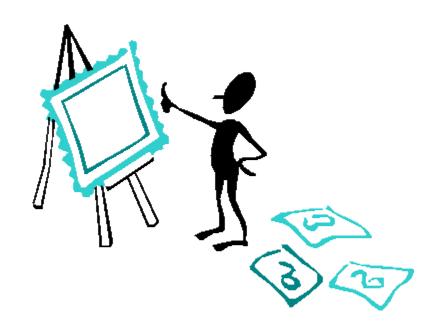
PATH ANALYSIS

Outline

- Introduction
- Definition
- Basic assumptions
- Decomposition
- Path coefficients
- Effects
- Application
- □ The causality problem



Path analysis: introduction

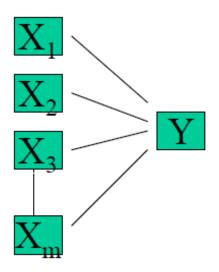
- Statistical procedure for analysing the structure using directly observable variables
- Introduced in 1934 by Sewall Wright (american genetic scientist)
- □ In the 60s-70s very popular in sociology
- ... is important because principles of path analysis also apply to structural models

- ... is a method for investigating an a priori postulated path model
- A path model is an explanation of why x and y are related to each other
- ... is conducted on the basis of (observed) covariances and correlations
- Major characteristic: estimation of directional and nondirectional effects

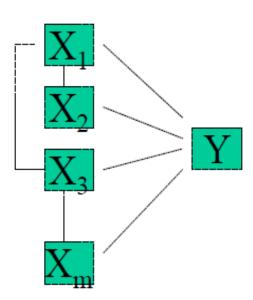
- Specificities of path analysis:
 - ... is for observable variables
 - ... requires one indicator only (actually no indicator!)
 - ... implicitly assums that there is no error of measurement

A comparison of path analysis and multiple regression

Multiple regression



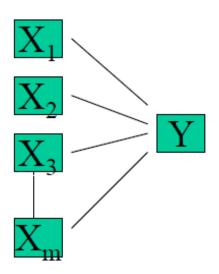
$$Y = \mathbf{a} + \beta_1 X_1 + ... + \beta_m X_m + E$$



i. e. X₃ can influence Y using different paths

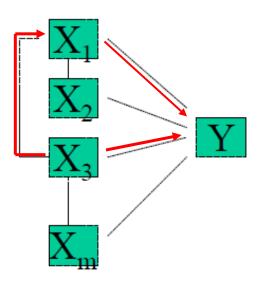
A comparison ...

Multiple regression



$$Y = \mathbf{a} + \beta_1 X_1 + ... + \beta_m X_m + E$$

Path analysis



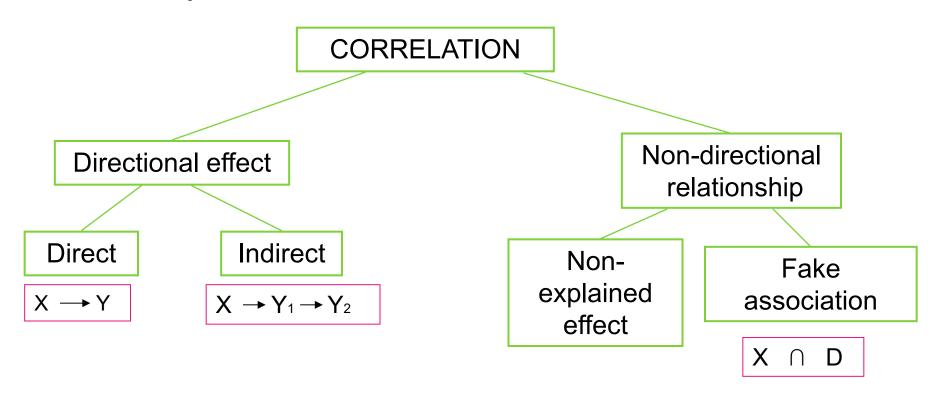
i. e. X₃ can influence Y using different paths (see red lines)

Path analysis: basic assumption

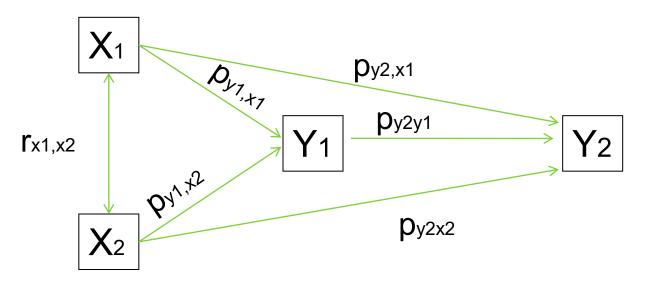
- A correlation can comprise several directional and non-directional effects
- Path analysis decomposes a correlation (or covariance) in directional and non-directional components

□ → "decomposition of correlations into effects"

Decomposition of effects:



- Simple path analysis model with
 - two independent variables X_1 and X_2 , a mediator variable Y_1 and a dependent variable Y_2

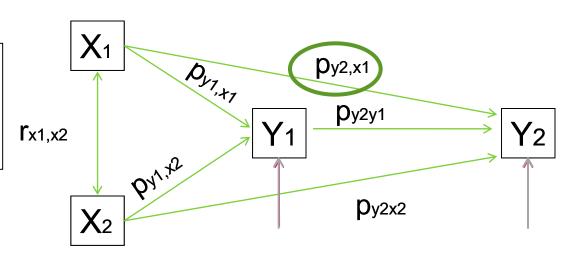


... the variables give rise to six correlations

Path analysis: decomposition

 \square Decomposition the correlation $r_{x1,y2}$.

DE = Direct effect
IE = Indirect effect
NE = by the model not explained
effect

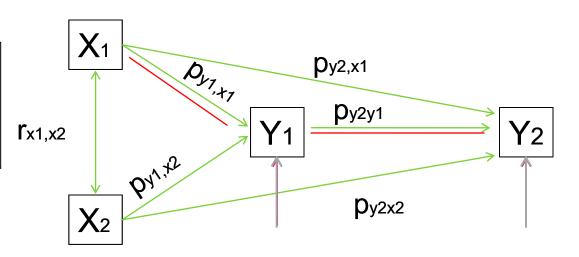


$$\mathbf{r}_{x_1,y_2} = p_{y_2,x_1} + \dots$$
(DE) +

- [Product-moment Korrelations (r)]
- Path coefficients (p)

 \square Decomposition the correlation $r_{x1,y2}$.

DE = Direct effect
IE = Indirect effect
NE = by the model not explained effect



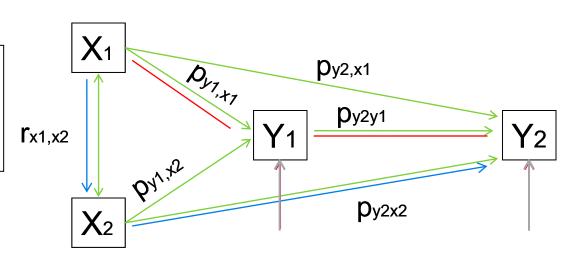
$$\mathbf{fx_{1,y_2}} = \mathbf{p}_{y_2,x_1} + (\mathbf{p}_{y_1,x_1}) \cdot (\mathbf{p}_{y_2,y_1}) + \dots$$

$$(DE) + (IE) + \dots$$

- [Product-moment Korrelations (r)]
- Path coefficients (p)

\square Decomposition the correlation $r_{x1,y2}$.

DE = Direct effect
IE = Indirect effect
NE = by the model not explained effect



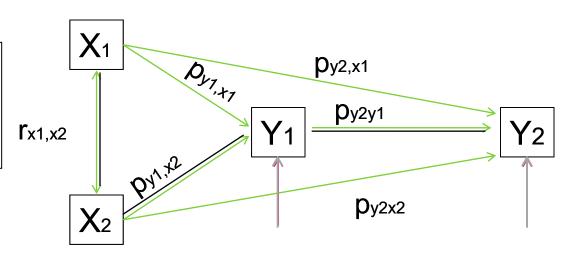
$$\mathbf{fx_{1,y_{2}}} = \mathbf{p}y_{2,x_{1}} + (\mathbf{p}y_{1,x_{1}}) \cdot (\mathbf{p}y_{2,y_{1}}) + (\mathbf{f}x_{1,x_{2}}) \cdot (\mathbf{p}y_{2,x_{2}}) + \dots$$

$$(DE) + (IE) + (NE) + \dots$$

- [Product-moment Korrelations (r)]
- Path coefficients (p)

 \square Decomposition the correlation $r_{x1,y2}$.

DE = Direct effect
IE = Indirect effect
NE = by the model not explained
effect



$$\mathbf{r}_{x_1,y_2} = p_{y_2,x_1} + (p_{y_1,x_1}) \cdot (p_{y_2,y_1}) + (\mathbf{r}_{x_1,x_2}) \cdot (p_{y_2,x_2}) + (\mathbf{r}_{x_1,x_2}) \cdot (p_{y_2,y_1})$$

$$(DE) + (IE) + (NE) + (NE)$$

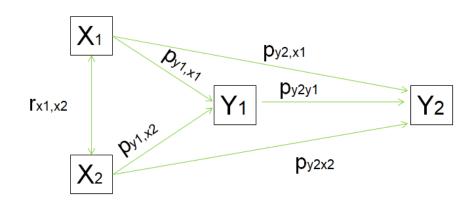
- [Product-moment Korrelations (r)]
- Path coefficients (p)

- Decomposition:
- $r_{x1y1} = p_{y1x1} + (r_{x1x2}) \cdot (p_{y1x2})$
- $r_{x2y1} = p_{y1x2} + (r_{x1x2}) \cdot (p_{y1x1})$
- $r_{x_1y_2} = p_{y_2x_1} + (p_{y_1x_1}) \cdot (p_{y_2y_1}) + (r_{x_1x_2}) \cdot (p_{y_2x_2}) + (r_{x_1x_2}) \cdot (p_{y_1x_2}) \cdot (p_{y_2y_1})$

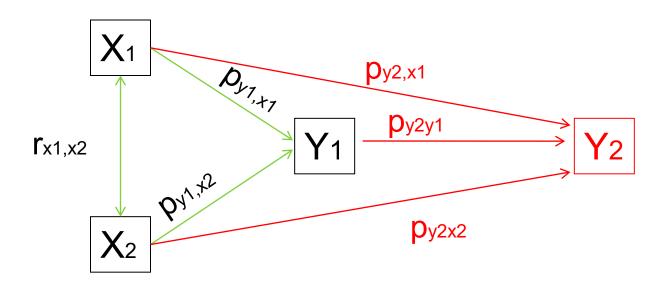
 $r_{x1,x2}$ $r_{x1,x2}$

- Decomposition:
- $r_{x1y1} = p_{y1x1} + (r_{x1x2}) \cdot (p_{y1x2})$
- $r_{x2y1} = p_{y1x2} + (r_{x1x2}) \cdot (p_{y1x1})$
- $r_{x_1y_2} = p_{y_2x_1} + (p_{y_1x_1}) \cdot (p_{y_2y_1}) + (r_{x_1x_2}) \cdot (p_{y_2x_2}) + (r_{x_1x_2}) \cdot (p_{y_1x_2}) \cdot (p_{y_2y_1})$
- $r_{x2y2} = p_{y2x2} + (p_{y1x2}) \cdot (p_{y2y1}) + (r_{x1x2}) \cdot (p_{y2x1}) + (r_{x1x2}) \cdot (p_{y1x1}) \cdot (p_{y1y2})$
- $r_{y1y2} = p_{y2y1}$

• • • • •

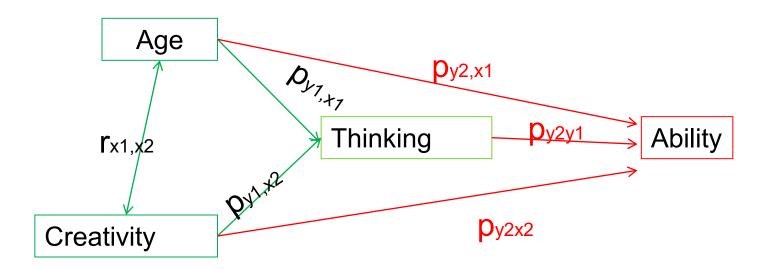


□ The new parts of the structure model



Example

- Age (X1); creativity (X2)
- Thinking (Y1); problem solving ability (Y2)



Decomposition for example:

- 1 age & creativity $(r_{x1x2}) = r_{x1x2}$
- 2 age & thinking $(r_{x1x2}) = p_{y1x1} + (r_{x1x2}) \cdot (p_{y1x2})$
- 3 creativity & thinking $(r_{x2y1}) = p_{y1x2} + (r_{x1x2}) \cdot (p_{y1x1})$

• 4 age & problem solving ability $(r_{x1x2}) = p_{y2x1} + (p_{y1x1}) \cdot (p_{y2y1}) + (r_{x1x2}) \cdot (p_{y2x2}) + (r_{x1x2}) \cdot (p_{y1x2}) \cdot (p_{y2y1})$

• 5 creativity & problem solving ability $(r_{x2y2}) = p_{y2x2} + (p_{y1x2}) \cdot (p_{y2y1}) + (r_{x1x2}) \cdot (p_{y2x1})$

+

 $(r_{x1x2})\cdot(p_{y1x1})\cdot(p_{y1y2})$

• 6 thinking & problem solving ability $(r_{y1y2}) = p_{y2y1}$

Path analysis: the unkowns

- Decomposition:
- $r_{x1y1} = p_{y1x1} + (r_{x1x2}) \cdot (p_{y1x2})$
- $r_{x2y1} = p_{y1x2} + (r_{x1x2}) \cdot (p_{y1x1})$
- $r_{x_1y_2} = p_{y_2x_1} + (p_{y_1x_1}) \cdot (p_{y_2y_1}) + (r_{x_1x_2}) \cdot (p_{y_2x_2}) + (r_{x_1x_2}) \cdot (p_{y_1x_2}) \cdot (p_{y_2y_1})$
- $r_{x2y2} = p_{y2x2} + (p_{y1x2}) \cdot (p_{y2y1}) + (r_{x1x2}) \cdot (p_{y2x1}) + (r_{x1x2}) \cdot (p_{y1x1}) \cdot (p_{y1y2})$

• • • • •

→ Series of linear equations

Path analysis: path coefficients

- Decomposition:
- $r_{x1y1} = p_{y1x1} + (r_{x1x2}) \cdot (p_{y1x2})$
- $r_{x2y1} = p_{y1x2} + (r_{x1x2}) \cdot (p_{y1x1})$
- $r_{x_1y_2} = p_{y_2x_1} + (p_{y_1x_1}) \cdot (p_{y_2y_1}) + (r_{x_1x_2}) \cdot (p_{y_2x_2}) + (r_{x_1x_2}) \cdot (p_{y_1x_2}) \cdot (p_{y_2y_1})$
- $r_{x2y2} = p_{y2x2} + (p_{y1x2}) \cdot (p_{y2y1}) + (r_{x1x2}) \cdot (p_{y2x1}) + (r_{x1x2}) \cdot (p_{y1x1}) \cdot (p_{y1y2})$

• • • •

→ Series of linear equations

- with path coefficients as unknowns
- the path coefficients can be determined if their number corresponds to the number of equations
- the path coefficients can be estimated if their number is smaller than the number of equations

 Demonstration of how to find estimates of the path coefficients

Given are r_{x1y1} , r_{x2y1} and r_{x1x2} and the following decompositions:

$$r_{x1y1} = p_{y1x1} + (r_{x1x2}) \cdot (p_{y1x2})$$
 (1)

$$r_{x2y1} = p_{y1x2} + (r_{x1x2}) \cdot (p_{y1x1})$$
 (2)

(1) -> (3) -
$$p_{y1x1}$$
 = - r_{x1y1} + $r_{x1x2} \times p_{y1x2}$

(3) -> (4)
$$p_{y1x1} = r_{x1y1} - r_{x1x2} \times p_{y1x2}$$

(2) -> (5)
$$r_{x2y1} = p_{y1x2} + r_{x1x2} \times (r_{x1y1} - r_{x1x2} \times p_{y1x2})$$

(5) -> (6)
$$r_{x2y1} = p_{y1x2} + r_{x1x2} \times r_{x1y1} - r_{x1x2} \times r_{x1x2} \times p_{y1x2}$$

 Demonstration of how to find estimates of the path coefficients

• • • • •

(2) -> (5)
$$r_{x2y1} = p_{y1x2} + r_{x1x2} \times (r_{x1y1} - r_{x1x2} \times p_{y1x2})$$

(5) -> (6) $r_{x2y1} = p_{y1x2} + r_{x1x2} \times r_{x1y1} - r_{x1x2} \times r_{x1x2} \times p_{y1x2}$
(6) -> (7) $r_{x2y1} = p_{y1x2} \times (1 - r_{x1x2} \times r_{x1x2}) + r_{x1x2} \times r_{x1y1}$
(7) -> (8) $p_{y1x2} \times (1 - r_{x1x2} \times r_{x1x2}) = r_{x2y1} - r_{x1x2} \times r_{x1y1}$
(8) -> (9) $p_{y1x2} = \frac{r_{x2y1} - r_{x1x2} \times r_{x1y1}}{1 - r_{x1x2} \times r_{x1y2}}$

 Demonstration of how to find estimates of the path coefficients

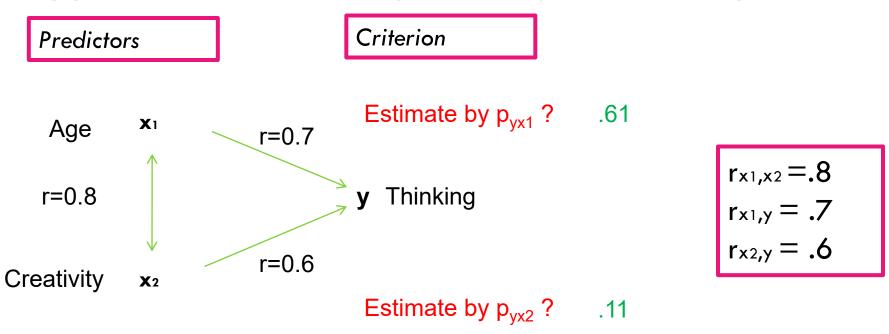
• • • • •

(7) -> (8)
$$p_{y1x2} = \frac{r_{x2y1} - r_{x1x2} \times r_{x1y1}}{1 - r_{x1x2} \times r_{x1x2}}$$

... it corresponds to the standardized partial regression coefficent:

$$\beta_{y1x2.x1} = \frac{r_{x2y1} - r_{x1x2} \times r_{x1y1}}{1 - r_{x1x2}^2}$$

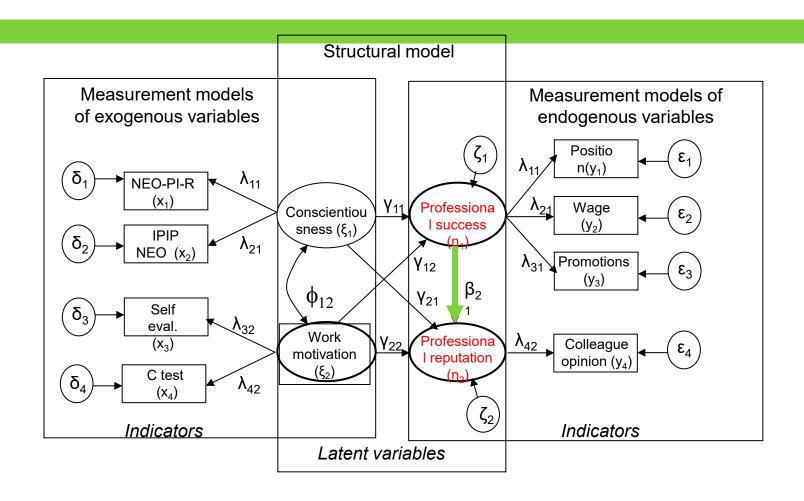
Application to the example of regression analysis



□ Note:

Formally the contribution of path analysis to SEM is apparent as a new parameter matrix:

the BETA matrix



□ Note 1:

In simple structural models multiple regression and path analysis do equally well.

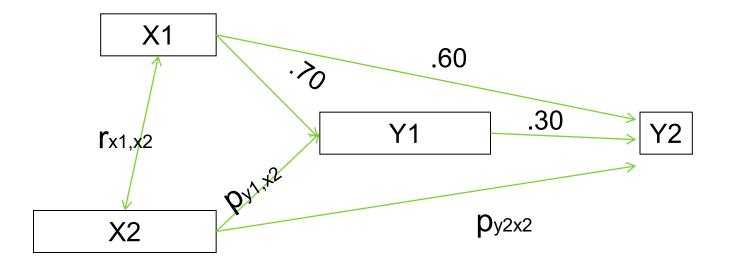
But a complex path model can includes structural unites that cannot be realized as a multiple regression model.

Because of path analysis new parameters become available: these are measures of indirect effects.

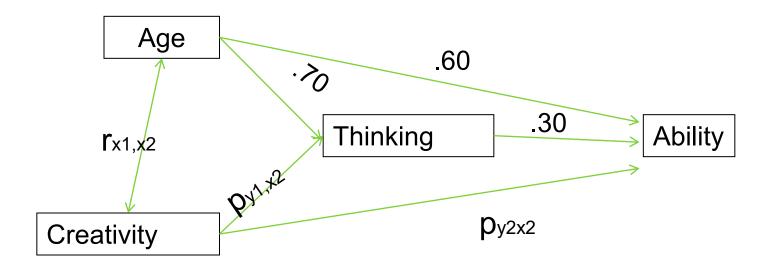
Path analysis: effects

Effect estimation:

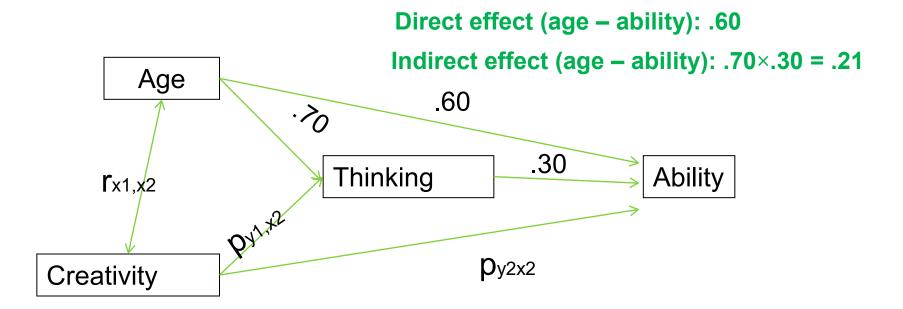
- Direct effects correspond to path coefficients
- Indirect effects are estimated by multiplying path coefficients



- □ Example with path coefficients added:
- Age (X1); creativity (X2)
- Thinking (Y1); problem solving ability (Y2)



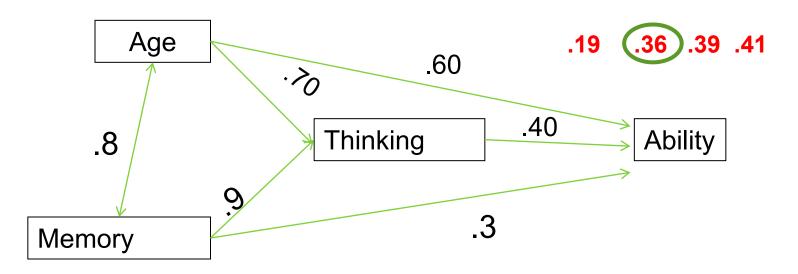
- Example with path coefficients added:
- Age (X1); creativity (X2)
- Thinking (Y1); problem solving ability (Y2)



Path analysis practice

- Example with path coefficients added:
- □ Age (X1); memory (X2)
- Thinking (Y1); problem solving ability (Y2)

Determine the indirect effect of memory on ability!



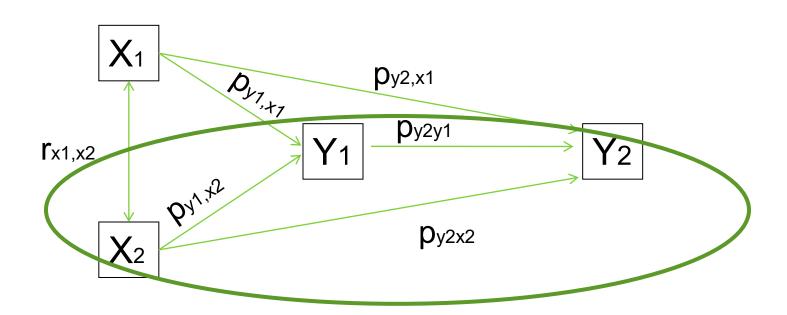
Consequences for parameter estimation:

□ Parameter estimation can be realized as search for the solution(s) of a system of linear equations (i.e. in a somewhat different way as in regression analysis)

Even in complex structures parameter estimation can be conducted on the basis of correlations

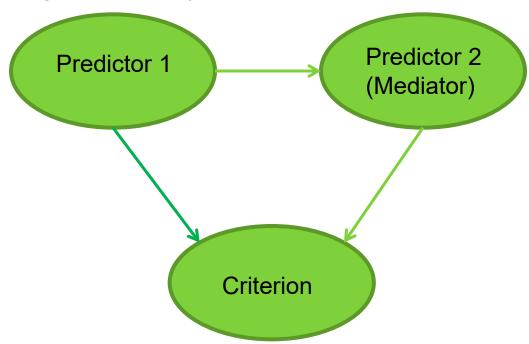
Path analysis: application

In application frequently the focus is on parts of the complete simple path model:

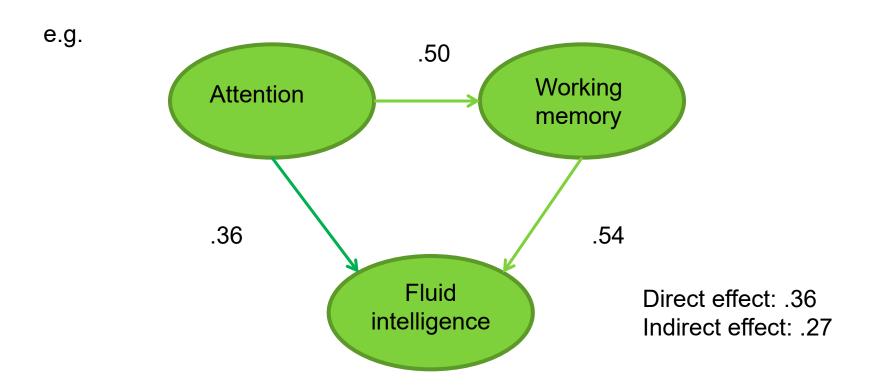


In application frequently the focus is on parts of the complete simple path model:

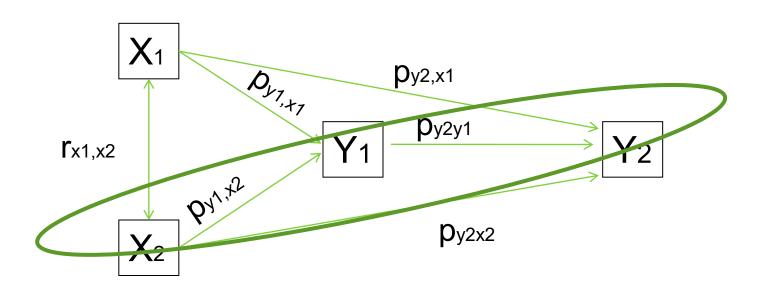
Model for testing the hierarchy of predictors



In application frequently the focus is on parts of the complete simple path model:



In application frequently the focus is on parts of the complete simple path model:



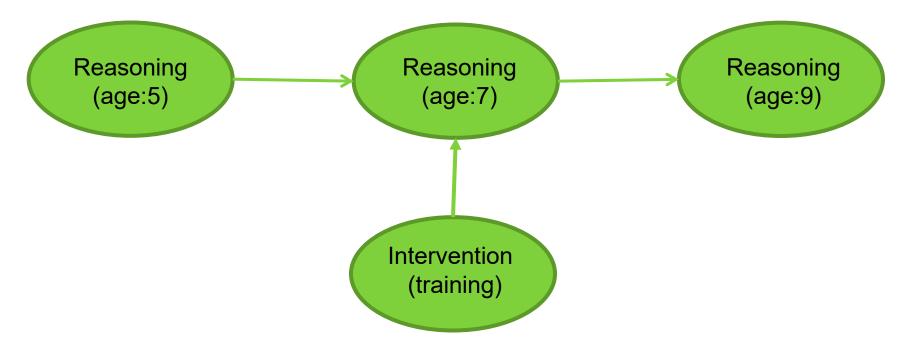
In application frequently the focus is on parts of the complete simple path model:

Developmental model (mediation model)



In application frequently the focus is on parts of the complete simple path model:

Developmental model (mediation model)



Path analysis brings about new structural feature

- ... increases the complexity of models that can possibly be investigated
- enable investigations on the basis of covariances and correlations

The causality problem

- □ The "causality" problem of SEM
 - □ There is disagreement among SEM researchers regarding the status of the outcome of SEM:

Does SEM inform us of

- a causal consequences
- or effects / influences?
- e.g. .. high working memory capacity *causes* high intelligence
- e.g. .. working memory capacity *influences* the degree of intelligence

- □ Problem "causality"
 - The terms "causality" and "causal" are occasionally used for the relationships at the latent level
 - ... but what does "causality" mean?
 - turning the switch for the light "causes" the light bulb to illuminate the room

It is correct, that the "turning of the switch" causes this specific event!

But taking a *general perspective minimizes* the importance of the "turning of the switch"

... because it would not work if there were no electricity

- □ Problem "causality"
 - The terms "causality" and "causal" are occasionally used for the relationships at the latent level
 - ... but what does "causality" mean?
 - it may be argued: "the cause for student X to solve an arithmetic task is (a high degree of) intelligence"

But taking a general perspective minimizes the importance of "intelligence " ... because solving the task is not possible without **reading ability**, **knowledge of rules**, ...

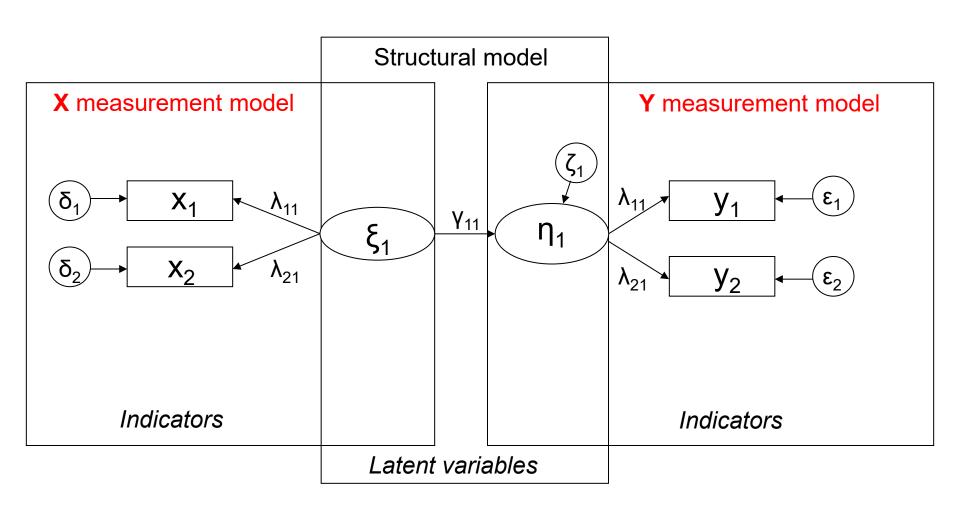
- Problem "causality"
 - The terms "causality" and "causal" are occasionally used for the relationships at the latent level
 - In science there is the established opinion that experimentation is necessary in order to justify the assumption of causality
 - experimentation marked the *beginning of scientific psychology*
 - experimentation includes ...
 - the willful manipulation of the phenomenon
 - several treatment levels
 - the control of random influences
 - there is random assignment

- Problem "causality"
 - The terms "causality" and "causal" are occasionally used for the relationships at the latent level
 - Poponents of the causality assumptions argue ...
 - ... the <u>absence of error</u> or other influences at the latent level in SEM guarantee that there is <u>only one source of effect</u> that is the exogeneous variable
 - ... so that experimentation is not necessary

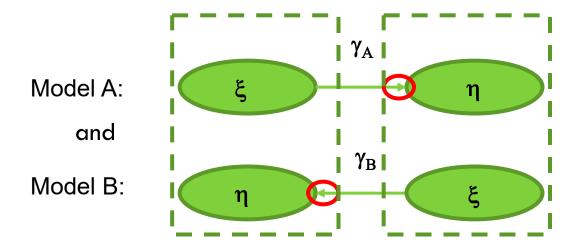
- Problem "causality"
 - The terms "causality" and "causal" are occasionally used for the relationships at the latent level

- Their opponents argue ...
 - ... that the denotation as "directional influence" or "effect" is much more appropriate since there is usually no perfect relationship between predictor and criterion variables

... the direction of the influence may not even be reflected by the regression weight correctly (regarding the question which variable influences the other variable)



- Further problems in SEM
 - In some cases there is even the situation that



i.e. both models lead to the same parameter estimates and model fit: $\gamma_A = \gamma_B$

Summary and brush up:

CORRELATION
PARTIAL CORRELATION
MULTIPLE REGRESSION
PATH ANALYSIS



- □ 2. Path ... an assumed way of influence
- □ 3. Mediation ... indirect influence
- □ 4. Decomposition ... subdivision into effects
- □ 5. Effect ... influence

QUESTIONS REGARDING COURSE UNIT 7

- What is a path coefficient?
- What is a mediation variable?
- What kinds of effects are considered in path analysis?
- How many indicators are required in path analysis?

Literature

- Kline, R. B. (2011). Principles and practices of structural equation modeling (3rd edition) (Chapter 2: Basic statistical concepts: correlations and regression, Chapter 5: Introduction to path analysis). New York, NJ: The Guilford Press.
- Cohen, J., Cohen, P., West, S. G. & Aiken, L. S. (2003). Applied multiple regression/correlation analysis for the behavioral sciences (Partial regression, partial correlation, direct and indirect effects: S. 64-79). Mahwah, N.J.:
 Lawerence Erlbaum.