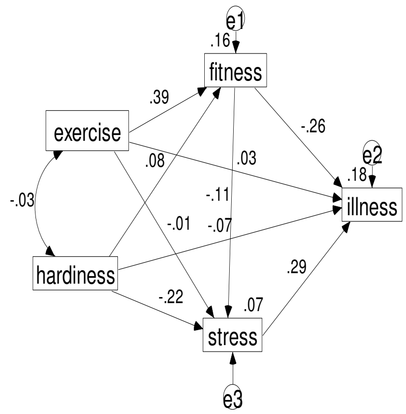
Slide 1

Exercise Illness Example continued Standardized estimates



To get R^2 values turn on "squared multiple correlations" under Analysis properties in AMOS. R^2 does not change whether causal variables are simply correlated compared to causing one another. Often users think that if earlier causal relationships are included this leads to larger R^2

Slide 2

Counting the number of parameters to be estimated

1. All direct effects (single head arrows)
2. All Covariances (double head arrows)
3. Variance of all purely exogenous variables (this includes all error terms since they are also exogenous)

From the Exercise Illness example, Kline (1998) pp. 114-117

$\rightarrow$ $Illness = \beta_1 Fitness + \beta_2 Stress + \beta_3 Exercise + \beta_4 Hardy + \epsilon_1$
Implied Variance of Illness:
$Var(Illness) = \beta_1^2 Var(Fit) + \beta_2^2 Var(Stress) + \beta_3^2 Var(Ex) + \beta_4^2 Var(Hardy) + Var(\epsilon_1) +$
$2\beta_1\beta_2 Cov(Fit, Stress) + 2\beta_1\beta_3 Cov(Fit, Ex) + 2\beta_1\beta_4 Cov(Fit, Hardy) + 2\beta_2\beta_3 Cov(Stress, Ex) +$
$2\beta_2\beta_4 Cov(stress, Hardy) + 2\beta_3\beta_4 Cov(Ex, Hardy)$

$\rightarrow$ $Fitness = \beta_5 Exercise + \beta_6 Hardy + \epsilon_2$
Implied Variance of Fitness:
$Var(Fit) = \beta_5^2 Var(Ex) + \beta_6^2 Var(Hardy) + 2\beta_5\beta_6 Cov(Ex, Hardy) + Var(\epsilon_2)$

$\rightarrow$ $Stress = \beta_7 Fitness + \beta_8 Exercise + \beta_9 Hardy + \epsilon_3$
Implied Variance of Stress:
$Var(Stress) = \beta_7^2 Var(Fit) + \beta_8^2 Var(Ex) + \beta_9^2 Var(Hardy) + Var(\epsilon_3) +$
$2\beta_7\beta_8 Cov(Fit, Ex) + 2\beta_7\beta_9 Cov(Fit, Hardy) + 2\beta_8\beta_9 Cov(Ex, Hardy)$

15 parameters = 9 direct effects + 1 covariance + 5 variances (i.e. 2 exogenous observed variables + 3 error variances)

Slide 3

Standarized/Unstandarized Coefficients

Unstandardized: $\leftrightarrow$ is a covarainace

Standardized: $\leftrightarrow$ is a correlation

$\hat{Corr}(X,Y) = \frac{\hat{Cov}(X,Y)}{\sqrt{\hat{Var}X}\sqrt{\hat{Var}Y}}$

Unstandardized regression coefficient: $\hat{\beta}_{Y on X}$

Standardized regression coefficient: $\hat{\beta}_{Y on X}\frac{\sqrt{\hat{Var}X}}{\sqrt{\hat{Var}Y}}$

Slide 4

Testing the overall fit of the path model

Test for the fit of the proposed model covariance structure compared to the saturated model.

$H_0 : \mathbf{\Sigma} = \mathbf{\Sigma}(\boldsymbol{\theta})$
$H_A : \mathbf{\Sigma} = \mathbf{S}$

Create the likelihood ratio test statistics and compare to a chi-square distribution with degrees of freedom = $\frac{p(p+1)}{2}$ - # of parameters estimated

If every variable has an arrow (single or double headed) connecting it to every other variable, then the model is saturated. This means the estimated covariances will be equal to the observed covariances.

For the Illness/Exercise example d.f. = 5*6/2 - 15 = 0.

It is not useful to consider the chi-square test for a saturated model, instead what we are often interested in is determining whether a model with some relationships fixed to zero fits as well as the saturated model. This amounts to testing regression coefficients equal to zero.

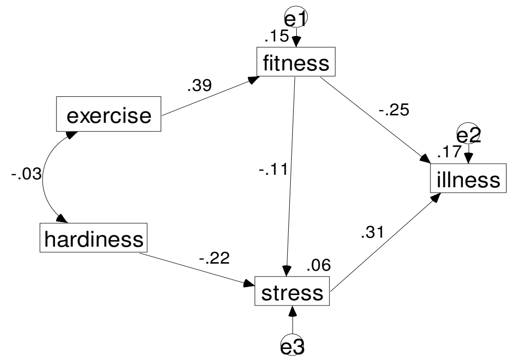
Slide 5

Exercise/Illness example

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	11	5.92143	4	.20509	1.48036
Saturated model	15	.00000	0		
Independence model	5	165.49898	10	.00000	16.54990



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Common cause path model - testing partial correlation zero Example (from Kline p. 29)

	X	Y	W
X shoe-size	1		
Y vocabulary breadth	.5	1	
W age	.8	.6	1

$$r_{xy \cdot w} = \frac{.5 - .8 * .6}{\sqrt{(1 - .8^2)(1 - .6^2)}} = \frac{.02}{.48} = .04$$

The association between shoe-size and vocabulary breadth is explained by the common cause of age. PUT PATH DIAGRAM

Similar to Negative affectivity example in HW5 Is it NA that is causing the relationship between self-reported medical conditions complaints?

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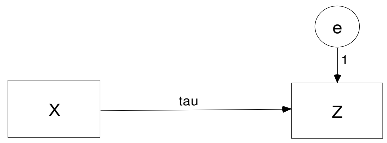
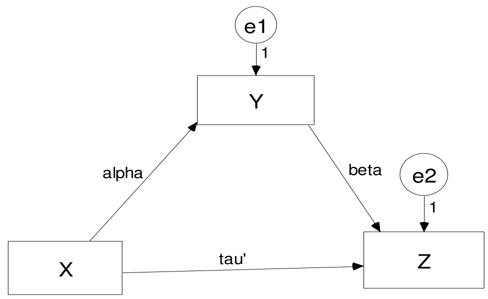
Mediation - Total and Partial

Generally when we talk about mediation we are asking whether the causal relationship between two variables



can be broken down into a series of intermediate causal paths.



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Mediation - Total and Partial

Logical Steps to testing for a mediator:

1. Test if there is a significant relationship between X and Z (i.e. is there a significant total causal effect of X on Z), record this effect τ
2. Test if there is significant relationship between X and Y (i.e. is there a significant total causal effect of X on Y), record this effect α.
3. Estimate the effect that X and Y have simultaneously on Z, record the Y on Z effect as β, record the X on Z effect as τ'.

If τ' is not significantly different than zero, then the causal effect of X on Z is fully mediated by Y. If $|\tau'| < |\tau|$ but τ' is still statistically significant, then we say that the relationship between X and Z is partially mediated by Y.

Sometimes see $\frac{|\tau|-|\tau'|}{|\tau|}$ presented as the percent of the total causal effect of X on Z explained by the mediator Y.

Mediation - Total and Partial

	Z	X	Y
Z unhealthy wt control	1		
X teased	.5	1	
Y depression	.8	.6	1

$\tau = .5$, $\alpha = .6$, $\beta = \frac{.8-.5*.6}{1-.6^2} = .78$, $\tau' = \frac{.5-.8*.6}{1-.6^2} = .03$

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Action theory and Conceptual theory Mediation in interventions

Given that an intervention or clinical trial (experiment) has been conducted where a program or drug or treatment has been given to some people and not others, it is possible to make statements about **actual** causal effects rather than **assumed** causal effects. The ideas and estimation are identical to what we've done so far with path analysis, the only difference is how the data were generated in the first place (i.e. by an experiment).

Entire area of study called "Evaluation Theory" revolves around how to decide when and how a policy or intervention or action has made a positive change.

Chen HT (1990) *Theory driven evaluations*. Sage, Newbury Park, CA.
Two critical aspects in the design and implementation of intervention

1. Conceptual theory - what are the causes of the outcome
2. Action Theory - what kind of intervention is needed to positively change those causes

Slide 10

Slide 11

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Drug and Alcohol Dependence 68 (2002) S69–S83

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Mediation designs for tobacco prevention research

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Abstract

This paper describes research designs and statistical analyses to investigate how tobacco prevention programs achieve their effects on tobacco use. A theoretical approach to program development and evaluation useful for any prevention program guides the analysis. The theoretical approach focuses on action theory for how the program affects mediating variables and on conceptual theory for how mediating variables are related to tobacco use. Information on the mediating mechanisms by which tobacco prevention programs achieve effects is useful for the development of efficient programs and provides a test of the theoretical basis of prevention efforts. Examples of these potential mediating mechanisms are described including mediated effects through attitudes, social norms, beliefs about positive consequences, and accessibility to tobacco. Prior research provides evidence that changes in social norms are a critical mediating mechanism for successful tobacco prevention. Analysis of mediating variables in single group designs with multiple mediators are described as well as multiple group randomized designs which are the most likely to accurately uncover important mediating mechanisms. More complicated dismantling and constructive designs are described and illustrated based on current findings from tobacco research. Mediation analysis for categorical outcomes and more complicated statistical methods are outlined.

Keywords: Tobacco; Adolescents; Mediation; Indirect effects; Prevention; Methodology

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From MacKinnon DP, Taborga MP, Morgan-Lopez AA (2002) "Mediation designs for tobacco prevention research" *Drug and Alcohol Dependence*, 68, S69-S83.

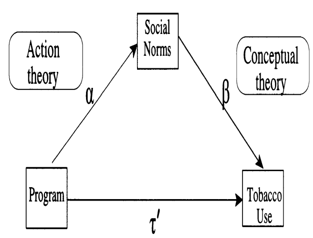

Fig. 1. One mediator model illustrating the incorporation of action theory and conceptual theory for tobacco use prevention. The mediator variable for this illustration is social norms.

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From MacKinnon DP, Taborga MP, Morgan-Lopez AA (2002) "Mediation designs for tobacco prevention research" *Drug and Alcohol Dependence*, 68, S69-S83.

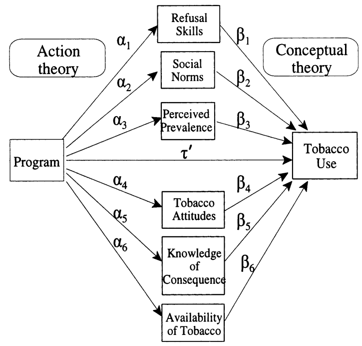

Fig. 2. One independent variable, six-mediator model illustrating the incorporation of action theory and conceptual theory for tobacco use prevention.

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Suppression Effect

The saying that correlation does not prove causation should be complimented by saying that a lack of correlation does not disprove causation (Bollen, 1989, p.52)

	# of errors	boredom	intelligence
# of errors	1		
boredom	.35	1	
intelligence	0	.7	1

Consider the following path diagram:

$$\tau' = \frac{0 - .35 * .7}{1 - .7^2} = -.48$$

When $|\tau'| > |\tau|$, this is an indication that Y is a suppressor variable, that is, it is masking the relationship between X and Z. You don't see a bivariate relationship unless you adjust for the suppressor variable.

In the example above boredom is suppressing the relationship between intelligence and the number of errors made.

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Equivalent Models

Two models are equivalent if they are covariance equivalent, i.e. if every covariance matrix generated by one model (through some choice of parameters) can also be generated by the others.

For a detailed study of equivalent models check out:

- MacCallum R.C., Wegener, D.T., Uchino, B.N. and Fabrigan, L.R. (1993) "The problem of equivalent models in applications of covariance structure analysis" Psychological Bulletin Vol 144, No. 1, 185-199.
- Lee, S., and Hershberger, S. (1990). A simple rule for generating equivalent models in covariance structure modeling. Multivariate Behavioral Research, 25, 313-334.
- Raykov, and Penev (1999). On SEM equivalence. Multivariate Behavioral Research, 34, 199-244.

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Equivalent Models

Empirically we can choose whether models in Column 1 are better than Column 2 (or vica versa). But empirically we cannot choose which model within each column is better because they are equivalent

Column 1 Column2

- Example in a clinical trial: Tollefson GD, Sanger TM (1997) "Negative Symptoms: A path analytic approach to a double-blind, placebo- and haloperidol-controlled clinical trial with olanzapine" *American Journal of Psychiatry*, 154(4), 466-474.
- Confounding, when does W need to be included or not
- Moderators (interactions)
- Wall and Li (2003) paper about multiple regression

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