EUSPR/SPAN workshop on Mediation Analysis

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What is this workshop about?

- Overview of the conceptual basis of mediation and moderation
- Understanding basic conceptual assumptions underlying the test of mediating and moderating factors
- Overview of the methodological advancements
- Providing examples of different mediation and moderation models

What are the GOALs of the workshop?

- Understanding the current state-of-the-art approach to test mediating and moderating mechanisms
- Providing a guide and motivation for further exploration and learning
- Having some fun time!

"In the absence of a concern for such mediating or intervening mechanisms, one ends up with facts, but with incomplete understanding."

Morris Rosenberg, 1968

How are we doing in prevention research?

Sandler et al.'s (2011) review of parenting programs

"The findings… provide evidence of the effects to prevent a wide range of problem outcomes and to promote competencies from one to twenty years later. However, there is a paucity of evidence concerning the processes that account for program effects."

In plain language: We don't **really** know how and why the parenting programs work.

Some numbers from Sandler et al. (2011)

- Out of 46 randomized controlled trials they reviewed, only 10 reported findings on mediation
- No mediation test among the studies on infancy/toddlerhood programs
- Most available mediation tests used the outdated technique of Baron & Kenny (1986), which is known for producing biased estimates
- No study tested mediation when the outcome was not changed by the program

It seems that, AT LEAST, we don't know about how and why parenting programs have effects on outcomes

What do we usually study?

The fundamental question in prevention studies:

Is the program effective?

1. Is it effective on primary outcomes?
   - e.g., alcohol use
2. Is it effective on secondary outcomes?
   - e.g., delinquency
3. Is it effective on intermediary outcomes?
   - e.g., parents' behavior, refusal skills, social skills, etc.

Does "**effect testing**" inform us about the prevention programs?

All programs start with an underlying theory

Intervening with the risk/protective factor may prevent underage drinking.

Örebro Prevention Program - ÖPP

Program theory:

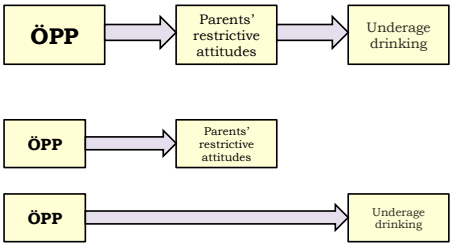
ÖPP assumed that promoting parents' restrictive attitudes may prevent underage drinking.

Effect testing approach answer:

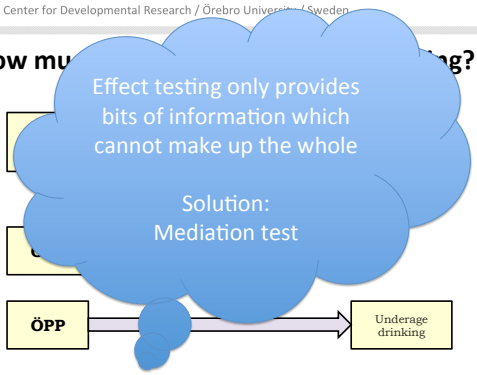
1. Does ÖPP reduce underage drinking?

2. Does ÖPP promote parents' restrictive attitudes towards drinking?

How much we learned from effect testing?



How mu…ng?



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What is mediation?

Mediation is also called as indirect effect.

Indirect effect

X → M → Y

In plain language:

- X is related to Y because of its effect on M
- If X does not effect M, it does not effect Y
- X effecting M does not guarantee X effecting Y
- M has to effect Y

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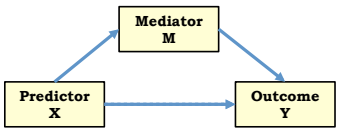
What is mediating variable?

Graphical display of a mediation model.



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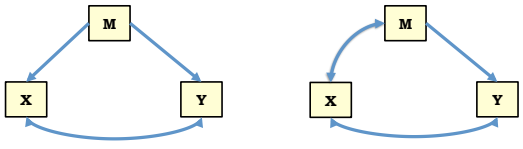
What is mediation?

Third variable effect

X, M, and Y could be related to each other in different ways.

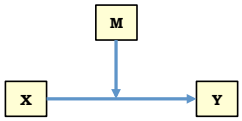


Spurious Association
X and Y have a common cause

Epiphenomenal Association
X is associated with the causal antecedent of Y

Third variable effect

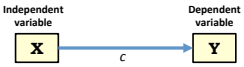
X, M, and Y could be related to each other in different ways.



Moderation Effect
M modifies the effect of X on Y

Mediation model

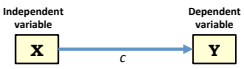
Basic equations in a mediation model



$$Y = i_1 + cX + e_1$$

Mediation model

Basic equations in a mediation model



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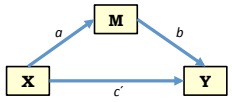
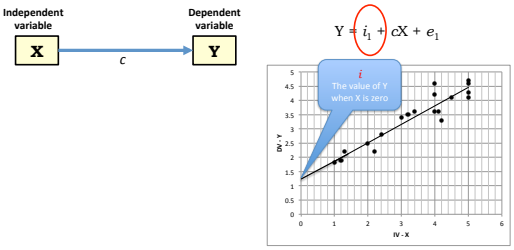


$$Y = i_2 + c'X + bM + e_2$$

$$M = i_3 + aX + e_3$$

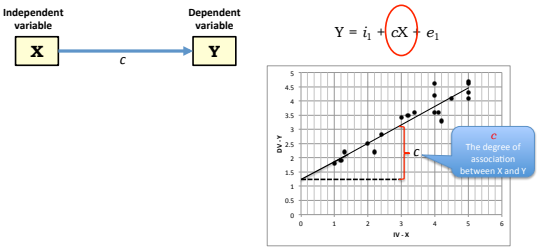
Mediation model

Basic equations in a mediation model



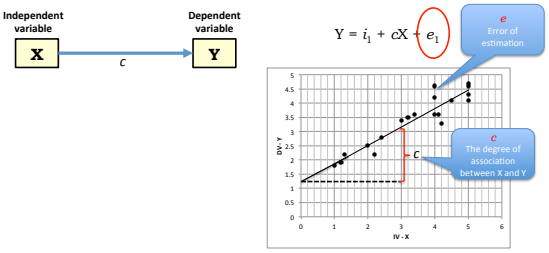
Mediation model

Basic equations in a mediation model



Mediation model

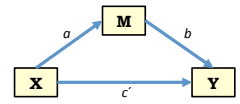
Basic equations in a mediation model



Mediation model

Basic equations in a mediation model

$$Y = i_1 + cX + e_1$$



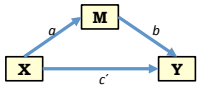
$$Y = i_2 + c'X + bM + e_2$$

$$M = i_3 + aX + e_3$$

Effect partitioning

Total effect
The effect of X on Y, without considering the role of M

Direct effect
- The effect of X on Y, after controlling for the effect of M
- Represented by ***c´***

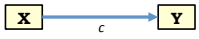


Mediated effect
- The effect of X on Y, over its effect on M
- Represented by ***a*b***

Total effect = direct effect + indirect effect = *c´* + *a*b*

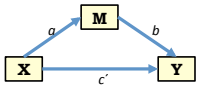
Effect partitioning

Total effect = direct effect + indirect effect = *c´* + *a*b*



Mediated effect, ***a*b,*** is equal to the difference between total and direct effect

a*b* = *c* - *c´

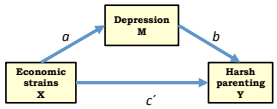


Note:
The estimated values of ***a*b*** would be equal to ***c*** - ***c´*** in OLS regression.

BUT, the estimated values may not be equal to each other in logistic and multilevel regression models because of the differences in standard error estimates.

Example: Estimating mediation equations

$Y = i_1 + cX + e_1$



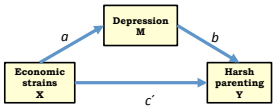
$Y = i_2 + c'X + bM + e_2$

$M = i_3 + aX + e_3$

Example: Estimating mediation equations

Why do parents with low income use hash parenting practices?

- It could be possible that economic problems result in elevated depressive symptoms, which in turn, leads to use of harsh parenting practices.



Estimating mediation equations

$Y = i_1 + cX + e_1$

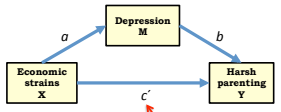
```
regression
/dependent harsh_parenting
/method=enter economic_strains .
```

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.543	.077		32.871	.000
	economic_strains	.101	.027	.112	3.668	.000

a. Dependent Variable: harsh_parenting

Estimating mediation equations



$$Y = i_2 + c'X + bM + e_2$$

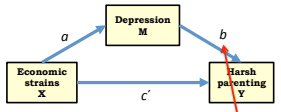
```
regression
/dependent harsh_parenting
/method=enter depression economic_strains .
```

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.137	.095		22.563	.000
	depression	.248	.034	.226	7.191	.000
	economic_strains	.038	.028	.042	1.342	.180

a. Dependent Variable: harsh_parenting

Estimating mediation equations



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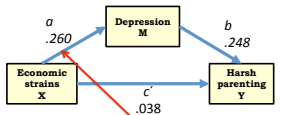


$$M = i_3 + aX + e_3$$

```
regression
/dependent depression
/method=enter economic_strains .
```

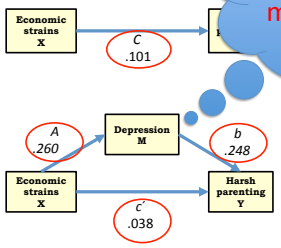
Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.656	.066		25.048	.000
	economic_strains	.260	.024	.318	11.057	.000

a. Dependent Variable: depression

Estimating mediatio

So, what?
Is there a mediation effect?



Indirect effect = a*b = .260*.248
= .064

Indirect effect = a*b = c – c´
c – c´= .101-.038) = .063

Total effect = direct + indirect effect
= .038 +.063) = .101

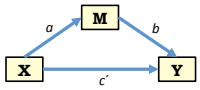
Testing for mediation effect

Causal steps approach

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology*, *51*(6), 1173-1182.

Cited 40 785 times according to *scholar.google.com*

Testing for mediation effect

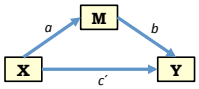


Problems with the causal steps approach

1. X has significant effect on Y
2. X has significant effect on M
3. M has a significant effect on Y, controlling for X
4. X has non-significant effect on Y when M is controlled for, or the magnitude of c´ is substantially reduced

- It is not reasonable to require full mediation
- There could be other mediators which were not included in the model
- Partial mediation is as equally important as full mediation

Testing for mediation effect



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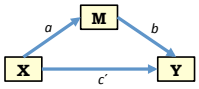
1. X has significant effect on Y
2. X has significant effect on M
3. M has a significant effect on Y, controlling for X
4. X has non-significant effect on Y when M is controlled for, or the magnitude of c´ is substantially reduced

- Mediation effect of X on Y is possible when there is no direct effect.
- In some cases, it is not reasonable to expect an association between X and Y without X changing the level of M

Testing for mediation effect



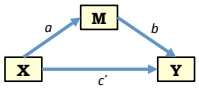
Problems with the causal steps approach

1. X has significant effect on Y
2. X
3.
4.

Conclusion

Causal steps approach of Baron & Kenny (1986) has problems. Two of the steps may not be met even when there is a mediation effect. In addition, causal steps approach has the lowest power to detect mediation among others (MacKinnon et al., 2002).

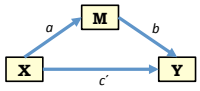
Testing for mediation effect



Testing the significance of indirect effect

- Significance of the indirect effect could be tested to infer mediation effect.
- Indirect effect estimates as $c - c'$ or $a*b$ could be tested for its significance
- Testing $a*b$ is more common because of the problems of $c - c'$
- The test involves dividing the indirect effect by its standard error, and comparing the value to a normal distribution table

Testing for mediation effect



Testing the significance of indirect effect

Sobel test is the most common test of significance of the indirect effect

Indirect effect

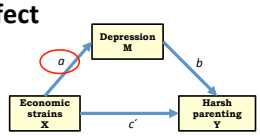
$$\text{Sobel test} = Z = \frac{ab}{\sqrt{b^2 s_a^2 + a^2 s_b^2 + s_a^2 s_b^2}}$$

Pooled standard error of indirect effect

Testing for mediation effect

Testing the significance of indirect effect

$$Z = \frac{ab}{\sqrt{b^2 s_a^2 + a^2 s_b^2 + s_a^2 s_b^2}}$$



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a. Dependent Variable: depression

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
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a. Dependent Variable: harsh_parenting

Testing for mediation effect

Testing the significance of indirect effect

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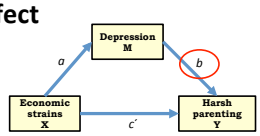

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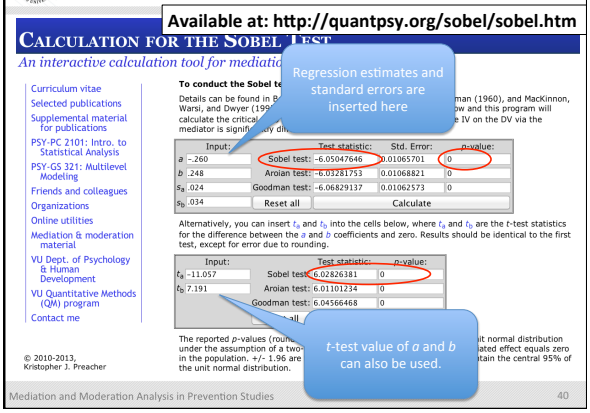
a. Dependent Variable: harsh_parenting

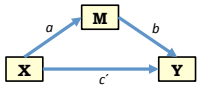
Available at: http://quantpsy.org/sobel/sobel.htm



Regression estimates and standard errors are inserted here

t-test value of *a* and *b* can also be used.

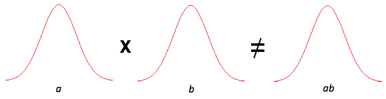
Testing for mediation effect



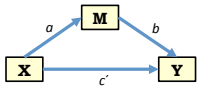
Problems with Sobel test

- Sobel test is based on normal distribution assumption
- *z-value* is evaluated on normal distribution critical values of significance
- a*b must be normally distributed for an accurate test of z, but a*b is often not normally distributed

$$Z = \frac{ab}{\sqrt{b^2 s_a^2 + a^2 s_b^2 + s_a^2 s_b^2}}$$



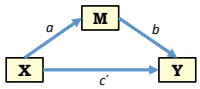
Testing for mediation effect



Problems with Sobel test

- Sobel test is not the best approach to test indirect effect
- Simulation studies showed that Sobel test can produce biased results
- **Use Sobel test only when**
  - you have relatively large sample sizes (N > 1000)
  - you have normally distributed estimates of ***a*** and ***b***
  - Even if ***a*** and ***b*** are normally distributed, ***a**b*** may not be normally distributed
- As a safeguard, do not use Sobel test when other methods are available

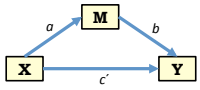
Testing for mediation effect



What is the recommended method?

- Methods using the actual distribution of ***a*b*** is superior to other approaches
- Using resampling methods (bootstrapping) and methods based on the distribution of the product of ***a*b*** is the best approach
- Use asymmetric confidence intervals in addition to significance testing of indirect effect to reach robust conclusion about the mediation effect

Testing for mediation effect



Assumptions of mediation:

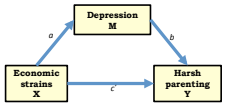
1. **The model is correctly specified**
   X → M → Y is the actual causal ordering, not M → X → Y
   - Use theory to build up your mediation model
   - Use evidence from previous experimental studies, prevention trials, or strong correlations
2. **No misspecification due to omitted variables that cause the variables in the model**
3. **No misspecification due to poor measurement**
4. **No interaction between X and M**
   - It is best to test for interaction

More examples

Testing Single Mediation Model in MPlus

Example: Single mediator model in MPlus

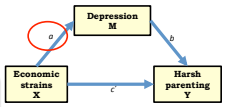
To use resampling method to estimate indirect effect and its confidence interval




```
ANALYSIS:
   BOOTSTRAP = 1000;

MODEL:
   depress ON strains;        ! X --> M
   harsh ON depress strains;  ! M --> Y, controlling for X

MODEL INDIRECT:
   harsh IND depress strains; !Indirect effect of X on Y through M

OUTPUT: SAMP STDYX CINTERVAL (BOOTSTRAP);
```


Example: Single mediator model in MPlus

Defines the effect of X on M, a

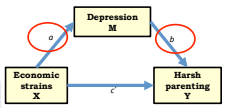



```
ANALYSIS:
   BOOTSTRAP = 1000;

MODEL:
   depress ON strains;        ! X --> M
   harsh ON depress strains;  ! M --> Y, controlling for X

MODEL INDIRECT:
   harsh IND depress strains; !Indirect effect of X on Y through M

OUTPUT: SAMP STDYX CINTERVAL (BOOTSTRAP);
```


Example: Single mediator model in MPlus

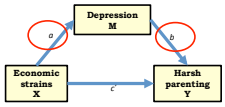
Defines the effect of X on M, a

Defines the effect of M on Y, *b*




```
ANALYSIS:
   BOOTSTRAP = 1000;

MODEL:
   depress ON strains;        ! X --> M
   harsh ON depress strains;  ! M --> Y, controlling for X

MODEL INDIRECT:
   harsh IND depress strains; !Indirect effect o

OUTPUT: SAMP STDYX CINTERVAL (BOOTSTRAP);
```

Example: Single mediator model in MPlus

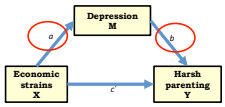


Estimates *a*b*

```
ANALYSIS:
   BOOTSTRA
MODEL:
   depress ON s      s;          ! X --> M
   harsh ON dep      s strains;  ! M --> Y, controlling for X
MODEL INDIRECT:
   harsh IND depress strains; !Indirect effect of X on Y through M
OUTPUT: SAMP STDYX CINTERVAL (BOOTSTRAP);
```

Request bootstrapped confidence intervals

Example: Single mediator model in MPlus




```
ANALYSIS:
   BOOTSTRAP = 1000;
MODEL:
   depress ON strains;         ! X --> M
   harsh ON depress strains;   ! M --> Y, controlling for X
MODEL INDIRECT:
   harsh IND depress strains; !Indirect effect of X on Y through M
OUTPUT: SAMP STDYX CINTERVAL (BOOTSTRAP);
```

Request bootstrapped confidence intervals

Example: Single mediator model in MPlus

```
SUMMARY OF ANALYSIS

Number of groups                                                 1
Number of observations                                        1061

Number of dependent variables                                    2
Number of independent variables                                  1
Number of continuous latent variables                            0

Observed dependent variables

  Continuous
   DEPRESS     HARSH

Observed independent variables
   STRAINS


Estimator                                                       ML
Information matrix                                        OBSERVED
Maximum number of iterations                                 1000
Convergence criterion                                  0.500D-04
Maximum number of steepest descent iterations                  20
Number of bootstrap draws
    Requested                                                1000
    Completed                                                1000
```

Example: Single mediator model in MPlus

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
DEPRESS ON				
STRAINS	0.259	0.026	9.793	0.000
HARSH ON				
DEPRESS	0.248	0.036	6.797	0.000
STRAINS	0.038	0.030	1.258	0.208
Intercepts				
DEPRESS	1.657	0.076	21.787	0.000
HARSH	2.137	0.100	21.395	0.000
Residual Variances				
DEPRESS	0.318	0.014	23.204	0.000
HARSH	0.400	0.019	20.776	0.000

Example: Single mediator model in MPlus

a
X has significant effect on M

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
DEPRESS ON				
STRAINS	0.259	0.026	9.793	0.000
HARSH ON				
DEPRESS	0.248	0.036	6.797	0.000
STRAINS	0.038	0.030	1.258	0.208
Intercepts				
DEPRESS	1.657	0.076	21.787	0.000
HARSH	2.137	0.100	21.395	0.000
Residual Variances				
DEPRESS	0.318	0.014	23.204	0.000
HARSH	0.400	0.019	20.776	0.000

Example: Single mediator model in MPlus

b
M has significant effect on Y

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
DEPRESS ON				
STRAINS	0.259	0.026	9.793	0.000
HARSH ON				
DEPRESS	0.248	0.036	6.797	0.000
STRAINS	0.038	0.030	1.258	0.208
Intercepts				
DEPRESS	1.657	0.076	21.787	0.000
HARSH	2.137	0.100	21.395	0.000
Residual Variances				
DEPRESS	0.318	0.014	23.204	0.000
HARSH	0.400	0.019	20.776	0.000

Example: Single mediator model in MPlus

c'
X has no significant direct effect on Y, controlling for M

```
MODEL RESULTS

                                                    Two-Tailed
                    Estimate       S.E.  E     S.E.    P-Value

 DEPRESS  ON
    STRAINS            0.259      0.026       9.793      0.000

 HARSH    ON
    DEPRESS            0.248      0.036       6.797      0.000
    STRAINS            0.038      0.030       1.258      0.208

 Intercepts
    DEPRESS            1.657      0.076      21.787      0.000
    HARSH              2.137      0.100      21.395      0.000

 Residual Variances
    DEPRESS            0.318      0.014      23.204      0.000
    HARSH              0.400      0.019      20.776      0.000
```

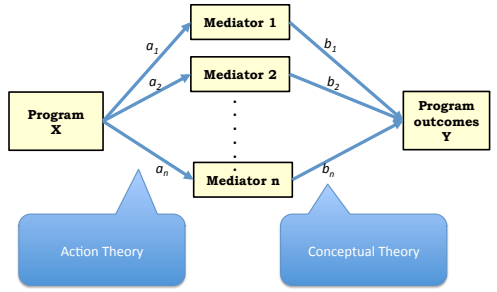

Example: Single mediator model in MPlus

```
TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

Effects from STRAINS to HARSH
  Sum of indirect      0.064      0.012       5.476      0.000
  Specific indirect

    HARSH
    DEPRESS
    STRAINS            0.064      0.012       5.476      0.000
```

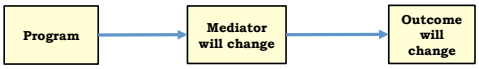
95% Confidence Interval
Lower bound = .043 Upper bound = .088

Testing Mediation in Prevention Programs

Testing Mediation in Prevention Programs

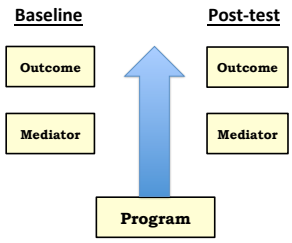


Testing Mediation in Prevention Programs

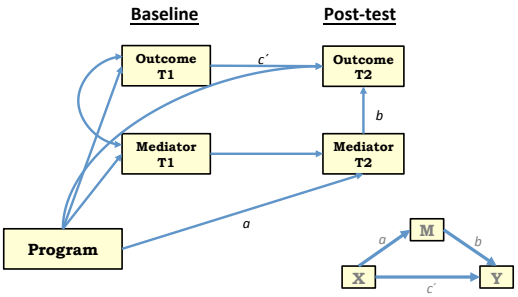


- In prevention programs, the major interest is **change**
- **Program should change the mediators**
- **The change in mediators should lead to change in outcome**
- **Thus,** test of mediation in prevention requires at least two observations for mediators and outcomes

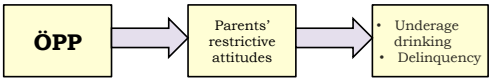
Testing Mediation in Prevention Programs



Testing Mediation in Prevention Programs

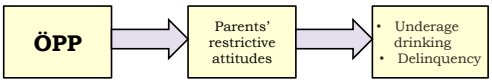


Example: Örebro Prevention Program

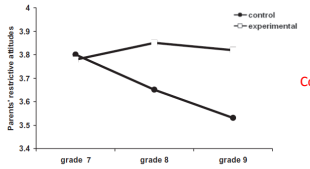


- A brief alcohol use prevention program for adolescents
- Efficacy Trial: Matched-control
- N = 669
- Measurements
  - Baseline (T1)
  - 18 months after baseline (T2)
  - 12 months after T2, 30 months from baseline

Example: Örebro Prevention Program

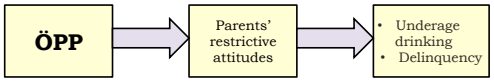


Koutakis, Stattin, & Kerr (2008). Addiction.



Cohen d = .44

Example: Örebro Prevention Program



Koutakis, Stattin, & Kerr (2008). Addiction.

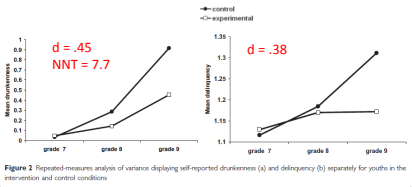
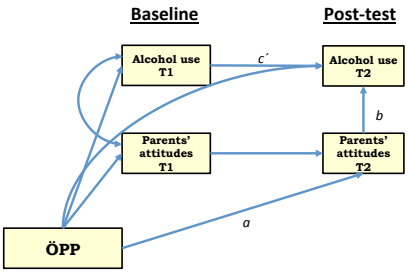


Figure 2 Repeated-measures analysis of variance displaying self-reported drunkenness (a) and delinquency (b) separately for youths in the intervention and control conditions

Example: Örebro Prevention Program



Example: Örebro Prevention Program

```
ANALYSIS:
    BOOTSTRAP=1000;

MODEL:
!Mediation model, c´, a, and b, respectively.
    alcoholT2 ON program;
    attitudeT2 ON program;
    alcoholT2 ON attitudeT2;

!Stability paths, controling for T1 measurement of mediator and outcome.
    attitudeT2 ON attitudeT1;
    alcoholT2 ON alcoholT1;

!Baseline estimates.
    alcoholT1 attitudeT1 ON program;
    alcoholT1 WITH attitudeT1;

MODEL INDIRECT:
    alcoholT2 IND attitudeT2 program;
```

Example: Örebro Prevention Program

```
OREBRO PREVENTION PROJECT.

SUMMARY OF ANALYSIS

Number of groups                                                 1
Number of observations                                         669

Number of dependent variables                                    4
Number of independent variables                                  1
Number of continuous latent variables                            0

Observed dependent variables
```



```
MODEL FIT INFORMATION

Number of Free Parameters                       16

Loglikelihood

          H0 Value                       -2410.694
          H1 Value                       -2410.622

Information Criteria

          Akaike (AIC)                    4853.389
          Bayesian (BIC)                  4925.481
          Sample-Size Adjusted BIC        4874.680
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit

          Value                              0.145
          Degrees of Freedom                     2
          P-Value                           0.9300

RMSEA (Root Mean Square Error Of Approximation)

          Estimate                           0.000
          90 Percent C.I.                    0.000  0.023
          Probability RMSEA <= .05           0.986

CFI/TLI

          CFI                                1.000
          TLI                                1.093

Chi-Square Test of Model Fit for the Baseline Model

          Value                            109.675
          Degrees of Freedom                    10
          P-Value                           0.0000

SRMR (Standardized Root Mean Square Residual)

          Value                              0.003
```

The model fits well

Example: Örebro Prevention Program

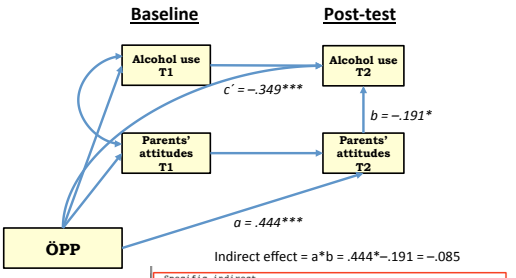
```
MODEL RESULTS

                                                    Two-Tailed
                  Estimate       S.E.  Est./S.E.    P-Value

alcoholT2  ON
   program         -0.349      0.108     -3.238      0.001
   attitudeT2      -0.191      0.095     -2.004      0.045
   alcoholT1        0.566      0.272      2.077      0.038

attitudeT2  ON
   program          0.444      0.063      7.074      0.000
   attitudeT1       0.487      0.103      4.745      0.000

alcoholT1  ON
   program         -0.014      0.029     -0.481      0.630

attitudeT1  ON
   program          0.074      0.045      1.646      0.100

alcoholT1  WITH
   attitudeT1      -0.004      0.009     -0.493      0.622
```

Example: Örebro Prevention Program

TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Effects from program to alcoholT2				
Sum of indirect	-0.085	0.035	-2.417	0.007
Specific indirect				
alcoholT2 attitudeT2 program	-0.085	0.035	-2.417	0.007

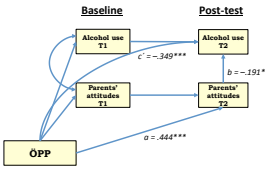
Example: Örebro Prevention Program



Indirect effect = a*b = .444*–.191 = –.085

Specific indirect				
alcoholT2 attitudeT2 program	-0.085	0.035	-2.417	0.007

Example: Örebro Prevention Program



ÖPP significantly reduced alcohol use among adolescents.

The effect of the program on alcohol use is mediated by parents' restrictive attitudes.

Reasons to test for mediation

1. **Manipulation check:** We can identify if the program activities were able to change the mediators
2. **Feedback for improvement:** Results may suggest that certain program components need improvement, or measures of mediators need improvement
3. **Information on mediators, and program effect:** If program changes the mediators, the program effect might be observed later, or the mediator is not a critical factor to change outcome
4. **Test of program theory:** Mediation test identify how the program achieved its effects on the outcomes

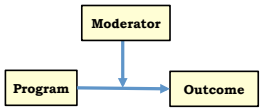
Reasons to test for mediation

5. **Theoretical value:** Randomized prevention trials are optimal experimental designs to test theories of human development and behavior change
6. **Practical implications:** Identifying what mediating mechanisms work inform revisions and improvements of program content. It is possible to omit program components which aim to change ineffective mediators

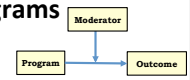
Moderation Effect

What is a moderation?

The association between X and Y varies at different levels of the moderator, M.



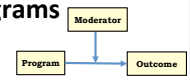
Moderation in prevention programs



Test of moderation is common in prevention studies.

- Is the program more effective for **boys than girls**?
- Is the program effect larger for **highly educated** parents than the parents with **lower education**?
- Is the program implemented in **schools** more effective than the program implemented in **community centers**?
- Are there differences between **cultural/ethnic groups** in how much change due to the program?

Moderation in prevention programs

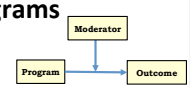


Test of Moderation

- i.e., interaction test
- Aiken & West (1991)
  - Center the variables to prevent nonessential multicollinearity
    Centered X = X – Mean of X.
  - Code dichotomous variables as 0 and 1
  - Include the IV, moderator, and the interaction term in the same regression equation

Moderation in prevention programs

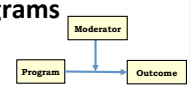
Test of Moderation



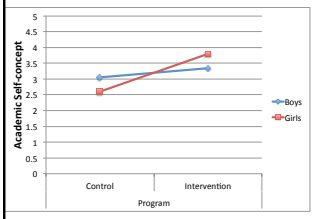
- Plot the interaction to help interpretation
- Use 1 Standard Deviation above or below the mean for levels of continuous variables
- Or, use the minimum and maximum values of the measurement scale
- **Run a simple slope test for accurate interpretation of effect at the levels of moderator**

Moderation in prevention programs

Test of Moderation



- **Run a simple slope test for accurate interpretation of effect at the levels of moderator**



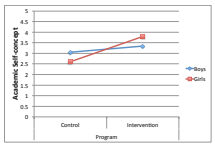
Finding from a randomized post-test only design.

- There is significant Program X Gender interaction.
- Girls have lower academic self-concept than boys in the control group.
- Girls have higher academic self-concept than boys in the intervention group.
- Girls seems to benefit from the program.
- What about the boys?

Moderation in prevention programs

Interpretation of an interaction effect without simple slope test is either

- incomplete
- or, inaccurate



There are practical tools to plot and run simple slope tests.
Kristopher J. Preacher's web site: http://www.quantpsy.org/interact/index.html

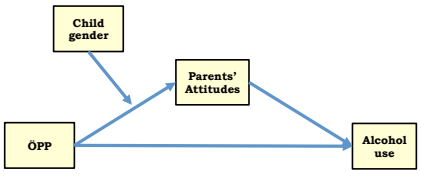
Jeremy Dawson's web site: http://www.jeremydawson.co.uk/slopes.htm

MODERATED MEDIATION

Moderated mediation

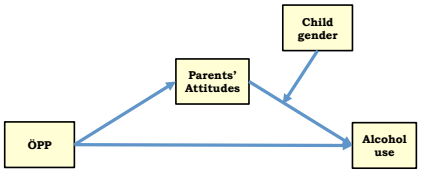
- The mediation process that explain why X is related to Y may not apply to all groups
- A moderator may influence how well a mediator explain why X is related to Y
- In prevention programs, a mediating process may only apply for a specific group with certain characteristics

Moderated mediation



- Child gender may moderate the effect of intervention on the changes in parents' attitudes.
- Parents of girls may be more likely to maintain their strict attitudes against alcohol use whereas parents of boys may become more lenient.
- Thus, the program might be more effective for girls than boys.

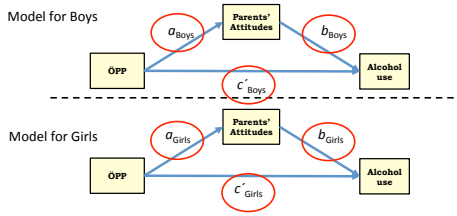
Moderated mediation



- Child gender may moderate the effect of parent attitudes towards alcohol use
- Girls may be less likely to use alcohol when their parents have strict attitudes against alcohol use whereas boys may not be affected by their parents attitudes
- Thus, the program might be more effective for girls than boys

Testing moderated mediation

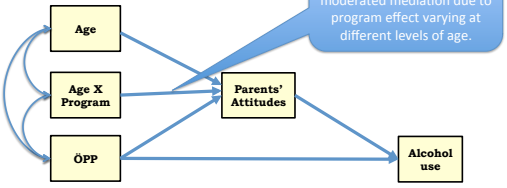
- When the moderator is dichotomous or categorical, **multiple group analysis** is a practical approach



Testing moderated mediation

- When the moderator is a continuous v… the interaction term should be used in th…

Significant age X Program interaction suggest moderated mediation due to program effect varying at different levels of age.



Plotting and simple slope tests are necessary for proper interpretation.

Testing moderated mediation

KRISTOPHER J. PREACHER

Vanderbilt University

- Curriculum vitae
- Selected publications
- Supplemental material for publications
- PSY-PC 2101: Intro. to Statistical Analysis
- PSY-GS 321: Multilevel Modeling
- Friends and colleagues
- Organizations
- Online utilities
- Mediation & moderation material
- VU Dept. of Psychology & Human Development
- VU Quantitative Methods (QM) program
- Contact me

Moderation (Interaction Effect) Material

Interaction Utilities to accompany Bauer & Curran (2006), Curran, Bauer, & Willoughby (2006), and Preacher, Curran, & Bauer (2006) papers on probing interaction effects.
A primer on understanding interpreting interaction effects in multiple linear regression

Mediation (Indirect Effect) Material

R package MBESS contains several utilities to accompany Preacher & Kelley (2011) paper on effect size in mediation.
SPSS macro to accompany Hayes & Preacher (2010) paper on nonlinear mediation.
SPSS macro (for three-path mediator models) to accompany Hayes, Preacher, & Myers (2010) chapter.
Monte Carlo calculator for creating sampling distributions and confidence intervals for indirect effects.
Monte Carlo calculator for creating sampling distributions and confidence intervals for indirect effects in 1-1-1 multilevel models.
SPSS and SAS macros to accompany Preacher & Hayes (2004) paper on mediation.
SPSS macro, Mplus code, and Mathematica code to accompany Preacher, Rucker, & Hayes (2007) on moderated mediation models.
SPSS and SAS macros to accompany Preacher & Hayes (2008) on multiple mediator models.
Supplemental material to accompany Preacher and Hayes (2008) paper on multiple mediation models.
Sobel test calculator for simple mediation effects.
Mplus syntax to accompany Selig & Preacher (2009) paper on longitudinal

Multiple Mediation Models

Multiple mediation models

- As modern theories on human development postulate, problematic behaviors are the result of many factors that interact together during the development of the individual.
- As a consequence, interventions are meant to reduce problematic behaviors through modifying multiple factors.

Giannotta F., Vigna-Taglianti F., Galanti MR., Scatigna M., & Faggiano F. (in press). Short-Term Mediating Factors of a School-Based Intervention to Prevent Youth Substance Use in Europe. *Journal of Adolescent Health*.

Unplugged

- It is 12-hour class program based on a comprehensive social-influence approach.
- According to the leading theories of the social influence approach (social learning and social norms), drug use initiation is the result of influence from the social context, namely peers and media.
- Normative education and resistance skills training included in prevention curricula are thought to reduce the effect of social influence by modifying attitudes, beliefs, and normative perceptions, finally supporting the development of general social skills and skills to resist social pressures.

Unplugged

- Unplugged aims at modifying the beliefs about consequences of substance use, the attitudes towards drug use, the ability to resist an offer of alcohol, cigarettes or cannabis (refusal skills) and the perception of prevalence of use among peers, in order to prevent and reduce substance use.

Conceptual model of change

Note. We controlled for gender and age effects. We also allowed covariations among variables within time, and we controlled for the initial levels of the variables at baseline


```
!THIS IS A RECUDES MODEL TO SAVE SPACE.

    CLUSTERING IS COUNTRY; !Observations are nested in countries.

ANALYSIS:
    TYPE=COMPLEX; !Estimate bias corrected standard error for parameter
                  !estimates and model fit for nested data.
MODEL:
    !Stability paths, controlling for the initial levels of variables.

    smokeT2 ON smokeT1;                    ! program outcome.
    positivebeliefT2 ON positivebeliefsT1;  !mediator 1.
    negativebeliefsT2 ON negativebeliefsT1; !mediator 2.

    !effects of mediator on outcome.
    smokeT2 on positivebeliefT2 negativebeliefsT2; !"b" parameters

    !effects of programm on mediators.
    positivebeliefT2 negativebeliefsT2 ON program; !"a" parameters

    !effects of program on outcome
    smokeT2 ON program;                           !"c'" parameter

MODEL INDIRECT:
    smokeT2 IND positivebeliefT2 program; !provides test of indirect effect through positive beliefs.
    smokeT2 IND negativebeliefT2 program; !provides test of indirect effect through negative beliefs.

OUTPUT: samp stdyx CINT; !asking for sample statistics, standardized estimates and confidence intervals.
```


Multiple mediation models

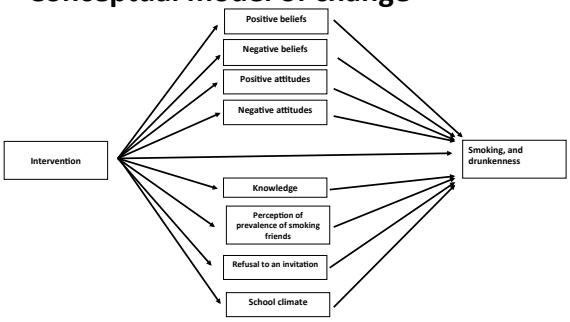
- The difference between single mediator models and multiple mediator models is the same as the one between simple linear regression models and multiple regressions models. Specifically:

- First, testing the total indirect effect of the mediating factors would allow to test the overall mediating impact of expected mediating factors.

- Second, it is possible to determine to what extent specific mediating factors mediate the intervention effect, controlling for the presence of the other mediators in the model. In other words, it is possible to establish the unique influence of the single mediators.

– Moreover, when several simple mediation hypotheses are each tested in separate models, they might produce biased results. As mediating factors are usually moderately correlated, single mediator models may lead to an overestimation or underestimation of the effect of each mediator (Judd & Kenny, 1981).

Conceptual model of change



Let's test this model first using a single mediation approach, then with a multiple mediation approach.

(Please note that in the following models for all constructs, except for knowledge, higher scores indicate higher level of risk, so that negative values of path a indicate a reduction of the risk level).

Analysis I

I fitted multilevel single mediation models in MPlus 6. As the randomization occurred at school level, we entered school as second level, and individuals as first level. To control for variability across centers, we used the stratification option in Mplus. In all models I controlled for gender, age and for the initial levels of the variables at baseline. I allowed co-variations among all variables within time.

Single mediator models

Mediators (Tobacco)	Path a β (s.e.)	Path b β (s.e.)	Indirect effects Path a*b β (s.e.)
Positive attitudes towards drugs	-.035*(.016)	.189**(.014)	-.023*(.011)
Negative attitudes towards drugs	n.s.	.135* (.011)	n.s.
Positive beliefs tobacco	-.043*(.020)	.095*(.011)	-.004*(.002)
Negative beliefs tobacco	-.027† (.017)	.087**(.010)	-.008† (.005)
Knowledge about tobacco	.049*(.021)	n.s.	n.s.
Refusal skills	-.025*(.012)	.336**(.015)	-.008*(.004)
Perception of number of smokers friends	-.049*(.020)	.132**(.009)	-.022*(.009)
School climate	-.047*(.026)	.035*(.013)	-.006† (.003)

*p<.05, **p<.001, †p<.05 one tailed.

Analysis II

We fitted multilevel multiple mediation models in MPlus 6, entering in the model all the hypothesized mediators simultaneously . As the randomization occurred at school level, we entered school as second level, and individuals as first level. To control for variability across centers, we used the stratification option in Mplus. In all models we controlled for gender, age and for the initial levels of the variables at baseline. We allowed co-variations among all variables within time.

Multiple mediator model

Mediators (Tobacco)	Path a β (s.e.)	Path b β (s.e.)	Indirect effects Path a*b β (s.e.)
Positive attitudes towards drugs	-.041*(.020)	.070**(.014)	-.003 † (.002)
Negative attitudes towards drugs	n.s.	.024* (.011)	n.s.
Positive beliefs tobacco	-.044*(.021)	n.s.	n.s.
Negative beliefs tobacco	-.029 † (.017)	n.s.	n.s.
Knowledge about tobacco	.049*(.021)	n.s.	n.s.
Refusal skills	-.030*(.015)	.279**(.016)	-.008*(.004)
Perception of number of smokers friends	-.051*(.020)	.070**(.009)	-.004*(.001)
School climate	-.047*(.021)	n.s.	n.s.

*p<.05, **p<.001, † p<.05 one tailed

Conclusion

Multiple mediation models prevent researchers to draw the inaccurate conclusions on the relative importance of each mediating factor.

Conclusion

Multiple mediation models are particularly useful when competing theories are tested (e.g. is more important resistance skills training or perceived norms about the behaviors?).

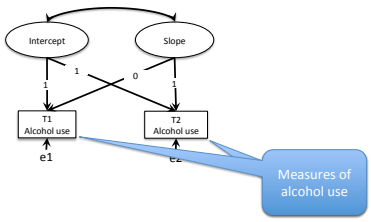
Ideally, the mediators should not be too correlated.

Latent Change Models

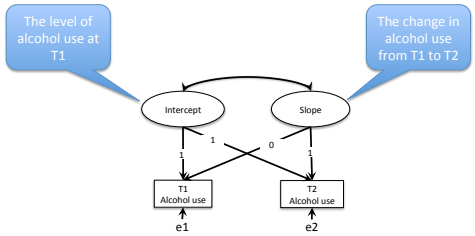
Latent Change Models

- Change in mediators and outcome can be modeled using latent change modeling
- Latent change model
  - A change model is composed of two components: Intercept and slope
  - Intercept: the level at baseline
  - Slope: amount of change from baseline to post-test
  - Both intercept and slope includes a mean and variance estimate

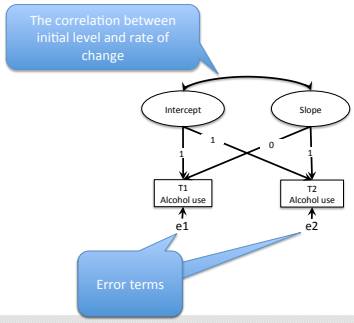
Latent Change Model



Latent Change Model



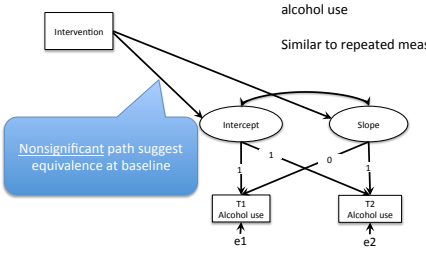
Latent Change Model



Latent Change Model

You can test the program effect on alcohol use

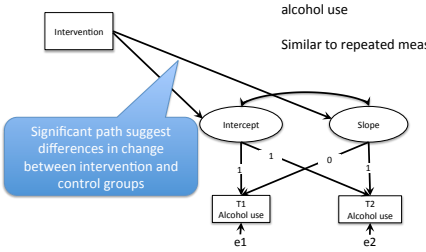
Similar to repeated measures ANOVA



Latent Change Model

You can test the program effect on alcohol use

Similar to repeated measures ANOVA

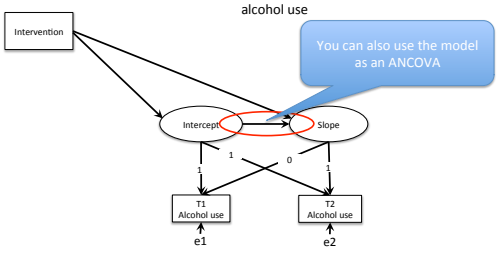


Significant path suggest differences in change between intervention and control groups


```
!latent change model example
!testing for program effect

         clustering is class; !observations are nested in classrooms.

ANALYSIS:
         TYPE=COMPLEX;

MODEL:
         i s | alcT1@0 alc@1;  !"i" intercept, "s" slope, "alc" alcohol use.
         alcT1@.08; alcT2@.05; !error variances were fixed for model identification.

         i ON OPP; !program effect on the initial level of alcohol use
         s ON OPP; !program effect on the change in alcohol use (s) from Time 1 to Time 2.
                          !OPP coded as 0=control condition, 1=OPP program.

OUTPUT: samp stdyx CINT;
```


Latent Change Model

You can test the program effect on alcohol use



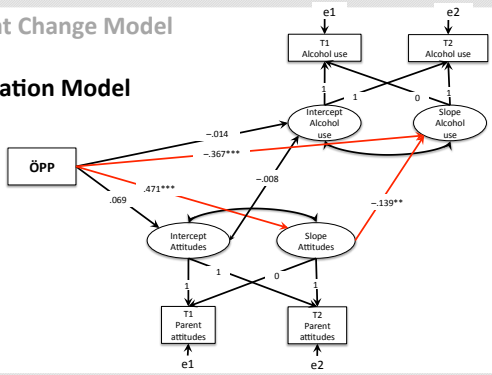
You can also use the model as an ANCOVA

Application of Latent Change Models

Testing the mediation mechanisms in ÖPP Program

Latent Change Model

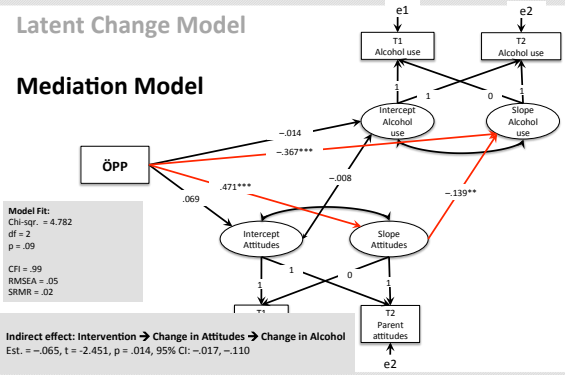
Mediation Model




```
!mediation test with latent change model
        clustering is class; !observations are nested in classrooms.
ANALYSIS:
        TYPE=COMPLEX;
MODEL:
        !change in alcohol use.
        i s | alcT1@0 alcT2@1;
        alcT1@.08; alcT2@.05;

        !change in parent attitudes
        i1 s1 | attT1@0 attT2@1;
        alcT1@.12; alcT2@.09;

        i ON OPP; !program effect on the initial level of alcohol use
        s ON OPP; !program effect on the change in alcohol use (s) from Time 1 to Time 2.
                  !OPP coded as 0=control condition, 1=OPP program.
OUTPUT: samp stdyx CINT;
```

Latent Change Model

Mediation Model



Model Fit:
Chi-sqr. = 4.782
df = 2
p = .09

CFI = .99
RMSEA = .05
SRMR = .02

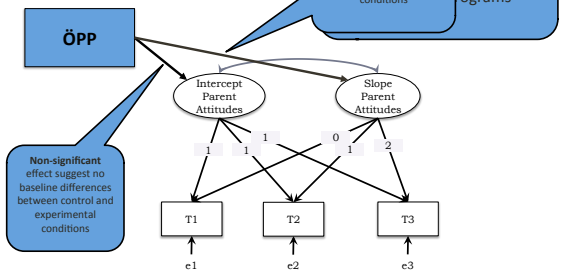
Indirect effect: Intervention → Change in Attitudes → Change in Alcohol
Est. = −.065, t = -2.451, p = .014, 95% CI: −.017, −.110

Latent Growth Models

Latent Growth Model

Significant effect suggest different developmental trends across the control and experimental conditions

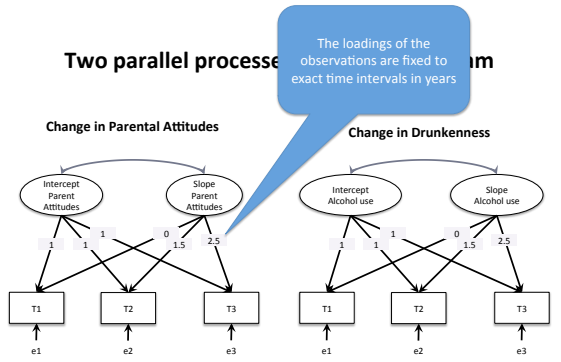
odels are well change over utcomes of rograms



Non-significant effect suggest no baseline differences between control and experimental conditions

Two parallel processe… …m

The loadings of the observations are fixed to exact time intervals in years

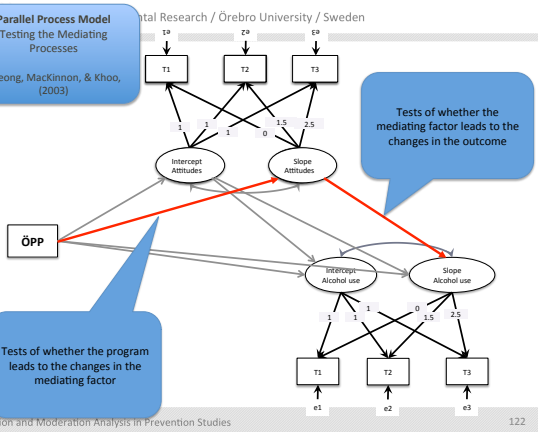


Parallel Process Model
Testing the Mediating Processes

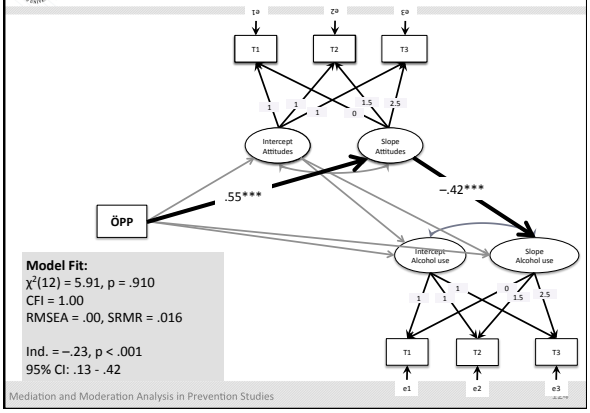
Cheong, MacKinnon, & Khoo, (2003)

Tests of whether the mediating factor leads to the changes in the outcome

Tests of whether the program leads to the changes in the mediating factor




```
!mediation test with latent growth model

        clustering is class; !observations are nested in classrooms.

ANALYSIS:
        TYPE=COMPLEX;

MODEL:
        !growth in alcohol use.
        i s | alcT1@0 alcT2@1.5 alcT3@2.5;

        !growth in parent attitudes.
        i1 s1 | attT1@0 attT2@1.5 attT3@2.5;

        !specification of mediation model.
        i1 ON OPP;
        s1 ON OPP; !estimate of "a"
        i ON i1;
        s ON s1;   !estimate of "b"
        i ON OPP;
        s ON OPP;  !estimate of c´

MODEL INDIRECT:
        s IND s1 OPP; !test of indirect effect of OPP on youths' alcohol use
                      !through its effect on the changes in parent attitudes.

OUTPUT: samp stdyx CINT;
```

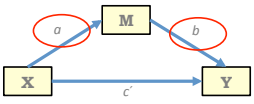


Power
Reliability
Effect Size

Power, Reliability, and Effect Size

Power in Mediation Model

- Power of the test of indirect effect is generally lower than the power of the test of a regression coefficient
- The problem arises due to imperfect reliability of the mediator and the outcome

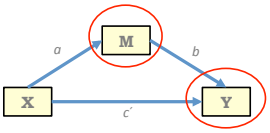


Indirect effect = ***a*b***

Power, Reliability, and Effect Size

Reliability in Mediation Model

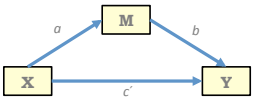
- For adequate power and accurate interpretation of the findings, mediator and the outcome measures should be reliable
- Using reliable measures, or latent variables to model mediator and outcome should be preferred



Power, Reliability, and Effect Size

Reliability in Mediation Model

- Sample size requirement for power is related to reliability of the measures, and the effect sizes
- For single mediator models, a sample of 200, when measures are reliable and effect size small to moderate, should ne sufficient to test indirect effect using resampling methods



Power, Reliability, and Effect Size

Effect size in Mediation Model

- The size of mediated effect is generally very low in mediation models. This is due to the computation of mediated effect; ***a*b***
- *Percent explained variance by indirect effect* relative to the direct effect was suggested by some. But, this method is not accurate, specially when program does not have direct effect on outcome.
- There are some suggested effect size estimates, but they have not been tested yet
- Best alternative today is interpreting the effect sizes of the estimates ***a*** and ***b*** in a mediation model rather than an overall effect size for mediated effect.

Suggested Readings

Mackinnon, D. P. (2008). Introduction to statistical mediation analysis. Lawrence Erlbaum and Associates.

MacKinnon, D. P., Fairchild, A. J., & Fritz, M. S. (2007). Mediation analysis. *Annual Review of Psychology*, *58*, 593-614.

Fairchild, A. J., & MacKinnon, D. P. (2009). A general model for testing mediation and moderation effects. *Prevention Science*, *10*(2), 87-99.

Fritz, M. S., & MacKinnon, D. P. (2008). A graphical representation of the mediated effect. *Behavior Research Methods*, *40*(1), 55-60.

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MacKinnon, D. P., Lockwood, C. M., Hoffman, J. M., West, S. G., & Sheets, V. (2002). A comparison of methods to test mediation and other intervening variable effects. *Psychological Methods*, *7*(1), 83-104.

Preacher, K. J., Zhang, Z., & Zyphur, M. J. (2011). Alternative methods for assessing mediation in multilevel data: The advantages of multilevel SEM. *Structural Equation Modeling*, *18*, 161-182.

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Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*, 879-891.

Zhang, Z., Zyphur, M. J., & Preacher, K. J. (2009). Testing multilevel mediation using hierarchical linear models: Problems and solutions. *Organizational Research Methods*, *12*, 695-719.

*Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers*, *36*, 717-731.

Web Resources for Mediation and Moderation Analysis

- Kristopher J. Preacher's web site: http://www.quantpsy.org/interact/index.html
- David Kenny's web site: http://davidakenny.net/cm/mediate.htm
- Jeremy Dawson's web site: http://www.jeremydawson.co.uk/slopes.htm

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