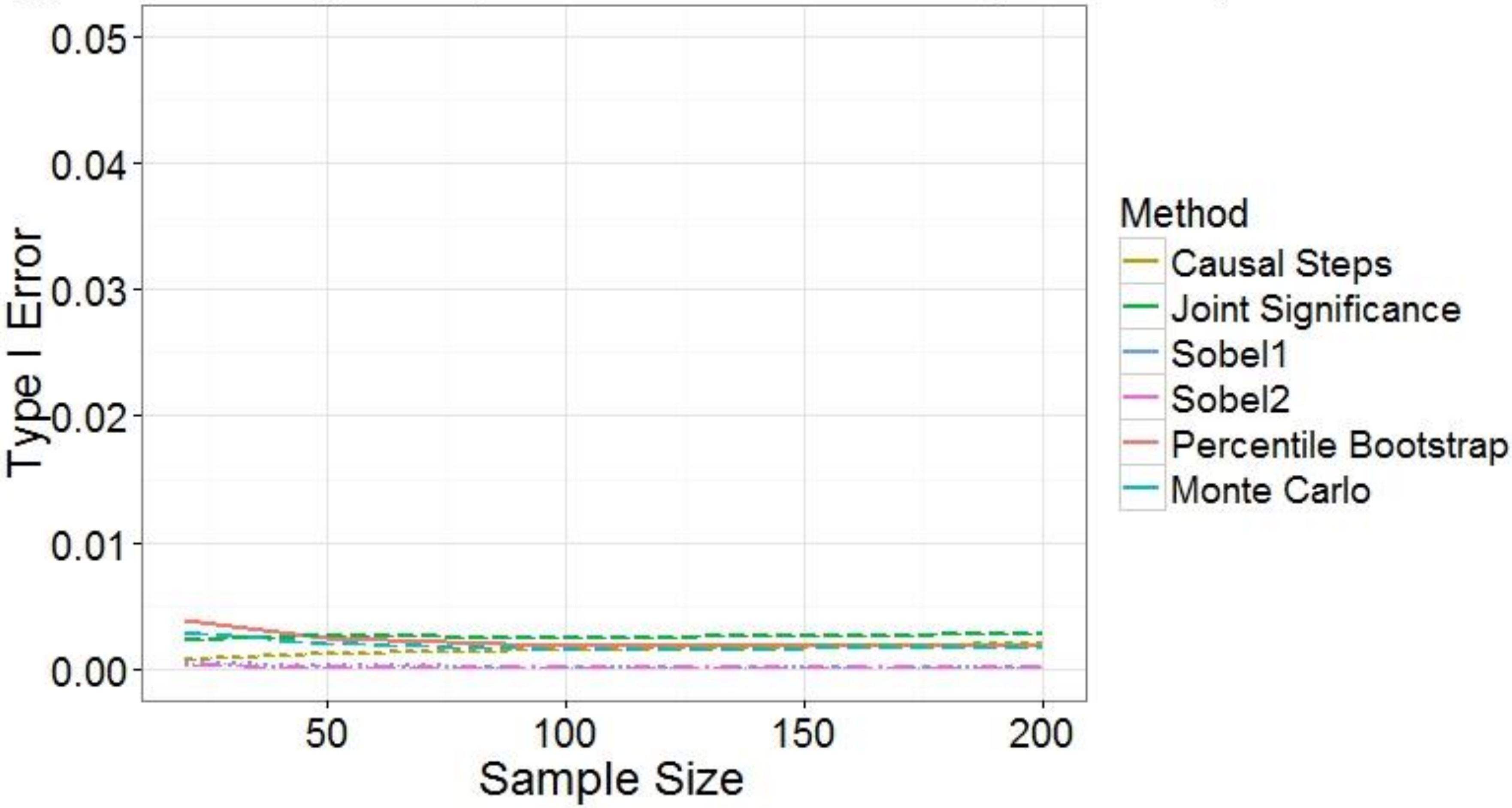
Recorded rejection rate for each method in each condition (α = .05)

Montoya, 2017, *SEPA*



Type I Error by Sample Size and Method
Type I Error
0.05
0.04
0.03
0.02
0.01
0.00
50
100
150
200
Sample Size
Method
Causal Steps
Joint Significance
Sobel1
Sobel2
Percentile Bootstrap
Monte Carlo

Type I Error by Sample Size and Method (a & b = 0)



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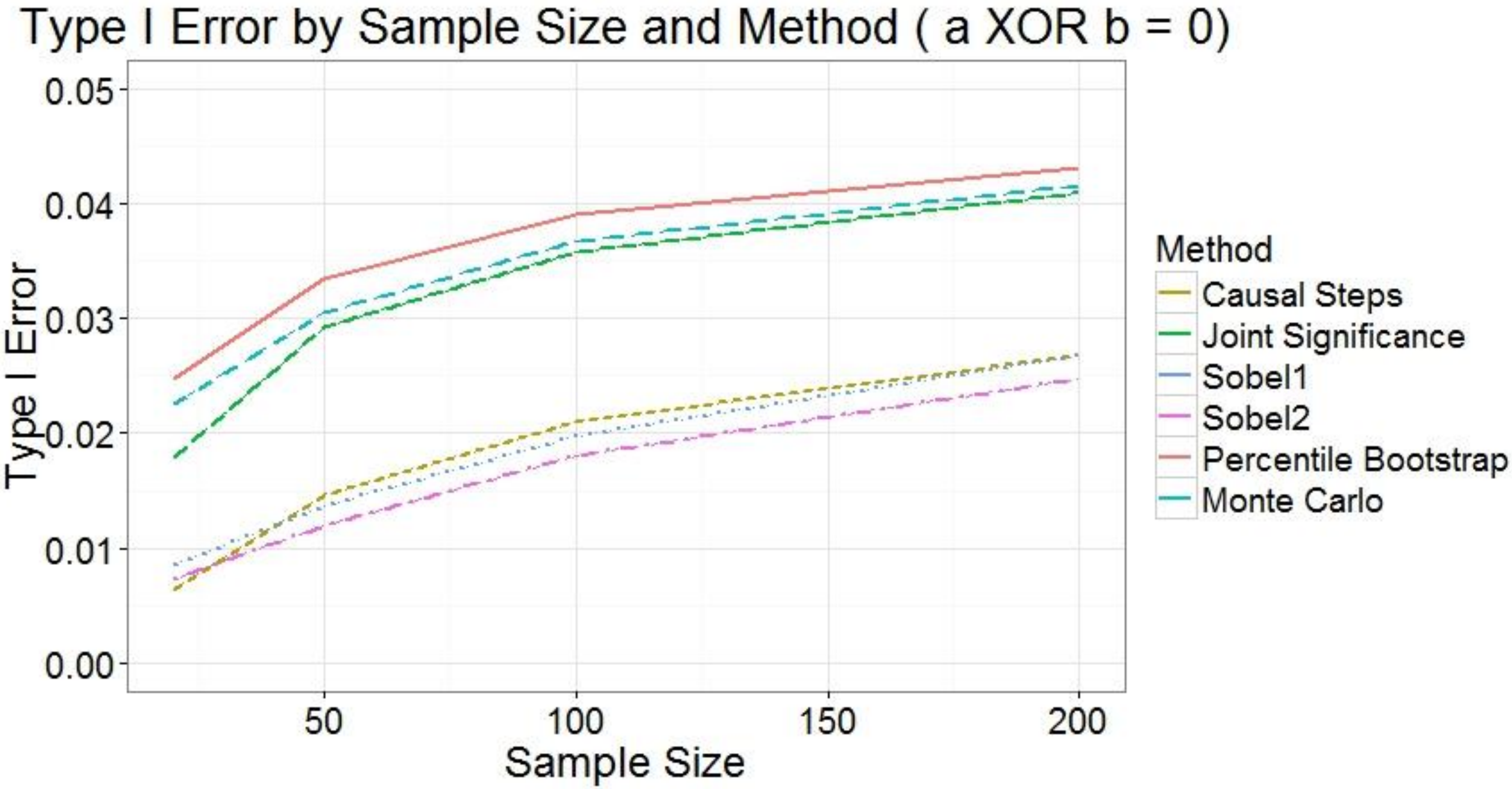

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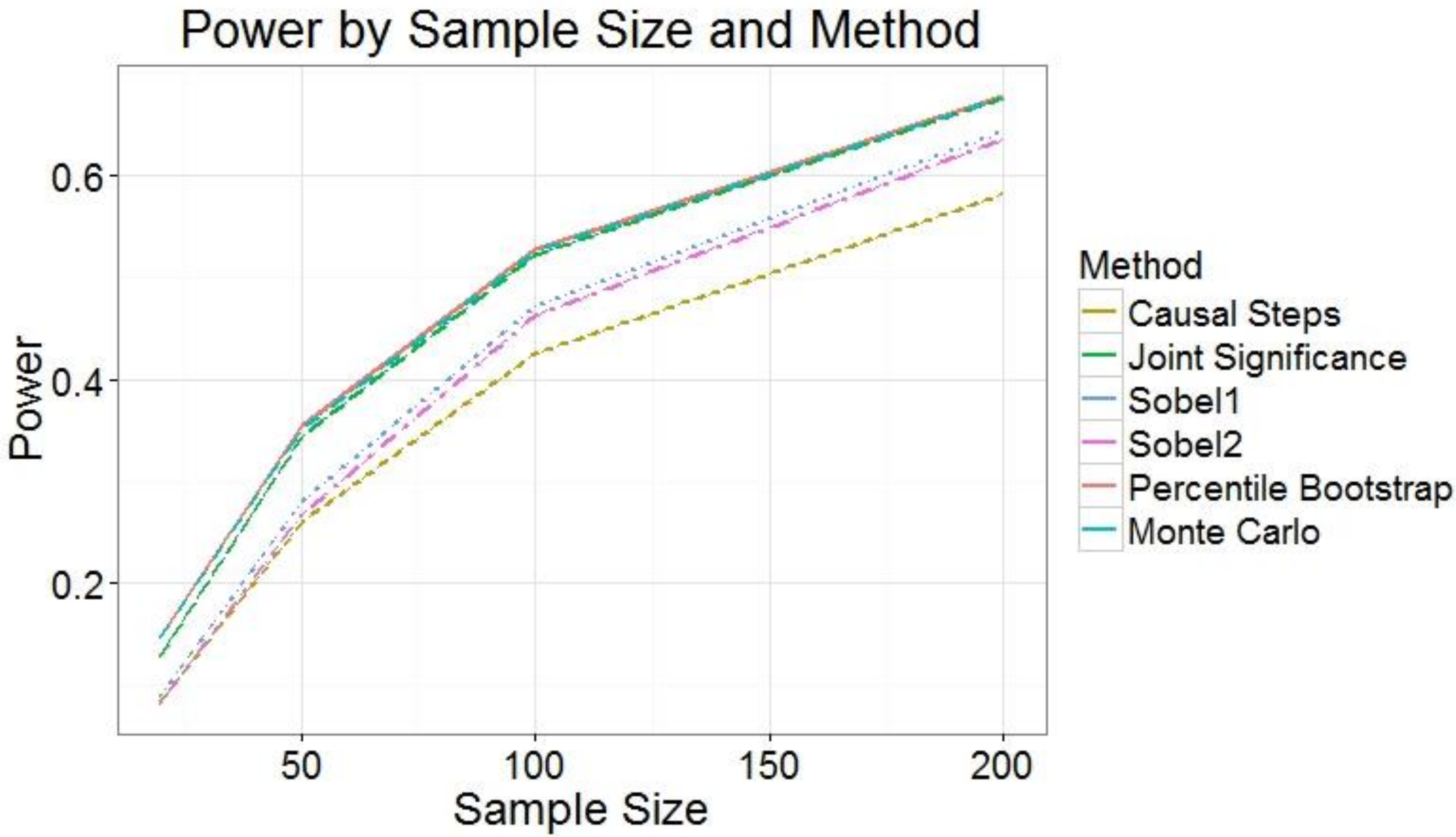

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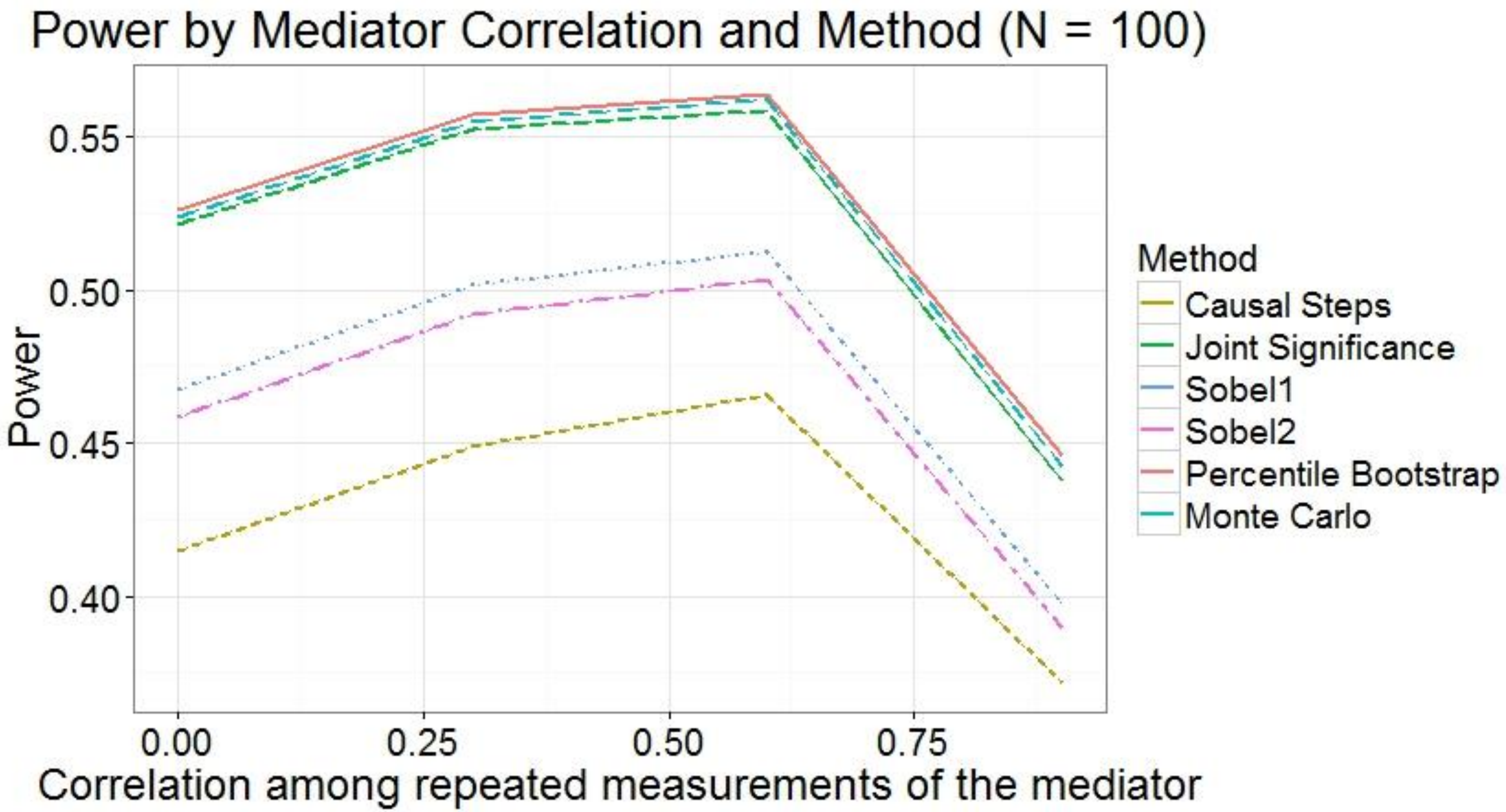

Montoya, 2017, *SEPA*

Implications

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

provide point estimates and confidence intervals for the indirect effect

- Within-subjects designs buy 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)

So if it's better, how do we do it?

Montoya, 2017, *SEPA*

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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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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6

- MEMORE can assess 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);
```

Coming in 2019: *Statistical mediation analysis: Within-subjects designs.* By Hayes, Montoya, Preacher, and Page-Gould. Guilford Press

Montoya & Hayes, *2017*

```
************************** MEMORE Procedure for SPSS *************************
Variables:
Y = buy2     buy1
M = hazard2  hazard1

Computed Variables:
Ydiff =          buy2       -        buy1
Mdiff =          hazard2    -        hazard1
Mavg =  (        hazard2    +        hazard1  )         /2        Centered

Sample Size:   22
```

Model Information

```
******************************************************************************
Outcome: Ydiff =  buy2       -        buy1

Model
        Effect         SE          t         df          p       LLCI       ULCI
'X'     -.5636      .1932    -2.9168    21.0000      .0082     -.9655     -.1618
```

Total Effect Model

```
******************************************************************************
Outcome: Mdiff =  hazard2    -        hazard1

Model
        Effect         SE          t         df          p       LLCI       ULCI
'X'      .8000      .2579     3.1024    21.0000      .0054      .2637     1.3363
```

Model for M_2-M_1

```
******************************************************************************
Outcome: Ydiff =  buy2       -        buy1

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .7721      .5961      .3667    14.0213     2.0000    19.0000      .0002

Model
           coeff         SE          t         df          p       LLCI       ULCI
'X'       -.0851      .1577     -.5399    19.0000      .5955     -.4152      .2449
Mdiff     -.5981      .1131    -5.2869    19.0000      .0000     -.8349     -.3613
Mavg      -.1818      .1683    -1.0803    19.0000      .2935     -.5341      .1705
```

Model for Y_2-Y_1

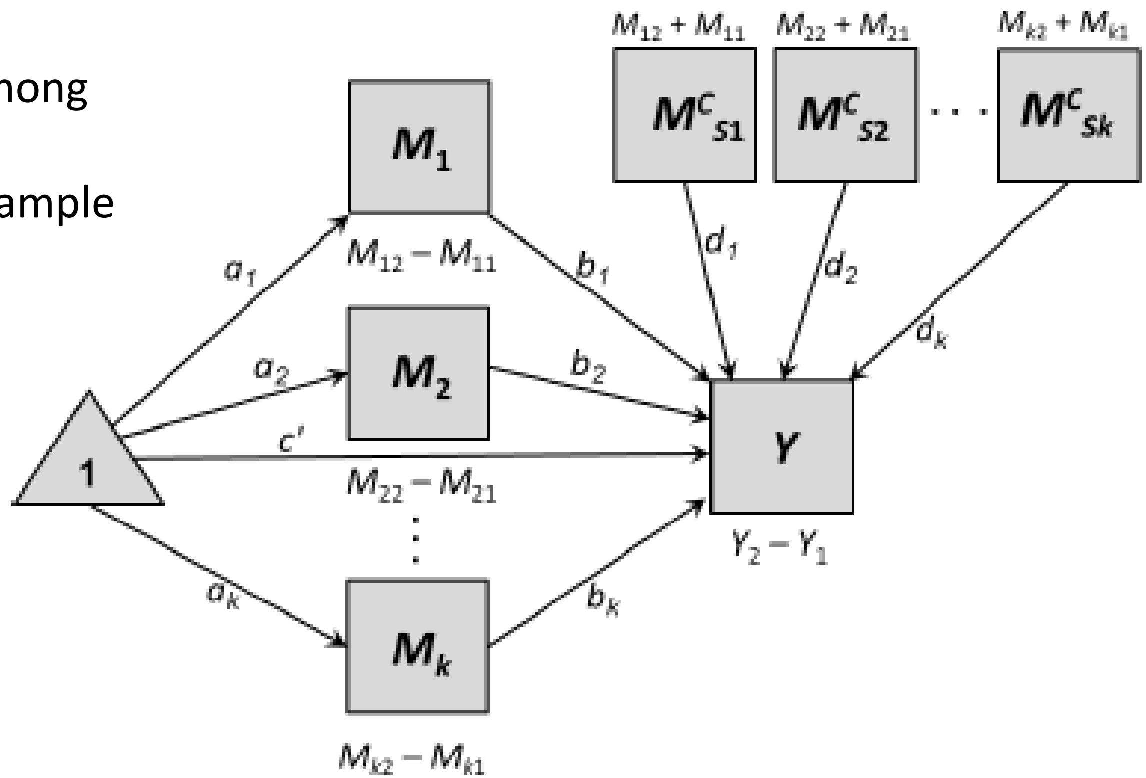
```
********************* TOTAL, DIRECT, AND INDIRECT EFFECTS *********************

Total effect of X on Y
     Effect         SE          t         df          p       LLCI       ULCI
     -.5636      .1932    -2.9168    21.0000      .0082     -.9655     -.1618

Direct effect of X on Y
     Effect         SE          t         df          p       LLCI       ULCI
     -.0851      .1577     -.5399    19.0000      .5955     -.4152      .2449

Indirect Effect of X on Y through M
          Effect     BootSE   BootLLCI   BootULCI
Ind1      -.4785      .1363     -.7423     -.2063

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

Total, Direct, and Indirect Effects

Multiple Mediation Models: Parallel

Simple or Multiple Parallel Mediation

- Up to 5 mediators
- Three methods of inference
  - Sobel test
  - Monte Carlo CI
  - Bootstrapping (Percentile or BC)
- Pairwise contrasts among indirect effects
- Can save bootstrap sample

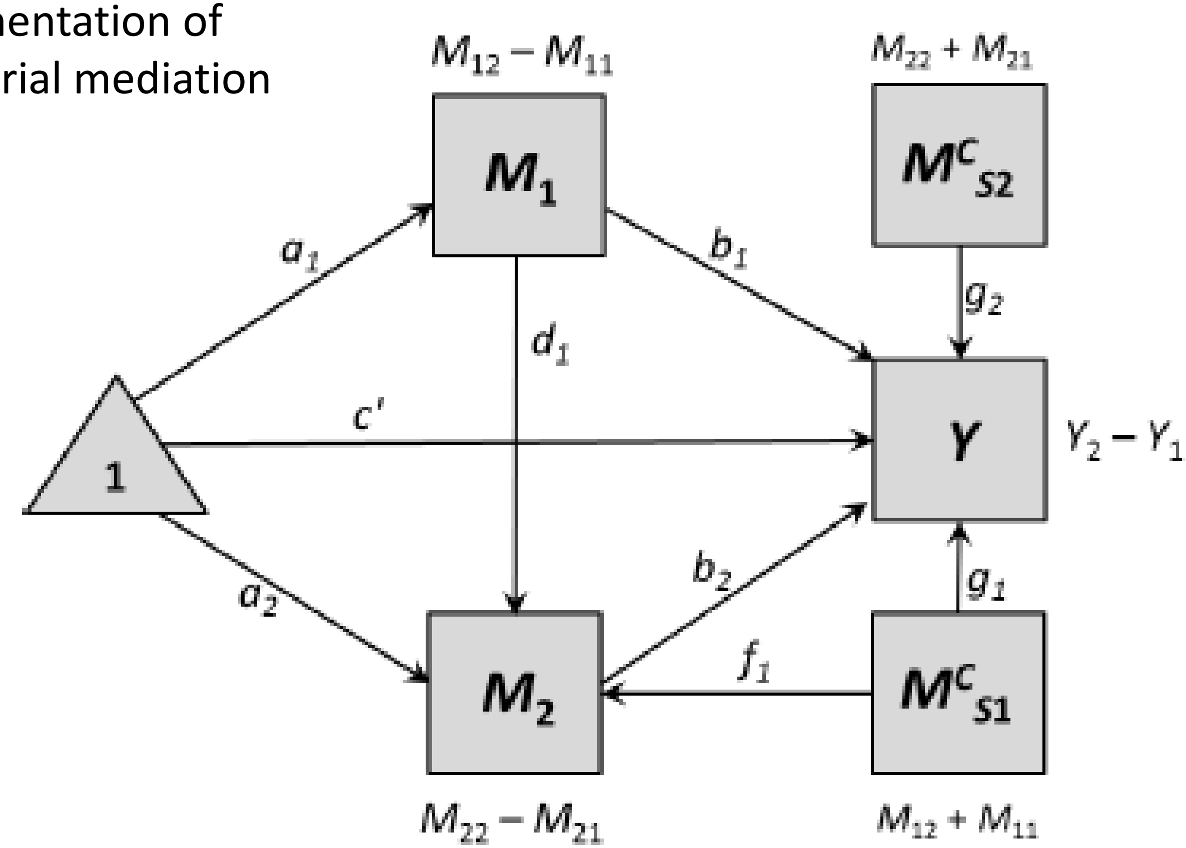


Montoya & Hayes, *2017*

Multiple Mediation Models: Serial

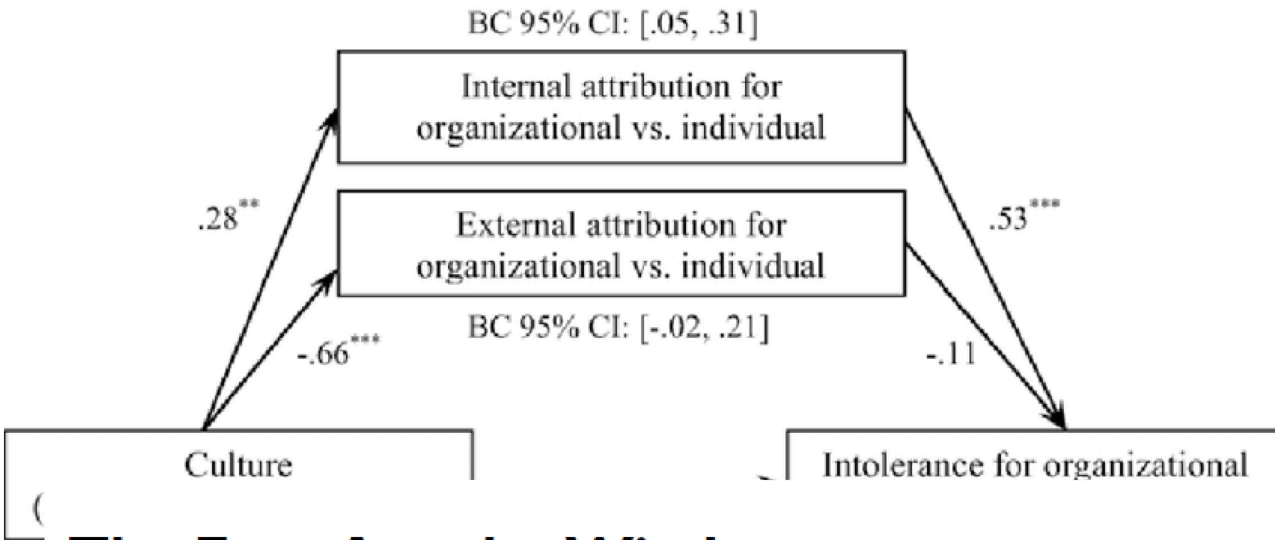
Serial Mediation

- Add `serial = 1`
- Current version: 2 mediators
- New version: Up to 5 mediators
- Serial argument will lead to easier implementation of moderated serial mediation



Montoya & Hayes, *2017*

Examples of Using MEMORE



542/17/$12.00 http://dx.doi.org/10.1037/emo0000271

s of Being Moved

ert and Janis H. Zickfeld

The Eyes Are the Windows to the Mind: Direct Eye Gaze Triggers the Ascription of Others' Minds

Personality and Social
Psychology Bulletin
2016, Vol. 42(12) 1666–1677

DOI: 10.1177/0146167216669124
pspb.sagepub.com
SAGE

Saara Khalid[1], Jason C. Deska[1], and Kurt Hugenberg[1]

Intermediary Influence of the Brain

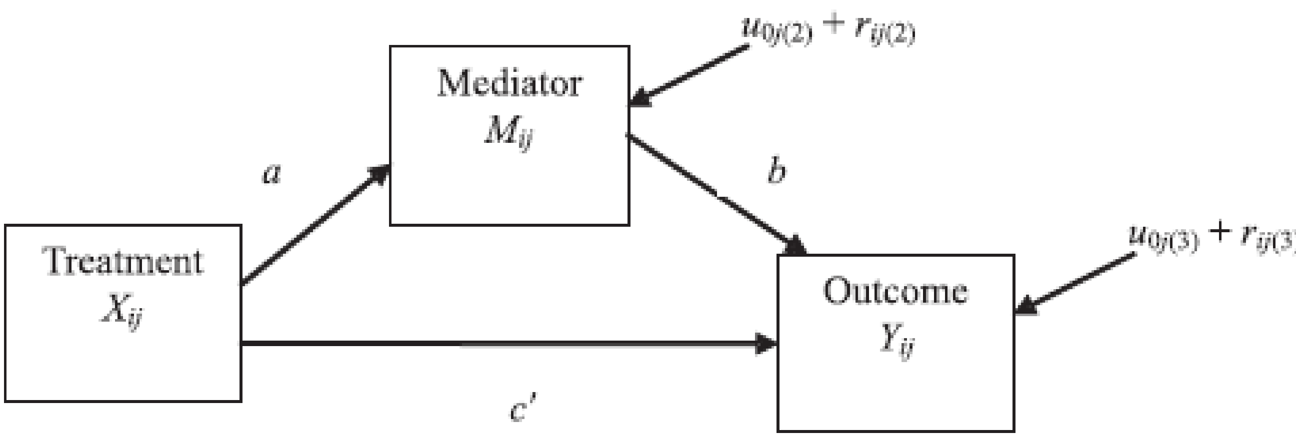
Siobhán Harty, Francesco Sella and Roi Cohen Kadosh*

Department of Experimental Psychology, University of Oxford, Oxford, UK

Evaluating Methods

- Need to compare and evaluate when certain methods are better than others, and provide reasonable recommendations to substantive researchers about when to use which method.

- Alternative methods may be useful for answering these questions
  - Structural Equation Modeling
  - Multilevel Modeling



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

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

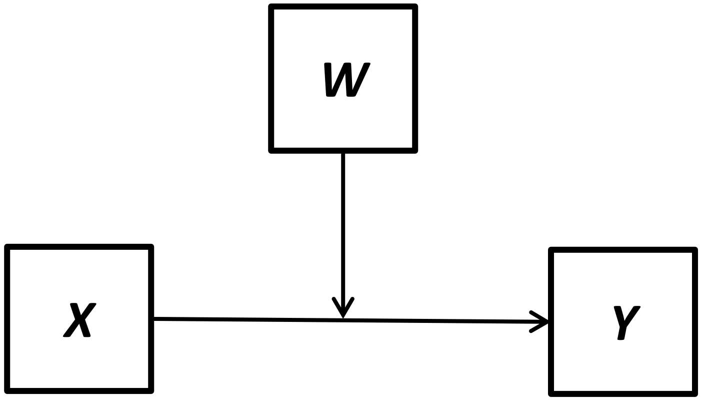
Preacher, Montoya, Hayes; Montoya, *dissertation*

Overview

- Personal History and Philosophy
- Introduction to Mediation
- Two-Instance Repeated Measures Designs
  - Mediation
  - **Moderation**
  - Conditional Process Analysis (AKA Moderated Mediation)
- New Designs & New Questions

Moderation: A New Question

What does this relationship depend on?
When does an effect exist or not exist?
When is it positive and when is it negative?



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*.

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

X and *W* are frequently described as “interacting” in their prediction of *Y*.

Examples of Moderation in Psychology

E.E. Accortt et al.

Development and Psychopathology **28** (2016), 447–457

doi:10.1017/S0954579415000498

Genetic moderation of the as
romantic involvement and de
serotonin transporter
and family discord

LISA R. STARR[a] AND CONSTANC
[a]*University of Rochester; and* [b]*Universit*

Journal of Intellec

N. V. Rodas *et al.*

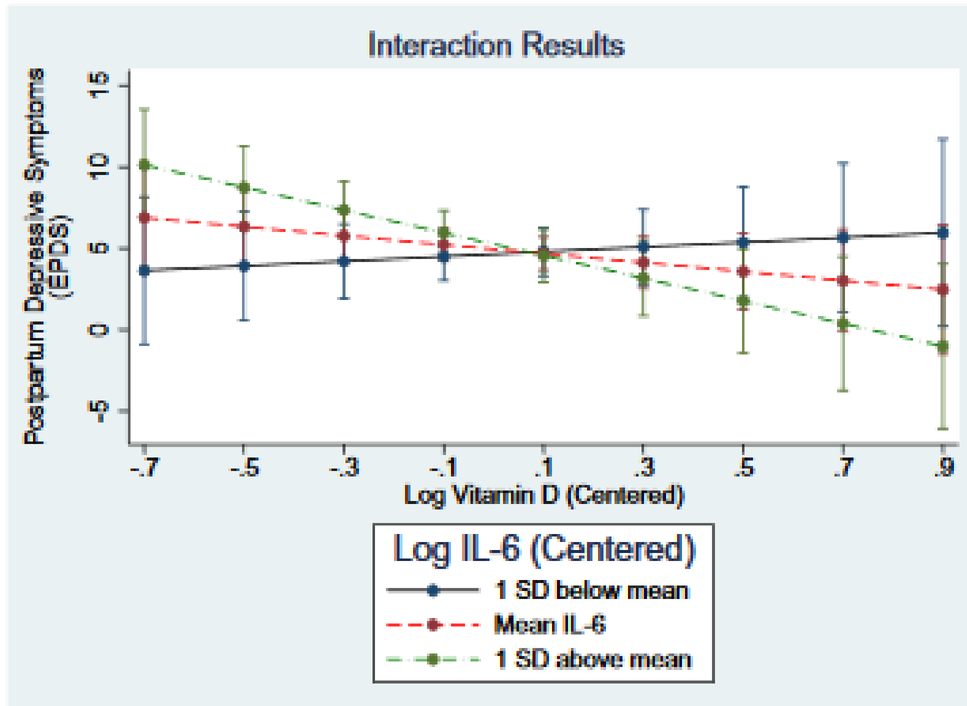


Fig. 1 Interleukin-6 (IL-6) significantly moderates the relationship between log 25(OH)D and EPDS

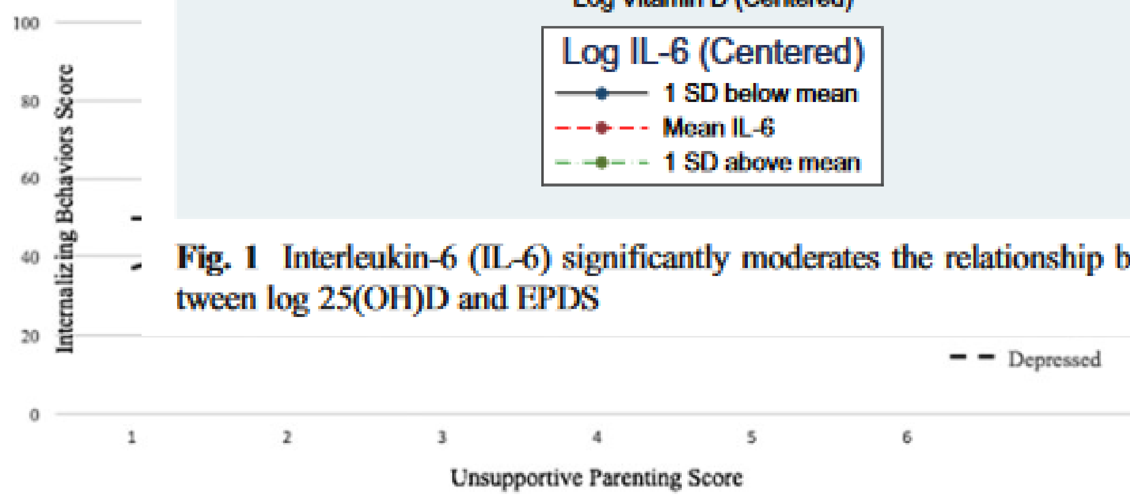


Figure 1 Interaction between father unsupportive parenting and father depression on child internalising behaviour problems.

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.

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Does the degree to which *W* predicts *Y* depend on which instance a person is in?

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**.

Moderation in Two-Instance Repeated-Measures Designs

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

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

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

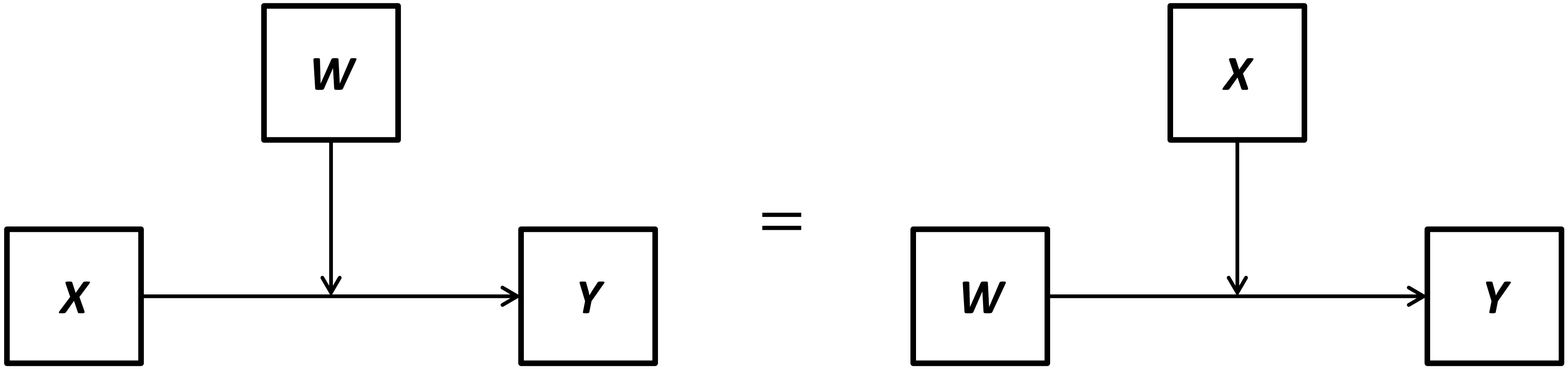
Symmetry in Within-Subjects Moderation

Does the effect of instance depend on *W*?

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

$Y_{2i} - Y_{1i}$ is a quantification of the effect of instance, which means that if *W* predicts $Y_{2i} - Y_{1i}$ then the effect of instance depends on *W*.

b_1 is a test of exactly that!



What's Missing?

- Probing Conditional Effects
  - Pick-a-point approach
  - Johnson-Neyman
- How to deal with multiple moderators
  - Three-way interacts etc.
  - Multiple two-way interactions

Issues all addressed in Montoya (*under review*) Moderation analysis in two-instance repeated-measures designs: Probing methods and multiple moderator models

Montoya, *under review*

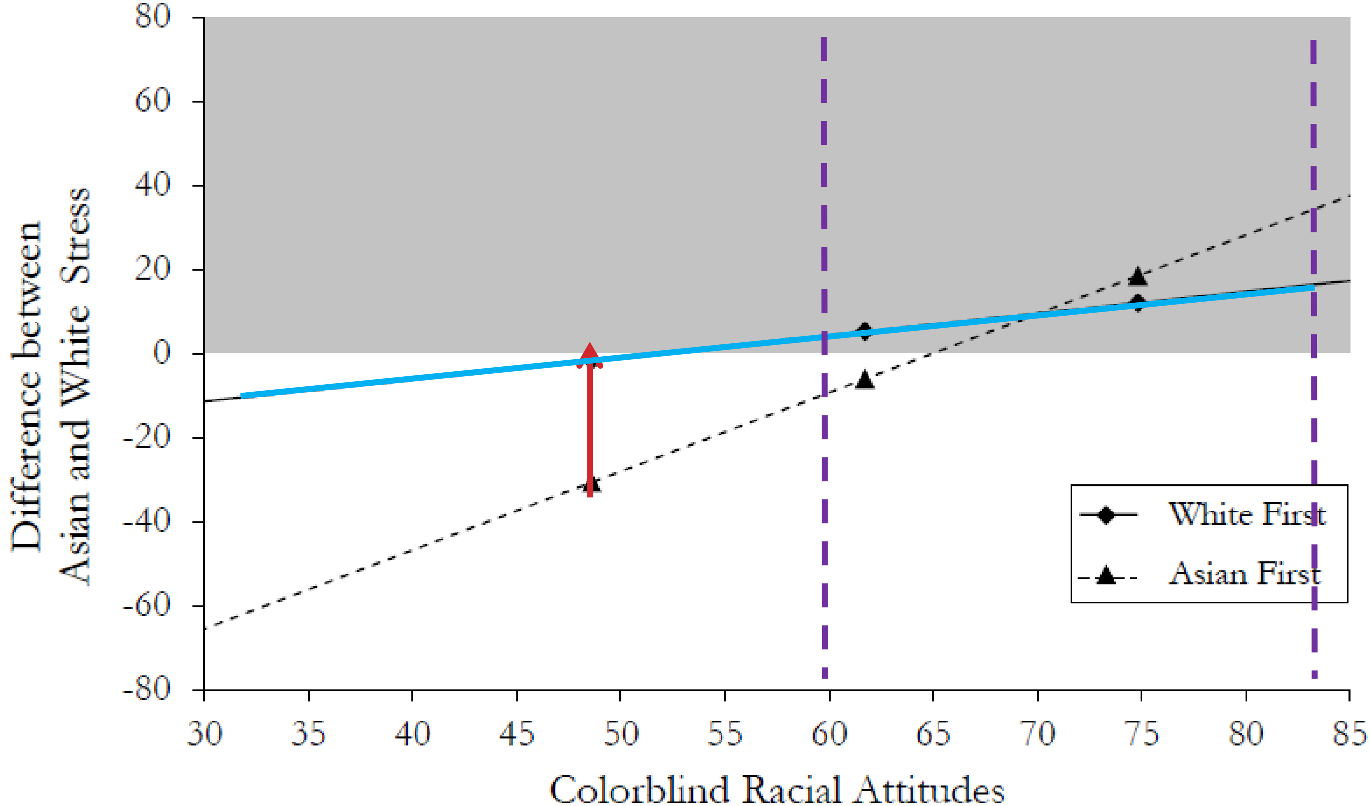
Does the effect of avatar race on stress depend on colorblind racial attitudes?

Sample of 28 white American college students successively operate Black, Asian, and White racialized avatars in predominantly White environment in Second Life

X: Avatar Race (White, Black, Asian)

W: Colorblind Racial Attitudes

Y: Stress as measured by heart rate variability



Tawa, J. & **Montoya, A. K.** (under review) White students physiological stress while operating non-White avatars and the moderating role of awareness of racial privilege.

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

Select a value of the moderator (W)

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

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

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

Squared standard error of b_0

Covariance of b_0 and b_1

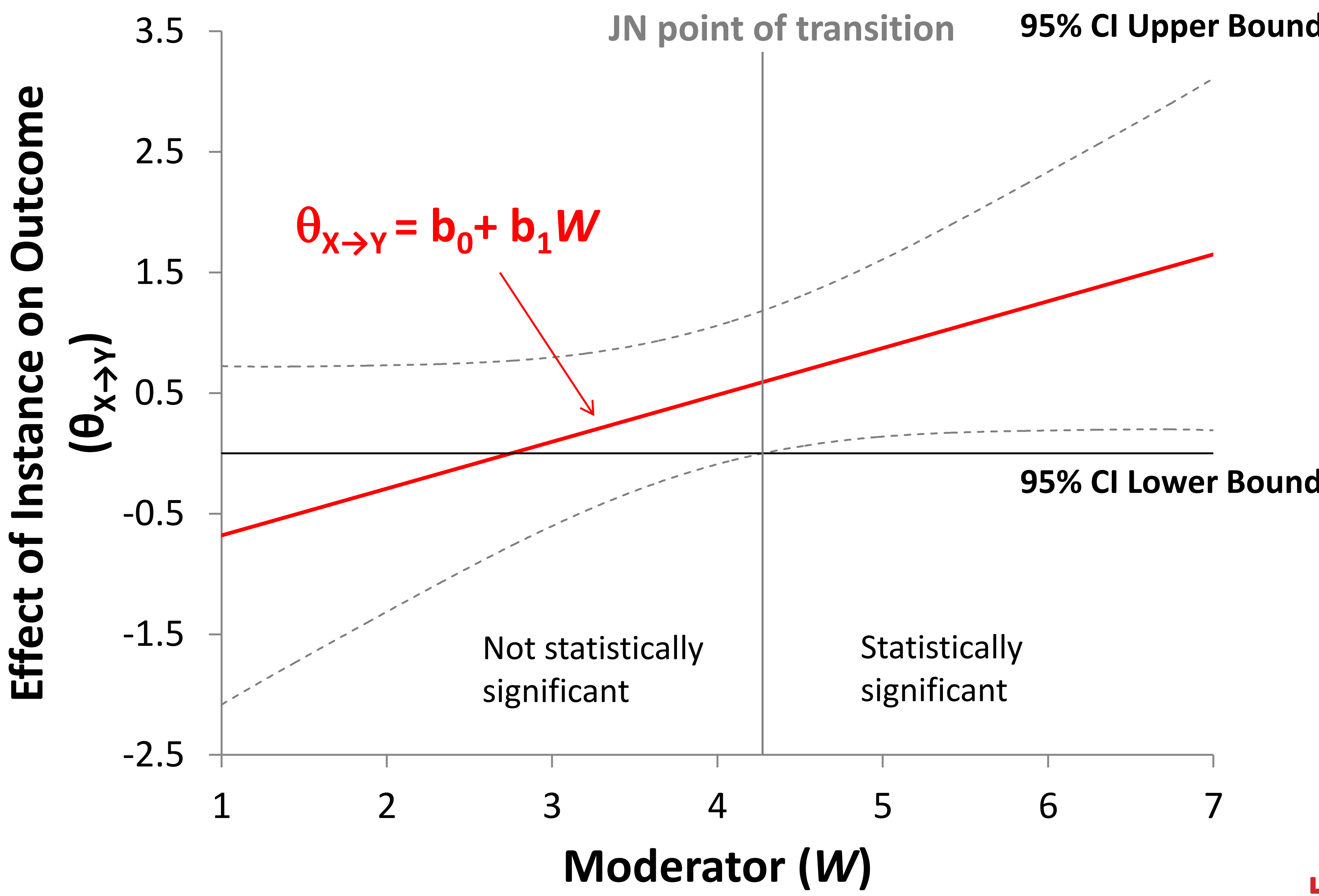
Squared standard error of b_1

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.

$$\frac{\theta_{X \to Y}(W)}{s_{\theta_{X \to Y}(W)}} \sim t_{df}$$

Montoya, *under review*

A Plot of the “Region of Significance”



The Johnson-Neyman Technique

Find the value or values of the moderator (*W*) the conditional effect of instance is exactly significant.

Do not need to select values of *W* in advance.

What value of *W* produces a ratio of $\theta_{X \rightarrow Y}(W)$ to its standard error exactly equal to the critical *t* value (t_{crit}) required to reject the null hypothesis that $\theta_{X \rightarrow Y}(W)$ is equal to zero at that value of *W*?

$$t_{crit} = \frac{b_0 + b_1 W}{\sqrt{s_{b_0}^2 + 2W s_{b_0 b_1} + W^2 s_{b_1}^2}}$$

Isolating *W* yields to the solution in the form of a quadratic equation which always has two roots, though not always two that are interpretable.

Montoya, *under review*

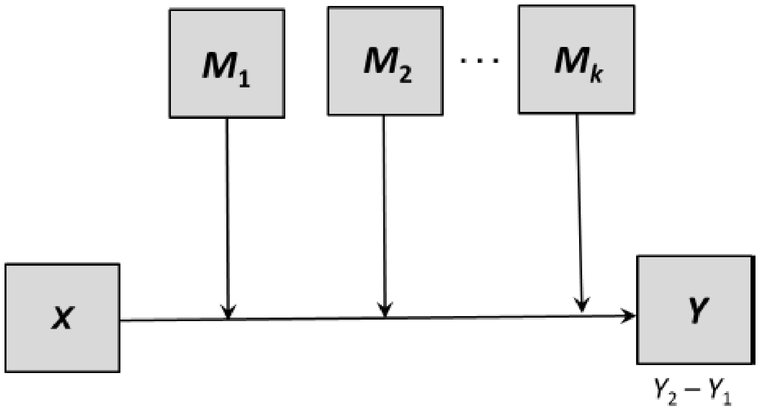
MEMORE

MEMORE will estimate and probe moderation models when the focal predictor is a repeated-measures variable.

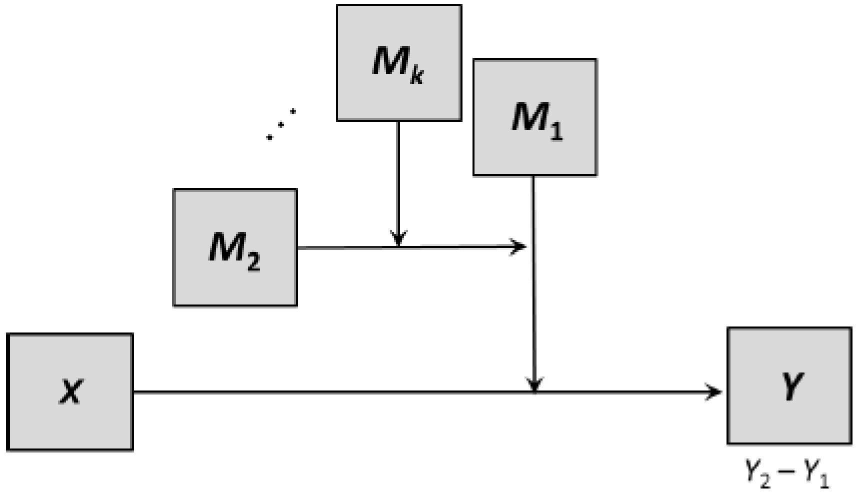
Multiple moderator models are also included!

- Can have up to 5 moderators

Model 2: Additive Moderation



Model 3: Multiplicative Moderation

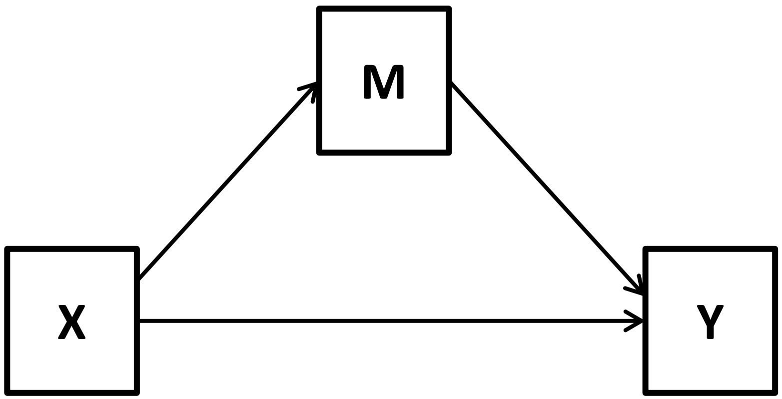


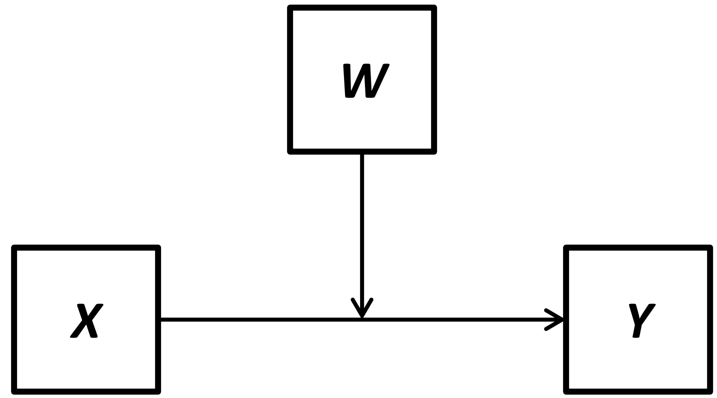
Montoya, *under review*

Overview

- Personal History and Philosophy
- Introduction to Mediation
- Two-Instance Repeated Measures Designs
  - Mediation
  - Moderation
  - **Conditional Process Analysis (AKA Moderated Mediation)**
- New Designs & New Questions

Combining Mediation and Moderation: Conditional Process Analysis





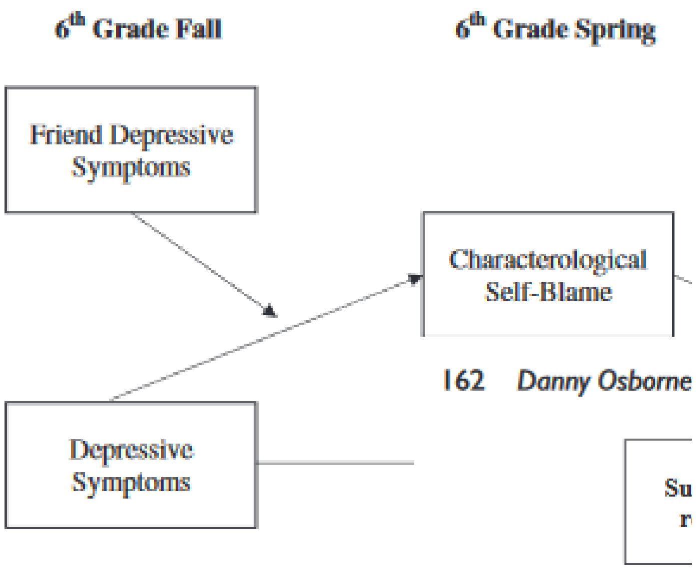
Research questions:

- 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.*

Examples of CPA in Psychology

H.L. Schacter, J. Juvonen / Journal of Applied Developmental I



162 *Danny Osborne*

Fig. 1. Conceptual mod

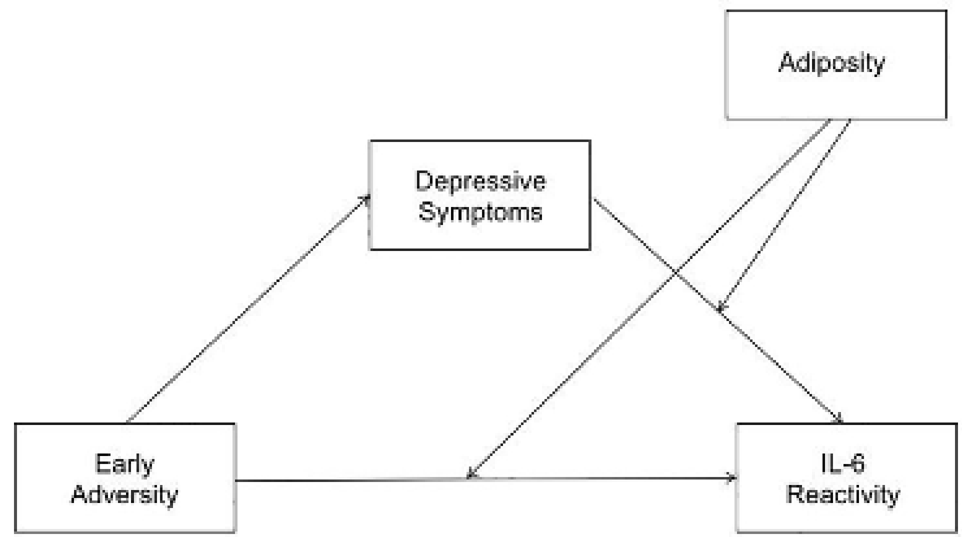


Fig. 1. Conceptual moderated mediation model of adiposity (i.e., BMI or WC) moderating the extent to which depressive symptoms mediates the association between early adversity and IL-6 reactivity.

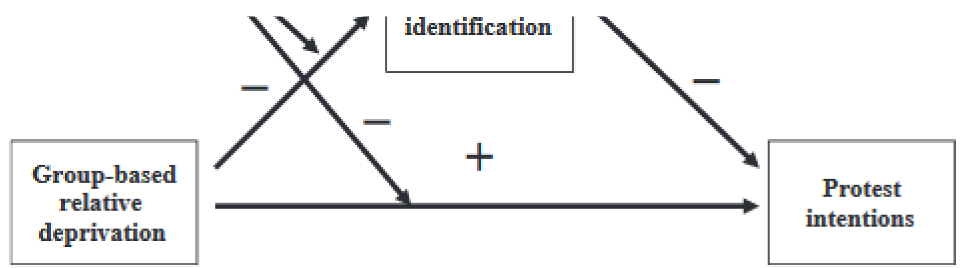


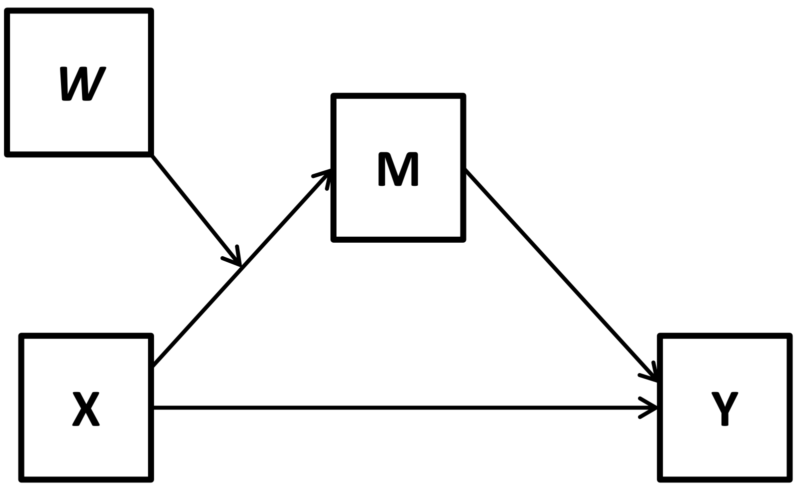
Figure 1. Schematic overview of the hypothesized moderated indirect effect of group-based relative deprivation on protest intentions through drops in university identification at varying levels of subgroup respect.

CPA in Two-Instance Repeated-Measures Designs

Using the path analytic approach outlined in Montoya & Hayes (2017) we can now allow for moderation of a mediated pathway.

No pre-existing work addresses this type of question with this type of data.

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



Between subjects version

Montoya, *dissertation*

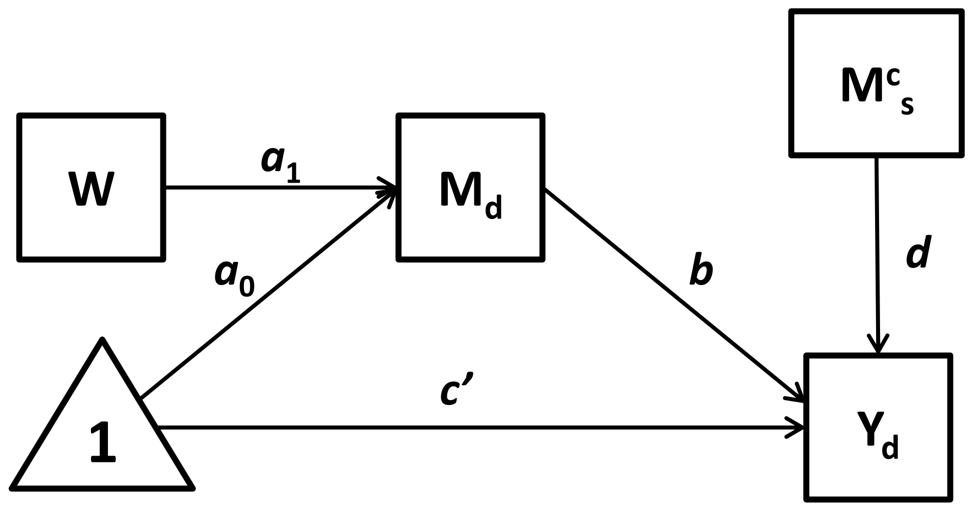
Translating to Path Model

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

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

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

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



What is the indirect effect?

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

Indirect effect is a *function* of the moderator

Montoya, *dissertation*

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 estimate 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

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

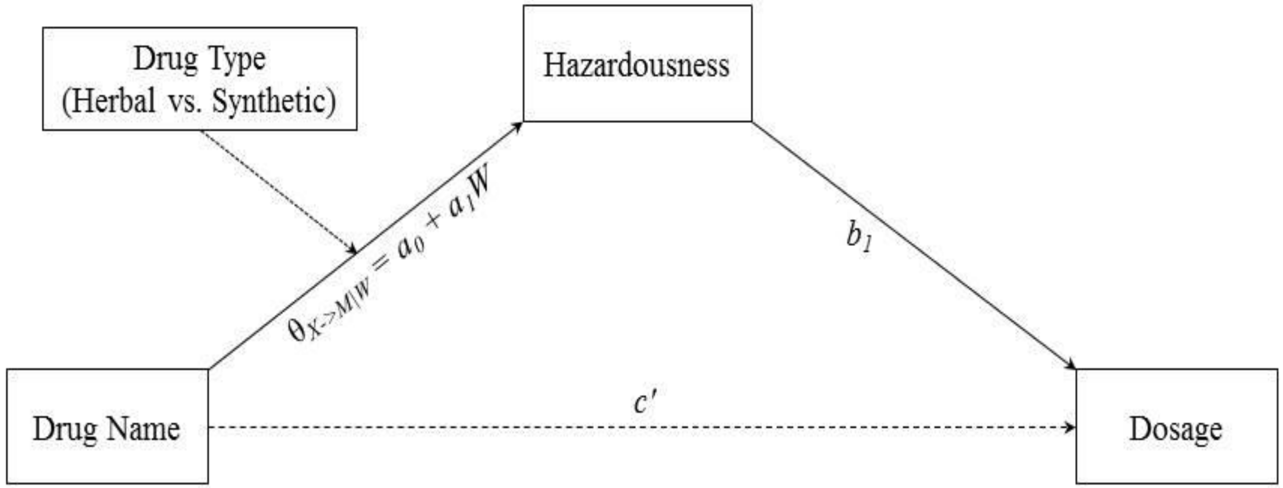
$a_1 b$ can be called the **index of moderated mediation**

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

Montoya, *dissertation*

Do simple names increase drug dosing through perceptions of safety? Does it depend on type of drug?

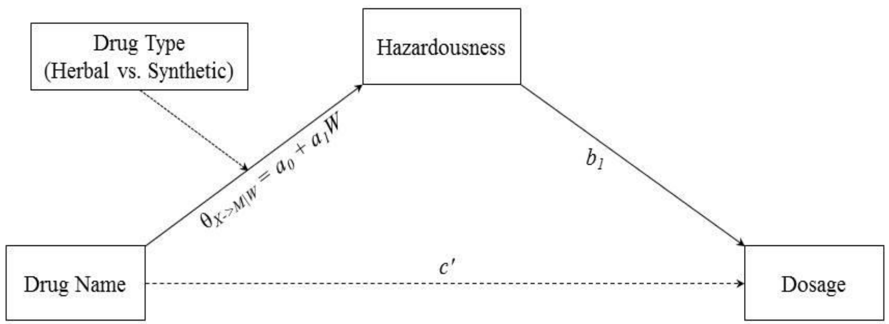
The Dark Side of Fluency: Fluent Names Increase Drug Dosing
S. Dohle & **A. K. Montoya** (in press) *Journal of Experimental Psychology: Applied*



Hypothesis: Complex drug names would decrease dosing through an increase in perceived hazardousness, and a subsequent negative effect of hazardousness on dosing.

Hypothesis: Drug names would have more of an effect on perceived hazardousness for synthetic compared to herbal drugs.

Do simple names increase drug dosing through perceptions of safety? Does it depend on type of drug?



We found that in **both** the herbal and synthetic condition, more complex names were perceived as more hazardous. There was no significant difference based on drug type.

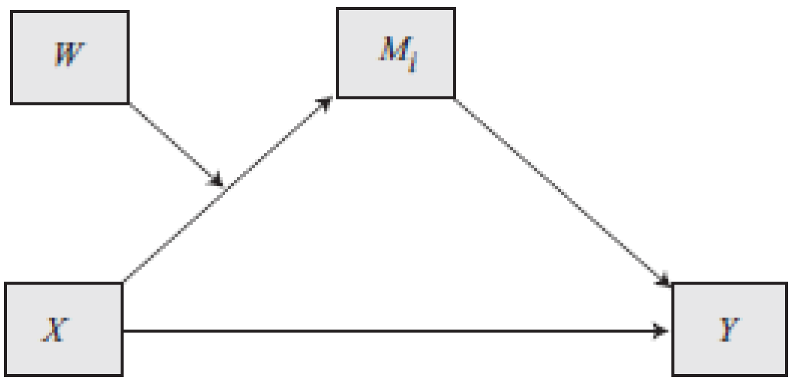
Higher perceived hazardousness was significantly related to reduced drug dosage.

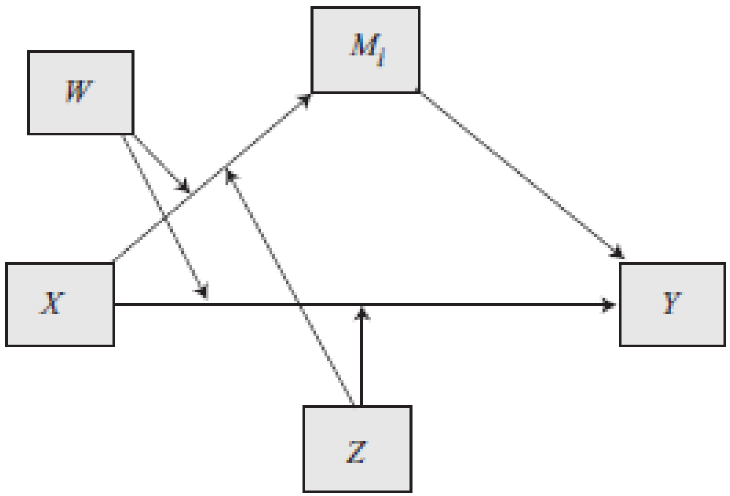
The indirect effect in the in both conditions such that more complex names led to lower doses through hazardousness [Herbal: a_0b = -6.78 [-11.18, -3.40], Synthetic: $(a_0+a_1)b$ = -7.70 [-11.98, -3.91]].

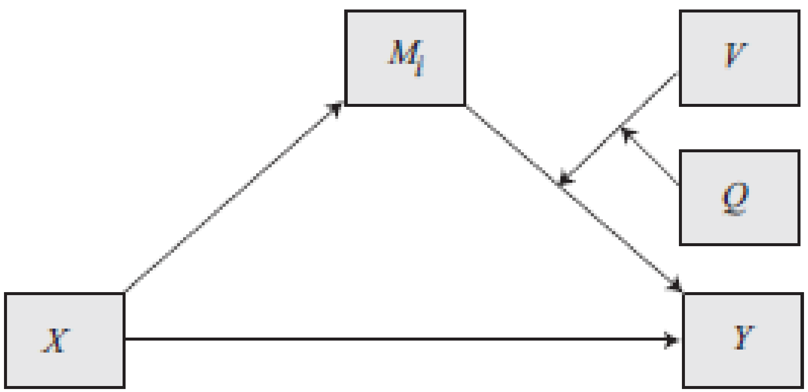
The *index of moderated mediation* was not significantly different from zero (a_1b = -.92 [-3.89, 1.58]) . Therefore we concluded there was no strong evidence that drug type influenced the indirect effect of drug name complexity on dosage through hazardousness.

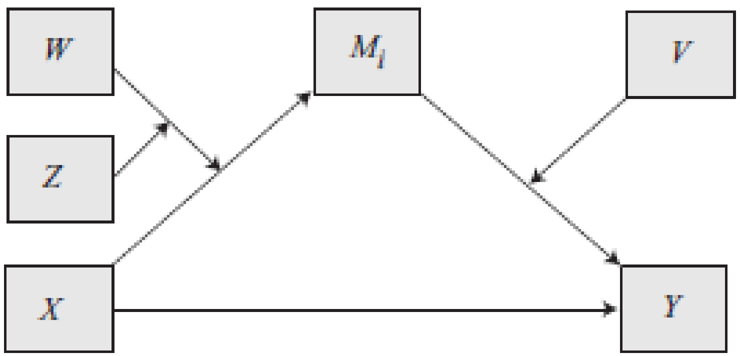
Coming Soon: MEMORE Models 4 - …

MEMORE will be expanded to include a variety of moderated mediation models.









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    - Conditional Process Analysis (AKA Moderated Mediation)
- **New Designs & New Questions**

Future Directions

New Designs:

- More than two conditions / instances
- New types of data
  - Counts
  - Survival Times

Generalized linear mixed models

New Questions:

- Meta-analysis
  - Effect size in mediation
  - Meta-analysis of mediation
  - Meta-mediation analysis

Summary

- Mediation, moderation, and conditional process analysis are very important to answering research questions in psychology
- These methods for repeated-measures designs are under-developed
- I've made headway in developing these methods for two-instance repeated measures designs
  - Path analytic approach
  - Easy to use tool
- There is much work to do in expanding these analyses in repeated-measures designs
- Linear regression based methods need to be compared to structural equation modeling approaches and multilevel approaches
- Future Directions:
  - Generalized Linear Mixed Models
  - Meta-analysis

Resources

I am available for questions now and forever via email at montoya.29@osu.edu

Things to look forward to:

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

MEMORE can be downloaded from akmontoya.com

Slides available at
github.com/akmontoya/UCLA2017

Thank you!

National Science Foundation
WHERE DISCOVERIES BEGIN

The Mechanisms and Contingencies (MAC) Lab
The Ohio State University

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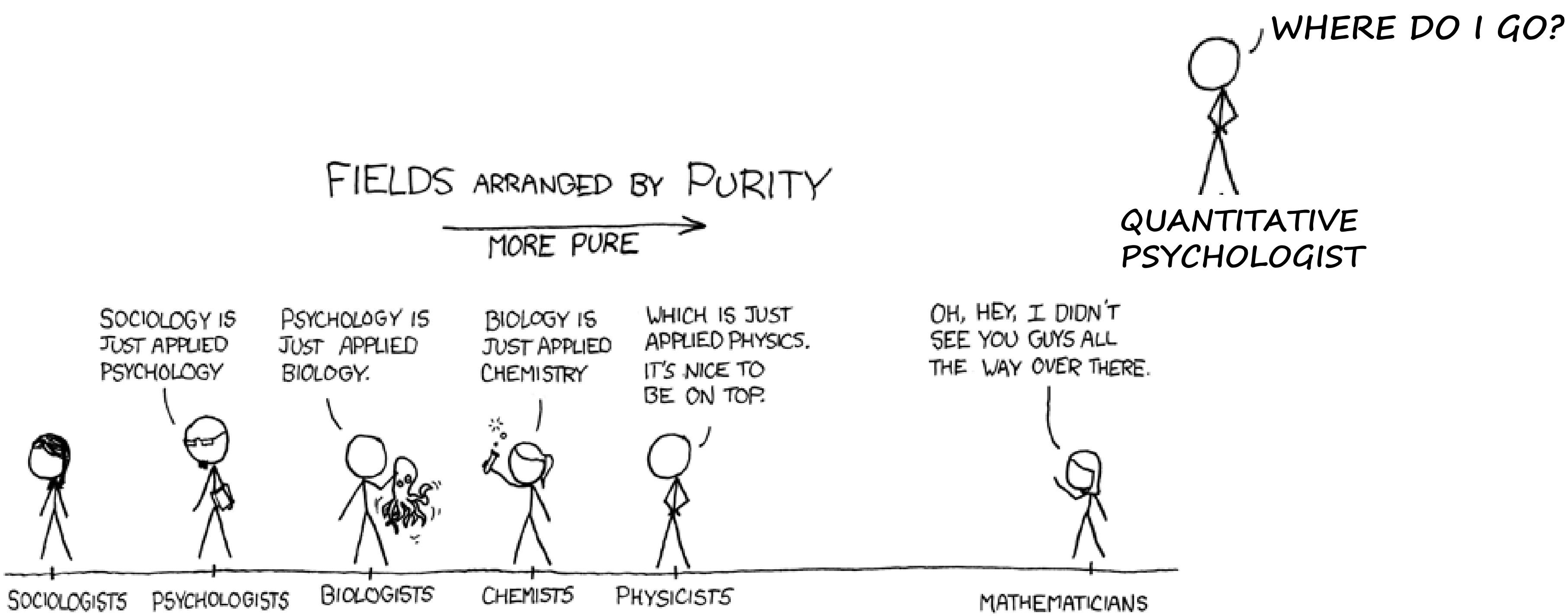

Two-Condition Repeated Measures Mediation

We can quantify paths of influence in the the two condition repeated measures case.

3. Does difference in *M* predict a difference in *Y*?

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

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

Look at how the difference in *M* affects the difference in *Y*, subtract these two equations.

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

Then apply a rotation to get:

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

This means if we regress the difference in *Y*'s onto the difference and sum of the *M*'s, the regression coefficient for the difference in *M*'s will estimate the average effect of *M* on *Y.*

$$\widehat{Y_{1i} - Y_{2i}} = \hat{h} + \hat{b}(M_{1i} - M_{2i}) + \hat{d}\,(M_{1i} + M_{2i})$$

Judd, Kenny, and McClelland 2001

Two-Condition Repeated Measures Mediation

We can quantify paths of influence in the the two condition repeated measures case.

4. Does the difference in *M* account for all the difference in *Y*?

As noted before, differences between *Y*'s reflect an effect of *X*, so expected differences in *Y*'s when the differences in *M*'s is zero reflect the direct effect.

$$\boldsymbol{E}(Y_{1i} - Y_{2i}) = h + b(M_{1i} - M_{2i}) + d(M_{1i} + M_{2i})$$

The quantity h reflects the expected difference in *Y*'s when the difference in *M*'s is zero and the sum of *M*'s is zero. Grand mean centering the sum term renders the intercept of this equation interpretable as the average difference between conditions on *Y* after accounting for differences in *M*.

$$\boldsymbol{E}(Y_{1i} - Y_{2i}) = h + d\frac{1}{n}\sum_{i=1}^{n}(M_{1i} + M_{2i}) + b(M_{1i} - M_{2i}) + d(M_{1i} + M_{2i} - \frac{1}{n}\sum_{i=1}^{n}(M_{1i} + M_{2i})$$

Thus $h + d\frac{1}{n}\sum_{i=1}^{n}(M_{1i} + M_{2i})$ is a quantification of the direct effect. An estimate of this value could be the intercept from the following equation:

$$\widehat{Y_{1i} - Y_{2i}} = \widehat{c'} + \hat{b}(M_{1i} - M_{2i}) + \hat{d}\,(M_{1i} + M_{2i} - \frac{1}{n}\sum_{i=1}^{n}(M_{1i} + M_{2i}))$$

Judd, Kenny, and McClelland 2001