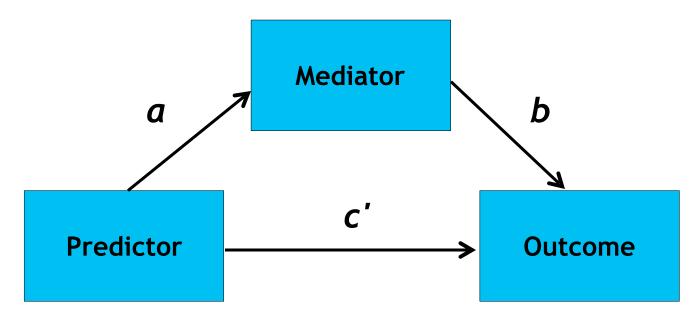
ACCURATE INDIRECT EFFECTS IN MULTILEVEL MEDIATION FOR REPEATED MEASURES DATA

Amanda Sharples and Elizabeth Page-Gould University of Toronto





Mediation

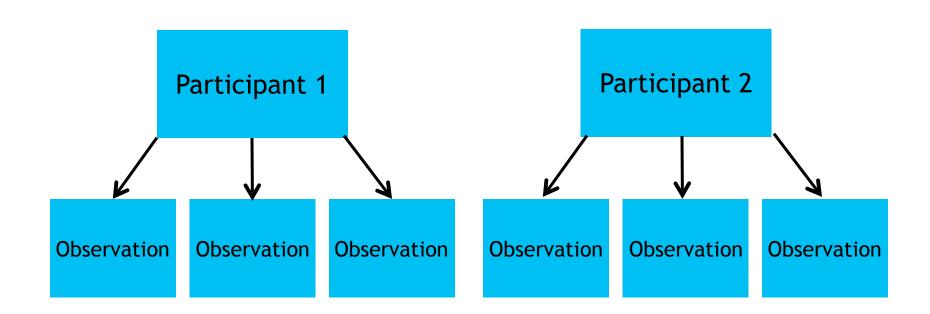






Multilevel Models

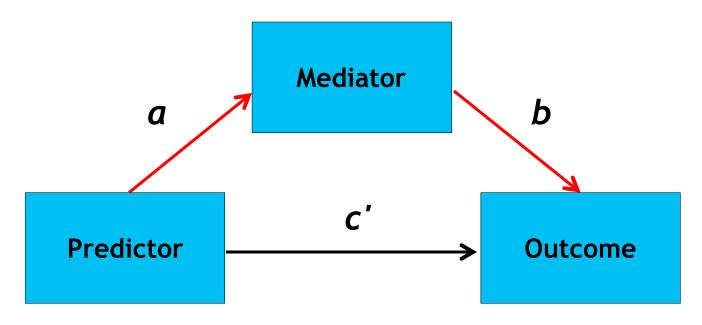
Nested (Repeated Measures) Data







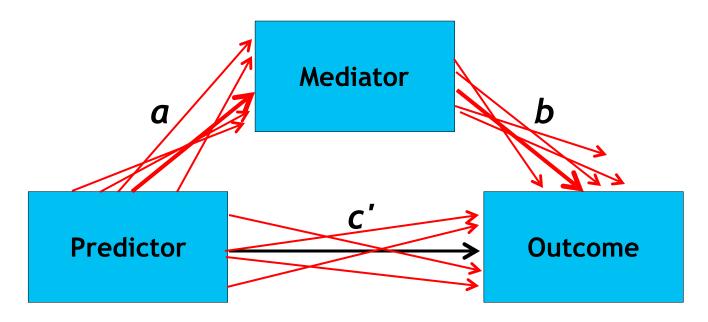
Multilevel Mediation







Multilevel Mediation

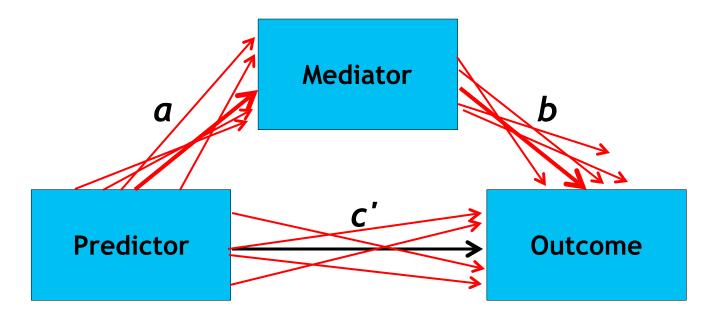






The Wrong Way to Do Multilevel Mediation

USE FIXED SLOPES TO CALCULATE INDIRECT EFFECT







Why is this Bad?

- The indirect effect is biased.
 - So the total effect is biased too.
- They are biased by how much the random slopes a and b cova

Bauer, Preacher, & Gil (2006); Kenny, Korchmaros, and Bolger (2003)

Bias =
$$COV(a_i, b_i) = \sigma_{ab}$$

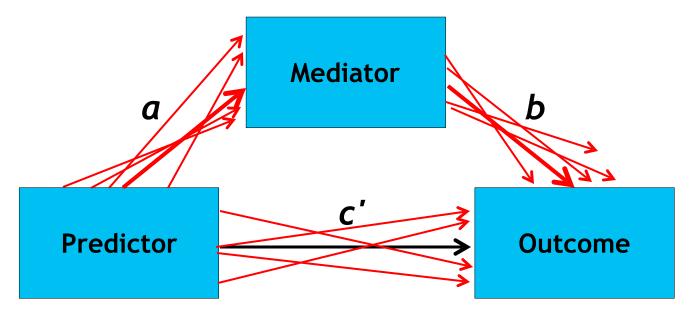
Real indirect effect = $(a \times b) + COV(a_i, b_i)$
Real total effect = $(a \times b) + COV(a_i, b_i) + c'$





The Right Way to Do Multilevel Mediation

TAKE RANDOM SLOPES INTO ACCOUNT



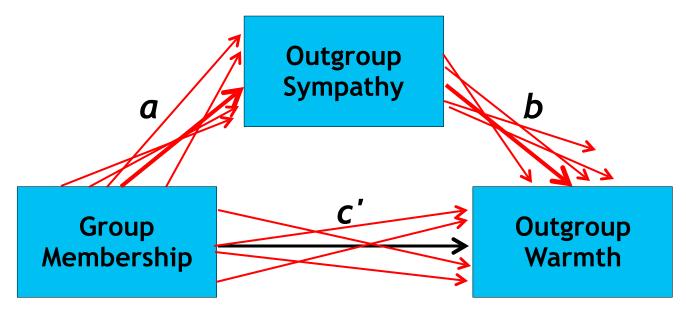
Indirect effect = Mean $(a_i \times b_i)$ Total effect = Mean(Indirect effect_i + c'_i)





The Right Way to Do Multilevel Mediation

TAKE RANDOM SLOPES INTO ACCOUNT



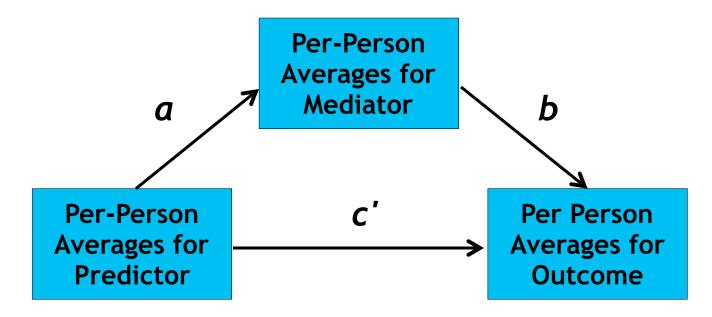
Indirect effect = Mean $(a_i \times b_i)$ Total effect = Mean(Indirect effect_i + c'_i)





An OK Way to Do Multilevel Mediation

USE AGGREGATE REPEATED MEASURES FOR EACH PARTICIPAN



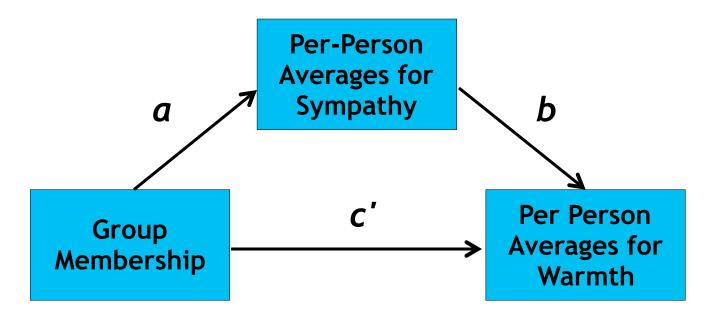
(Unbiased) Indirect effect = $a \times b$ (Unbiased) Total effect = Indirect effect + c'





An OK Way to Do Multilevel Mediation

USE AGGREGATE REPEATED MEASURES FOR EACH PARTICIPAN



(Unbiased) Indirect effect = $a \times b$ (Unbiased) Total effect = Indirect effect + c'





How do we determine the robustness of our effects?

• There have been approaches put forward, but...



How do we determine the robustness of our effects?

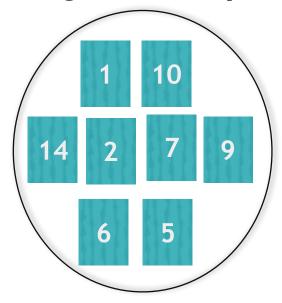
• There have been approaches put forward, but...

- Bootstrapping is ideal because
 - It does not require the assumption that the random effects are normally distributed.
 - It is already ubiquitous in social psychology (especially in mediation analysis)



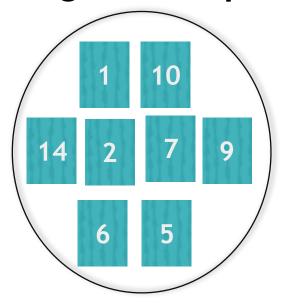


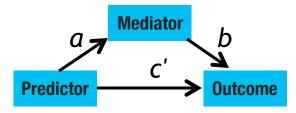
Original Sample





Original Sample

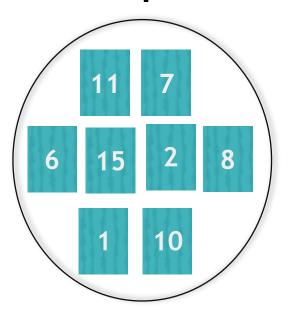




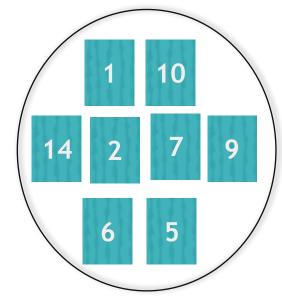


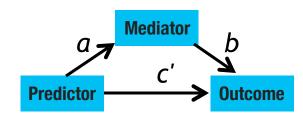


Resample 1

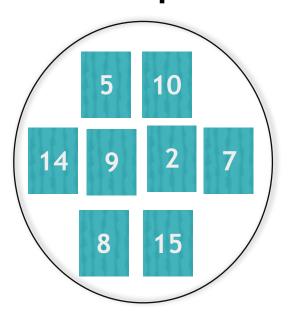


Original Sample





Resample 2



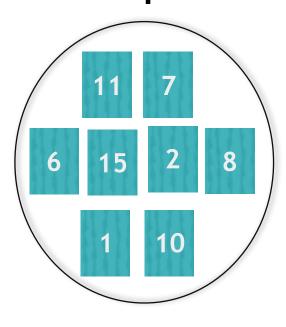


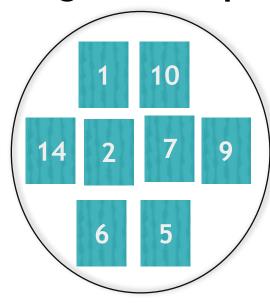


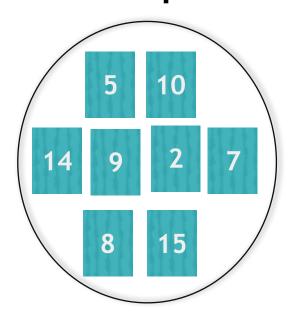
Resample 1

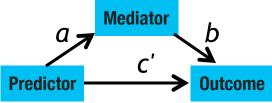
Original Sample

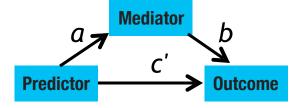
Resample 2

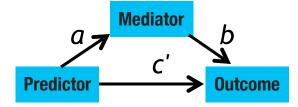














Goals of Current Demonstration

- Demonstrate how you can calculate unbiased indirect and total effects in multilevel mediation models.
- Demonstrate how you can use a bootstrapping approach to estimate confidence intervals for your effects.



Research Questions

- Will people rate their target in-group more warmly than target outgroups?
- Can this be explained by greater sympathy toward the target in-group (i.e., an indirect effect).



Method: Sample

- N = 340 (community members)
- 62% female, 38% male
- Age range: 16-75
- Ethnicity: 33% White, 28% East Asian, 28% South Asian, 5% Black, 3% Arab, 2% Latino



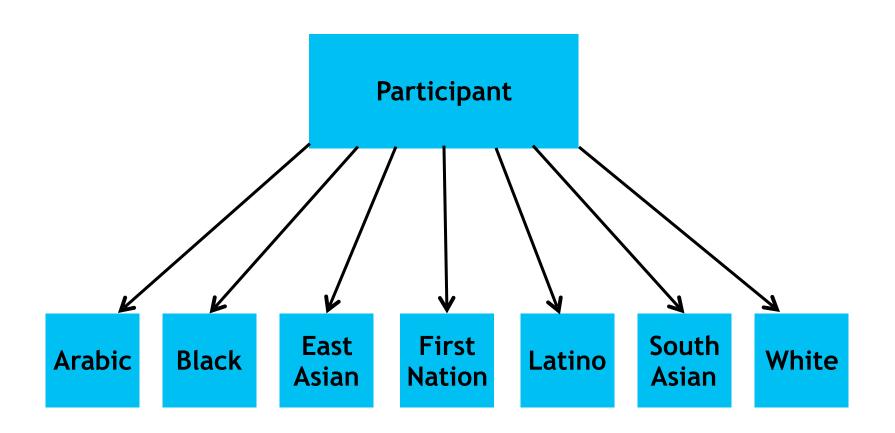
Method: Questionnaire

- Demographic information (e.g., ethnicity).
- Sympathy (0 = not at all sympathetic to 10 = very sympathetic) toward 7 target ethnic groups.
- Warmth (0 = cold to 10 = warm) toward 7 target ethnic groups.

Arabic Black East Asian First Nation Latino South Asian White











Method: Questionnaire

Bootstrap Analysis in R:

- Created a function "indirect.mlm"
 - Runs the relevant multilevel models in each resample
 - Multiplies together the <u>random</u> a and b slopes and takes the mean of these products
- Use the "boot" package to do the multilevel mediation



Between-Person Effects:

- Indirect effect = a × b
- Total effect = Indirect effect + c'

Within-Person Effects:

- Unbiased Indirect effect = Mean $(a_i \times b_i)$
- Unbiased Total effect = Mean(Indirect effect_i +



```
boot(data=data.set, R=1000,
strata=ID,
statistic=indirect.mlm,
y="warmth", x="target",
mediator="sympathy", group.id="ID")
```





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boot(data=data.set, R=1000,
strata=ID,
statistic=indirect.mlm,
y="warmth", x="target",
mediator="sympathy", group.id="ID",
between.m=T,
uncentered.x=F)
```



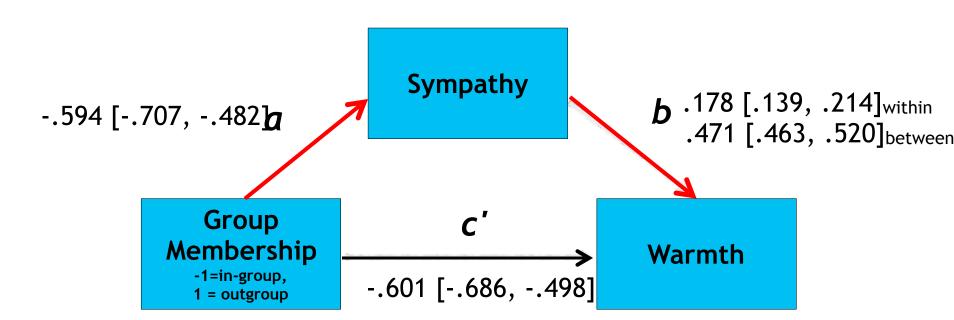


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Results (unbiased)

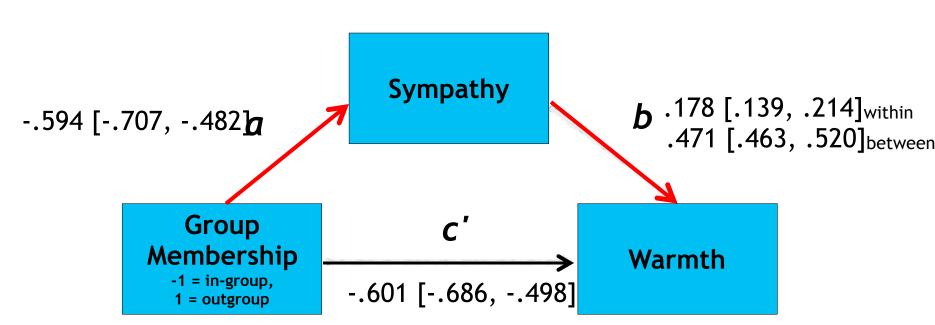


Total effect = -.733 [-.823, -.643]





Results (biased)



Total effect = -.784 [-.871, -.696]





Bias in indirect effect:

Biased: $ab_{within} = -.106 [-.138, -.076]$

Unbiased: $ab_{within} = -.131[-.180, -.103]$

Difference = .025 [.015, .058] = σ_{ab}





Bias in indirect effect:

Biased: $ab_{within} = -.106 [-.138, -.076]$

Unbiased: $ab_{within} = -.131 [-.180, -.103]$

Difference = .025 [.015, .058] =
$$\sigma_{ab}$$

• Difference between biased and unbiased effects is equal to covariance betwee random slopes for paths a and b.





Bias in total effect:

Biased: c = -.784[-.871, -.696]

Unbiased: c = -.733 [-.823, -.643]

Difference = -.052 [-.086, -.020]





Bias in total effect:

Biased: c = -.784 [-.871, -.696]

Unbiased: c = -.733 [-.823, -.643]

Difference = -.052 [-.086, -.020]

Difference between biased and unbiased total effect is equal to

 $ab_{unbiased} - ab_{biased} + \sigma_{ab}$





- Download R script to run this analysis
 - www.page-gould.com/r/indirectmlm



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Take Home Message

- Proof of concept
 - You can bootstrap indirect effects in multilevel mediation analysis.

www.page-gould.com/r/indirectmlm







Thank you!

Co-author

Elizabeth Page-Gould



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 - Social Psychophysiology and Quantitative Methods Lab (SPRQL)
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 - Ontario Graduate
 Scholarship

Awarded to Page-Gould:

- Canada Research Chairs
- Canada Foundation for Innovation
- Connaught Fund New Researcher Award
- Ontario Ministry of Research & Innovation
- Social Sciences and Humanities Research Council (SSHRC) Insight Grants





Questions directed to any speaker?



