San Diego State University

Multilevel Mediation for Implementation Science

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Overview

- Empirical example
- Review of mediation
- Review of multilevel modeling
- Importance of centering
- Combining mediation and multilevel modeling: Multilevel mediation
- Alternative models to be explored
- Consideration of Bayesian estimation

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Empirical Example

- Baseline measures of a longitudinal study (LOCI)
- 293 providers are nested in 59 clinics
  - Level-1: Provider; Level-2: Clinic
- Self-reported measures of:

  - **Norms**
    - *Implementation Citizenship Behavior Scale* [ICBS]
  - **Openness towards evidence-based practice**
    - *How open are you to trying new practices?* [OPEMN]
  - **Intentions**
    - *Evidence based treatment intentions* [EBTI]

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Mediation Analysis

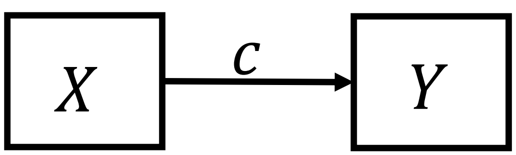
- ***Mediation*** is a concept
  - *The effect of one variable (X) on another (Y) passes through a mediator (M)*

  - *The total effect of one variable (X) on another (Y) may be separated into a part that is direct, and a part which is indirect and passes through a mediator (M)*

Mediation Analysis

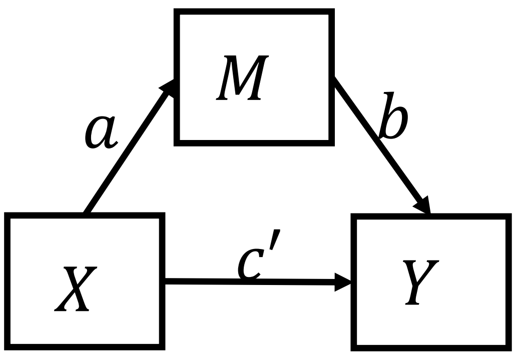
- ***Mediation*** is a concept
  - *The total effect of one variable on another may be separated into a part that is direct, and a part which is indirect and passes through a mediator (M)*

Total Effect: *c*



Direct Effect: *c'*
Indirect Effect: *ab*

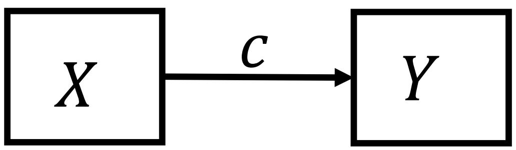
Total Effect = ab + c' = c



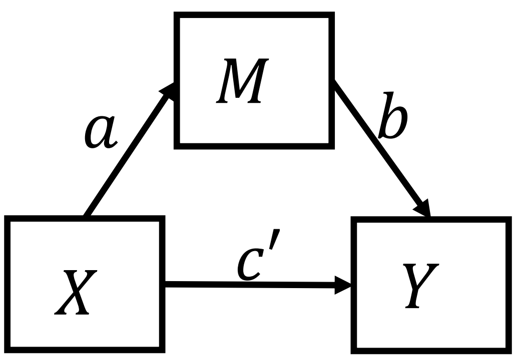
Mediation Analysis

Direct Effect: c'
Indirect Effect: ab

Total Effect: $ab + c' = c$



$$Y = b_{0Y} + cX + e_Y$$
$$X = b_{0X} + e_X$$



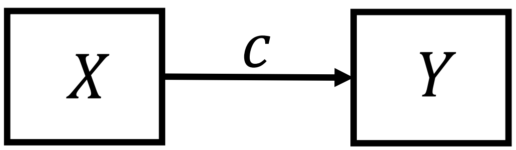
$$Y = b_{0Y} + c'X + e_Y$$
$$M = b_{0M} + aX + e_M$$
$$X = b_{0X} + e_X$$

Mediation Analysis

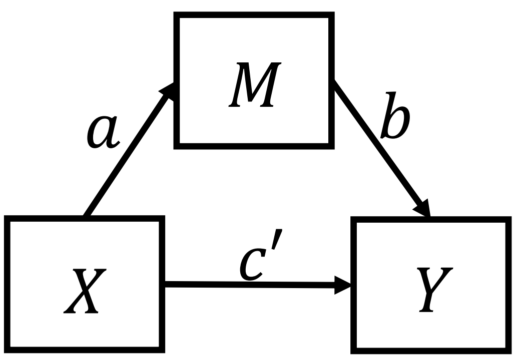
- Baseline measures of a longitudinal study (LOCI)
- 293 providers are nested in **59 clinics**
  - Level-1: Provider; **Level-2: Clinic**
- **Average self-reported responses across providers in a clinic**

  - **Norms (X)**
    - *Implementation Citizenship Behavior Scale* [ICBS]
  - **Openness (M)**
    - *How open are you to trying new practices?* [OPEMN]
  - **Intentions (Y)**
    - *Evidence based treatment intentions* [EBTI]

Mediation Analysis



	Est.	***p***
c	.500	<.001



	Est.	***p***
a	.238	.006
b	.767	<.001
ab	.183	.022
c'	.317	.017
$c' + ab$	.500	<.001

X: Norms (ICBS)
M: Openness (OPEMN)
Y: Intentions (EBTI)

Direct Effect: c'
Indirect Effect: ab

Total Effect = $ab + c' = c$

Mediation Analysis

- ***Mediation*** is a concept
  - *The total effect of one variable on another passes through another variable*

- Causality is assumed
  - Just like it is in every other model
  - Don’t assume if it doesn’t make sense; just like in every other model

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Multilevel Modeling

- ***Multilevel Modeling*** is a statistical framework
  - *Measures may be separated according to an observed grouping structure, and measures from the same group are not independent*

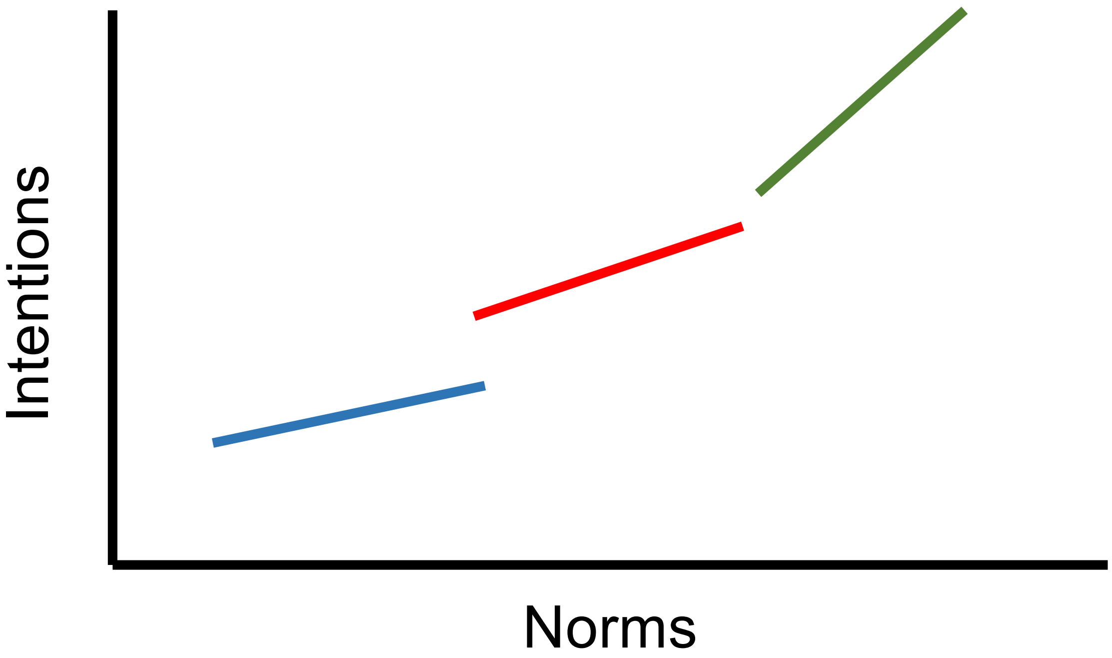
Multilevel Modeling

- ***<u>Multilevel Modeling</u>*** is a statistical framework
  - *Measures may be separated according to an observed grouping structure, and measures from the same group are not independent*

  - Our empirical example: 293 providers nested into 59 different clinics
    - *Possible that those providers in the same clinic are more related to one another than providers across difference clinics*

Multilevel Modeling

X: Norms (ICBS)
Y: Intentions (EBTI)



Each group (clinic) has its own intercept and slope

Multilevel Modeling

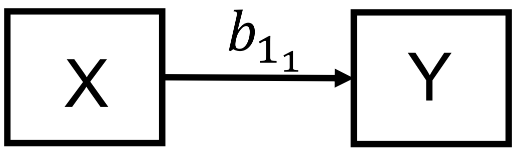
- Let there be G groups, and groups are labeled g = 1, 2, 3, …, G
- Our empirical example has 59 clinics, so G = 59
- Model may be written as
  - $Y_{ig} = b_{0_g} + b_{1_g} X_{ig} + e_{Y_{ig}}$

<u>Group 1</u>

$$X \xrightarrow{b_{1_1}} Y$$

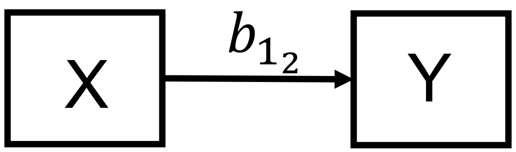
$$Y_{i1} = b_{0_1} + b_{1_1} X_{i1} + e_{Y_{i1}}$$

Group 1



$$Y_{i1} = b_{0_1} + b_{1_1}X_{i1} + e_{Y_{i1}}$$

Group 2



$$Y_{i2} = b_{0_2} + b_{1_2}X_{i2} + e_{Y_{i2}}$$

Group 1

$$X \xrightarrow{b_{1_1}} Y \qquad Y_{i1} = b_{0_1} + b_{1_1}X_{i1} + e_{Y_{i1}}$$

Group 2

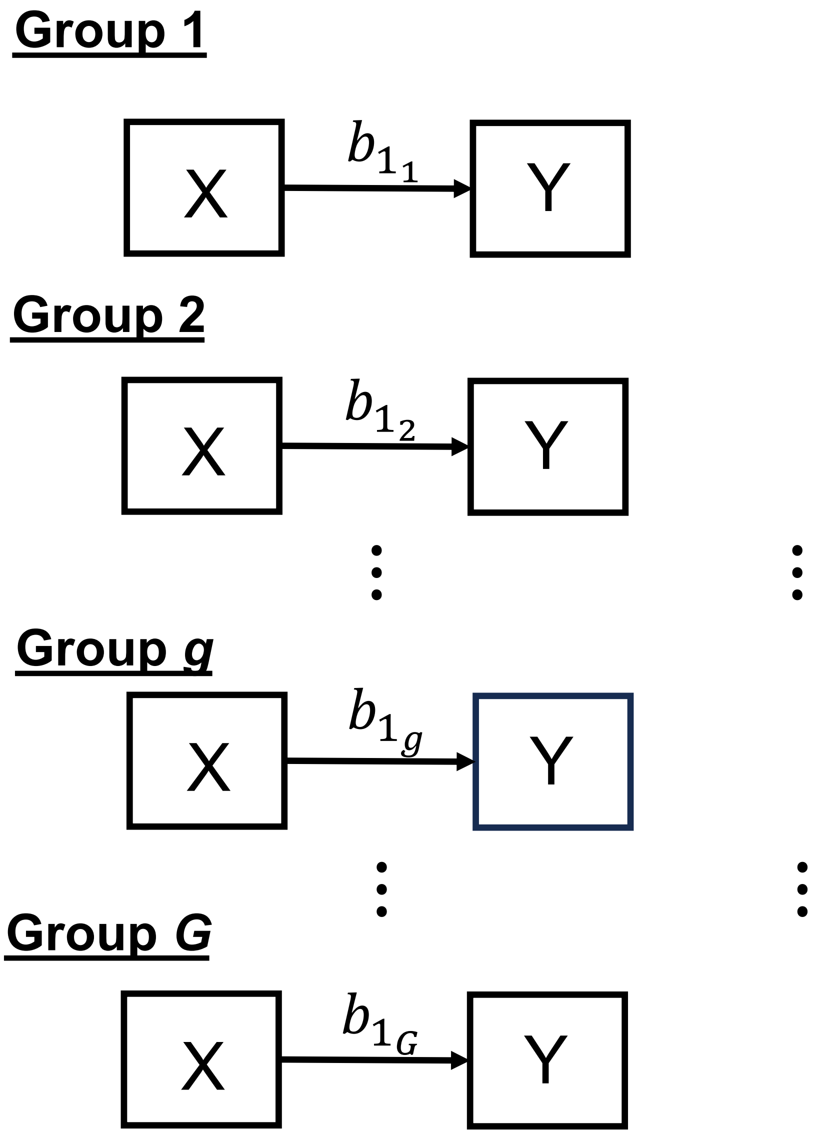
$$X \xrightarrow{b_{1_2}} Y \qquad Y_{i2} = b_{0_2} + b_{1_2}X_{i2} + e_{Y_{i2}}$$

$$\vdots \qquad \vdots \qquad \vdots \qquad \vdots \qquad \vdots$$

Group *g*

$$X \xrightarrow{b_{1_g}} Y \qquad Y_{ig} = b_{0_g} + b_{1_g}X_{ig} + e_{Y_{ig}}$$

$$\vdots \qquad \vdots \qquad \vdots \qquad \vdots \qquad \vdots$$



$$Y_{i1} = b_{0_1} + b_{1_1} X_{i1} + e_{Y_{i1}}$$

$$Y_{i2} = b_{0_2} + b_{1_2} X_{i2} + e_{Y_{i2}}$$

$$\vdots \qquad \vdots \qquad \vdots \qquad \vdots$$

$$Y_{ig} = b_{0_g} + b_{1_g} X_{ig} + e_{Y_{ig}}$$

$$\vdots \qquad \vdots \qquad \vdots \qquad \vdots$$

$$Y_{ig} = b_{0_G} + b_{1_G} X_{iG} + e_{Y_{iG}}$$

Multilevel Modeling

- Let there be G groups, and groups are labeled g = 1, 2, 3, …, G
- Model may be written as
  - $Y_{ig} = b_{0_g} + b_{1_g} X_{ig} + e_{Y_{ig}}$
  - b_{0_g} and b_{1_g} are assumed to follow a multivariate normal distribution
    - $\begin{bmatrix} b_{0_g} \\ b_{1_g} \end{bmatrix} \sim MVN\left(\begin{bmatrix} \mu_{b\,0} \\ \mu_{b\,1} \end{bmatrix}, \begin{bmatrix} \sigma_{b_0}^2 & \\ \sigma_{b_0, b_1} & \sigma_{b_1}^2 \end{bmatrix} \right)$

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  - Residuals adhere to the same normal distribution across group
    - $[e_{Y_{ig}}] \sim N\left(0, \left[\sigma_{e_Y}^2\right]\right)$

Multilevel Modeling

- Let there be G groups, and groups are labeled g = 1, 2, 3, …, G
- Model may be written as

<u>Level-1</u>

- $Y_{ig} = b_{0_g} + b_1 X_{ig} + e_{Y_{ig}}$

<u>Level-2</u>

- $b_{0_g} = \gamma_{00} + u_{0_g}$
- $b_{1_g} = \gamma_{10} + u_{1_g}$

- $\begin{bmatrix} b_{0_g} \\ b_{1_g} \end{bmatrix} \sim MVN\left(\begin{bmatrix} \gamma_{00} \\ \gamma_{10} \end{bmatrix}, \begin{bmatrix} \sigma^2_{u_0} & \\ \sigma_{u_0,u_1} & \sigma^2_{u_1} \end{bmatrix} \right)$

Multilevel Modeling

- ***<u>Concept of Multilevel Modeling</u>***
  - *Dependence is accounted for by ‘modeling the structure’, and assuming residuals are independent after modeling the grouping structure*

- ***<u>In Practice</u>***
  - Estimate separate intercepts and slopes for each group
  - Assume intercepts/slopes follow a multivariate normal
  - Assume residual follow a normal distribution with the same variance across groups
  - Assume residuals are independent
    - *Yay assumptions!*

Multilevel Modeling

X: Norms (ICBS)
Y: Intentions (EBTI)

Level-1

- $Y_{ig} = b_{0_g} + b_{1_g}X_{ig} + e_{Y_{ig}}$

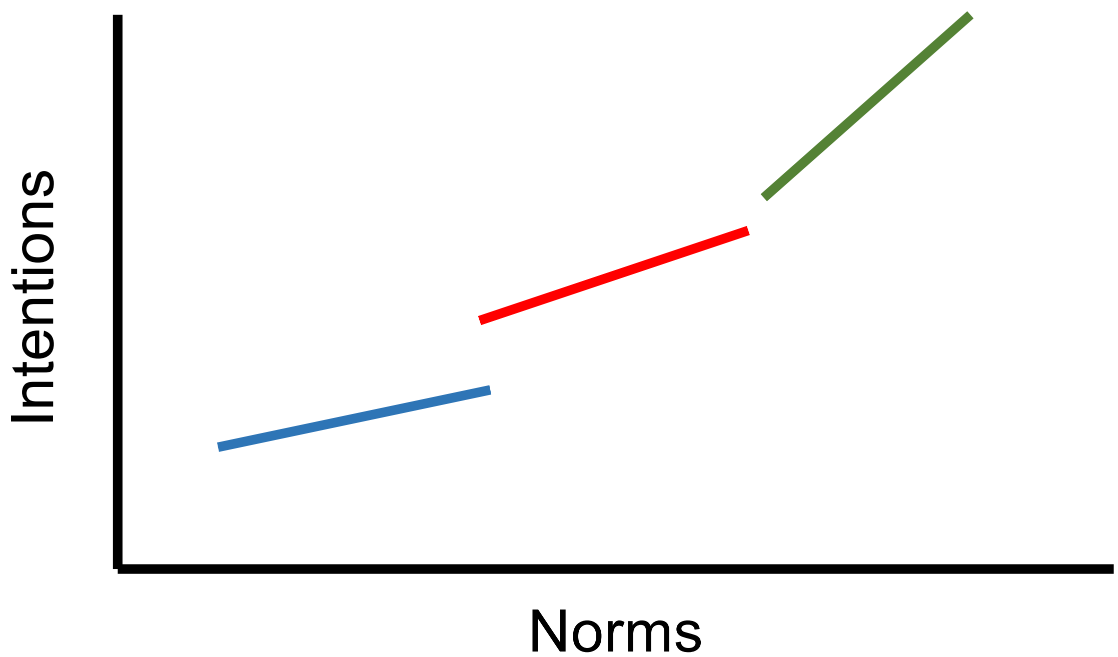
Level-2

- $b_{0_g} = \gamma_{00} + u_{0_g}$
- $b_{1_g} = \gamma_{10} + u_{1_g}$
- $\begin{bmatrix} b_{0_g} \\ b_{1_g} \end{bmatrix} \sim MVN\left(\begin{bmatrix} \gamma_{00} \\ \gamma_{10} \end{bmatrix}, \begin{bmatrix} \sigma^2_{u_0} & \\ \sigma_{u_0,u_1} & \sigma^2_{u_1} \end{bmatrix}\right)$

		Est.	***p***
μ_{b_0}	γ_{00}	3.757	<.001
μ_{b_1}	γ_{10}	.525	<.001

Multilevel Modeling

X: Norms (ICBS)
Y: Intentions (EBTI)



Each group (clinic) has its own intercept and slope

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- Model may be written as
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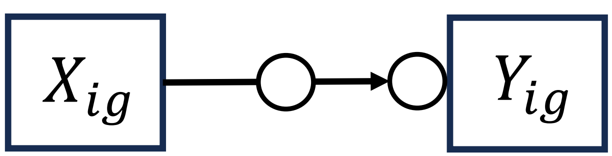
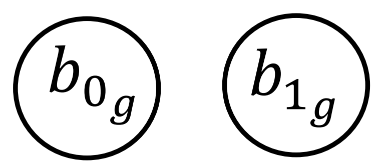
Level-1 Diagram



Level-2 Diagram



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Multilevel Modeling

- ***Centering is of utmost important in multilevel models***

Multilevel Modeling

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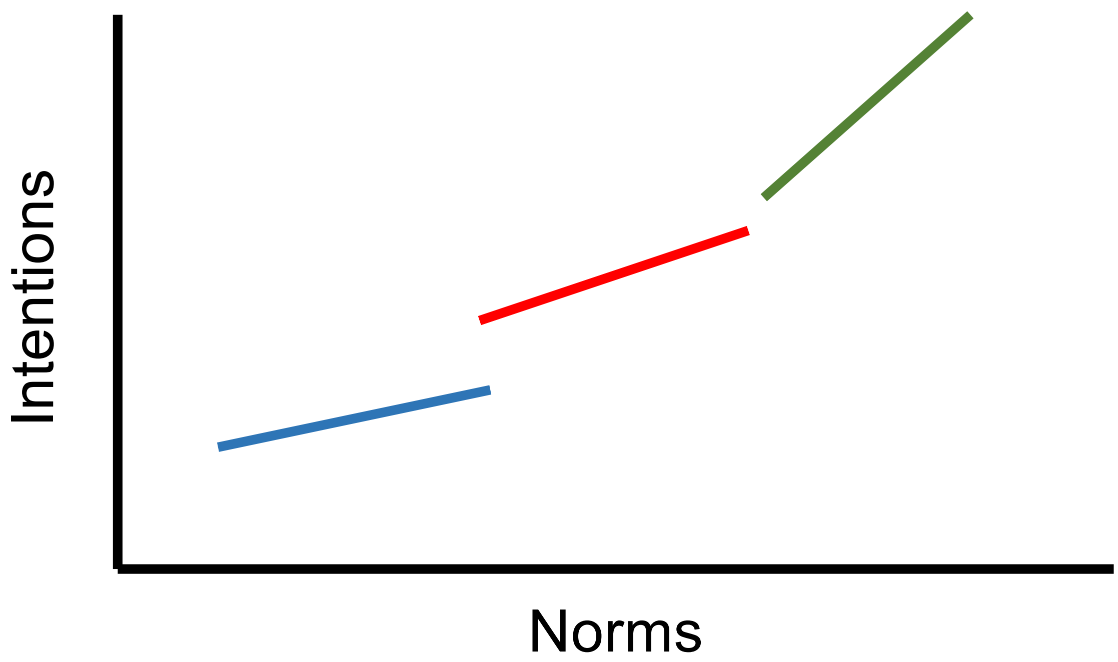
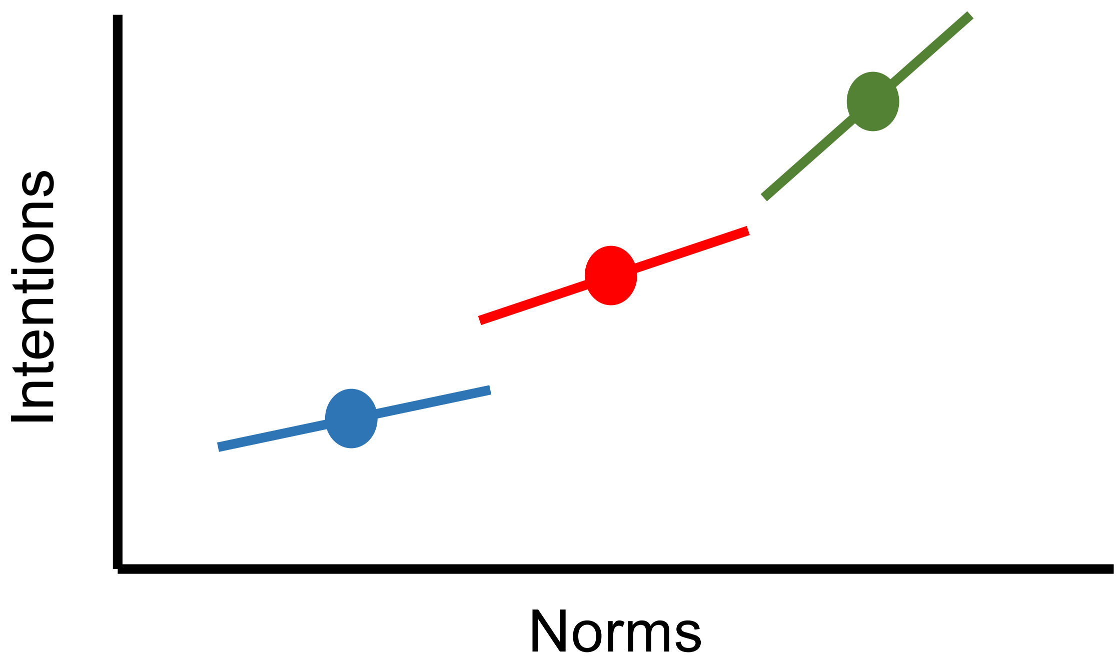


We can separate two *distinct* ways that X and Y are related

Multilevel Modeling

X: Norms (ICBS)
Y: Intentions (EBTI)



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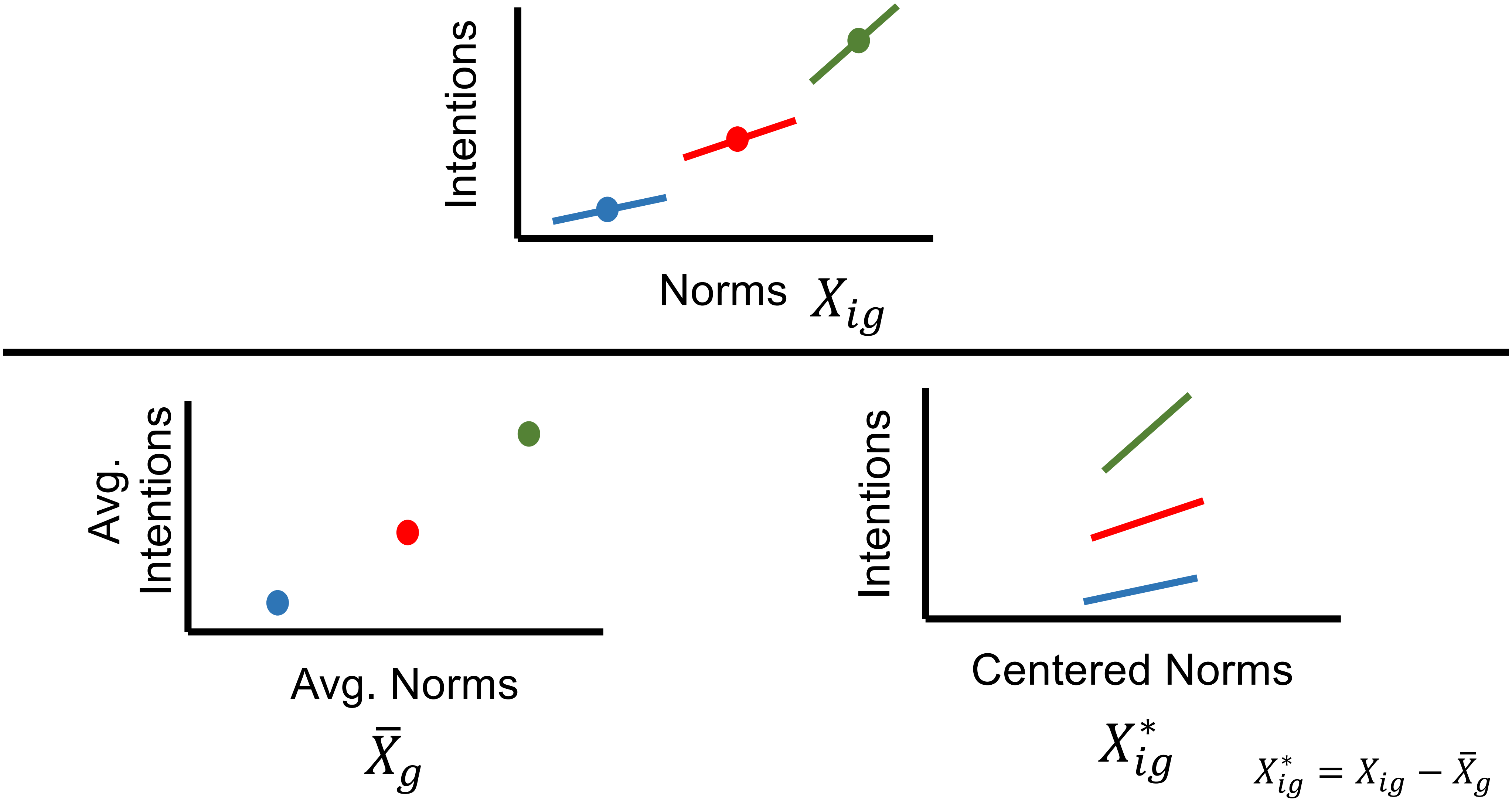
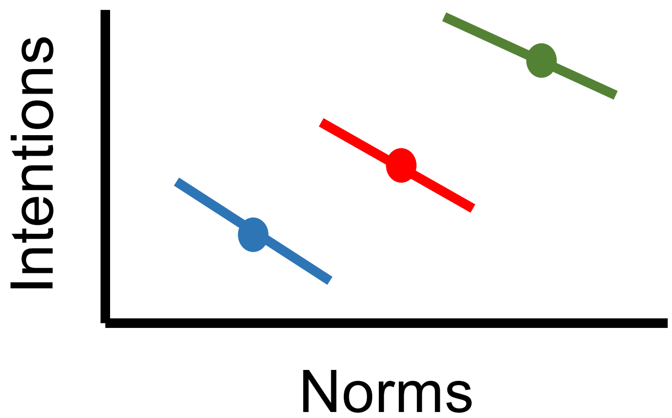
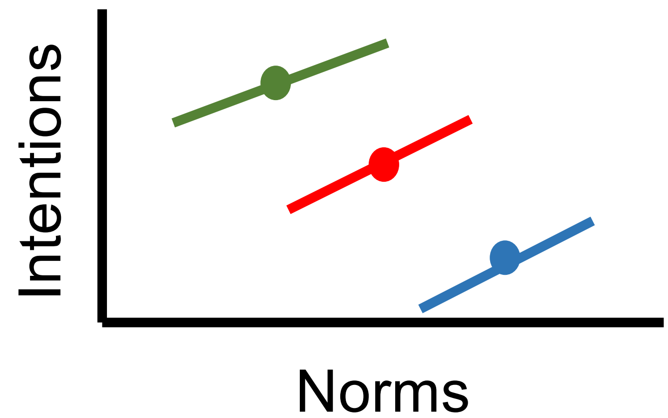


Intentions
Norms X_{ig}
Avg. Intentions
Avg. Norms
$\bar{X}_g$
Intentions
Centered Norms
X^*_{ig}
$X^*_{ig} = X_{ig} - \bar{X}_g$

Multilevel Modeling

X: Norms (ICBS)
Y: Intentions (EBTI)





Multilevel Modeling

- Let $X_{ig}^{*} = X_{ig} - \bar{X}_g$

Level 1 Model:

$$Y_{ig} = b_{0g} + b_{1g}X_{ig}^{*} + \varepsilon_{ig}$$

Level 2 Model:

$$b_{0g} = \gamma_{00} + u_{0g}$$

$$b_{1g} = \gamma_{10} + u_{1g}$$

γ_{10} *will give the average slope across the groups*

Commonly referred to as the 'within' effect

Multilevel Modeling

- Let $X_{ig}^{*} = X_{ig} - \bar{X}_g$

Level 1 Model:

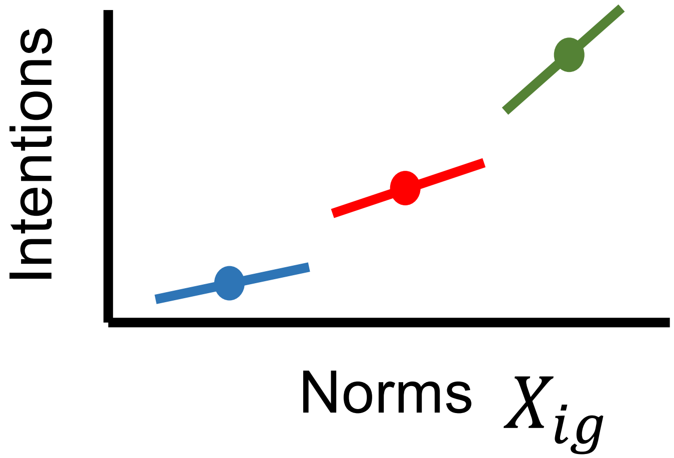
$$Y_{ig} = b_{0g} + b_{1g}X^{*}_{1ig} + \varepsilon_{ig}$$

Level 2 Model:

$$b_{0g} = \gamma_{00} + \gamma_{01}\bar{X}_g + u_{0g}$$
$$b_{1g} = \gamma_{10} + u_{1g}$$

γ_{01} *will estimate the association between group level average across* X *and* Y

Commonly referred to as the 'between' effect



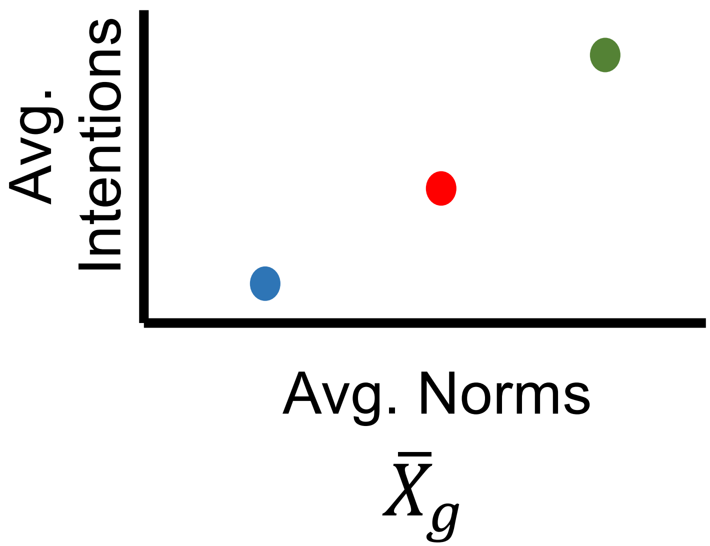
Level 1 Model:

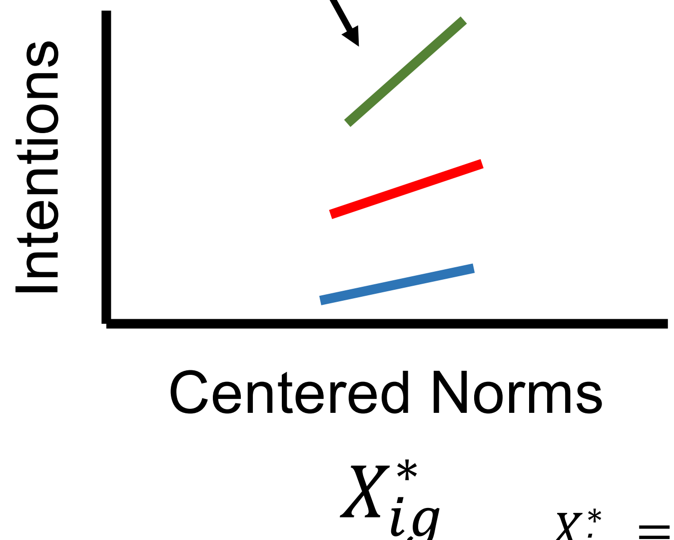
$$Y_{ig} = b_{0g} + b_{1g}X^{*}_{1ig} + \varepsilon_{ig}$$

Level 2 Model:

$$b_{0g} = \gamma_{00} + \gamma_{01}\bar{X}_g + u_{0g}$$

$$b_{1g} = \gamma_{10} + u_{1g}$$





$$X^{*}_{ig} = X_{ig} - \bar{X}_g$$

Multilevel Modeling

X: Norms (ICBS)
Y: Intentions (EBTI)

Level-1

$$Y_{ig} = b_{0_g} + b_{1_g} X_{ig} + e_{Y_{ig}}$$

Level-2

$$b_{0_g} = \gamma_{00} + u_{0_g}$$

$$b_{1_g} = \gamma_{10} + u_{1_g}$$

	Est.	*p*
γ_{00}	3.757	<.001
γ_{10}	.525	<.001

Level-1

$$Y_{ig} = b_{0_g} + b_{1_g} X^*_{ig} + e_{Y_{ig}}$$

Level-2

$$b_{0_g} = \gamma_{00} + \gamma_{01} \bar{X}_g + u_{0_g}$$

$$b_{1_g} = \gamma_{10} + u_{1_g}$$

	Est.	*p*
γ_{00}	4.412	<.001
γ_{10}	.505	<.001
γ_{01}	.539	<.001

Multilevel Modeling

- We can use multilevel modeling to examine between and within associations
- Hinges on centering
- Dependence is accounted for, if our assumptions hold

Multilevel Modeling

Level 1 Model:

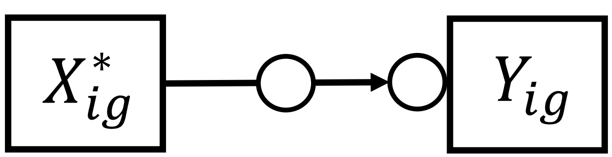
$$Y_{ig} = b_{0g} + b_{1g}X^{*}_{1ig} + \varepsilon_{ig}$$

Level 2 Model:

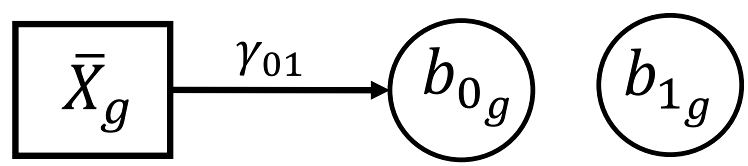
$$b_{0g} = \gamma_{00} + \gamma_{01}\bar{X}_g + u_{0g}$$

$$b_{1g} = \gamma_{10} + u_{1g}$$

Level-1 Diagram



Level-2 Diagram



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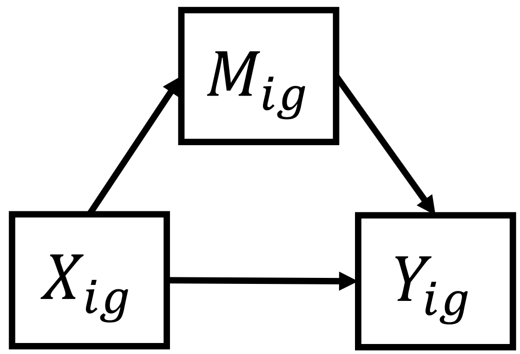
Multilevel Mediation

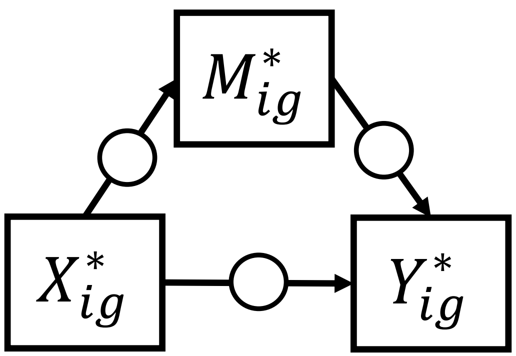
- ***Multilevel Mediation*** combines mediation analysis and multilevel modeling

- We can take the lessons we've learned from multilevel modeling (centering) and apply them to a mediation analysis

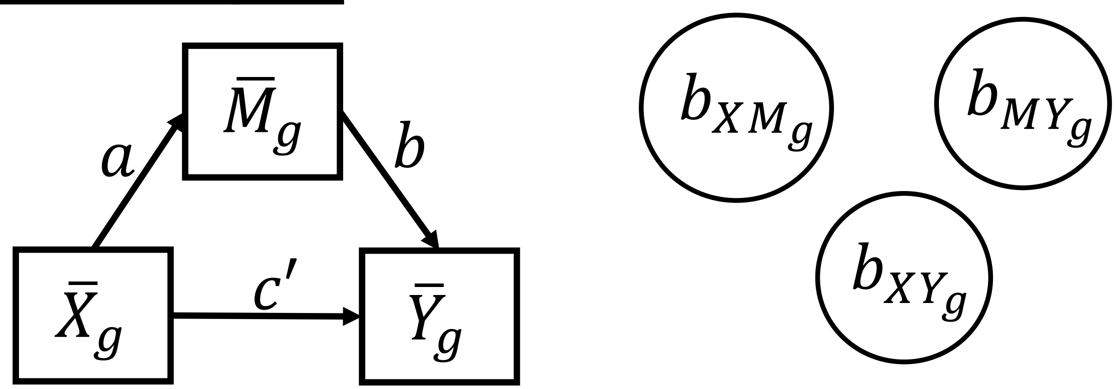
Multilevel Mediation



Level-1 Diagram



Level-2 Diagram



Multilevel Mediation

X: Norms (ICBS)
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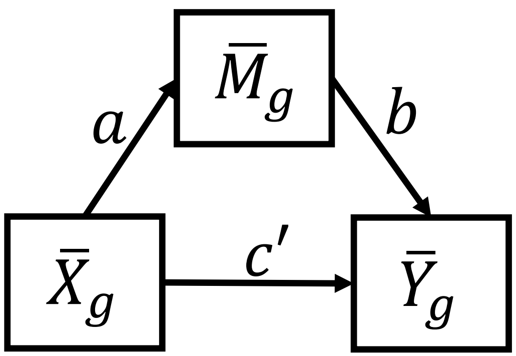
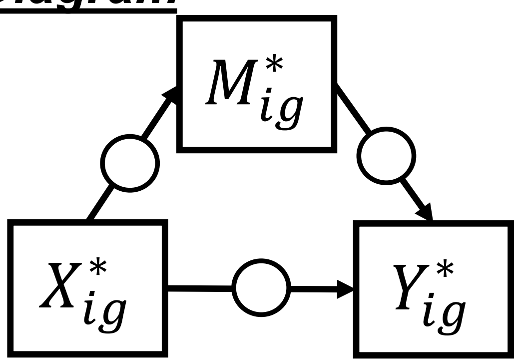
Y: Intentions (EBTI)

Level-2 Diagram



Level-1 Diagram



	Est.	***p***
a	.238	.008
b	.772	<.001
c'	.317	.020
ab	.175	.008
γ_{XM}	.050	.280
γ_{MY}	.457	<.001
γ_{YM}	.500	<.001

Multilevel Mediation

X: Norms (ICBS)
M: Openness (OPEMN)
Y: Intentions (EBTI)

Original Mediation Analysis

	Est.	***p***
a	.238	.006
b	.767	<.001
c'	.317	.017
ab	.183	.022

Multilevel Mediation Analysis

	Est.	***p***
a	.238	.008
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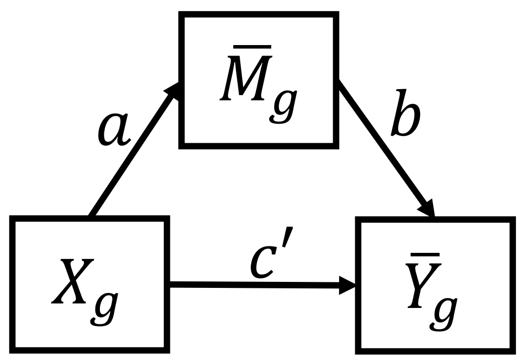
Alternative Multilevel Models

- X, M, and Y variables can be measured at level-1 or level-2
  - *Current example all variables measured at level-1*

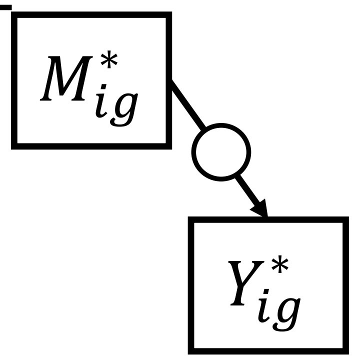
- 1-1-1 Model
- 2-1-1 Model
- 2-2-1 Model
- 2-1-2 Model

2-1-1 Multilevel Mediation

Level-2 Diagram

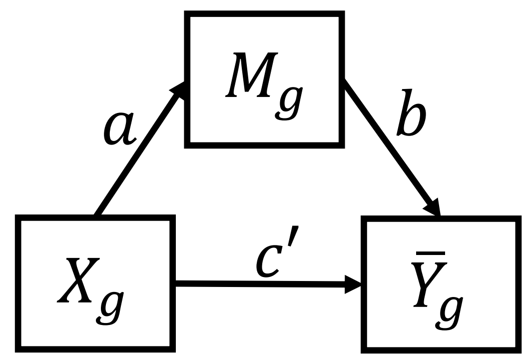


Level-1 Diagram



2-2-1 Multilevel Mediation

Level-2 Diagram



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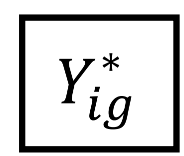


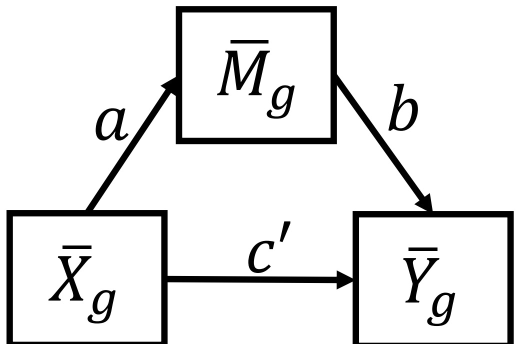
Alternative Multilevel Models

- Averages at level-2 can affect level-1 associations
- Commonly referred to as ‘cross-level interactions’

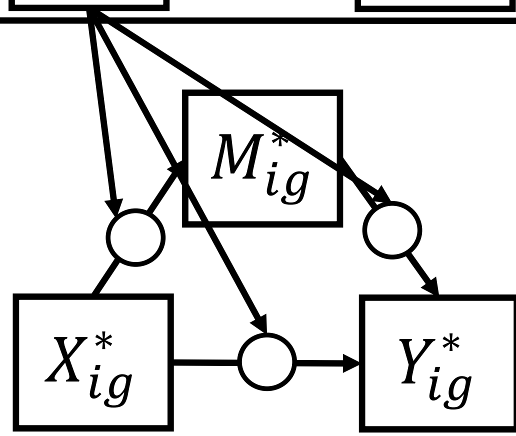
Multilevel Mediation

X: Norms (ICBS)
M: Openness (OPEMN)
Y: Intentions (EBTI)

Level-2 Diagram



Level-1 Diagram



Overview

- Empirical example
- Review of mediation
- Review of multilevel modeling
- Importance of centering
- Combining mediation and multilevel modeling: Multilevel mediation
- Alternative models to be explored
- Consideration of Bayesian estimation

Bayesian Estimation

- Multilevel mediation is a complex statistical model
  - *First paper publishing the full model was in 2010*

- The models rarely run with ML estimation
  - *The current example didn't run with ML*

- Bayesian estimation via M*plus* is more stable

Bayesian Estimation

- Multilevel mediation is a complex statistical model
  - *First paper publishing the full model was in 2010*
- The models rarely run with ML estimation
  - *The current example didn't run with ML*
- Bayesian estimation via M*plus* is more stable
- You don't need to be a 'Bayesian' to use Bayesian estimation
  - *Use the appropriate tool for the job*

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Thank you!

- Any questions?