# INTERVENTION OUTCOME EVALUATION

Using Structural Equation Models to Understand Change in Youth Interventions

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I. What is structural equation modeling?



structural equation modeling =

path analysis + factor analysis

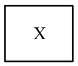


## Multiple Regression (equation)

$Y = a_1 + b_1X_1 + b_2X_2 + b_3X_3 + e_1$

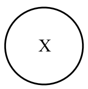
## Path Modeling “Building Blocks”

- Manifest variable




- Causal influence

- Latent variable

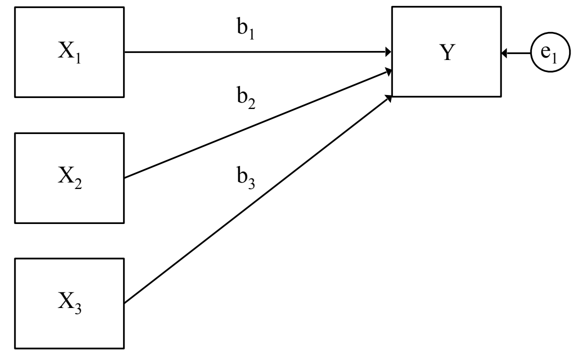



- Correlation



## Multiple Regression (path model)

$Y = a_1 + b_1X_1 + b_2X_2 + b_3X_3 + e_1$

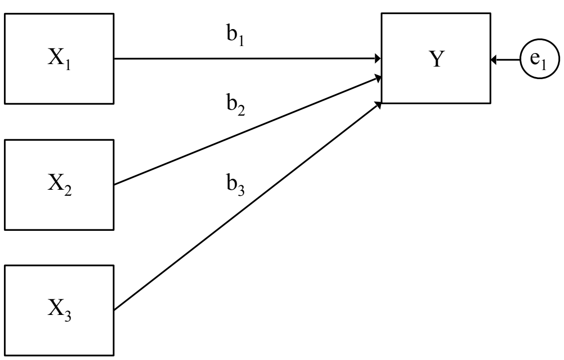





## Multiple Regression (path model)

$Y = a_1 + b_1X_1 + b_2X_2 + b_3X_3 + e_1$

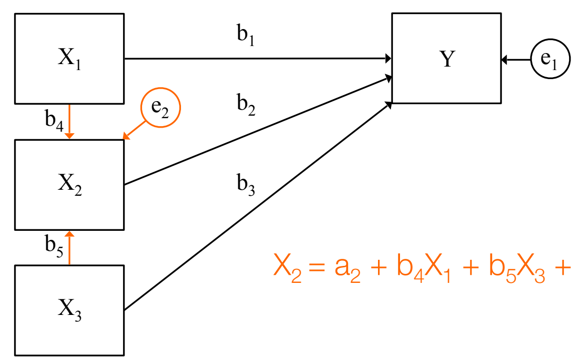
*Relations among X variables?*






## Path Analysis

$Y = a_1 + b_1X_1 + b_2X_2 + b_3X_3 + e_1$

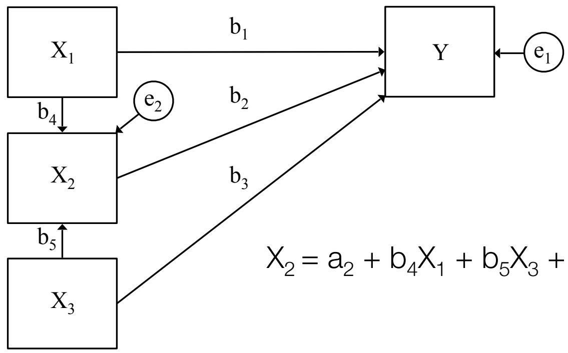



$X_2 = a_2 + b_4X_1 + b_5X_3 + e_2$

## Path Analysis

$Y = a_1 + b_1X_1 + b_2X_2 + b_3X_3 + e_1$

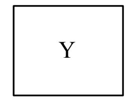
Account for measurement error?




$X_2 = a_2 + b_4X_1 + b_5X_3 + e_2$

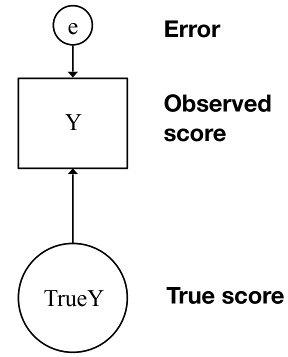


## Measurement Theory



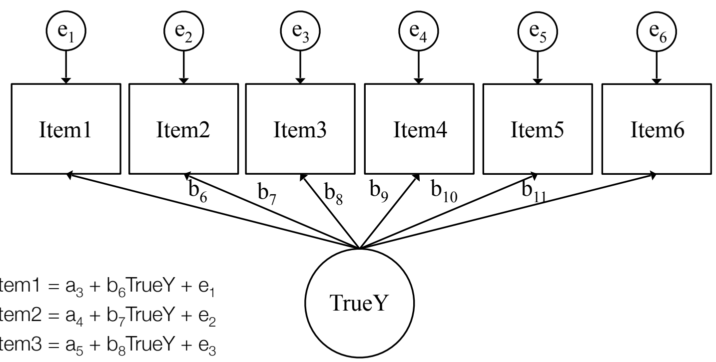

**Observed score (Y) = True score + Error**

**Cannot observe true score or error**






## Factor Analysis (Confirmatory)




$Item1 = a_3 + b_6TrueY + e_1$
$Item2 = a_4 + b_7TrueY + e_2$
$Item3 = a_5 + b_8TrueY + e_3$
$Item4 = a_6 + b_9TrueY + e_4$
$Item5 = a_7 + b_{10}TrueY + e_5$
$Item6 = a_8 + b_{11}TrueY + e_6$

(e.g., multiple items from one scale)



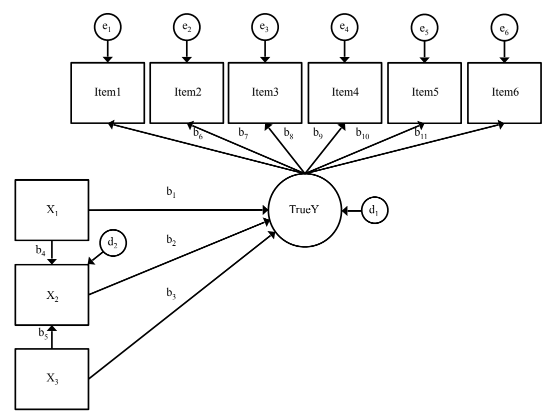
## Structural Equation Modeling

*Structural Model*

$TrueY = a_1 + b_1X_1 + b_2X_2 + b_3X_3 + d_1$
$X_2 = a_2 + b_4X_1 + b_5X_2 + d_2$

*Measurement Model*

$Item1 = a_3 + b_6TrueY + e_1$
$Item2 = a_4 + b_7TrueY + e_2$
$Item3 = a_5 + b_8TrueY + e_3$
$Item4 = a_6 + b_9TrueY + e_4$
$Item5 = a_7 + b_{10}TrueY + e_5$
$Item6 = a_8 + b_{11}TrueY + e_6$



## Structural Equation Modeling

*Structural Model*

$TrueY = a_1 + b_1X_1 + b_2X_2 + b_3X_3 + d_1$

$X_2 = a_2 + b_4X_1 + b_5X_2 + d_2$

*Measurement Model*

$Item1 = a_3 + b_6 TrueY + e_1$

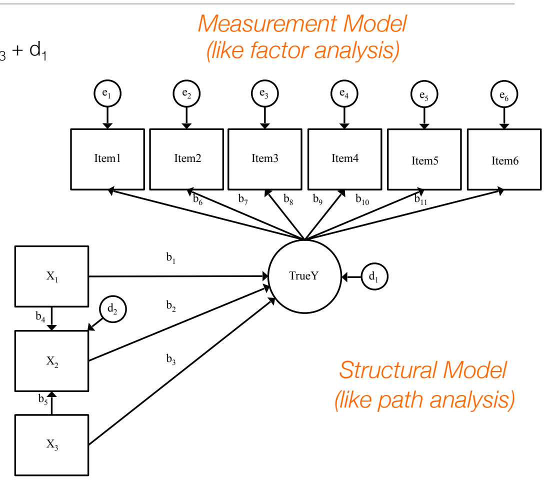
$Item2 = a_4 + b_7 TrueY + e_2$

$Item3 = a_5 + b_8 TrueY + e_3$

$Item4 = a_6 + b_9 TrueY + e_4$

$Item5 = a_7 + b_{10} TrueY + e_5$

$Item6 = a_8 + b_{11} TrueY + e_6$






## Advantages of structural equation modeling?

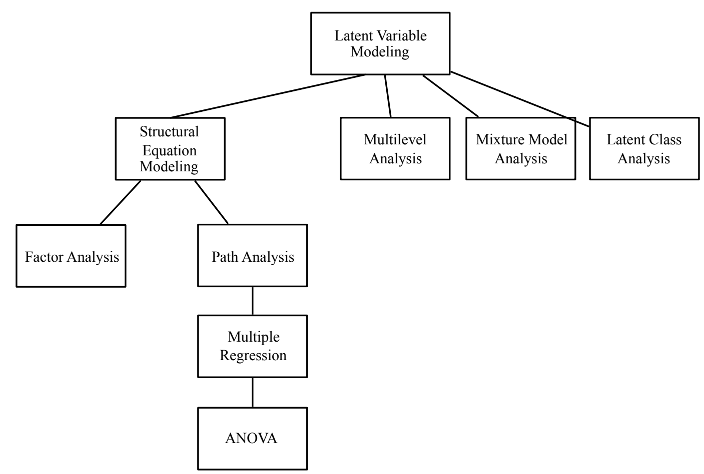
- More flexible representation of theory
- Can include a theory of measurement



## Advantages of structural equation modeling?

- Part of a “quiet methodological revolution” (Rogers, 2010) = shift away from null hypothesis significance testing to building and testing models
- SEM allows us to test models against each other (e.g., from competing theories)
- Part of a larger family of latent variable models






Kline (2015)

## II. Building Conceptual Models of Intervention Outcome

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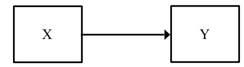
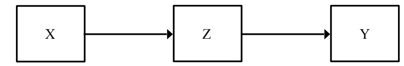
## Types of Relationships

**Direct Causal Relationship**




**Indirect Causal Relationship**




(Mediation)

Jaccard & Jaccoby (2010)

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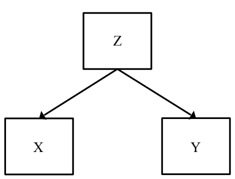
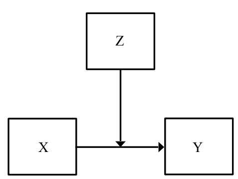
## Types of Relationships

**Spurious Relationship**




**Moderated Causal Relationship**




Jaccard & Jaccoby (2010)

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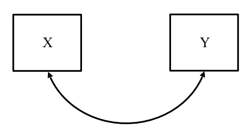
## Types of Relationships

**Unanalyzed Relationship (Correlation)**




Jaccard & Jaccoby (2010)

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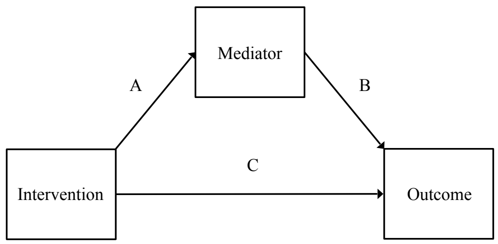
## Basic Outcome Mediation Model

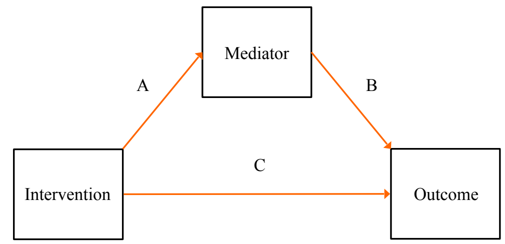



From the treatment intervention literature

- Focus on specificity of effect (like specific effect of a drug)
- Mediator = “mechanism” of change



## Basic Outcome Mediation Model

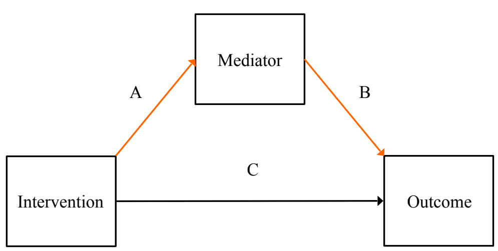



Does this intervention work?

Total Effect = A*B + C



## Basic Outcome Mediation Model

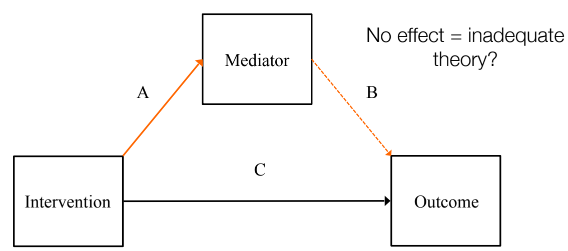



Does this intervention work?
Does the intervention work according to theory?

Total Effect = A*B + C
Indirect Effect = A*B



## Basic Outcome Mediation Model




Does this intervention work?
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Total Effect = A*B + C
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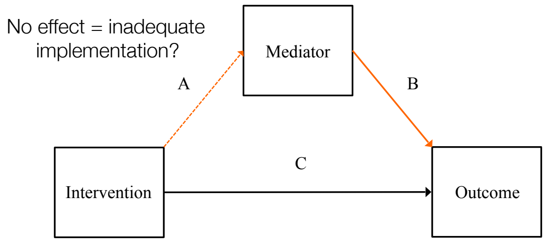
## Basic Outcome Mediation Model




Does this intervention work?
Does the intervention work according to theory?

Total Effect = A*B + C
Indirect Effect = A*B

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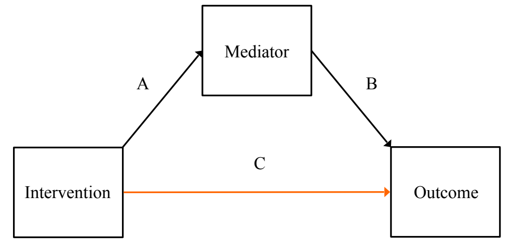
## Basic Outcome Mediation Model




Does this intervention work?
Does the intervention work according to theory?
Does the intervention work via other mechanisms?

Total Effect = A*B + C
Indirect Effect = A*B
Direct Effect = C

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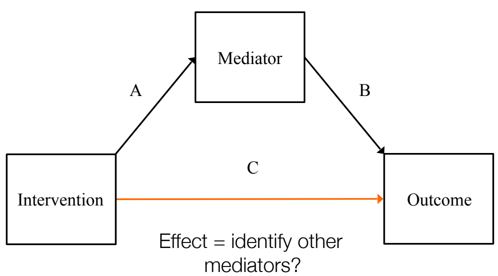
## Basic Outcome Mediation Model




Does this intervention work?
Does the intervention work according to theory?
Does the intervention work via other mechanisms?

Total Effect = A*B + C
Indirect Effect = A*B
Direct Effect = C

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## Where does intervention theory come from?

- Logic models
- Program principles about how it works
- Practitioner beliefs about how it works

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## Example: Communities In Schools (CIS)

- Largest U.S. school dropout prevention network
  - 2300 schools/community-based sites
  - 1.5 million students served
  - Guided by the "Five Basics"



## Five Basics

1. A one-on-one relationship with a caring adult
2. A safe place to learn and grow
3. A healthy start and a healthy future
4. A marketable skill to use upon graduation
5. A chance to give back to peers and community



## Example: Communities In Schools (CIS)

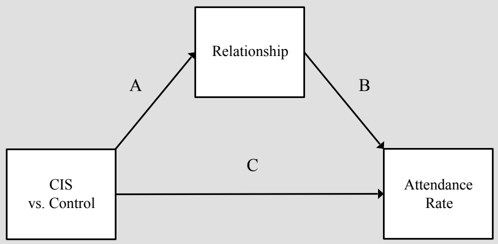
- Randomized Controlled Trial of CIS in Austin, TX.
  - Using ANCOVA, Baseline to End of Year effect on:
    - Attendance rate ($d$ = .45)
    - GPA ($d$ = .38)
    - Credit Completion ($d$ = .38)



## Example: Communities In Schools (CIS)

- Outcomes:
  - Attendance rate
  - GPA
  - Credit Completion
- Hypothesized "mechanisms" of change:
  - Relationship
  - Safety
  - Health
  - Skills
  - Giving back

## CIS Example

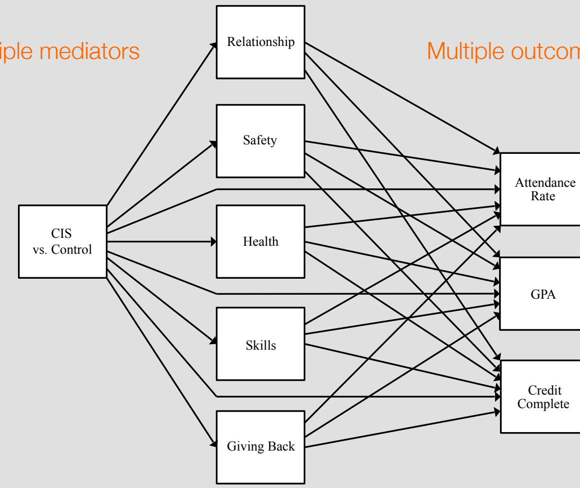





## CIS Example

Multiple mediators

Multiple outcomes

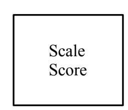




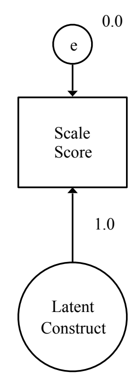

# III. Building Measurement Models



## Single Indicator



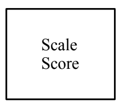

Single indicator



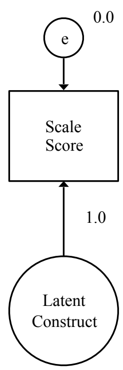

Single indicator

## 1. Single Indicator

*Account for measurement error?*




Single indicator




Single indicator

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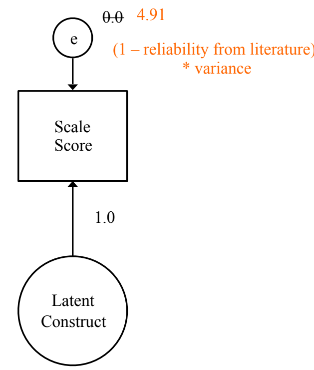
## Single Indicator

*Account for measurement error?*

We can include a correction for measurement error by setting error variance to previously established reliability level.

However, it is better to have multiple indicators.




Single indicator

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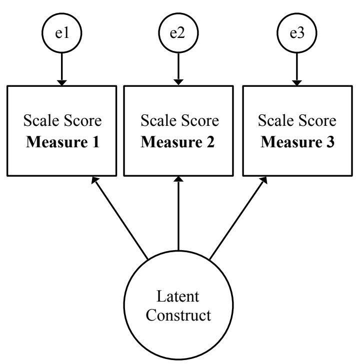
## Multiple Indicators—Multiple Measures




Multiple measures of same construct

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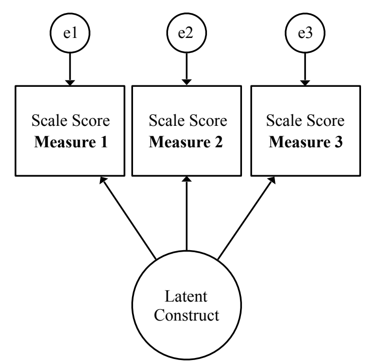
## Multiple Indicators—Multiple Measures




*Problem: Increases burden on participants*

Multiple measures of same construct

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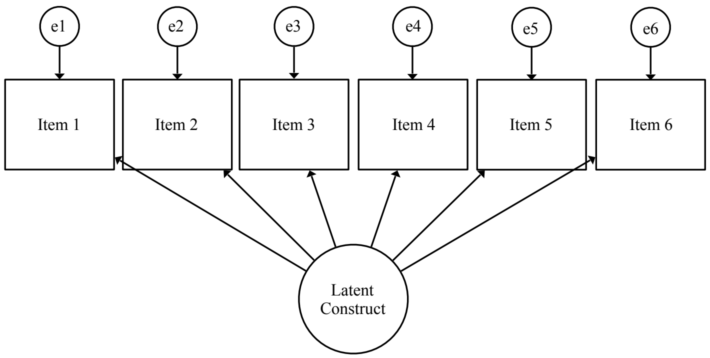
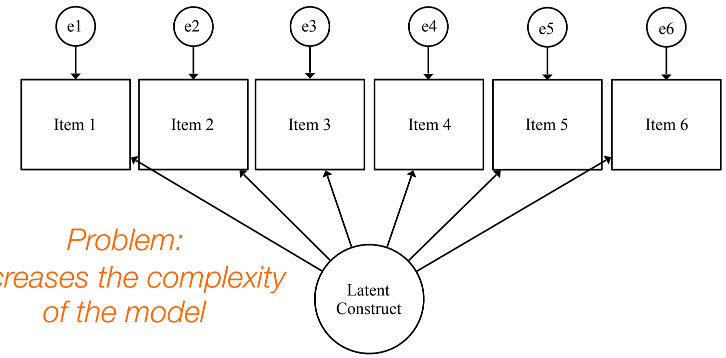
## Multiple Indicators—Multiple Items




Multiple items from one scale



## Multiple Indicators—Multiple Items

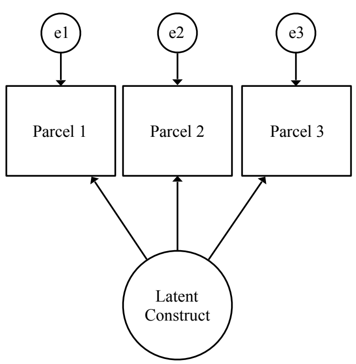



*Problem:*
*Increases the complexity of the model*

Multiple items from one scale



## Multiple Indicators—Parcels




Multiple parcels created from one scale



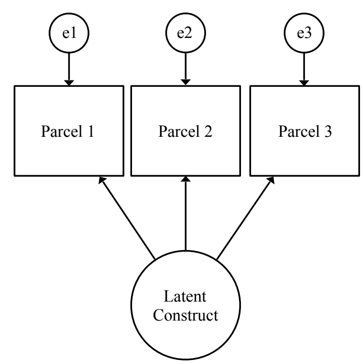
## Multiple Indicators—Parcels

**Balancing approach to parceling:**

Parcel 1 = average of highest loading and lowest loading items.

Parcel 2 = average of second-highest loading and second-lowest loading items.

Parcel 3 = average of third-highest loading and third-lowest loading items.




Multiple parcels created from one scale

Little (2013)

IV. Testing Structural Equation Models



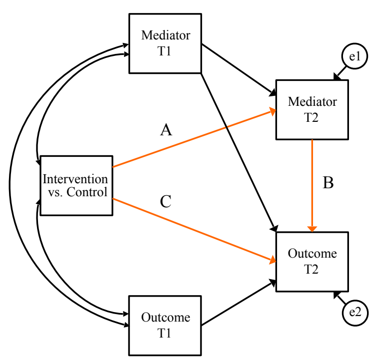
# Handout with models and Mplus code

- [www.eichas.net](http://www.eichas.net)
  - Presentation Materials
    - “HANDOUT for Intervention Outcome Evaluation”



## Model 1:
## Single Indicator
## Two Waves

*(Contemporaneous change)*




Does this intervention work?
Does the intervention work according to theory?
Does the intervention work via other mechanisms?

Total Effect = A*B + C
Indirect Effect = A*B
Direct Effect = C



# Mplus Code Example: Model 1

```
TITLE:  Model 1 Single Indicator Two Waves

DATA:  file  = file location.dat !tells Mplus where the data is

VARIABLE:
NAMES ARE interv med1 med2 out1 out2; !all variables in dataset
USEVARIABLES ARE interv med1 med2 out1 out2; !variables analyzed
MISSING = all(999); !tells Mplus which cells are missing data

ANALYSIS:
ESTIMATOR = mlr; !robust maximum likelihood

MODEL:
med2 on med1 interv; !equation 1
out2 on out1 med1 med2 interv; !equation 2

MODEL INDIRECT:
out2 IND interv; !provides indirect effects from interv to out2

OUTPUT: sampstat standardized cinterval;
```

## Mplus Code Example: Model 1

```
TITLE:  Model 1 Single Indicator Two Waves

DATA:  file  = file location.dat !tells Mplus where the data is

VARIABLE:
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ESTIMATOR = mlr; !robust maximum likelihood

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med2 on med1 interv; !equation 1
out2 on out1 med1 med2 interv; !equation 2

MODEL INDIRECT:
out2 IND interv; !provides indirect effects from interv to out2

OUTPUT: sampstat standardized cinterval;
```



## Mplus Output Example: Model 1

```
MODEL FIT INFORMATION

Chi-Square Test of Model Fit

          Value                              2.389*
          Degrees of Freedom                     1
          P-Value                           0.1222          <-
          Scaling Correction Factor         0.8911
            for MLR

RMSEA (Root Mean Square Error Of Approximation)

          Estimate                           0.079          <-
          90 Percent C.I.                    0.000  0.213
          Probability RMSEA <= .05           0.223

CFI/TLI

          CFI                                0.983
          TLI                                0.884          <-

SRMR (Standardized Root Mean Square Residual)

          Value                              0.026          <-
```



## Mplus Output Example: Model 1 continued

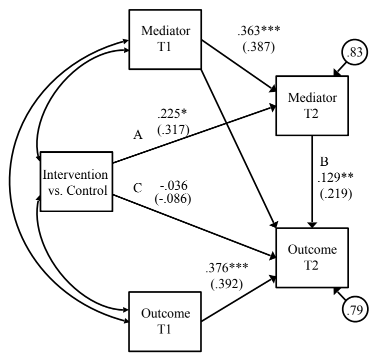
```
MODEL RESULTS

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

 MED2     ON
    MED1               0.363      0.064      5.684      0.000
    INTERV             0.225      0.089      2.521      0.012    <- A

 OUT2     ON
    OUT1               0.376      0.059      6.371      0.000
    MED1               0.012      0.037      0.330      0.741
    MED2               0.129      0.039      3.302      0.001    <- B
    INTERV            -0.036      0.052     -0.701      0.483    <- C

 Intercepts
    MED2               2.536      0.261      9.705      0.000
    OUT2               1.557      0.237      6.574      0.000

 Residual Variances
    MED2               0.420      0.042     10.076      0.000
    OUT2               0.139      0.014      9.894      0.000
```



## Mplus Output Example: Model 1 continued

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


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

Effects from INTERV to OUT2

  Total               -0.007      0.051     -0.141      0.888    <- C + A*B
  Total indirect       0.029      0.015      1.978      0.048

  Specific indirect

    OUT2
    MED2
    INTERV             0.029      0.015      1.978      0.048    <- A*B

  Direct
    OUT2
    INTERV            -0.036      0.052     -0.701      0.483    <- C
```

## Model 1: Results




Total Effect = A*B + C = -.007
Indirect Effect = A*B = .029*
Direct Effect = C = -.036

Although the indirect effect indicates statistical mediation, the total effect is near zero. This may occur if the positive effect via one mediator is canceled out by negative effects via other mediators not included in the model. The next challenge would be to identify these other mediators and model them.



## **Issue 1**: Statistical significance of indirect effect

- Best options for dealing with nonsymmetrical confidence intervals

1. Bootstrapped confidence intervals (a resampling procedure)
2. Monte Carlo confidence intervals (from:[http://quantpsy.org/medmc/medmc.htm](http://quantpsy.org/medmc/medmc.htm))
3. Bayesian confidence intervals (if using a Bayesian estimator)



## Mplus Code Example: Model 1, bootstrap

```
TITLE:  Model 1 Single Indicator Two Waves

DATA:  file  = file location.dat !tells Mplus where the data is

VARIABLE:
NAMES ARE interv med1 med2 out1 out2; !all variables in dataset
USEVARIABLES ARE interv med1 med2 out1 out2; !variables analyzed
MISSING = all(999); !tells Mplus which cells are missing data

ANALYSIS:
BOOTSTRAP = 1000; !specifies the number of samples

MODEL:
med2 on med1 interv; !equation 1
out2 on out1 med1 med2 interv; !equation 2

MODEL INDIRECT:
out2 IND interv; !provides indirect effects from interv to out2

!specifies bias-corrected bootstrapping
OUTPUT: sampstat standardized cinterval(bcbootstrap);
```



## Mplus Output Example: Model 1, bootstrap

**NON-BOOTSTRAPPED RESULTS**

CONFIDENCE INTERVALS OF TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

| | Lower .5% | Lower 2.5% | Lower 5% | Estimate | Upper 5% | Upper 2.5% | Upper .5% |
|---|---|---|---|---|---|---|---|
| Effects from INTERV to OUT2 | | | | | | | |
| Specific indirect | | | | | | | |
| OUT2 MED2 INTERV | -0.009 | 0.000 | 0.005 | 0.029 | 0.053 | 0.058 | 0.067 |

**BOOTSTRAPPED RESULTS**

CONFIDENCE INTERVALS OF TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

| | Lower .5% | Lower 2.5% | Lower 5% | Estimate | Upper 5% | Upper 2.5% | Upper .5% |
|---|---|---|---|---|---|---|---|
| Effects from INTERV to OUT2 | | | | | | | |
| Specific indirect | | | | | | | |
| OUT2 MED2 INTERV | 0.002 | 0.006 | 0.009 | 0.029 | 0.062 | 0.067 | 0.076 |

## Bayesian Structural Equation Modeling

- In Bayesian analysis, parameters are variables that have distributions.
- For each parameter, a **prior distribution** is updated with estimates based on observed data to generate a **posterior distribution**.
- The prior distribution is specified before the analysis to reflect prior knowledge about the parameters.



## Bayesian Structural Equation Modeling

- The prior distribution is specified before the analysis to reflect prior knowledge about the parameters.
  - **Informative prior distributions** specify that before data were collected some candidate parameter values were more probable than others (Zyphur & Oswald, 2013).
  - **Non-informative prior distributions** specify that before the data were collected no candidate parameter values were more probable than others.



## Bayesian Structural Equation Modeling

- The posterior distribution reflects updated knowledge about parameters based on the observed data.
- The updated parameter estimates allow direct probabilistic statements about the parameters
  - that are not based on hypothetical replications of the data as in the frequentist tradition (Zyphur & Oswald, 2013).



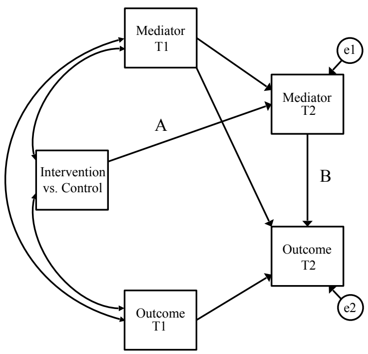
## **Issue 2**: Partial versus complete mediation

- Cannot conclude the direct effect on the outcome (path C) is zero—would be accepting the null hypothesis

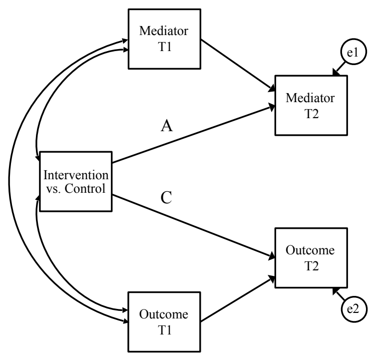
1. Instead, test competing models.

## Testing Competing Models

Model 1b



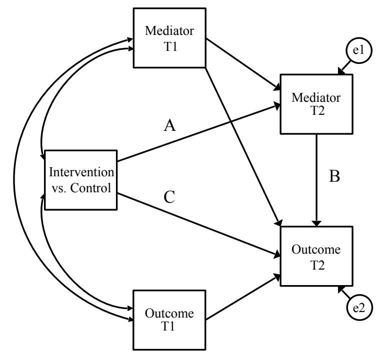

Model 1c






## Testing Competing Models

Model 1




Model 1b and Model 1c are nested within (are subsets of) Model 1.

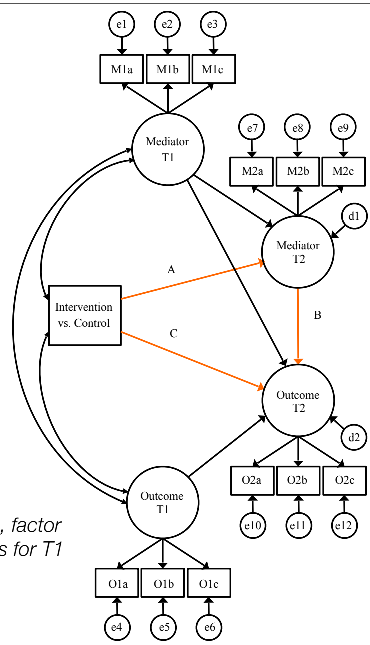
Model 1 can be tested against both models with a nested chi square test.

The basic logic is that if the more parsimonious model does not have significantly worse fit compared to the more complex model, the parsimonious model is preferred.



## Model 2:
## Multiple Indicators
## Two Waves

*(Contemporaneous change)*




*Specify equal form, factor loadings, intercepts for T1 and T2.*



## **Issue 3**: Longitudinal measurement equivalence

- Change in construct or change in measurement?
  - Equal form (*configural invariance*) = same factor structure over time.
  - Equal factor loadings (*weak factorial invariance*) = same relations between indicators and constructs over time.
  - Equal intercepts (*strong factorial invariance*) = same indicator intercepts over time.

Brown (2015); Little (2013)

## Mplus Code Example: Model 2

```
TITLE:  Model 2 Multiple Indicators Two Waves
DATA:  file  = file location.dat

VARIABLE:
NAMES ARE cluster interv med1a med1b med1c med2a med2b med2c
med3a med3b med3c out1a out1b out1c out2a out2b out2c out3a
out3b out3c;
USEVARIABLES ARE interv med1a med1b med1c med2a med2b med2c
out1a out1b out1c out2a out2b out2c;
MISSING = all(999);

ANALYSIS:
ESTIMATOR = mlr;
```



## Mplus Code Example: Model 2 (continued)

```
MODEL:
!measurement model (equal form, equal factor loadings, equal intercepts)
med1 by med1a* (a) !specifies equal factor loading across time
med1b (b)
med1c (c);
med1@1;
med2 by med2a* (a)
med2b (b)
med2c (c);
med2@1;
out1 by out1a* (d)
out1b (e)
out1c (f);
out1@1;
out2 by out2a* (d)
out2b (e)
out2c (f);
out2@1;

[med1a@0]; [med2a@0]; [out1a@0]; [out2a@0]; !fix 1st indicator intercept at 0
[med1*]; [med2*]; [out1*]; [out2*]; !estimate latent factor means
[med1b med2b] (1); [med1c med2c] (2); !fix indicator intercepts to be equal
[out1b out2b] (3); [out1c out2c] (4); !fix indicator intercepts to be equal
```



## Mplus Code Example: Model 2 (continued)

```
MODEL:
!measurement model (equal form, equal factor loadings, equal intercepts)
med1 by med1a* (a) !specifies equal factor loading across time
med1b (b)
med1c (c);
med1@1;
med2 by med2a* (a)
med2b (b)
med2c (c);
med2@1;
out1 by out1a* (d)
out1b (e)
out1c (f);
out1@1;
out2 by out2a* (d)
out2b (e)
out2c (f);
out2@1;

[med1a@0]; [med2a@0]; [out1a@0]; [out2a@0]; !fix 1st indicator intercept at 0
[med1*]; [med2*]; [out1*]; [out2*]; !estimate latent factor means
[med1b med2b] (1); [med1c med2c] (2); !fix indicator intercepts to be equal
[out1b out2b] (3); [out1c out2c] (4); !fix indicator intercepts to be equal
```



## Mplus Code Example: Model 2 (continued)

```
!structural model
med2 on med1 interv;
out2 on out1 med1 med2 interv;

MODEL INDIRECT:
Out2 IND interv;

OUTPUT: sampstat standardized cinterval;
```

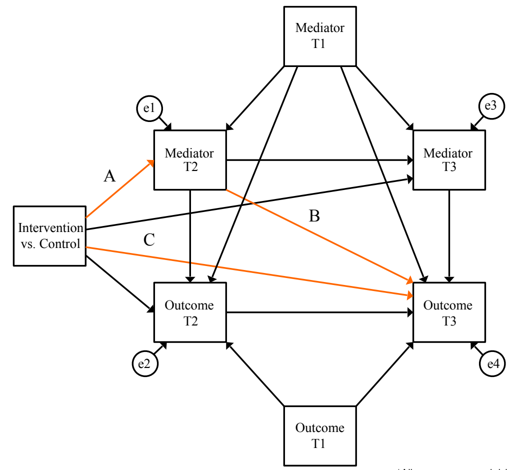
## **Issue 4**: Timing

- Change in the mediator should occur before change in the outcome
  - Need a lag between measurement of mediator and measurement of outcome.
  - Ideally, time intervals are guided by theory
    - Pre-post-follow?
    - Pre-midpoint-post?

Little (2013)



## Model 3: Single Indicator Three Waves

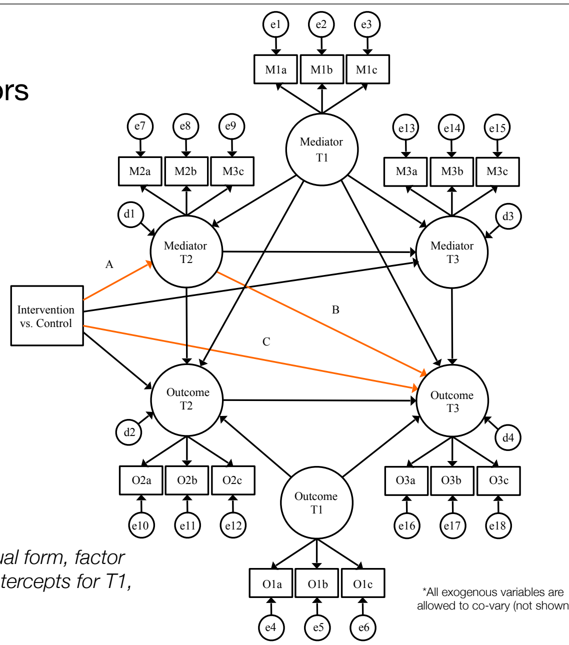



*All exogenous variables are allowed to co-vary (not shown)

Based on Silverman, Kurtines, Jaccard, & Pina (2009)



## Model 4: Multiple Indicators Three Waves




*Specify equal form, factor loadings, intercepts for T1, T2, and T3.*

*All exogenous variables are allowed to co-vary (not shown)



## **Issue 5**: Multilevel data (nested data)

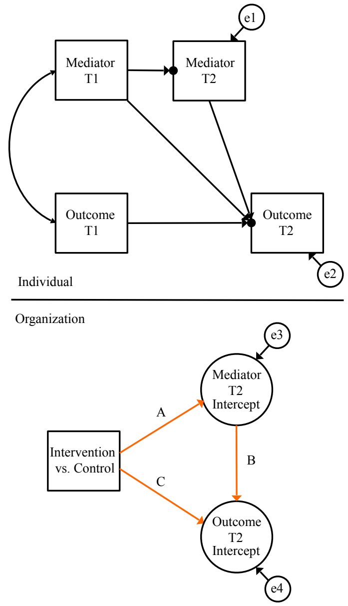
- Non-independence of observations because of a shared context (e.g., classrooms).
- Is understanding the source of dependence important?
  - If yes, model it (make hypotheses about it) using multilevel SEM.
  - If no, take into account non-independence by using an adjustments to standard errors and the chi square test of model fit.

Little (2013)

## Model 5:
## Multilevel Single Indicator Two Waves

*Intercepts-as-outcomes*

- A model is specified at both within (individual) and between (organization) levels
- Individual level: Intercepts are random effects that vary across clusters (e.g., schools)
- Organization level: Intercepts are latent variables that can be predicted by cluster-level variables

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## Mplus Code Example: Model 5

```
TITLE:  Model 5 Multilevel Single Indicator Two Waves
DATA:  file  = file location.dat

VARIABLE:
NAMES ARE cluster interv med1 med2 med3 out1 out2 out3;
USEVARIABLES ARE interv med1 med2 out1 out2;
MISSING = all(999);
CLUSTER = cluster; !specifies the cluster unit
BETWEEN = interv; !specifies that interv is a level 2 variable
WITHIN = med1 out1;

ANALYSIS:
TYPE = TWOLEVEL; !specifies a multilevel analysis with two levels
ESTIMATOR = mlr;
```

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## Mplus Code Example: Model 5

```
MODEL:
%within% !level 1 (individual level) model
med2 on med1;
out2 on out1 med1 med2;

%between% !level 2 (organization level) model
med2 on interv (a);
out2 on interv;
out2 on med2 (b);

MODEL CONSTRAINT: !to compute the indirect effect
NEW (indab);
indab = a*b;

OUTPUT: sampstat standardized cinterval;
```

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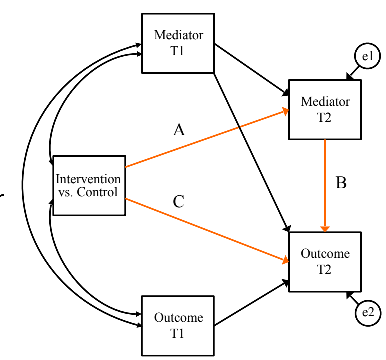
## Model 5:
## Alternative approach

*Single-level model with standard errors and chi square adjusted for complex structure.*

- Might use this approach if clustering is a nuisance rather than substantive
- Mplus: “TYPE = COMPLEX” invokes the Huber-White sandwich estimator.

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## **Issue 6**: Intraindividual change

- Panel models focus on individual differences.
- Growth curve models focus on intraindividual change, address questions about rate of change.
- Work best with four or more time points, but can be used with three time points (and, in a very limited way, with two time points).

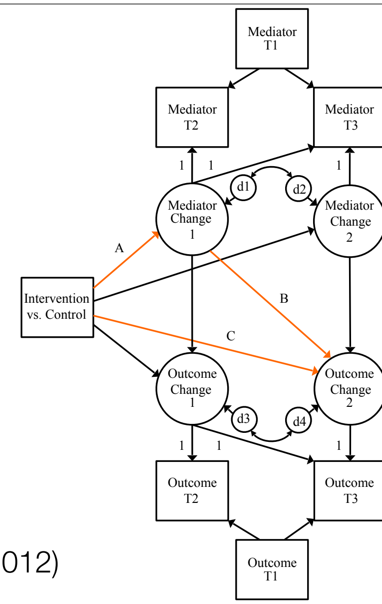
Little (2013)



## Model 6:
## Latent Change Model
## Three Waves

Change 1 = pre to posttest change

Change 2 = posttest to follow-up change




Based on Mara et al. (2012)



## Issues not discussed

- **Moderation**
  - Observed variables: product terms
  - Latent variables: XWITH feature in Mplus
- **Missing data**
  - Full Information Maximum Likelihood
  - Multiple Imputation



## Issues not discussed

- **Categorical outcomes**
  - WLSMV (weighted least squares with means- and variance-adjustment) in Mplus
- **Small samples**
  - Bayesian Structural Equation Modeling (example with noninformative priors in handout)
- **Intraindividual change**
  - Growth curve models (three wave model example in handout)

## Advantages of structural equation modeling?

- More flexible representation of theory
- Can include a theory of measurement
- Test models

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SEM

Theory → Model → Analysis

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SEM

*Intervention* Theory → *Outcome* Model → *Outcome* Analysis

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Thank you.

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