Table of Contents

New Insights in Power and Power Analysis in Mediation Models (Session Chair: Amanda Kay Montoya)

Power for Mediation Models: Using the pwr2ppl package (Chris Aberson)

Comparison of Inferential Methods for Power Analysis (Jessica Fossum)

Winsorized means as corrections for bias in the bias-corrected bootstrap test of mediation (Donna Chen)

The measurement of the mediator and its effect on detecting indirect effects (Oscar Gonzalez)

New Insights in Power and Power Analysis in Mediation Models

Chair: Amanda Montoya

Presenters: Jessica Fossum, Chris
Aberson, Donna Chen, Oscar Gonzalez

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Mediation Analysis: A Brief Overview

Used to investigate potential causal pathways by which an independent variable (X) affects a dependent variable (Y)

One or more mediators (M) are included in a model, and the *indirect effect* through that mediator measures the effect of X on Y through the mediator.

Exceedingly common in social and personality psychology!

Mediation Analysis: Statistical Model

Let a , b , c , and c' be quantifications of causal effects, such as regression coefficients in an OLS model (or maximum likelihood path estimates in a structural equation model)

$$\hat{Y} = c_0 + cX$$

c = “total effect”

$$\hat{M} = a_0 + aX$$

$a \times b$ = “indirect effect”

$$\hat{Y} = c'_0 + c'X + bM$$

c' = “direct effect”

Mediation Analysis: Limitations

Cannot be used to infer causal relationships, but rather relies on the **assumption** that estimates are causal

Even with random assignment on X , the relationship between M and Y may be:

- Reversed in order ($Y \rightarrow M$)
- Confounded by other variables

Estimating a mediation analysis switching M and Y cannot determine which causal order is correct (Thoemmes, 2015)

Mediation Analysis: Power

Statistical power is the probability of detecting an effect which exists in the population.

In mediation, the focus is on detecting the *indirect effect*

Power for mediation analysis is complex, because the sampling distribution of the indirect effect has an unusual shape.

Previous research suggests that many mediation analyses are underpowered, but we're here to help change that!

Mediation Analysis: Our goal

What tools make for easy-to-use power analysis?

Chris Aberson

Does choice of inferential method matter for power analysis?

Jessica Fossum

What alternatives are there to the bias-corrected bootstrap?

Donna Chen

How does measurement error impact power for mediation?

Oscar Gonzalez

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Power for Mediation Models: Using the pwr2ppl Package

Chris Aberson
Humboldt State University
github.com/chrisaberson/pwr2ppl

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Mediation and Conditional Process Analyses

- Simple mediation
 - Up to four mediating variable and two predictors
- Serial mediation
- Conditional process models 7, 8, 14, and 15 (a.k.a. the only ones that anyone actually uses)
- All use the joint significance test
 - Working on adding the incrementally better Monte Carlo estimate
 - Major advance over first release of pwr2ppl

Mediation and Conditional Process Analyses

- Several functions require specification of a full correlation matrix
- There are some options for specifying standardized paths for simpler models rather than correlations
- All assume normality

Data/Models for Single and Multiple Mediator Examples

	Neg. Contact	Anxiety	Real Threat	Symb. Threat
Neg. Contact				
Anxiety	.25			
Real Threat	.30	.40		
Symb. Threat	.30	.40	.70	
Attitudes	-.35	-.50	-.50	-.50

208

pwr2ppl::medjs (one mediator)

```
medjs(rx1m1, rx1y, rym1, mvars, pred, n, alpha)
```

rx1m1 is the correlation between the predictor variable (x) and the first mediator (m1). rx1y is the correlation between the 1st predictor variable (x1) and the outcome (y). rym1 is the correlation between the outcome variable (y) and the mediator (m1). mvars is the number of mediating variables. The function allows up to four. n is sample size and alpha defaults to .05. (Note: text uses med function – medjs is better)

```
medjs(rx1m1=.25, rx1y=-.35, rym1=-.5, mvars=1, pred=1, n=150)
```

```
## Sample size is 150
```

```
## Power is 0.884
```

medjs_paths allows for specification of paths rather than correlations

pwr2ppl::medjs (three mediators)

rx1m1 is the correlation between the predictor variable (x) and the first mediator (m1). rx1y is the correlation between the 1st predictor variable (x1) and the outcome (y). rym1 is the correlation between the outcome variable (y) and the mediator (m1). mvars is the number of mediating variables. The function allows up to four. n is sample size and alpha defaults to .05.

```
medjs(rx1m1=.3, rx1m2=.3, rx1m3=.25, rx1y=-.35, rym1=-.5, rym2=-.5, rym3 =  
-.5, rm1m2=.7, rm1m3=.4, rm2m3=.4, mvars=3, pred=1, n=335)  
## Sample size is 335  
## Power for M1 0.904  
## Power for M2 0.889  
## Power for M3 0.999
```

Serial Mediation

pwr2ppl::medserial

Inputs follow figure notation. All tests use joint significance

```
medserial(rxm1=.3, rxm2=.3, rxy=-.35, rym1=-.5, rym2=-.5, rm1m2=.7, n=150)
```

```
## Power for n = 150, mediator 1 is 0.749
```

```
## Power for n = 150, mediator 2 is 0.273
```

```
## Power for n = 150, serial mediation is 0.748
```

medserial_paths allows for path entry rather than correlations

Conditional Processes

- “Moderated Mediation”
- Many models possible
- I focus on Models 7, 8, 14, and 15 (I have no idea how these get numbered)
- Why just these four?
 - These were the only ones I saw in the literature
 - I certainly will entertain requests to build for other models
- These functions are not in the version of pwr2ppl on CRAN. Can only get them on my Github
- For brevity, I just show Model 7 – examples of the others are very similar in format and can be found at the end of this slidedeck

Notation Guide

- I will likely update the notation on these beta functions
- r_{xy} – corr between x and y
- r_{xm} – corr between x and m
- r_{xw} - corr between x and w
- r_{xxw} – corr between x and xw (interaction)
- r_{xmw} – corr between x and mw (interaction)
- Etc. with all the different combinations

Conditional Process (Model 7)

Moderation is interaction between X and W predicting the mediator

pwr2ppl::modmed7

New code rxw, rxwx etc. reflect W and WX terms

```
modmed7(rxm=.4, rxw=.4, rxxw=.3, rxy=.50, rmy=.3, rxw  
y=0, rwm=.45, rwxw=.25, rmxw=.2,  
rwy=.2, alpha=.05, rep=1000, n=400)
```

```
## Sample size is 400
```

```
## Power for Conditional Indirect Effect (Joint Sign  
ificance) 0.091
```

Looping Analyses for a range of values

```
for (i in seq(100,200,10))  
{  
  medjs(rx1m1=.25, rx1y=-.35, rym1=-.5,mvars=1,pred=1,n=i)}
```

- The first part, for (i in seq(, is what is a for-loop command. The basic idea is for each value in the sequence that follows, perform the command wrapped in the {}
- The three numbers that follow (100, 200, 10) feed values of 100 to 200 in increments of 10 to the medjs command below. This produces analyses for sample sizes of 100, 110, 120, 130, 140, 150, 160, 170, 180, 190, and 200
- Can do this with any function or value (e.g., correlations)

Looping for a Range of Correlations

- Can loop a range of correlations as well (.1 to .6 by .1)

```
for (i in seq(.1,.6,.1))  
{print(i)  
pwr2pp1::medjs(rx1m1=i, rx1y=-i, rym1=-i,mvars=1,pred=1,n=100)}
```

```
## [1] 0.1  
## Sample size is 100  
## Power is 0.025  
## [1] 0.2  
## Sample size is 100  
## Power is 0.185  
## [1] 0.3  
## Sample size is 100  
## Power is 0.536  
## [1] 0.4  
## Sample size is 100  
## Power is 0.815  
## [1] 0.5  
## Sample size is 100  
## Power is 0.93  
## [1] 0.6  
## Sample size is 100  
## Power is 0.974
```

To install

- `devtools::install_github("chrisaberson/pwr2ppl")`
- In some cases, users experience an error message reading as follows:
ERROR: dependencies 'car', 'ez', 'phia', 'afex', 'MBESS', 'lavaan' are not available for package 'pwr2ppl'
- Installing car, ez, phia, afex, MBESS, and lavaan manually will rectify this error.
- The conditional processes are in beta, so I want to leave them off CRAN until they've gotten some use

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Extras

- Extra slides demonstrate Models 8, 14, and 15

Conditional Process (Model 8)

- Interaction and W predict mediator and DV in this model

pwr2ppl::modmed8

```
modmed8(rwx=.2, rxm=.3, rxxw=0, rxy=.3, rwm=.4, rxww=0  
, rwy=.35, rwxw=.2, rxwm=.4, rxwy=0, rmy=.3, n=100, r  
ep=2000, alpha=.05)
```

```
## Sample size is 100
```

```
## Power for Conditional Indirect Effect (On Mediator) 0.321
```

```
## Power for Conditional Indirect Effect (On DV) 0.2685
```

Conditional Process (Model 14)

- Interaction and W on DV only

pwr2ppl::modmed14

```
modmed14(rxw=.2, rxm=.25, rxww=.2, rxwy=-.2, rxxw=.35,  
rxy=.3, rwm=.4, rwy=.35,  
rmy=.3, n=200, rep=1000, alpha=.05)
```

```
## Sample size is 200
```

```
## Power for Conditional Indirect Effect (Joint  
Significance - Recommended) 0.944
```

Conditional Process (Model 15)

- Interaction and W on DV and Mediator

pwr2ppl::modmed15

```
modmed15(rxw=.40, rxm=.4, rxwm=.0, rxy=.5, rwxw=.2, rwm=.45, rmwx=.3, rmww=.0, rxwx=.25, rwy=.2, rmwm=.45, rmy=.30, rmwy=.0, rwwm=.35, rwxxy=.3, rwmwx=.2, rep=5000, alpha=.05, n=400)
```

```
## Sample size is 400
```

```
## Power for Conditional Indirect Effect (On Mediator) 0.4436
```

```
## Power for Conditional Indirect Effect (On DV) 0.9936
```

Comparison of Inferential Methods for Power Analysis

Presented by:

Jessica L. Fossum

University of California, Los Angeles

#SPSP2021

Inferential Methods

Causal Steps Approach [1] <ul style="list-style-type: none">• Not used in practice• Mostly of historical value	Percentile Bootstrap Confidence Interval [4] <ul style="list-style-type: none">• Computationally and time intensive• Generally recommended method
Joint Significance Test [2] <ul style="list-style-type: none">• Efficient to compute• No confidence interval given	Bias-Corrected Bootstrap Confidence Interval [5] <ul style="list-style-type: none">• Computationally and time intensive• Inflated type I error rate
Sobel Test [3] <ul style="list-style-type: none">• Assumes distribution of ab is normal• Performs poorly in small samples	Monte Carlo Confidence Interval [6] <ul style="list-style-type: none">• Resampling Method• Assumes distributions of a and b are normal

Using the Methods

- Several tools available for power analysis in mediation, using different tests of the indirect effect:
 - **pwr2ppl** uses the Joint Significance Test or the Sobel Test (Aberson)
 - **MCpowerMed** uses Monte Carlo Confidence Interval (Schoemann, Boulton, & Short, 2007)
 - **Bmem** uses the Sobel Test or Percentile Bootstrap Confidence Interval (Zhang & Wang, 2013)
- Does the choice of inferential method matter for power analysis?

Power Curve

- Power analysis for mediation necessitates picking a sample size then figuring out the power
- Determining an adequate sample size requires running a power analysis many times
- Can take time to run
- Could we use a less computationally intensive test for the power analysis, then a different test for the data analysis?

Monte Carlo Simulations

- Simulation to determine sample size required using each inferential test to achieve 80% power for 16 effect size combinations (similar to Fritz & MacKinnon, 2007)
 - Effect sizes were standardized regression coefficients on the *a*-path and *b*-path (0.14, 0.26, 0.39, 0.59)
- Simulation to determine power level for each inferential test using the sample sizes determined in previous simulation

Sample Sizes for 80% Power

Effect Sizes $a = 0.39$ and $b = 0.39$

Power Analysis

Causal Steps Approach

Joint Significance Test

Sobel Test

Percentile Bootstrap Confidence Interval

Bias-corrected Bootstrap Confidence Interval

Monte Carlo Confidence Interval

Sample Sizes for 80% Power

Effect Sizes $a = 0.39$ and $b = 0.39$

Power Analysis	N
Causal Steps Approach	221
Joint Significance Test	210
Sobel Test	225
Percentile Bootstrap Confidence Interval	212
Bias-corrected Bootstrap Confidence Interval	195
Monte Carlo Confidence Interval	211

Sample Sizes for 80% Power

Effect Sizes $a = 0.39$ and $b = 0.39$

Data Analysis

Power Analysis	N	CS	JS	ST	PBCI	BCBCI	MCCI
Causal Steps Approach	221						
Joint Significance Test	210						
Sobel Test	225						
Percentile Bootstrap Confidence Interval	212						
Bias-corrected Bootstrap Confidence Interval	195						
Monte Carlo Confidence Interval	211						

Sample Sizes for 80% Power

Effect Sizes $a = 0.39$ and $b = 0.39$

Data Analysis

Power Analysis	N	CS	JS	ST	PBCI	BCBCI	MCCI
Causal Steps Approach	221	80.6					
Joint Significance Test	210	77.1					
Sobel Test	225	80.3					
Percentile Bootstrap Confidence Interval	212	77.7					
Bias-corrected Bootstrap Confidence Interval	195	74.6					
Monte Carlo Confidence Interval	211	77.8					

Sample Sizes for 80% Power

Effect Sizes $a = 0.39$ and $b = 0.39$

Data Analysis

Power Analysis	N	CS	JS	ST	PBCI	BCBCI	MCCI
Causal Steps Approach	221	80.6	82.9	79.1	83.0	85.5	83.1
Joint Significance Test	210	77.1	79.8	75.7	80.3	83.1	80.2
Sobel Test	225	80.3	82.4	78.9	82.8	85.3	82.7
Percentile Bootstrap Confidence Interval	212	77.7	80.2	76.2	80.5	83.6	80.4
Bias-corrected Bootstrap Confidence Interval	195	74.6	77.7	72.5	78.1	81.5	78.0
Monte Carlo Confidence Interval	211	77.8	80.0	75.7	80.4	83.2	80.3

- Power tends to be around 80%

Sample Sizes for 80% Power

Effect Sizes $a = 0.39$ and $b = 0.39$

Data Analysis

Power Analysis	N	CS	JS	ST	PBCI	BCBCI	MCCI
Causal Steps Approach	221	80.6	82.9	79.1	83.0	85.5	83.1
Joint Significance Test	210	77.1	79.8	75.7	80.3	83.1	80.2
Sobel Test	225	80.3	82.4	78.9	82.8	85.3	82.7
Percentile Bootstrap Confidence Interval	212	77.7	80.2	76.2	80.5	83.6	80.4
Bias-corrected Bootstrap Confidence Interval	195	74.6	77.7	72.5	78.1	81.5	78.0
Monte Carlo Confidence Interval	211	77.8	80.0	75.7	80.4	83.2	80.3

- Sometimes, power is very different from 80%

Power Agreement Among Tests

- Agreement in this study is defined as having power within 5% of another test

Proportion of Agreement

Power Analysis

Causal Steps Approach

Joint Significance Test

Sobel Test

Percentile Bootstrap Confidence Interval

Bias-corrected Bootstrap Confidence Interval

Monte Carlo Confidence Interval

Proportion of Agreement

	Data Analysis					
	CS	JS	ST	PBCI	BCBCI	MCCI
Power Analysis						
Causal Steps Approach						
Joint Significance Test						
Sobel Test						
Percentile Bootstrap Confidence Interval						
Bias-corrected Bootstrap Confidence Interval						
Monte Carlo Confidence Interval						

Proportion of Agreement

Power Analysis	Data Analysis					
	CS	JS	ST	PBCI	BCBCI	MCCI
Causal Steps Approach	1.00					
Joint Significance Test	.81					
Sobel Test	.75					
Percentile Bootstrap Confidence Interval	.81					
Bias-corrected Bootstrap Confidence Interval	.88					
Monte Carlo Confidence Interval	.81					

Proportion of Agreement

Power Analysis	Data Analysis					
	CS	JS	ST	PBCI	BCBCI	MCCI
Causal Steps Approach	1.00	.81	.81	.81	.88	.81
Joint Significance Test	.81	1.00	.69	1.00	.69	1.00
Sobel Test	.75	.69	1.00	.69	.94	.69
Percentile Bootstrap Confidence Interval	.81	1.00	.69	1.00	.69	1.00
Bias-corrected Bootstrap Confidence Interval	.88	.81	.75	.88	1.00	.88
Monte Carlo Confidence Interval	.81	1.00	.69	1.00	.69	1.00

Proportion of Agreement

Original Test	CS	JS	ST	PBCI	BCBCI	MCCI
Causal Steps Approach	1.00	.81	.81	.81	.88	.81
Joint Significance Test	.81	1.00	.69	1.00	.69	1.00
Sobel Test	.75	.69	1.00	.69	.94	.69
Percentile Bootstrap Confidence Interval	.81	1.00	.69	1.00	.69	1.00
Bias-corrected Bootstrap Confidence Interval	.88	.81	.75	.88	1.00	.88
Monte Carlo Confidence Interval	.81	1.00	.69	1.00	.69	1.00

Conclusion

- For normally distributed data, power analysis and data analysis for mediation can use any of the similarly performing inferential tests interchangeably
 - Joint Significance Test
 - Percentile Bootstrap Confidence Interval
 - Monte Carlo Confidence Interval

Discussion

- General recommendation for data analysis: **Percentile Bootstrap Confidence Interval**
 - Controls the type I error rate [7, 8]
 - Gives a confidence interval
 - Bias-corrected bootstrap confidence interval is never interchangeable
- Power analysis can be done using the **Joint Significance Test**
 - Faster, less computationally intensive
 - Confidence Interval is not necessary for power analysis

Future Directions

- Previous simulation work has shown that **violations of normality and heteroskedasticity** can affect the power of some of these tests (e.g., JS, MC), so we want to see if power analysis can still be used interchangeably in these cases
- Extend this comparison of tests to moderated mediation, where there are a lack of power analysis tools available

Thank You

- Contact information:
 - Jessica Fossum
 - jfossum@ucla.edu
- Please rate this session using the SPSP mobile app

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Range of Power

Original Test	CS	JS	ST	PBCI	BCBCI	MCCI
Causal Steps Approach	79.24-81.19	79.27-88.34	63.37-83.40	79.15-88.41	79.50-91.52	78.89-88.42
Joint Significance Test	68.04-80.86	79.29-81.38	63.60-79.94	79.08-80.85	79.74-86.23	79.17-80.92
Sobel Test	76.03-90.60	79.87-90.60	78.88-81.61	79.84-89.84	80.12-93.34	79.92-90.10
Percentile Bootstrap Confidence Interval	67.22-82.13	79.03-82.19	66.15-80.09	79.28-80.91	79.71-87.08	78.95-81.14
Bias-corrected Bootstrap Confidence Interval	59.38-80.41	73.27-80.43	84.94-79.87	72.61-80.55	79.13-81.51	72.49-80.46
Monte Carlo Confidence Interval	68.04-81.21	79.37-81.38	65.23-80.41	79.55-81.14	79.66-86.64	79.44-81.17

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Winsorized means as corrections for bias in the bias-corrected bootstrap test of mediation

Presented by:

Donna Chen

University of Nebraska—Lincoln

Background

- Sampling distribution of indirect effects is often **not normally distributed**, skewed
- Traditional normal-theory statistical tests may result in incorrect inferences (Lomnicki, 1967; Springer & Thompson, 1966)
- Popular solution: don't make distributional assumption at all—use nonparametric resampling methods, like bootstrapping! (Efron & Tibshirani, 1993; MacKinnon et al., 2004)

Bootstrapping

- Name derived from the idea of “pulling oneself up by one’s bootstrap” (Efron & Tibshirani, 1993, p. 5)
 - Generate a sampling distribution by resampling from original sample

Percentile Bootstrapping

- Exact values at the 2.5th and 97.5th percentiles on the bootstrap sampling distribution are used to form the 95% confidence interval (CI)

Bias-Corrected (BC) Bootstrapping

- Bias: proportion of bootstrapped mediated effect estimates that fall below the original indirect effect estimate
- Estimate of bias provides a measure of how far off the median of the bootstrap sampling distribution is from the original indirect effect estimate

Issue

- BC bootstrap has increased statistical power, BUT its Type I error rates are elevated for small sample sizes (i.e., $N = 25, 50, 100$)
- Fritz et al. (2012) found Type I error rates occur as interaction between path size and sample size
 - Type I error rates elevated with small sample sizes given medium or larger effect size of the nonzero path (either a or b)
- Is there a correction for bias that will keep the increased power without the inflated Type I error?

Potential Solution: Winsorized means

- Winsorized trimming replaces extreme values with a predetermined value that will “trim” a percentage of values from the tails (Lix & Keselman, 1998)

- Example: 20% Winsorized mean calculated by

$$\frac{2 + 2 + 3 + 4 + 5 + 6 + 7 + 8 + 9 + 9}{10}$$

- When non-normality and variance heterogeneity present, combining trimmed means with bootstrapping results in better Type I error control (Wilcox et al. 1998)

Simulation Study

- Progression of trimming levels in increments of 10
 - 0% trimming $\rightarrow z_{mean}$
 - 10%, 20%, 30%, 40% trimming $\rightarrow z_{win10}, z_{win20}, z_{win30}, z_{win40}$
 - 50% trimming $\rightarrow$ percentile bootstrap
 - Compared to original $\rightarrow z_0$
- Path effect sizes of a and b : 0, 0.14, 0.39, 0.59
 - Path effect size for c' fixed to 0
- Sample sizes: 50, 100, 250, 500, 1000

Results

Trimming
Type I Error

Trimming ↑
Power ↓

Empirical Example

- Athletes Training and Learning to Avoid Steroids (ATLAS) program (Goldberg et al., 1996)
 - Prevent high school football players from using anabolic androgenic steroids (AAS)
 - Healthy nutrition behaviors and appropriate strength training as alternatives to AAS use
 - Outcomes: AAS use intention and nutrition behaviors

Empirical Example

- For illustration only, treated sample as “population”
 - $N = 731$
 - Randomly sampled 50 students from original sample to illustrate performance of each correction for bias with small sample size
- Power: X = participation in ATLAS program, M = perceived susceptibility, Y = intention to use AAS
- Type I Error: X = participation in ATLAS program, M = normative beliefs of steroid use, Y = nutrition behaviors

Empirical Example

- Power

- Population: $\hat{a} = 0.595$, $\hat{b} = -0.096$, $\hat{a}\hat{b} = -0.057$
 - None of the CIs contained zero
- Sample: $\hat{a} = 0.892$, $\hat{b} = -0.300$, $\hat{a}\hat{b} = -0.267$
 - z_0 , z_{mean} , and z_{win10} correctly indicated perceived susceptibility to be a significant mediator.

- Type I Error

- Population: $\hat{a} = -0.153$, $\hat{b} = 0.001$, $\hat{a}\hat{b} = -0.0002$
 - All CIs contained zero
- Sample: $\hat{a} = -0.475$, $\hat{b} = -0.152$, $\hat{a}\hat{b} = 0.072$
 - z_0 and z_{mean} incorrectly indicated a significant mediator

Discussion

- Test selection depends on objective of study, cost functions, and research goals
 - Most concerned about not committing a Type I error → percentile bootstrap
 - Most concerned about not committing a Type II error → original BC bootstrap
 - Winsorized means offer varying levels of compromise between the elevated Type I error rate of the original BC bootstrap and the low power of the benchmark methods

Limitations & Future Directions

- In practice, missing data is a common occurrence, but it was not considered as a factor in this study
- Number of bootstraps in this paper was 1,000—future studies could consider different numbers of bootstraps
- Lower statistical power may be related to asymmetry, so asymmetric trimming using Winsorized means could be considered

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 - ATLAS data

Thank you! 😊

- donna.chen@huskers.unl.edu
- Handout for Winsorized trimming as correction for bias is uploaded.

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The measurement of the mediator and its effect on detecting indirect effects

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#SPSP2021

Assumptions of the mediation model

1. No unmeasured confounding among the variables
2. Temporal precedence among the variables
3. Correct functional form
4. **Variables are assessed well**

We argue that in order to identify mechanisms in a causal process and advance the theoretical understanding of phenomena, it is crucial to have clear interpretation and precise measurement of the (hypothesized) mechanisms involved[!!]

Gonzalez & Mackinnon (in press @ Psychological Methods)

Reliability and Validity of Mediators

- Validity (e.g., Gonzalez & MacKinnon, 2018)
 - Amount of evidence that support the interpretation of the mediator
 - Construct underrepresentation or construct-irrelevant variance
- Reliability (e.g., Gonzalez & MacKinnon, 2016)
 - Proportion of observed score variance that is true score variance
 - How is error dealt with in our models?
- How does measurement error and construct-irrelevant variance affect the power to detect significant indirect effects?

Illustration

From Chen, West, and Sousa (2006)...

- Quality of life [M]
 - 17-items quality of life scale, four facets
 - Cognition, mental health, disease worry, and vitality
 - Many observed or latent variable models could fit the data

Data-generating Model

Consider an intervention [X] that only changed unique aspects of the cognition quality of life facet [M], and in turn changed social functioning [Y].

- Population Model:
 - X is binary (.50/.50)
 - Y is continuous ($R^2 = .02$)
 - M is the unique part of cognition ($R^2 = .13$)
- Sample one dataset (N=400)
 - Present analysis
 - 1,000 Monte Carlo samples of power

Analysis: Observed Variable Models

Analysis: Latent Variable Models

Parameter Estimates

Table 3. *Parameter estimates, variance explained, and fit information on ten theoretical models to test the mediated effect of the influence of a treatment program on social activity through perceived quality of life.*

	<i>a</i> -path	<i>b</i> -path	r_{ab}	d.o.p. power	<i>a</i> -path power	<i>b</i> -path power	R_M^2	R_Y^2	RMSEA 95%CI	SRMR	CFI	RSE _a	RSE _b
Model I (data gen)	.696(.116)	.145(.047)	-.021	.867*	1.000	.867	.108	.030	.009[.000,.026]	.029	.999	.174	.336
Model A	2.338(.969)	.004(.004)	.000	.108	.683	.178	.014	.002	-	-	-	.403	1.029
Model B	1.886(.340)	.036(.012)	.000	.831*	1.000	.831	.072	.022	-	-	-	.176	.345
Model Bi	1.886(.340)	.041(.014)	.000	.831*	1.000	.831	.080	.024	-	-	-	.176	.345
Model C	1.886(.340)	.046(.015)	.000	.858*	1.000	.858	.072	.038	-	-	-	.176	.332
Model D	.078(.049)	.049(.095)	-.005	.027	.350	.095	.007	.001	.074[.066,.082]	.074	.925	.637	1.938
Model E	.397(.070)	.183(.067)	-.016	.766*	1.000	.766	.084	.020	.018[.000,.054]	.023	.999	.176	.377
Model F	.400(.071)	.231(.101)	-.013	.620*	1.000	.620	.084	.041	.019[.000,.032]	.031	.995	.176	.457
Model G	.064(.045)	.058(.103)	-.005	.020	.281	.093	.005	.001	.035[.025,.044]	.050	.982	.716	1.800
Model H	.073(.049)	.052(.096)	-.005	.022	.322	.094	.006	.001	.030[.017,.040]	.046	.988	.672	1.866

Power to detect $ab = .867$
*with distribution of product

Data-Generating Model

Model for data analysis

I)

Data-Generating Model

Power to detect $ab = .867$

Mediator is a summed score,
 b -path underestimated
Power to detect $ab = .108$

A)

Model for data analysis

Mediated Effect
Not Detected

Data-Generating Model

Power to detect $ab = .867$

H)

Models for data analysis

Mediated Effect
is Detected

Power = .831

Power = .831

Power = .766
higher RSE in b-path

Data-Generating Model

Power to detect $ab = .867$

Models for data analysis

Mediated Effect
is Detected

Data-Generating Model

Power to detect $ab = .867$

Power = .858

F)

Power = .620
higher RSE in b-path

Models for data analysis

General Comments

Summary

- Ten different mediation models to the same dataset
 - Models fit the data – a researcher could have theorized any of them
 - Some detected the mediated effect, and some missed it entirely
 - Trade-off between model complexity and parameter precision
- Accurate mediated effect estimation depends on the amount of true mediator variance that the representation of the mediator captures
 - Best performing model in each application
 - Best performing model in a simulation

Mediation as a Measurement Problem

- Causal processes may be unobserved (MacKinnon, 2008)
 - Parents characteristics to offspring characteristics = genes
 - Chemical input to chemical output = atoms
 - Unknown mechanisms until we had the tools to measure them
- Finding the true mediator = measurement problem
 - Right variable, right time, right place, with enough precision
 - Our tools are our assessments – refine our measurement theory of the mediator

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Thank you!

- For more, find me at <https://tarheels.live/gonzalez>
- Reach me at ogonza13@unc.edu
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