PSY792F SEM

Week 3 – Mediation

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Mediation (a.k.a. indirect effect)

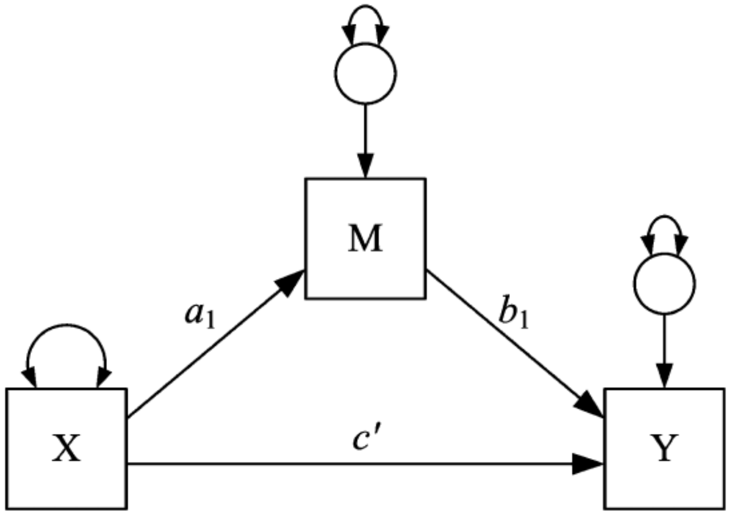


FIGURE 1 Simple mediation.

Definition

- Mediation, or an indirect effect, is said to occur when the causal effect of an independent variable (X) on a dependent variable (Y) is transmitted by a *mediator* (M). – Preacher, Rucker, Hayes (2007, p. 186)
- See Figure 1
- Some debate the usage of the terms "mediation" vs. "indirect effect"
  - I will use them interchangeably
- An indirect effect is a population quantity that must be estimated in the sample
- Answers the question: "By what means X exerts its effect on Y"
  - Important for testing mechanisms, and sequential (cross-sectional) or causal (longitudinal) chains

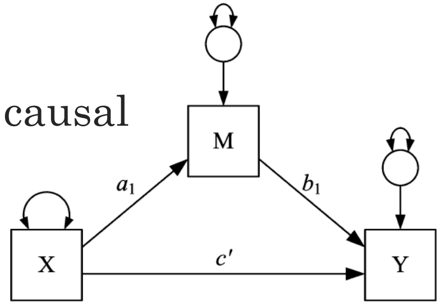


FIGURE 1 Simple mediation.

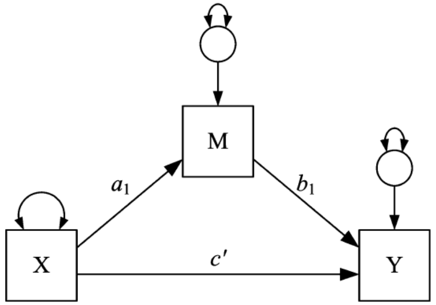
Temporality

- “Mediation implies a relationship between variables that cannot be reversed. X caused M, which caused Y; X happened first, then M, then Y” (Winer et al. 2016, p. 948)
- ”The mediation amounts to an indirect effect: X has a direct effect on Y (path C), but X has an indirect effect on Y through M (path C’).” p. 949
- Temporal Mediation – longitudinal data are collected and analyses are conducted to demonstrate that causal mechanisms occur over time.
- Atemporal mediation analyses - cross-sectional data are collected and mediation can be tested but a theory of why cannot be supported
    - Atemporal mediation partials out the relation between the predictor and the mediator from the predictor-outcome relation.
    - This approach precludes evidence for a causal chain, but provides information about the relation between the predictor and outcome variables when accounting for the shared relation among all variables in the model.
        - The term “indirect effects” is used to report on atemporal mediation effects.

- Winer, E.S., Cervone, D., Bryant, J., McKinney, C., Liu, R.T., Nadorff, M.R., 2016. Distinguishing mediational models and analyses in clinical psychology: atemporal associations do not imply causation. J. Clin. Psychol. 72, 947–955.

A little math…

- 2 equations can be used to represent Figure 1
- $Y = b_0 + c'X + b_1M + error$
- $M = a_1X + a_0 + error$
- c' – is not just c, because it represents Y on X controlling for Y on M
  - b_1 and c' are called conditional coefficients
- Old way of testing mediation:
  - c – c' (Baron & Kenny, 1987)
  - Accomplished in steps
- New way of testing mediation:
  - a_1b_1
    - MacKinnon et al (1995) showed $a_1b_1 = c - c'$
    - This is called the product of coefficients
      - Accomplished simultaneously



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Product of coefficients

- Many studies have shown that the causal steps approach (e.g., Baron & Kenny, 1987) suffers from low power

- The product of coefficients method (i.e., a_1b_1) is the correct way to test for mediation or indirect effects
- More specifically the ***distribution of the product*** strategy is the most accurate.
  - Need asymmetrical confidence intervals to test for statistical significance
    - Best practices
      - Bias-Corrected Bootstrapped CIs
      - Bayesian Credible Intervals
      - Monte Carlo Confidence Intervals

Assumptions

- Same assumptions hold as for Regression and Path Analysis
- Additional assumptions:
  - a_1 and b_1 are asymptotically independent and normally distributed
  - The product a_1b_1 is normally distributed
- At least the second assumption here is often violated
  - See R simulation
  - The product of two normals is not normal
    - Large sample: Leptokurtotic and Thin Tails
      - Likely to make a Type I error
    - Small sample: Leptokurtotic, Positively Skewed, Fat Tails
      - Likely to make a Type II error

Bias-Correcting with Bootstrapping

- The default in Mplus is to pretend that the product of distributions is normal and conduct a z-test – in this case called a Sobel Test
  - This is true with model indirect or model constraint
- Need asymmetrical CIs to account for the bias
- If all variables are (can be treated as) normally distributed can use
  - Bias-Corrected Bootstrapped CIs
    - Considers the sample as a pseudo-population
    - Approximates the population using a sampling distribution
    - Sampling distribution is created by resampling from your data thousands of times
    - CIs are calculated by taking the area under the curve of the sampling distribution
    - No assumptions need to be made about the sampling distribution
      - Thus the sampling distribution is often asymmetrical in accordance with the skewness of the sampling distribution

Two other methods

- Bayesian Credible Intervals
  - Bayesian estimation combines prior assumptions with sample data.
    - If the prior assumptions are non-informative, it reduces to ML estimation
    - Bayesian inferences are made using Markov Chain Monte Carlo procedures that mix the researchers priors with their sample data creating a posterior distribution
    - Bayesian Credible intervals are calculated on the posterior distribution
    - When priors are non-informative, you get the CI of your actual data, which will be asymmetrical
- Monte Carlo Confidence Intervals (MCCIs)
  - http://quantpsy.org/medmc/medmc.htm
  - Another resampling procedure that generates a few thousand models based on parameters in your model and calculates the CIs
  - This is really your only option when you have non-normal data (e.g., count, censored, zero-inflated)
  - Need Tech3 in Mplus

Effect Size of Indirect Effects

- Lots of debate and inconsistencies in the field
- Most examine the proportion of the total effect that is accounted for by the indirect effect
  - Can be based on departure from the null hypothesis
  - Can be based on practical importance
- A good effect size
  - Is scaled from 0 to 1 (i.e., standardized)
  - Does not change based on linear transformations
  - CIs can be generated for the effect size
  - Independent of sample size
  - Unbiased
  - Consistent
  - For review see Preacher & Kelley (2011)
    - Great article but the proposed effect size kappa-squared has been criticized and should not be used

Effect Size of Indirect Effects

- Most commonly used in psychology
  - $R_m = ab/c'$
    - Ratio of the indirect effect to the direct effect Sobel (1982)
    - Problems:
      - Has a large variance and is unstable unless $n > 5000$
      - ab varies inversely with c' – leads to instability
        - Minor fluctuations in ab and c' can lead to large fluctuations in their ratio and can become huge when c' is near 0
      - Not a proportion (it's a ratio)
  - $P_m = ab/c = ab/(ab+c')$
    - Ratio of the indirect effect to the total effect Alwin & Hauser (1975)
      - Loosely interpreted as the proportion of the total effect that is mediated
    - Also called: Validation Ratio, Mediation Ratio, or Relative Indirect Effect
    - Problems:
      - Misleading on practical importance (depending on the size of the total effect)
        - $P_m = .9$ for a small total effect is not as impressive as $P_m = .6$ for a large total effect
      - Not a proportion (it's a ratio) – it can exceed 1, especially when c' is small
      - Unstable with less than 500 observations

Upsilon

- Best practices for effect size reporting seems to be Preacher's yet to be published $\boldsymbol{\upsilon}$
- Described in detail in Mark Lachowicz's Master's thesis at Vanderbilt
  - Use the MBESS R Package
  - Its an improvement over the Kappa-squared described in Preacher & Kelly (2011)
    - $\boldsymbol{\kappa}^2$ is the magnitude of the indirect effect relative to the maximum possible indirect effect
  - $\boldsymbol{\upsilon}$ is the squared standardized indirect effect, and it can be interpreted as measure of explained variance
    - In other words, it is the total joint variance in Y accounted for by the IV and the Mediator(s)
    - Lachowicz notes:
      - benchmarks established for small, medium, and large effects sizes for R^2 measures would not be applicable
      - Any $\boldsymbol{\upsilon} > 1$ indicates that suppression or inconsistent mediation is evident
      - Benchmarks for small, medium, and large effect sizes can be established over time as the measure is employed in the reporting of results for a given field.

How to write the code

- New commands
  - Analysis:
    - Bootstrap=1000;
  - Output:
    - cinterval (bcbootstrap);
  - Model
    - Model indirect
    - Model constraint

How to write the code (2 ways)

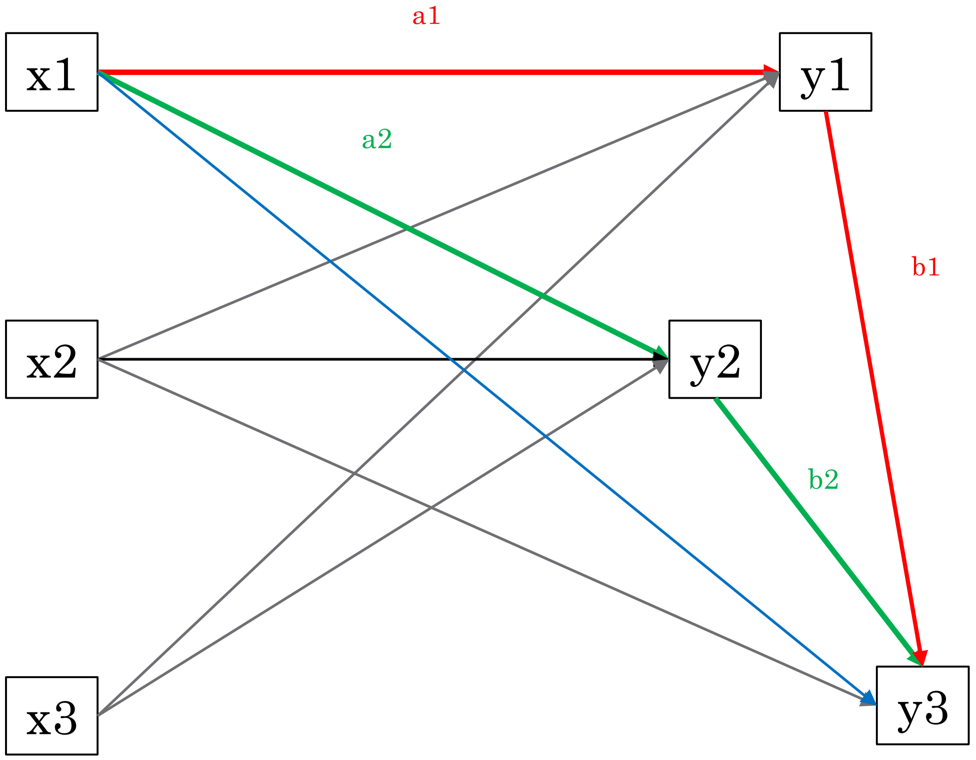
Using Model Indirect

```
DATA:
FILE IS ex3.11.dat;

VARIABLE:
NAMES ARE
y1-y3 x1-x3;

ANALYSIS:
BOOTSTRAP = 1000;

MODEL:
y1 y2 ON x1 x2 x3;
y3 ON y1 y2 x2;

MODEL INDIRECT:
y3 IND y1 x1;
y3 IND y2 x1;

OUTPUT:
CINTERVAL (bcbootstrap);
```

(Note: x1 should also be green)

Using Model Constraint

```
DATA:
FILE IS ex3.11.dat;

VARIABLE:
NAMES ARE
y1-y3 x1-x3;

ANALYSIS:
BOOTSTRAP = 1000;

MODEL:
y1 on x1 (a1);
y1 on x2;
y1 on x3;
y2 on x1 (a2);
y2 on x2;
y2 on x3;
y3 on y1 (b1);
y3 on y2 (b2);
y3 on x1 (c);
y3 on x2;

Model constraint:
new(ind1 ind2);
ind1 = a1*b1;
ind2 = a2*b2;

OUTPUT:
CINTERVAL (bcbootstrap);
```



How to read the results

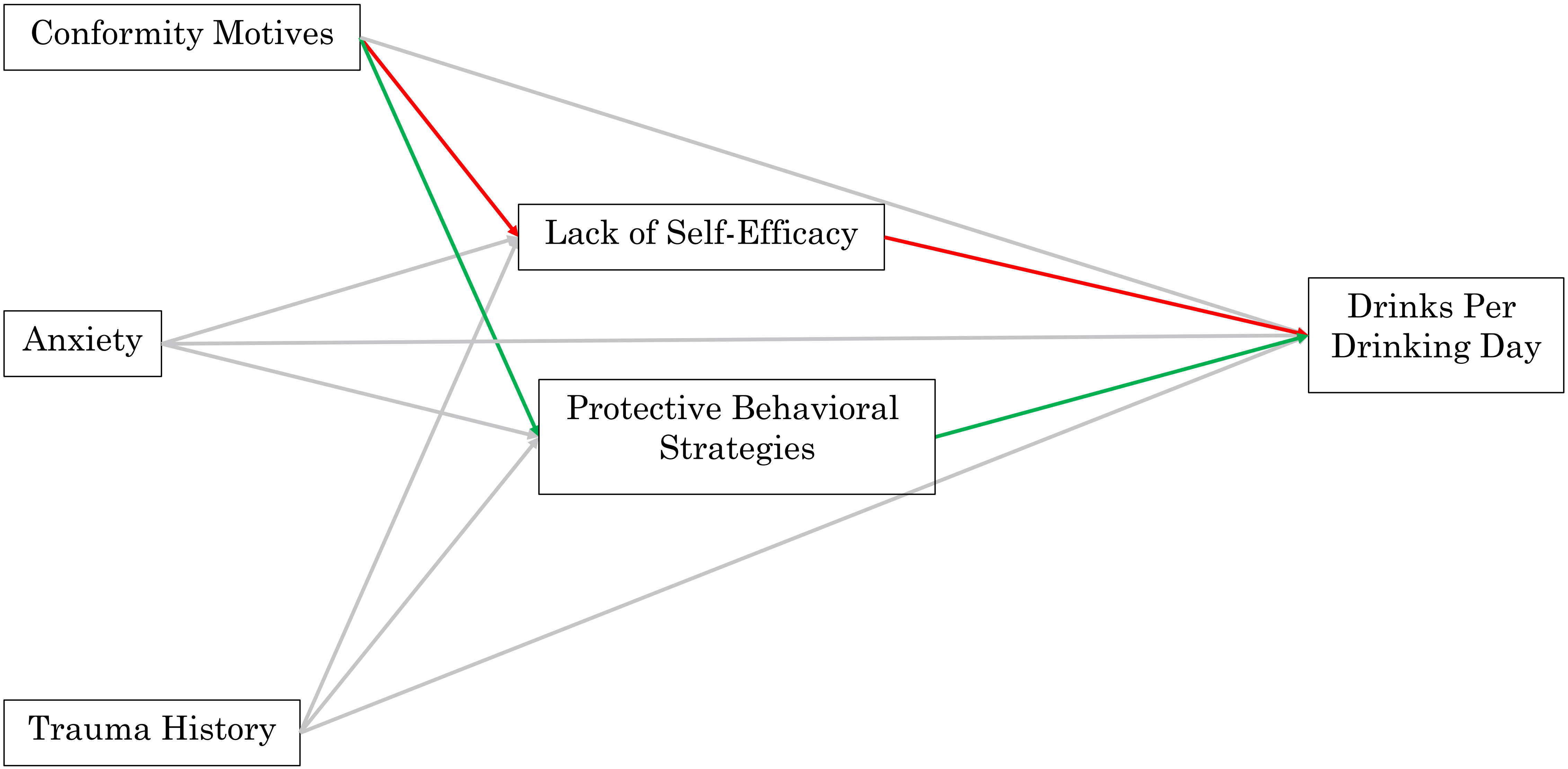
- Overall model fit – same as with path analysis
- Regression coefficients – same as with path analysis
  - These are your direct effects
- Indirect effects
  - Use Bias-Corrected Bootstrapped CIs that do not include 0 for significance of your indirect effects
- Can calculate effect size using R

How to write up the results

- Same set up as Path Analysis
- Add decisions about how you tested the indirect effect
  - Product of coefficients method
  - Bias-Corrected Bootstrapped CIs
- Provide a bit of rationale for these decisions to help a novice reader understand what you did or to convince a savvy reader that you know what you're doing
- Describe the sequential path if one emerged
- Or focus on the direct effects
- Make a table and draw a figure

How to interpret the results

- Start with an overview of the model you tested
- Highlight the important parts – typically this will be the indirect effects if significant
- Comment on sequential or causal pathways
- Describe direct effects
- Interpret effect size


Conformity Motives
Lack of Self-Efficacy
Anxiety
Drinks Per Drinking Day
Protective Behavioral Strategies
Trauma History