

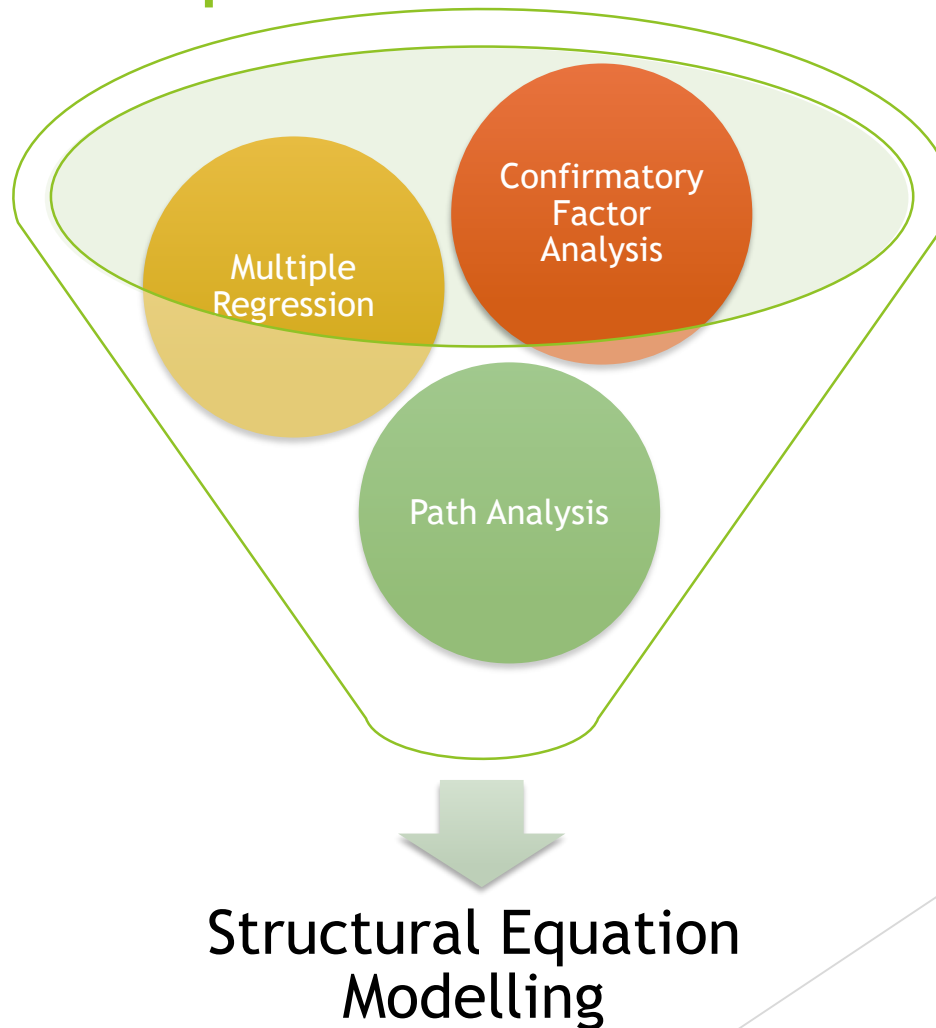
# A guide to the concepts of structural equation modelling

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DARE

# Structural Relationships and Latent Concepts

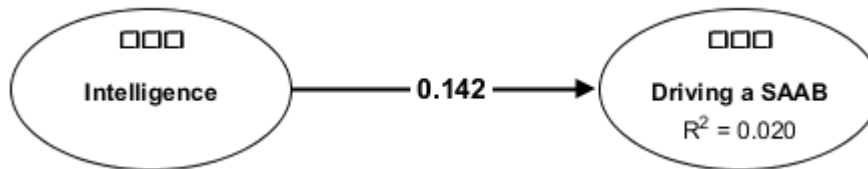
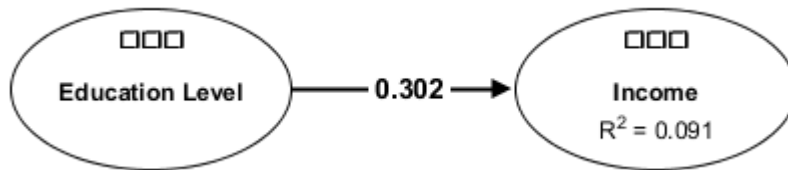


**Structural Equation  
Modelling**



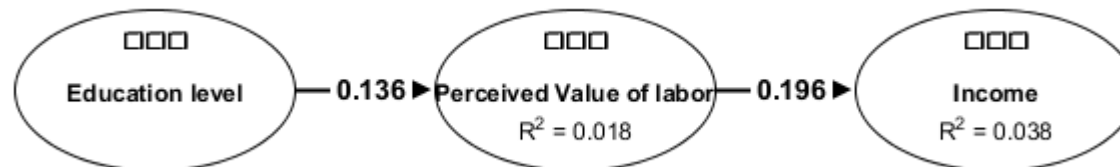
# Structural Relationships

Research starts with an conscious or unconscious hypothesis:



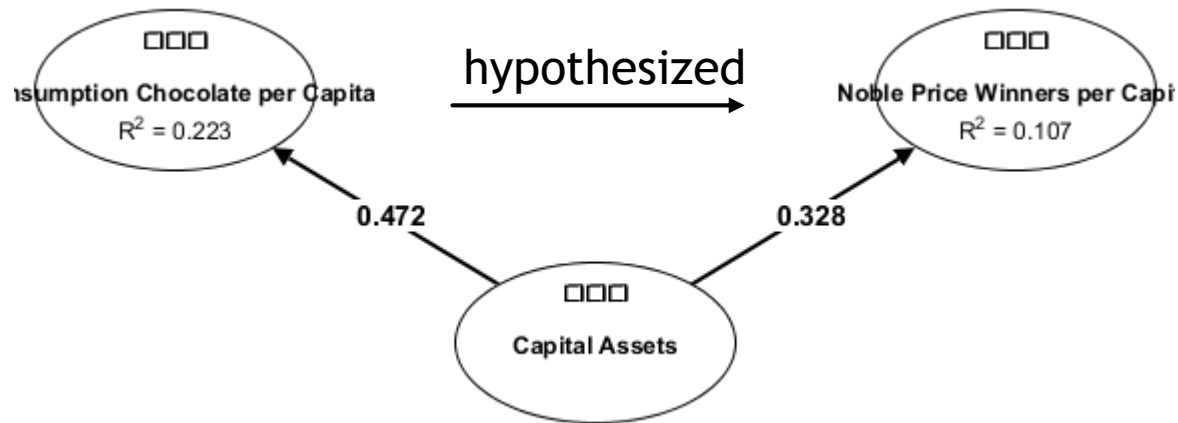
Causality?

The effect mechanism

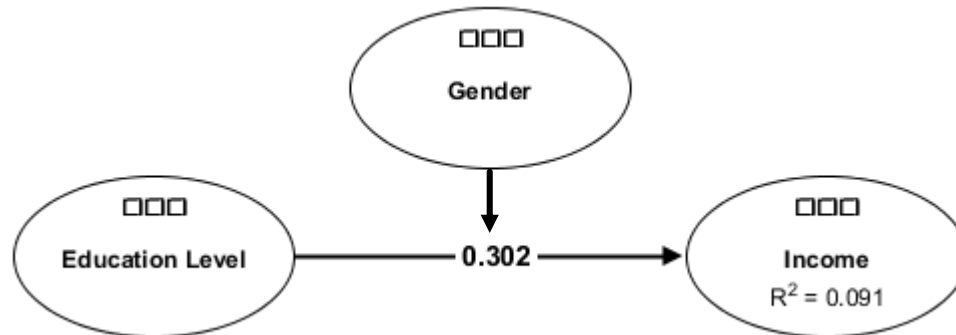


# Structural Relationships

Phantom Relationship: Revealing the need for a theoretical foundation

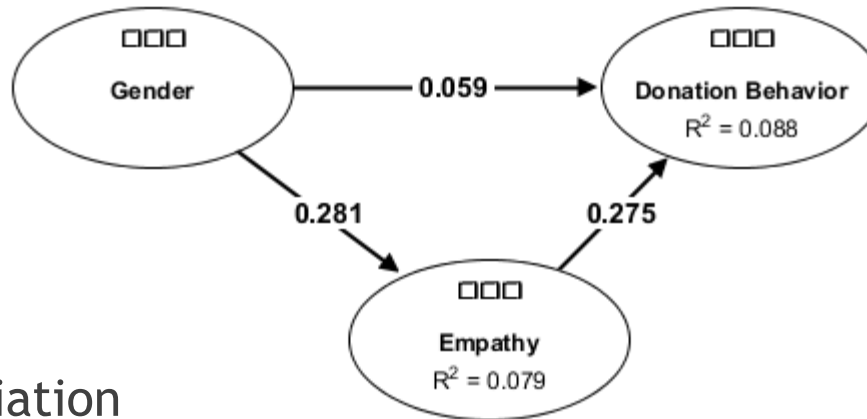


Moderated Relationship: Interaction Effects



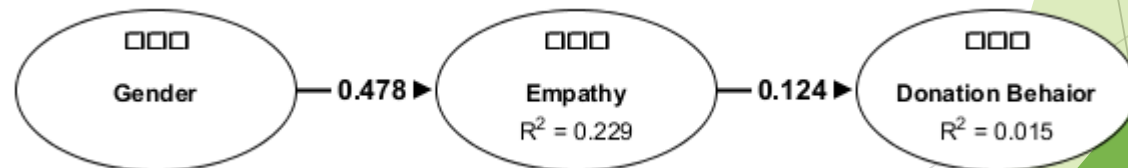
# Indirect effect: Triangle of Mediation

Direct and Indirect Relationship: Indirect Relationships, the backbone of theories



- ▶ Partial Mediation
  - ▶ Complementary
  - ▶ Competitive
- ▶ Full mediation
- ▶ No mediation

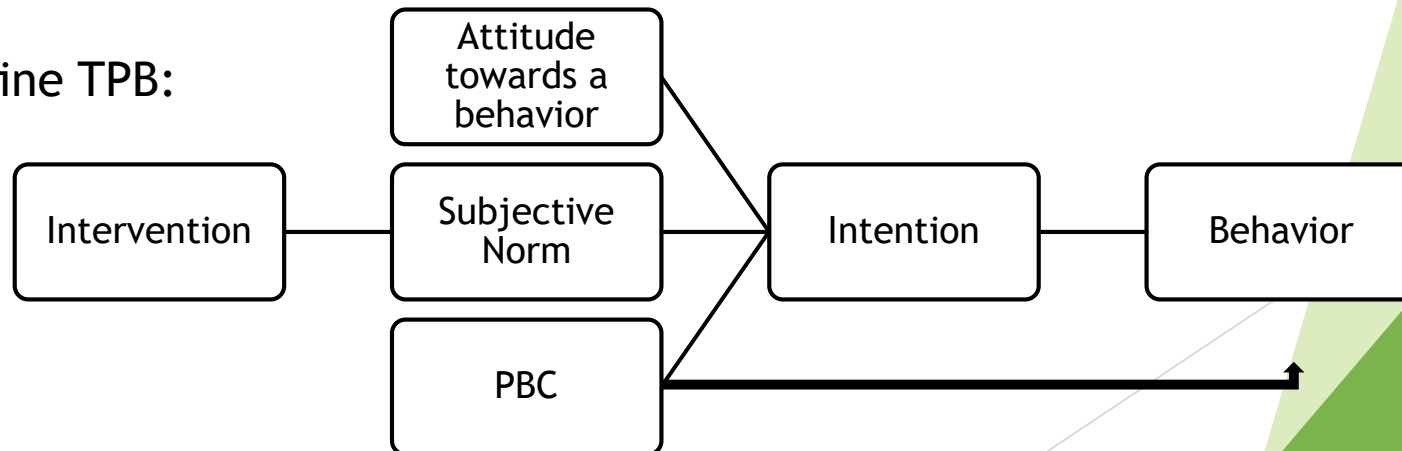
Willer, R. et al. (2015): What drives the gender gap in charitable giving? Lower empathy leads men to give less to poverty relief. In: *Social Science Research* 52, S. 83-98. DOI: 10.1016/j.ssresearch.2014.12.014



# Advantages of Path analysis

- ▶ Identify initial effects, even though final outcome may not be significantly affected
- ▶ Understand effect mechanism
- ▶ Understand parallel relationships
- ▶ Understand mediator and moderator
- ▶ Testing entire theories

Imagine TPB:

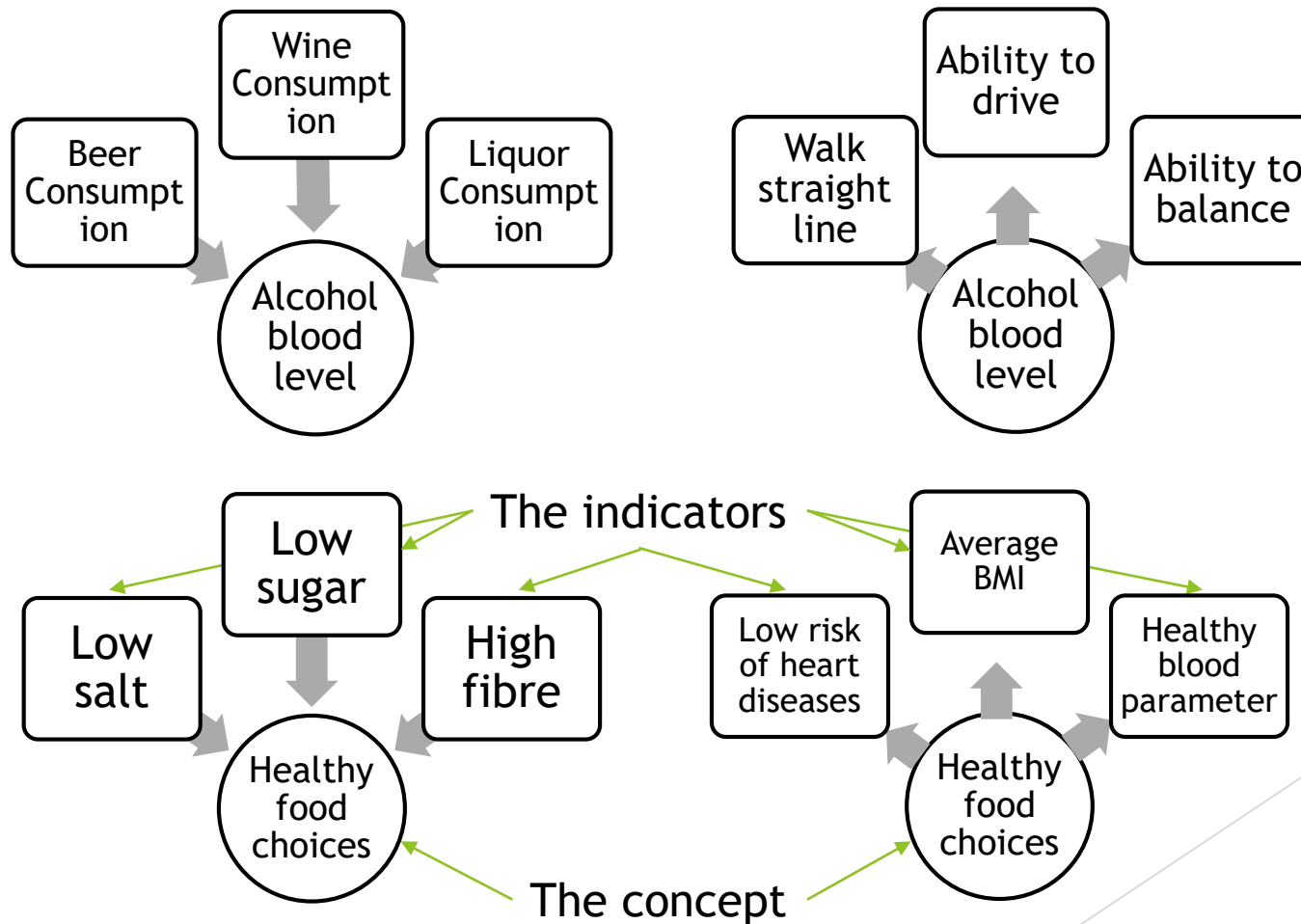


# The concept of latent variables (LV)

- ▶ A variable is not directly observable:
  - ▶ Hidden variables, e.g. Racism, quality of life, intelligence,
  - ▶ Abstract concepts or mental states, e.g. confidence, extraversion, wisdom, Sustainable behavior in the food domain, welfare
- ⇒ LV reduces dimensionality
- ⇒ LV lead to improved concept measurements, i.e. less measurement error
- ⇒ LV leads to inter-individual, i.e. generalizable concepts



# Latent Variables: formative vs. reflective





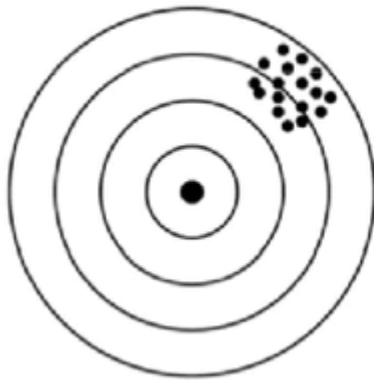
# Latent Variables: formative vs. reflective

Formative	Reflective
Direction of causality is from indicator to LV	Direction of causality is from LV to indicator
No reason to expect indicators to be correlated	Indicators should be correlated
Dropping an indicator from the measurement model increases error of LV measurement	Dropping an indicator may not induce error

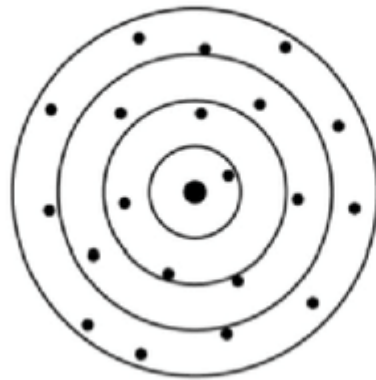


# Assessing Reflective Measurement Models

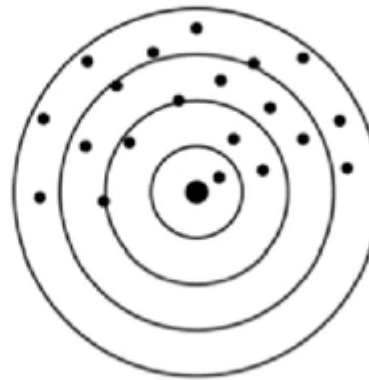
Reliability and Validity (Measurement error):



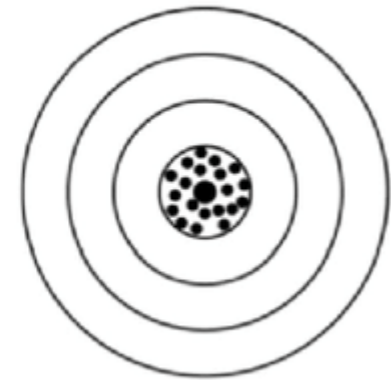
Reliable but not valid



Valid but not reliable



Neither reliable nor valid



Both reliable and valid

## ► Estimate Reliability and Validity



# Assessing Reflective Measurement Models

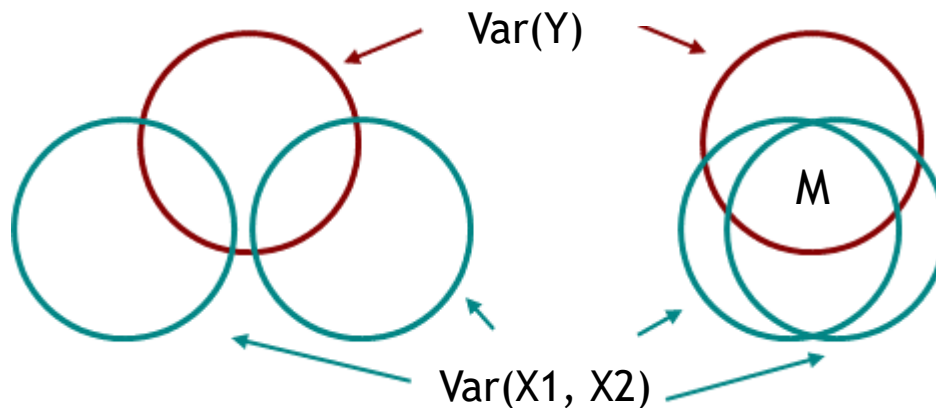
Reliability and Validity - capture measurement error:

1. **Concept Reliability:** Cronbach's alpha, Dijkstra-Henseler's rho
2. **Concept Validity**
  - ▶ **Convergence Validity:** Average Variance extracted, i.e. **AVE** (similar to explained variance concepts or LV explanatory power for indicator variance)
  - ▶ **Discriminant Validity** (Heterotrait-monotrait ratio of correlations, i.e. **HTMT** or Fornell-Larcker criterion: An LV should explain variance of its own indicators (AVE) better than indicators of other LVs)
3. **Indicator Reliability** (squared factor loadings): an indicator's explanatory power for an LV



# Assessing Formative Measurement Models

1. Indicator Relevance: factor loadings
2. Multicollinearity: Variance Inflation factor (VIF)



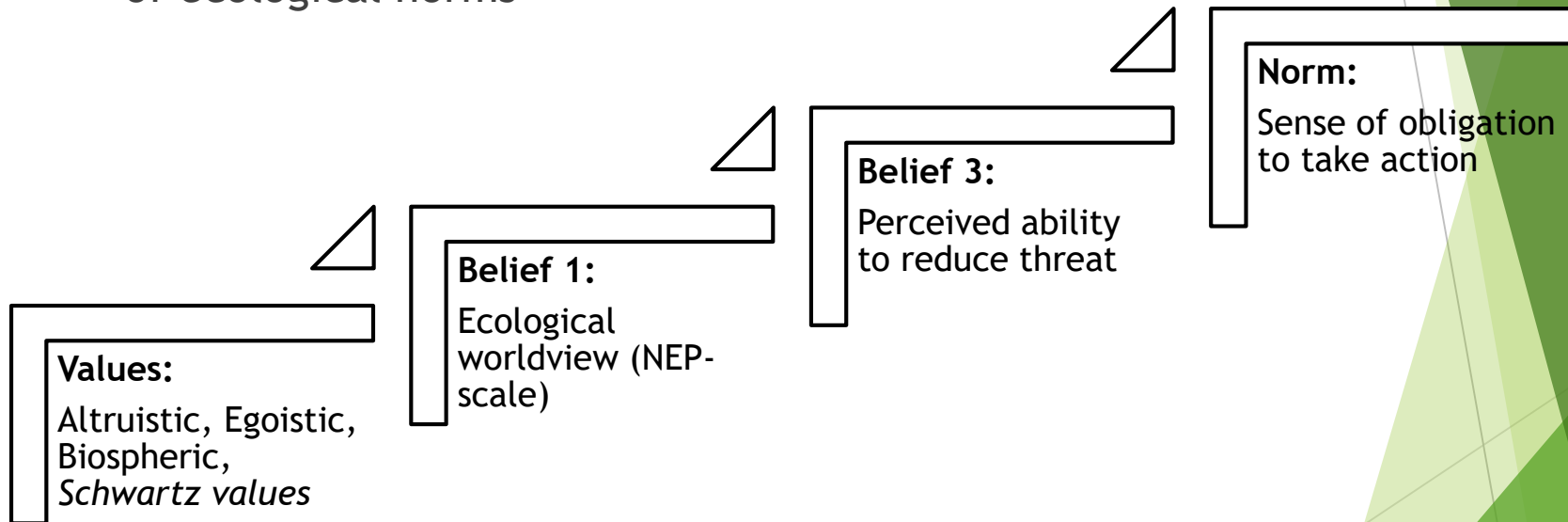
3. External validity: empirical confirmation





# Empirical Data: Value Belief Norm Theory (VBN)

- VBN-theory is hypothesized to explain the generation of ecological norms



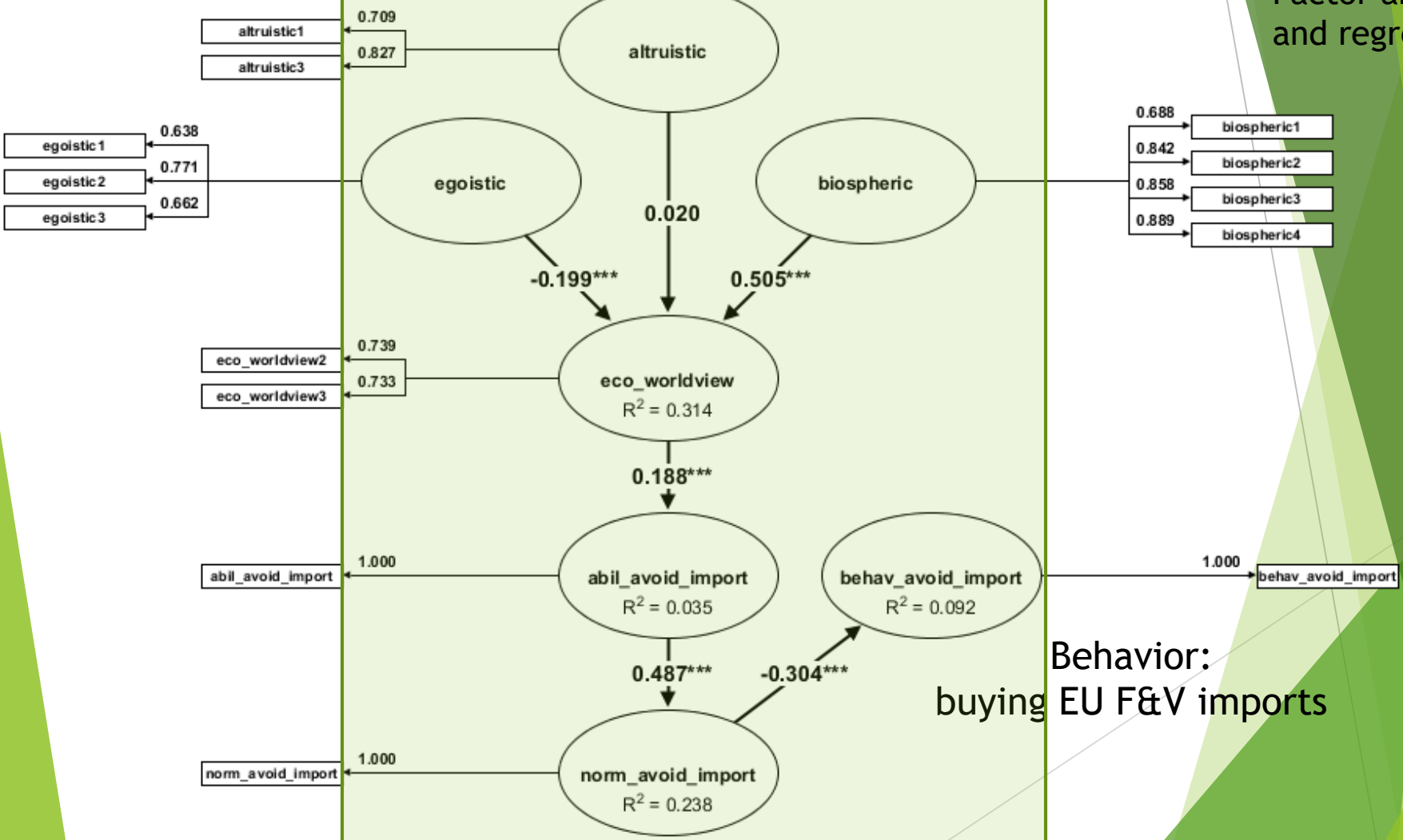


Factor analysis  
and regressions!

# Empricial Data: VBN-Theory (M1)

Outer model

Inner model



# Assessing Reflective Measurement Models: Construct Reliability

Construct	Dijkstra-Henseler's rho ( $\rho_A$ )	Jöreskog's rho ( $\rho_c$ )	Cronbach's alpha( $\alpha$ )
egoistic	0,7397	0,7330	0,7390
altruistic	0,7512	0,7435	0,7391
biospheric	0,8999	0,8926	0,8926
eco_worldview	0,7027	0,7027	0,7027
abil_avoid_import	1,0000	1,0000	
behav_avoid_import	1,0000	1,0000	
norm_avoid_import	1,0000	1,0000	

DHR > 0.7,  $C\alpha$  > 0.7 is advised



# Assessing Reflective Measurement Models: Convergence Validity

Construct	Average variance extracted (AVE)
egoistic	0,4796
altruistic	0,5932
biospheric	0,6770
eco_worldview	0,5417
abil_avoid_import	1,0000
behav_avoid_import	1,0000
norm_avoid_import	1,0000

Egoistic 4 dropped

**AVE > 0.5 advised**





# Assessing Reflective Measurement Models: Discriminant Validity

Construct	egoistic	altruistic	biospheric	eco_worldview	abil_avoid_import	behav_avoid_import	norm_avoid_import
egoistic	0,4796						
altruistic	0,0005	0,5932					
biospheric	0,0010	0,3599	0,6770				
eco_worldview	0,0463	0,1072	0,2738	0,5417			
abil_avoid_import	0,0151	0,0000	0,0055	0,0354	1,0000		
behav_avoid_import	0,0197	0,0029	0,0001	0,0049	0,0789	1,0000	
norm_avoid_import	0,0309	0,0104	0,0497	0,0714	0,2376	0,0924	1,0000

Forner Larcker Criterion or HTMT: An LV should explain variance of its own indicators better than indicators of other LVs

Solution: Merging or Dropping of concepts or indicators

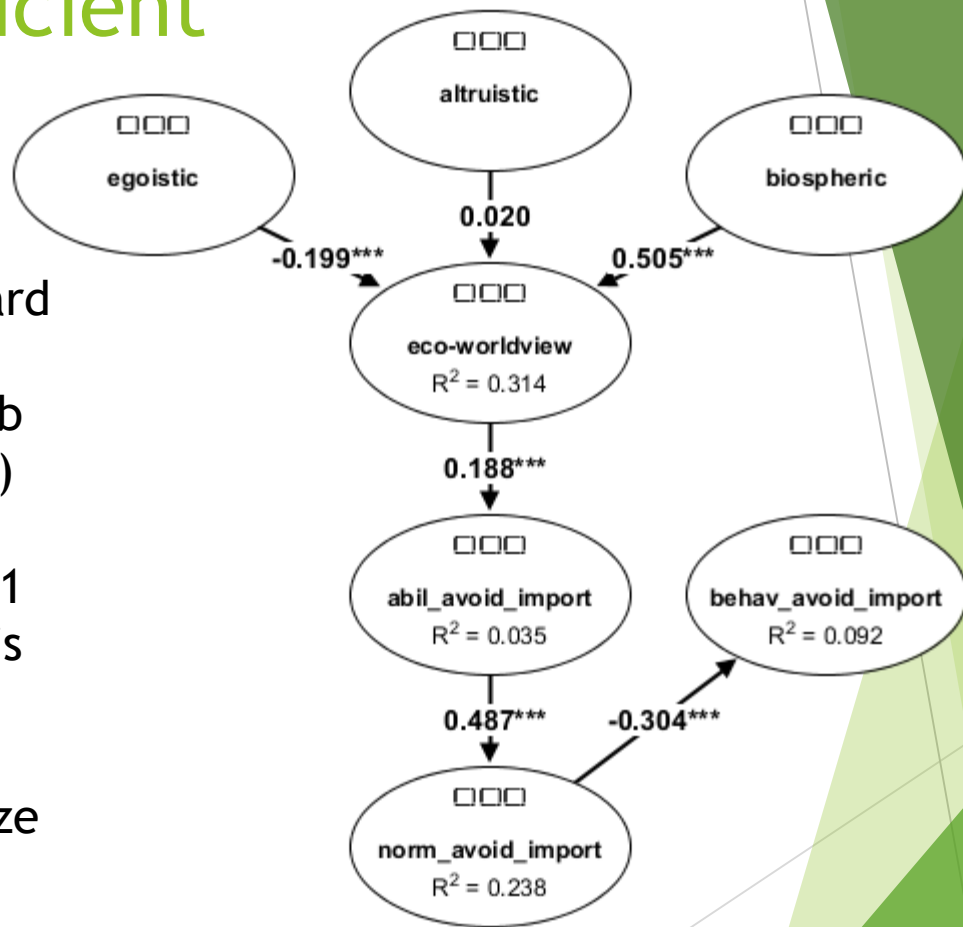




# Assessing the Structural models: The path coefficient

How to interpret the path coefficient?

1. PLS standardizes each var
  2. If X changes by one standard deviation Y changes by b standard deviations (with b being the path coefficient)
  3. Perfection correlation results in  $b=1$ , reverse  $b=-1$
  4. b holds if everything else is constant
- ⇒ Interpret sign  
⇒ Interpret relative effect size



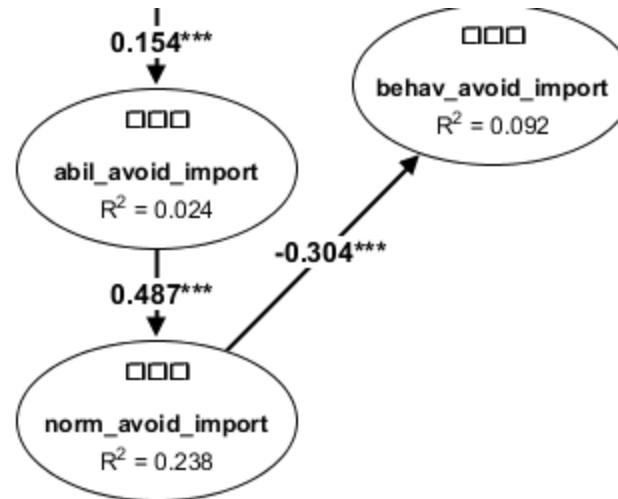


# Assessing the Structural models: the “objective” effect size ( $f^2$ )

$f^2$ -statistic:

Effect	Beta	Indirect effects	Total effect	Cohen's $f^2$
abil_avoid_import -> norm_avoid_import	0,4875		0,4875	0,3117
abil_avoid_import -> behav_avoid_import		-0,1482	-0,1482	
norm_avoid_import -> behav_avoid_import	-0,3039		-0,3039	0,1018

- Effect size based on  $f^2$  (threshold may depend on discipline):
  - $f^2 > 0,35$  strong effect
  - $f^2 > 0,15$  moderate effect
  - $f^2 > 0,02$  weak effect





# Assessing the Structural models: Significance and Bootstrapping

Can we assume our data to be normally distributed?

- ▶ Resampling method with replacement
  - ⇒ draw multiple samples to create a population
- ▶ Bootstrapping estimates a sampling distribution => standard errors =>
  - ▶ Confidence intervals, variance, prediction error and so on
  - ▶ No parametric tests, no normality assumptions
- ▶ Most recommend a bootstrap with repetitions  $\geq 999$  OR  $>N$

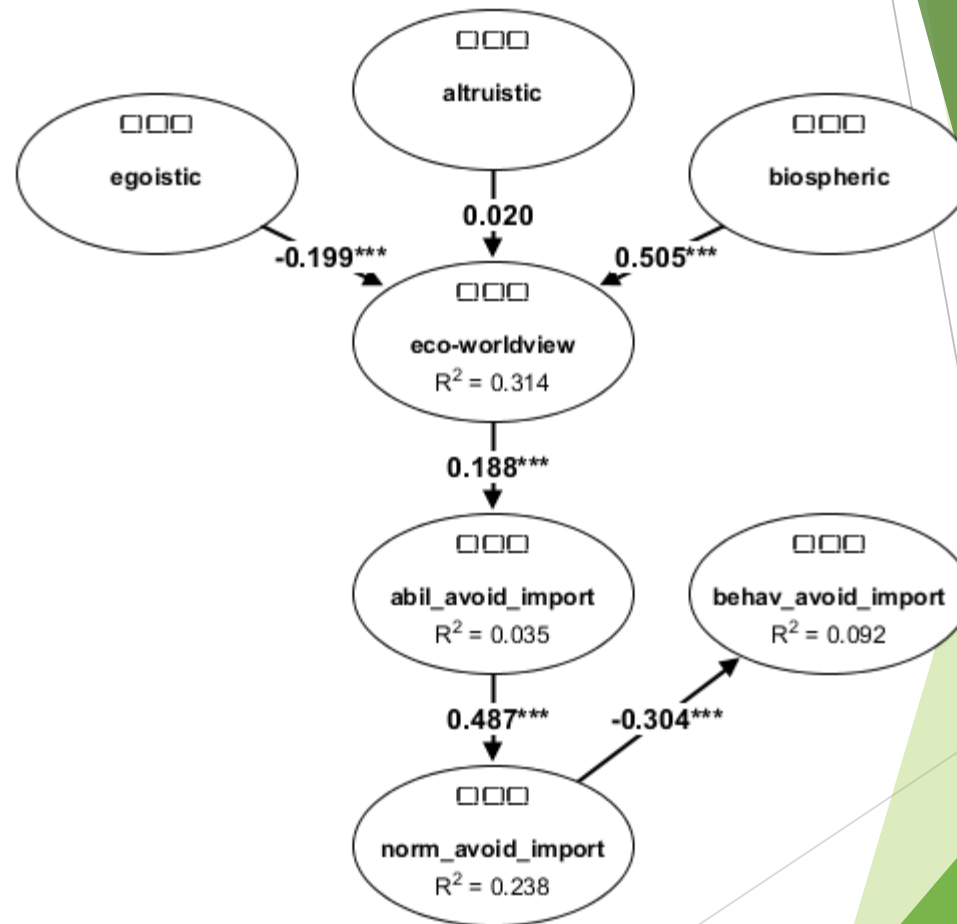
Sample	N	X -> Y
1	1000	0.51
2	1000	0.46
3	1000	0.43
4	1000	0.47
5	1000	0.3
6	1000	0.62
7	1000	0.5
8	1000	0.55
9	1000	0.38
10	1000	0.44
11	1000	0.46
12	1000	0.44
...	...	...
k	1000	0.52





# Assessing the Structural models: $R^2$

(Adj.)  $R^2$ : measures  
within sample prediction  
⇒ Here  $R^2$  is not global  
model fit criteria





# Assessing the Structural models: Overall model fit and prediction power

Compare different models			
	Value	HI95	HI99
SRMR	0,0575	0,0328	0,0402

- ▶ SRMR = standardized root mean square residual, the lower better,  $SRMR < 0.08$  is considered a good model fit
- ▶  $Q^2$ -predictive relevance
  - ▶ Blindfolding procedure: Blindfolding is a sample re-use technique, which systematically deletes data points and provides a prognosis of their original values



# Reason for SEM

- ▶ Identify initial effects
- ▶ Understand effect mechanism
- ▶ Understand parallel relationships
- ▶ Understand mediator and moderator
- ▶ Testing entire theories
- ▶ Measure structural relationships of latent variables
- ▶ Report on multiple hypothesis in 1 model
- ▶ Robust to non-normal data



# Conclusions

- ▶ Understand the structural relationships you hypothesize
- ▶ Measure your concepts as good as possible
- ▶ Provide evidence for both with SEM





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