

UiO : CEMO – Centre for Educational Measurement  
University of Oslo

R

# Mild Introduction to Structural Equation Modeling

## Workshop Oslo UseR! Group



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Centre for Educational Measurement at the University of Oslo (CEMO)

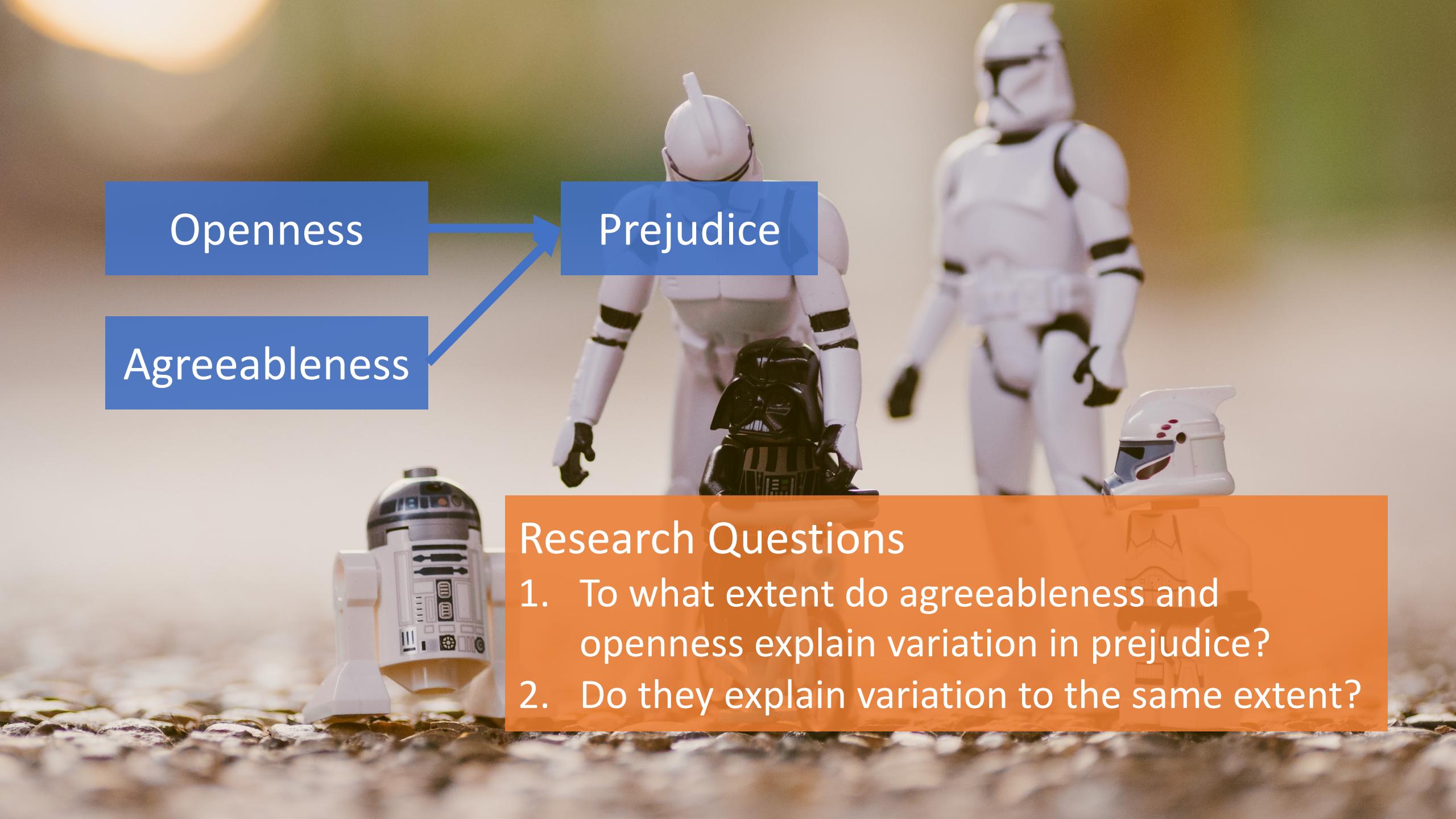
UseR! Oslo Workshop  
28.05.2020



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Openness

Prejudice

Agreeableness

### Research Questions

1. To what extent do agreeableness and openness explain variation in prejudice?
2. Do they explain variation to the same extent?



Some Background

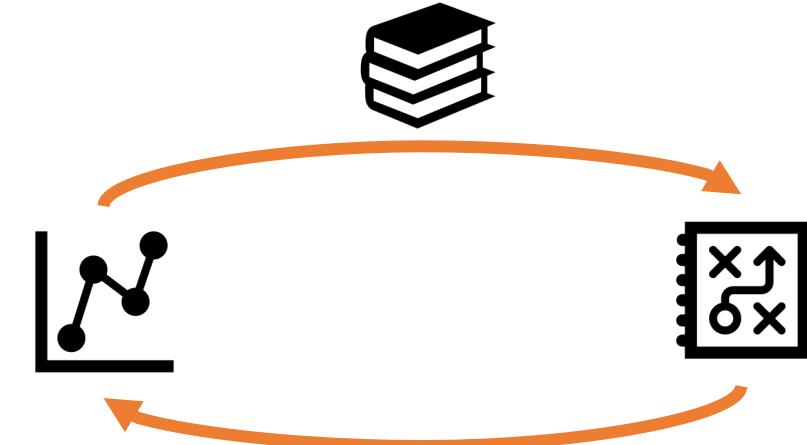


# Structural Equation Modeling (SEM)—Why?

## Definition

“Structural equation modeling can be defined as a class of methodologies that seeks to **represent hypotheses** about the *means, variances, and covariances* of observed data in terms of a smaller number of ‘structural’ parameters defined by a **hypothesized underlying conceptual or theoretical model.**”

(Kaplan, 2001, p. 15215)



SEM is a multivariate statistical modelling technique.  
We postulate a model, which may or may not fit the data.

(Kline, 2016)



# Structural Equation Modeling (SEM)—Why?

## What is so special about SEM?

- SEM can contain **latent (unobserved) variables** to represent constructs (i.e., measurement models) → Include random effects and control measurement error
- SEM can estimate **derived effects**, such as indirect effects in mediation models.
- SEM can be represented by **path diagrams**.
- SEM offers a **broad range of models**, including multi-group models, multilevel models, growth curve models, ...
- SEM can handle **full and summary data** (i.e., covariance matrix and mean vector).



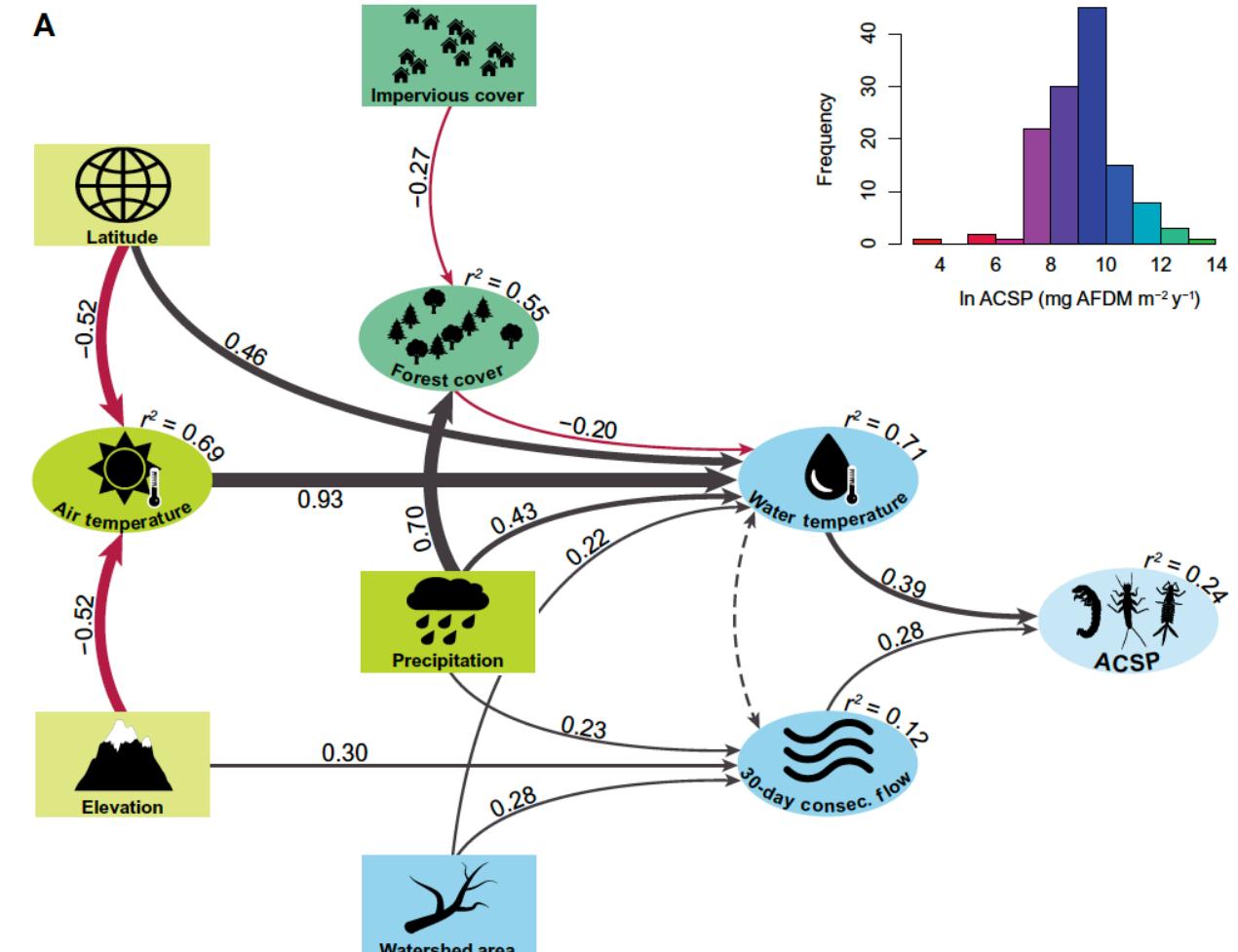
# Structural Equation Modeling (SEM)—What?

SCIENCE ADVANCES | RESEARCH ARTICLE

ECOLOGY

## Precipitation and temperature drive continental-scale patterns in stream invertebrate production

C. J. Patrick<sup>1</sup>\*, D. J. McGarvey<sup>2</sup>, J. H. Larson<sup>3</sup>, W. F. Cross<sup>4</sup>, D. C. Allen<sup>5</sup>, A. C. Benke<sup>6</sup>,  
T. Brey<sup>7</sup>, A. D. Huryn<sup>6</sup>, J. Jones<sup>8</sup>, C. A. Murphy<sup>9</sup>, C. Ruffing<sup>10</sup>, P. Saffarinia<sup>11</sup>,  
M. R. Whiles<sup>12</sup>, J. B. Wallace<sup>13</sup>, G. Woodward<sup>14</sup>



Identifying drivers of annual community secondary production (ACSP), defined as the sum of annual production of all invertebrate populations within a community (17), is particularly challenging ...



# Structural Equation Modeling (SEM)—What?

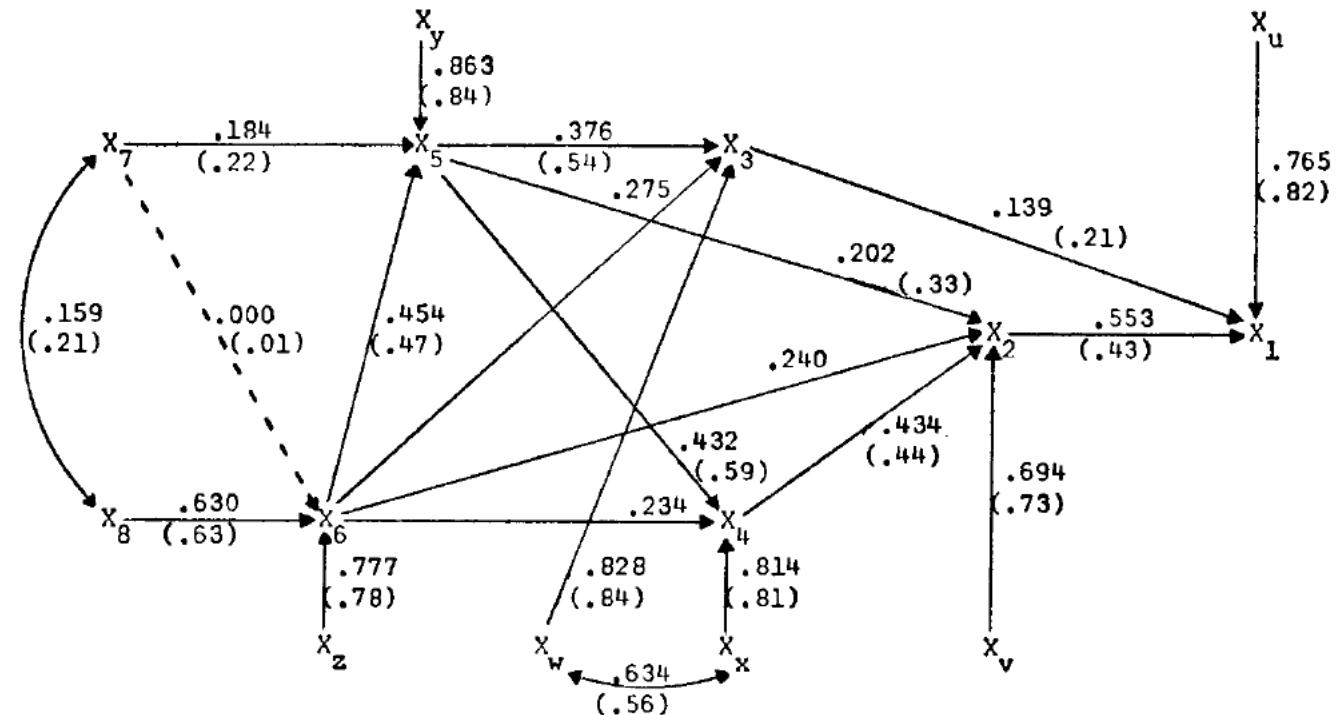
FIGURE 1. PATH COEFFICIENTS FOR ANTECEDENTS OF EDUCATIONAL AND OCCUPATIONAL ATTAINMENT WITH REVISED MODEL FOR FARM BOYS \*

THE EDUCATIONAL AND EARLY OCCUPATIONAL STATUS ATTAINMENT PROCESS: REPLICATION AND REVISION<sup>1</sup>

WILLIAM H. SEWELL, ARCHIBALD O. HALLER AND GEORGE W. OHLENDORF  
University of Wisconsin

American Sociological Review 1970, Vol. 35 (December):1014-1027

Relations between attainment, aspiration, socioeconomic status, mental ability, and academic performance



$x_1$  - Occupational Attainment

$x_2$  - Educational Attainment

$x_3$  - Level of Occupational Aspiration

$x_4$  - Level of Educational Aspiration

$x_5$  - Significant Others' Influence

$x_6$  - Academic Performance

$x_7$  - Socioeconomic Status

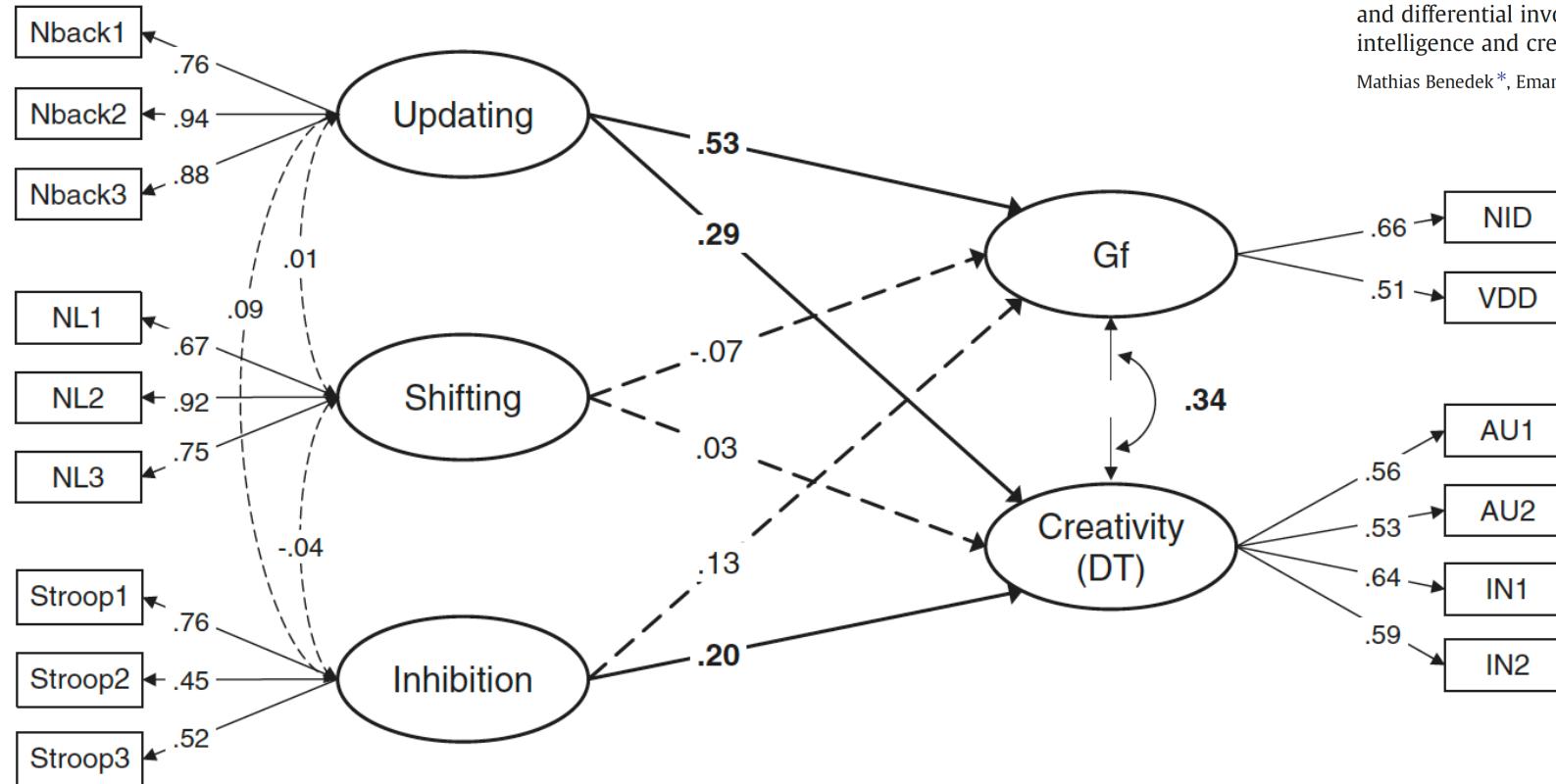
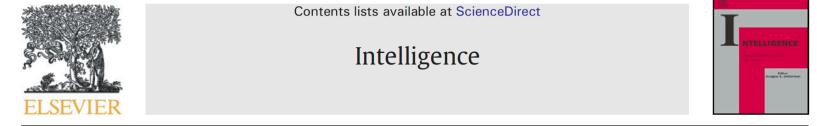
$x_8$  - Mental Ability



# Structural Equation Modeling (SEM)—What?

Intelligence 46 (2014) 73–83

Relations between creativity, intelligence, and executive functions



Intelligence, creativity, and cognitive control: The common and differential involvement of executive functions in intelligence and creativity

Mathias Benedek\*, Emanuel Jauk, Markus Sommer, Martin Arendasy, Aljoscha C. Neubauer





# Structural Equation Modeling (SEM)—How?

(Hoyle, 2012)

## Hypotheses and Theories



1. Model Specification

2. Model Identification

3. Model Estimation

4. Model Evaluation



# Structural Equation Modeling (SEM)—How?

(Hoyle, 2012)

## Hypotheses and Theories



### 1. Model Specification

### 2. Model Identification

### 3. Model Estimation

### 4. Model Evaluation

The “Grammar” of a model:

Translate the hypotheses/theories into testable models.

- Specification equations
- Structural and measurement part
- Define regressions, (co-)variances, latent variables, ...

Lavaan:

- Regression:  $Y \sim X$
- Covariance:  $Y \sim\sim X$
- Latent variable:  $\text{eta} =\sim x1+x2+x3$



# Structural Equation Modeling (SEM)—How?

(Hoyle, 2012)

## Hypotheses and Theories



### 1. Model Specification

### 2. Model Identification

### 3. Model Estimation

### 4. Model Evaluation

The “Feasibility Check” of a model:

Do we have enough information to estimate all model parameters?

- Observed information (from the data): variances, covariances, means
- Model parameters: variances, covariances, regression coefficients, intercepts, ...

Rule:

Have at least the same amount of observed information than model parameters → degrees of freedom of the model  $\geq 0$



# Structural Equation Modeling (SEM)–How?

(Hoyle, 2012)

## Hypotheses and Theories



1. Model Specification

2. Model Identification

3. Model Estimation

4. Model Evaluation

Estimating model parameters:

Reduce the discrepancy between the observed covariance matrix ( $S$ ) and the covariance matrix implied by the model ( $\Sigma$ ).

- Maximum likelihood estimation (ML)
- Weighted least squares (WLS)
- Bayesian estimation



# Structural Equation Modeling (SEM)—How?

(Hoyle, 2012)

## Hypotheses and Theories



### 1. Model Specification

### 2. Model Identification

### 3. Model Estimation

### 4. Model Evaluation

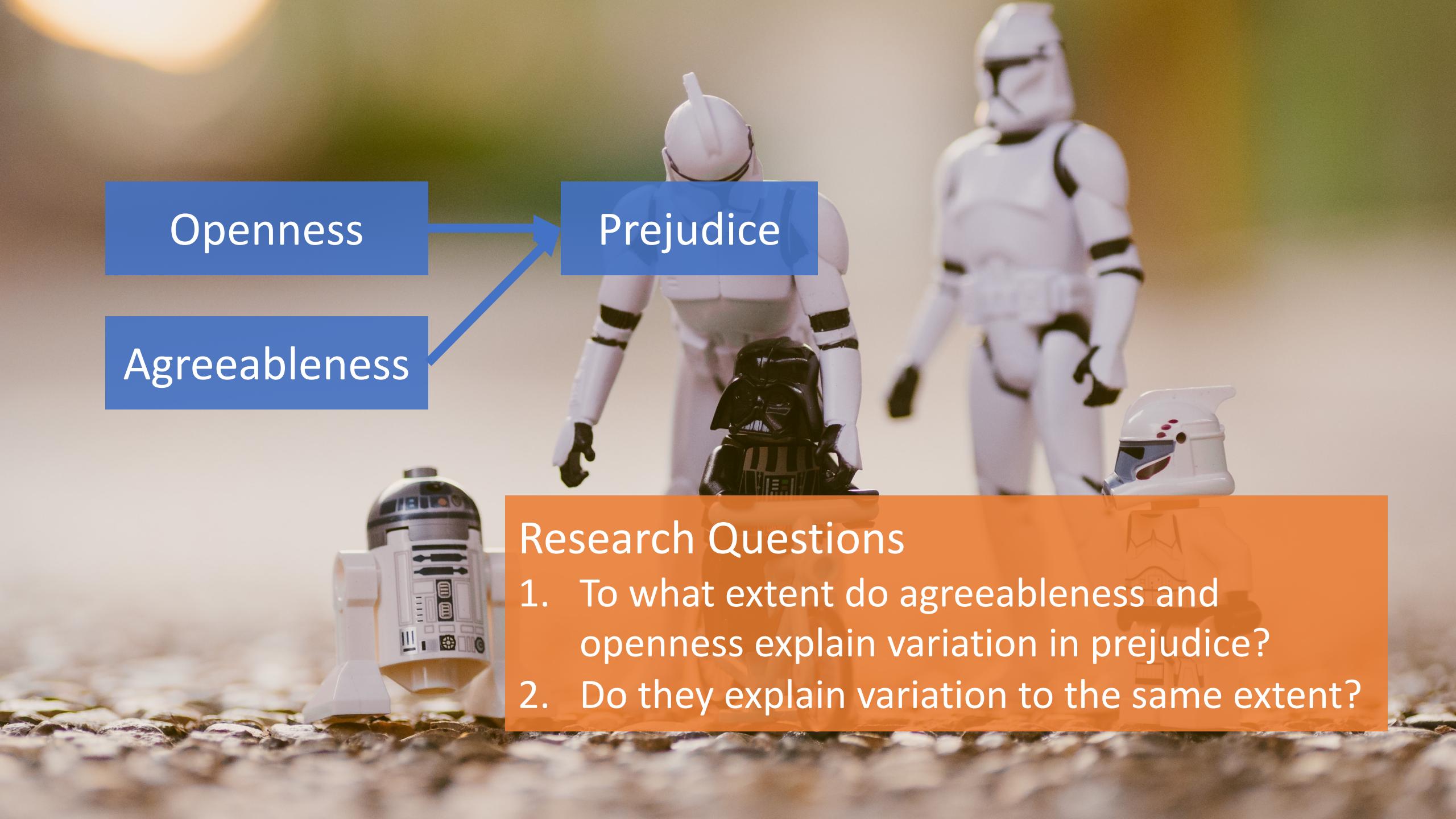
## Evaluate the model fit:

Well-fitting models show a small discrepancy between the **observed covariance matrix ( $S$ )** and the **covariance matrix implied by the model ( $\Sigma$ )**.

### Global fit

- Chi-square statistic  $\chi^2$
- Comparative Fit Index (CFI)
- Root Mean Square Error of Approximation (RMSEA)
- Standardized Root Mean Square Residual (SRMR)

“Rules”:  $\chi^2$  ns, CFI  $\geq .95$ , RMSEA  $\leq .08$ , SRMR  $\leq .08$



Openness

Prejudice

Agreeableness

### Research Questions

1. To what extent do agreeableness and openness explain variation in prejudice?
2. Do they explain variation to the same extent?



# SEM—Our Example for Today

Journal of Personality and Social Psychology  
2016, Vol. 111, No. 3, 367–395

© 2016 American Psychological Association  
0022-3514/16/\$12.00 http://dx.doi.org/10.1037/pspi0000064

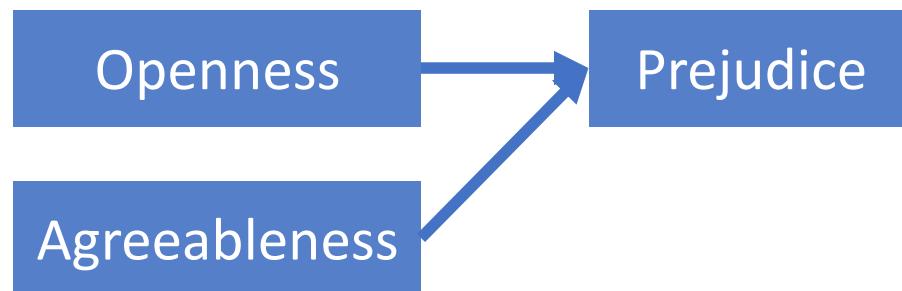
Is Group Membership Necessary for Understanding Generalized Prejudice?  
A Re-Evaluation of Why Prejudices Are Interrelated

Robin Bergh  
Harvard University and Uppsala University

Nazar Akrami  
Uppsala University

Jim Sidanius  
Harvard University

Chris G. Sibley  
University of Auckland



## Format

A data frame with 861 individuals, 10 composite scores, and gender:

EP Ethnic prejudice

SP Sexism

HP Sexual prejudice against gays and lesbians

DP Prejudice toward mentally people with disabilities

A1 Agreeableness indicator 1

A2 Agreeableness indicator 2

A3 Agreeableness indicator 3

01 Openness indicator 1

02 Openness indicator 2

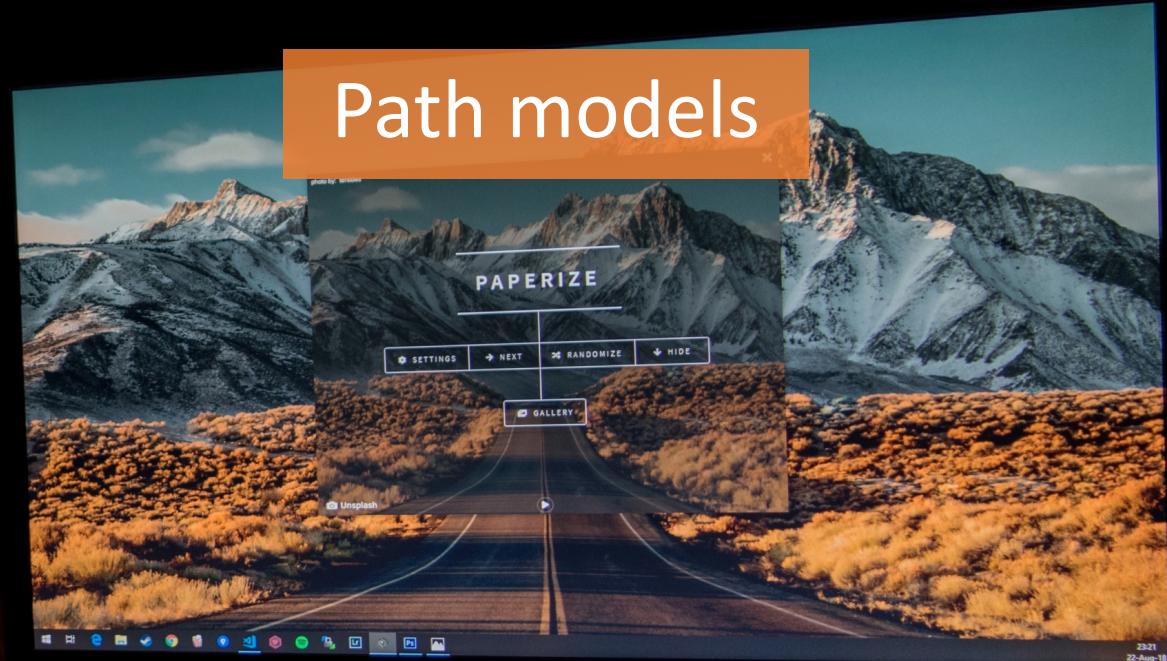
03 Openness indicator 3

gender gender

R package MPsychoR  
data (Bergh)

# SEM in lavaan

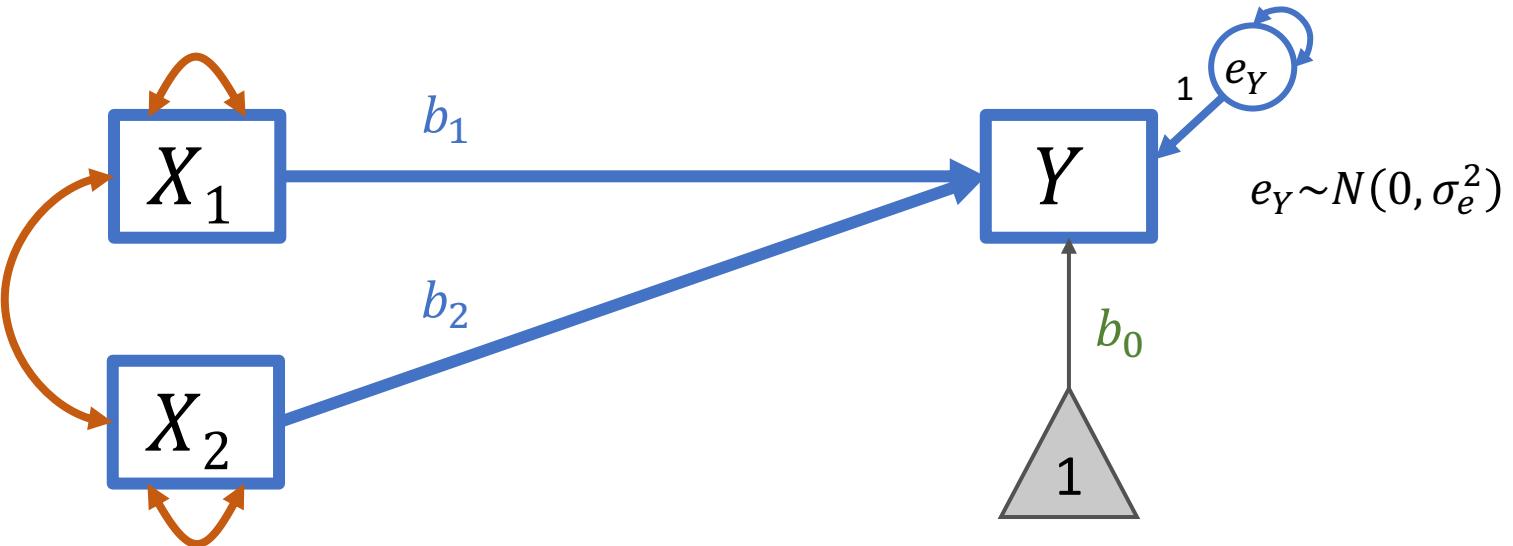
Path models



# Model 1

Simple linear regression model with two predictors

$$Y_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + e_{Yi}$$



## Data

$(y_i, x_{1i}, x_{2i})$  for persons  $i = 1, \dots, N$

$Y$	Prejudice
$X_1$	Openness to experience (sum score)
$X_2$	Agreeableness (sum score)

## Model 2

Mediation model with  
direct and indirect effects

Your turn

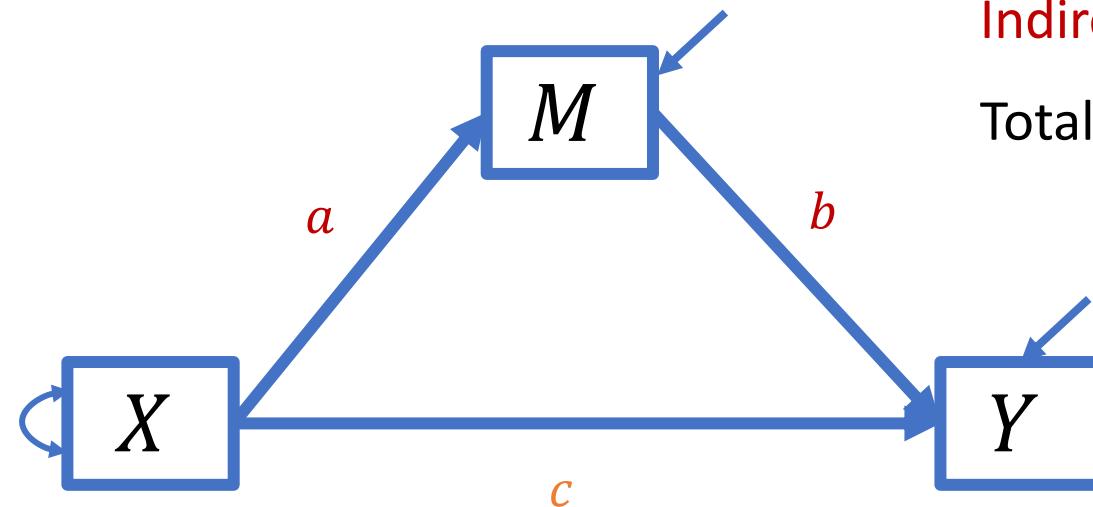
Specify and estimate  
this model in lavaan.

Data

$(y_i, m_i, x_i)$  for  
persons  $i = 1, \dots, N$

$$M_i = i_M + aX_i + e_{Mi}$$
$$Y_i = i_Y + bM_i + cX_i + e_{Yi}$$

Direct effect  $c$   
Indirect effect  $ab$   
Total effect  $ab + c$



$Y$  Prejudice  
 $M$  Openness to experience (sum score)  
 $X$  Agreeableness (sum score)

# SEM in lavaan

Models with latent variables

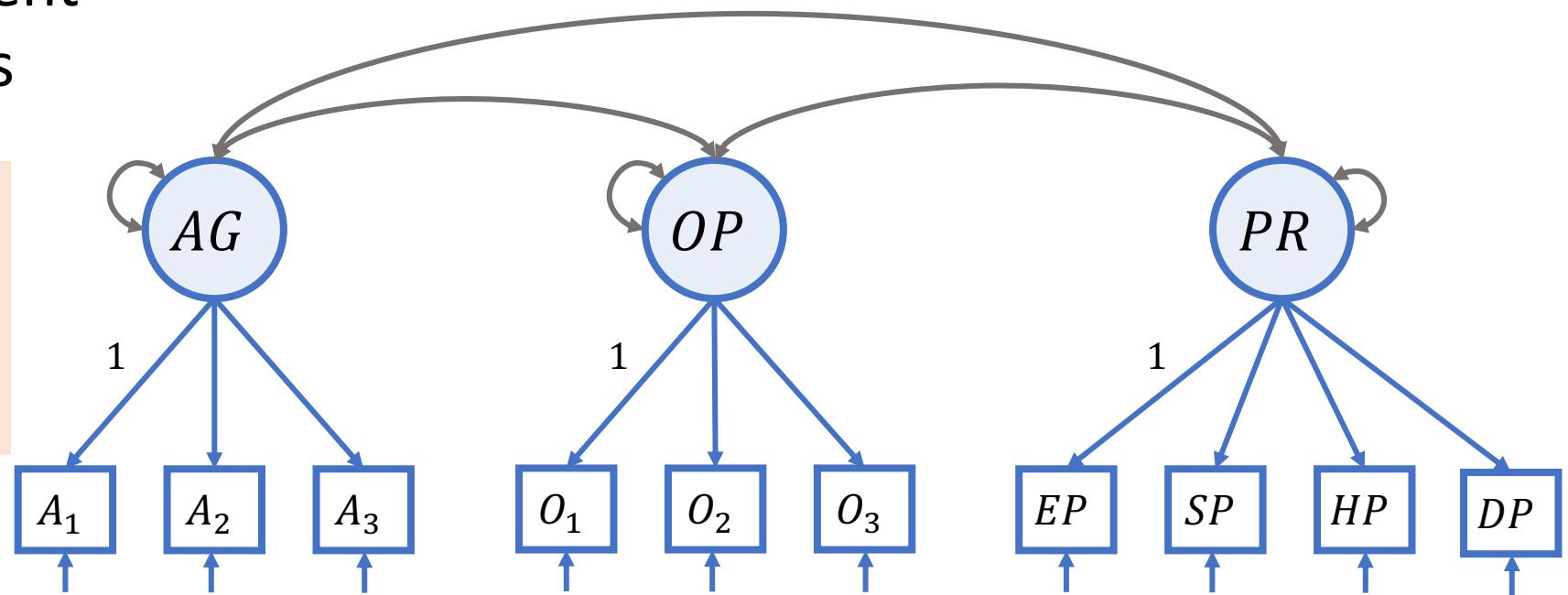


## Model 3: Measurement Model

Confirmatory factor analysis with three latent (unobserved) variables

Represent constructs as latent variables and separate the “true score” and measurement error.

**Data**  
 $(y_i, a_{1i}, \dots, d_{pi})$  for persons  $i = 1, \dots, N$



## Model 3b: Refined Measurement Model

Confirmatory factor analysis with three latent (unobserved) variables

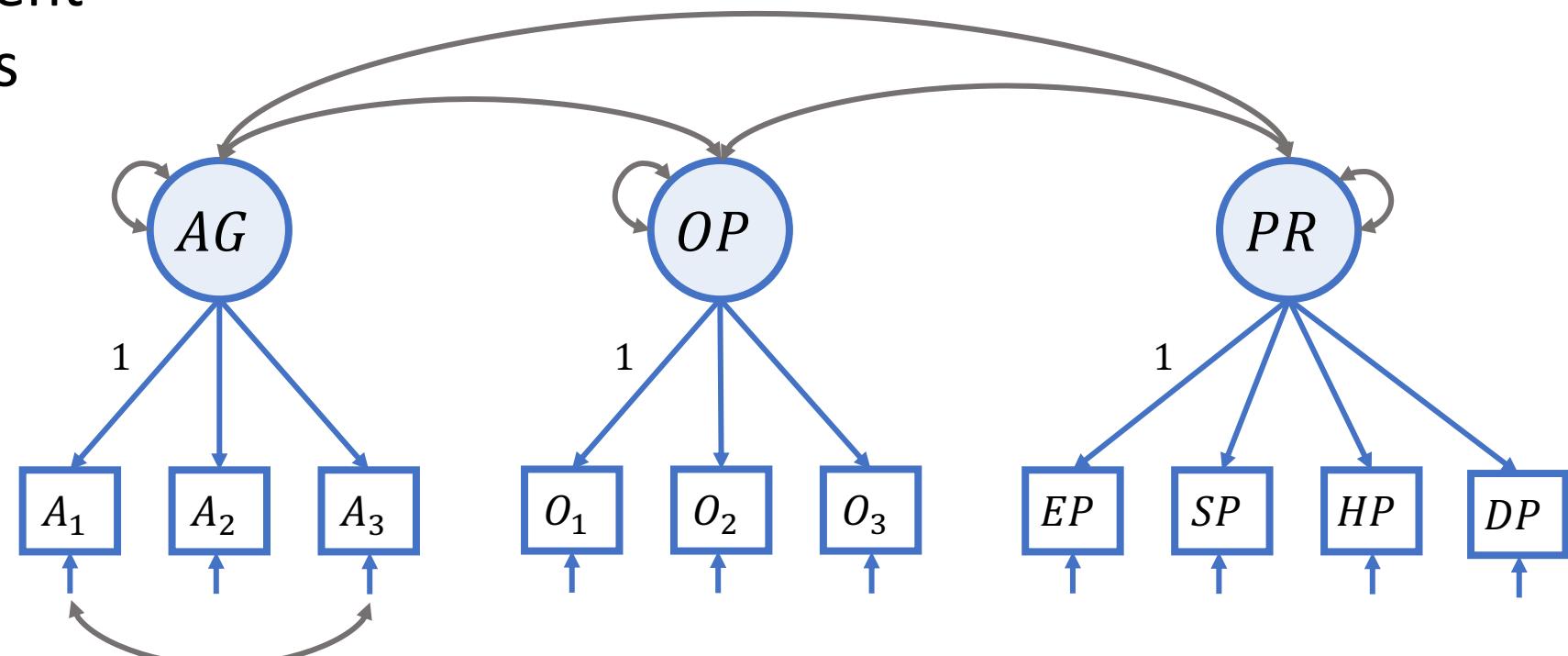
Your turn 

Specify and estimate this model in lavaan.

Data  
 $(y_i, a_{1i}, \dots, d_{pi})$  for persons  $i = 1, \dots, N$

Does this refined model fit better?

R



Covariance between residuals (perhaps due to item wording)

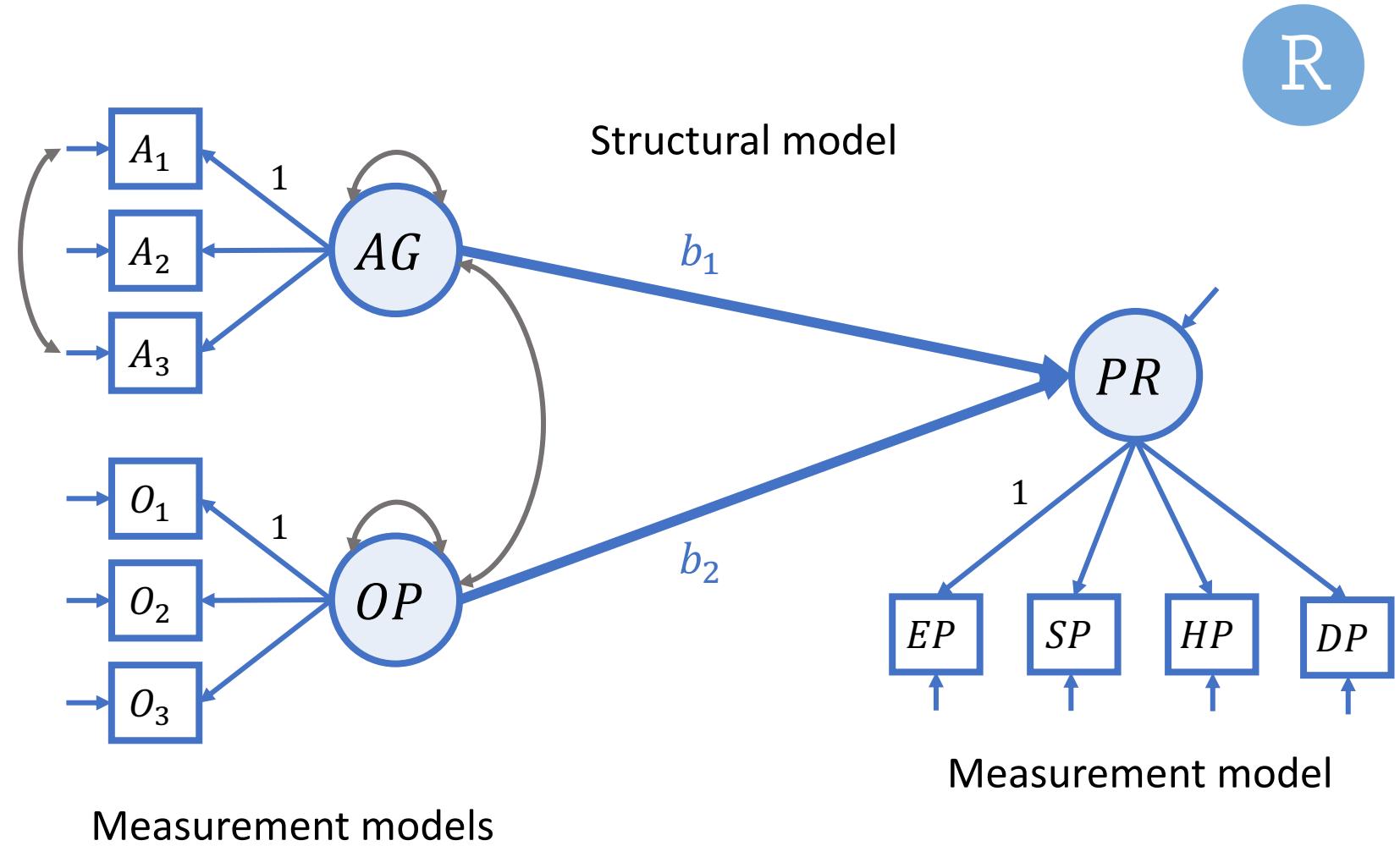
(Bergh et al., 2016; Mair, 2018)

## Model 4: Structural Equation Model

Structural equation  
model with  
directional paths

**Note**  
This model has a  
structural and a  
measurement part.

**Data**  
 $(y_i, a_{1i}, \dots, dp_i)$  for  
persons  $i = 1, \dots, N$



# SEM in lavaan

Add-on: Multi-group SEM

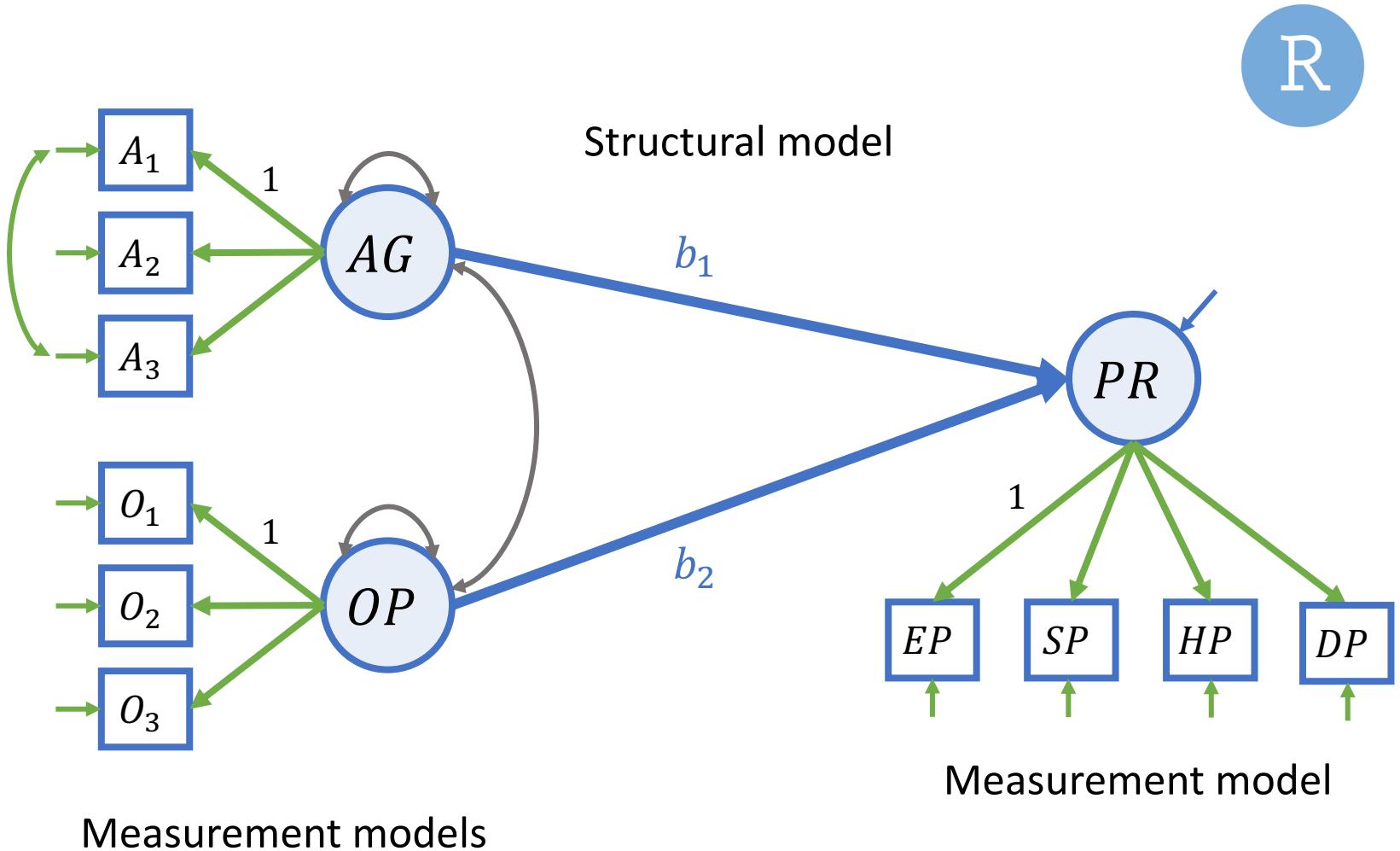


# Model 5: Multi-Group Structural Equation Model

Structural equation  
model across gender  
groups

**Note** ←  
This model assumes  
measurement invariance.

**Data**  
 $(y_i, a_{1i}, \dots, d_{pi})$  for  
persons  $i = 1, \dots, N$

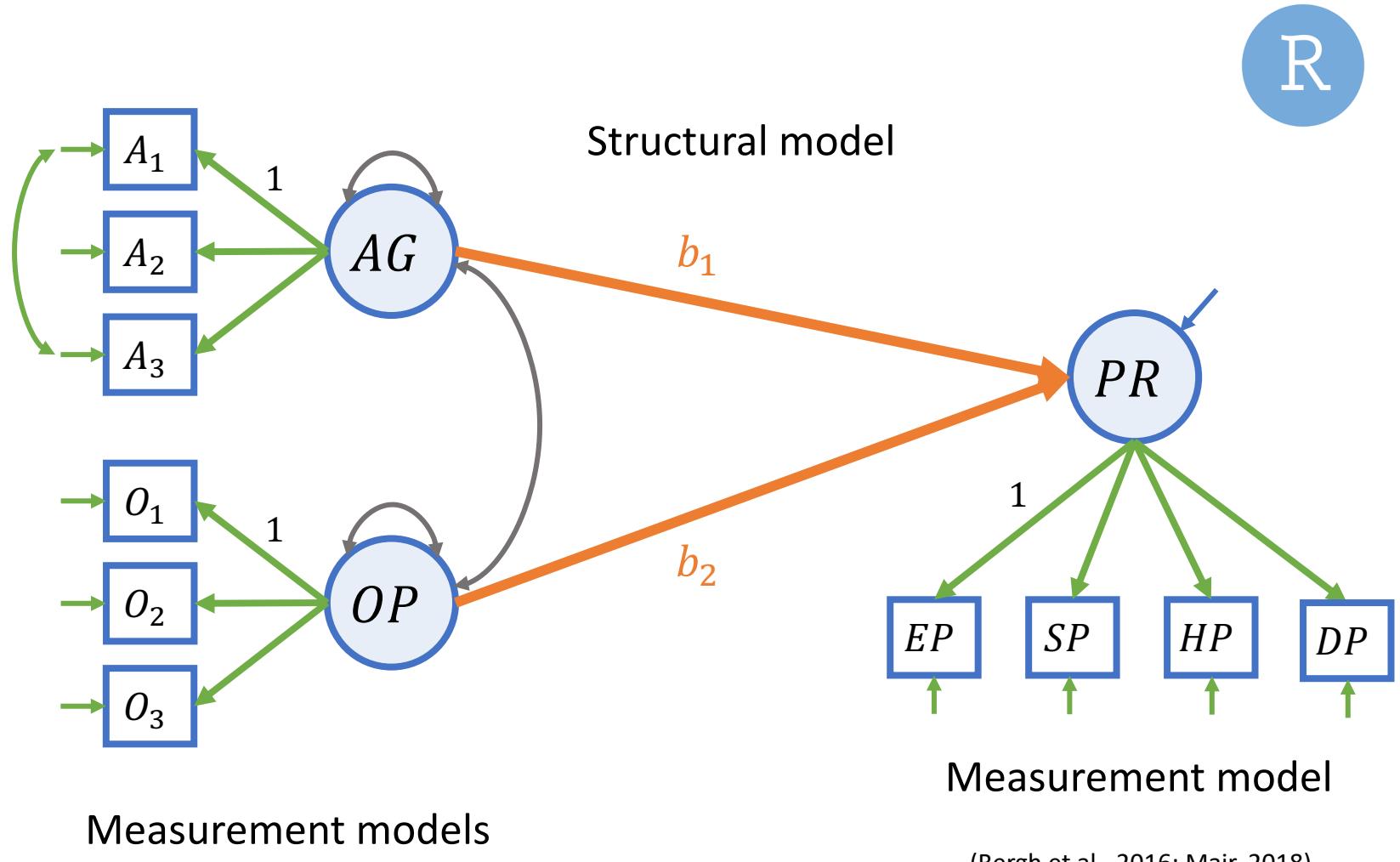


# Model 6: Multi-Group Structural Equation Model

Structural equation  
model across gender  
groups

**Note**  
This model assumes  
measurement and  
structural invariance.

**Data**  
 $(y_i, a_{1i}, \dots, dp_i)$  for  
persons  $i = 1, \dots, N$





Wait a minute...



# Structural Equation Modeling—What if?

(Rosseel, 2020)

Data are not normally distributed.

- Asymptotically distribution-free estimation
- ML estimation with robust standard errors and/or test statistics
- Bootstrapping

Data are missing.

- Full-information-maximum-likelihood
- Two-stage approach (*step 1*: mean vector and covariance matrix, *step 2*: SEM)
- Multiple imputation

Data are dependent (hierarchical).

- Multilevel SEM

Lavaan:

- `estimator="WLS", "WLSMV", ...; blavaan`
- `estimator="MLM", "MLR"; se="robust"; test="Satorra-Bentler"`
- `se="bootstrap"; test="bootstrap"`

Lavaan:

- `missing="FIML"`
- `missing="two.stage"`
- Use `mice` to create multiply imputed datasets and `runMI()` in `semTools`

Lavaan:

- `cluster="..." + level-specific model specification`
- `lavaan.survey`



Thank you!

## References

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