

# CFA - theory

The theory of Confirmatory Factor Analysis



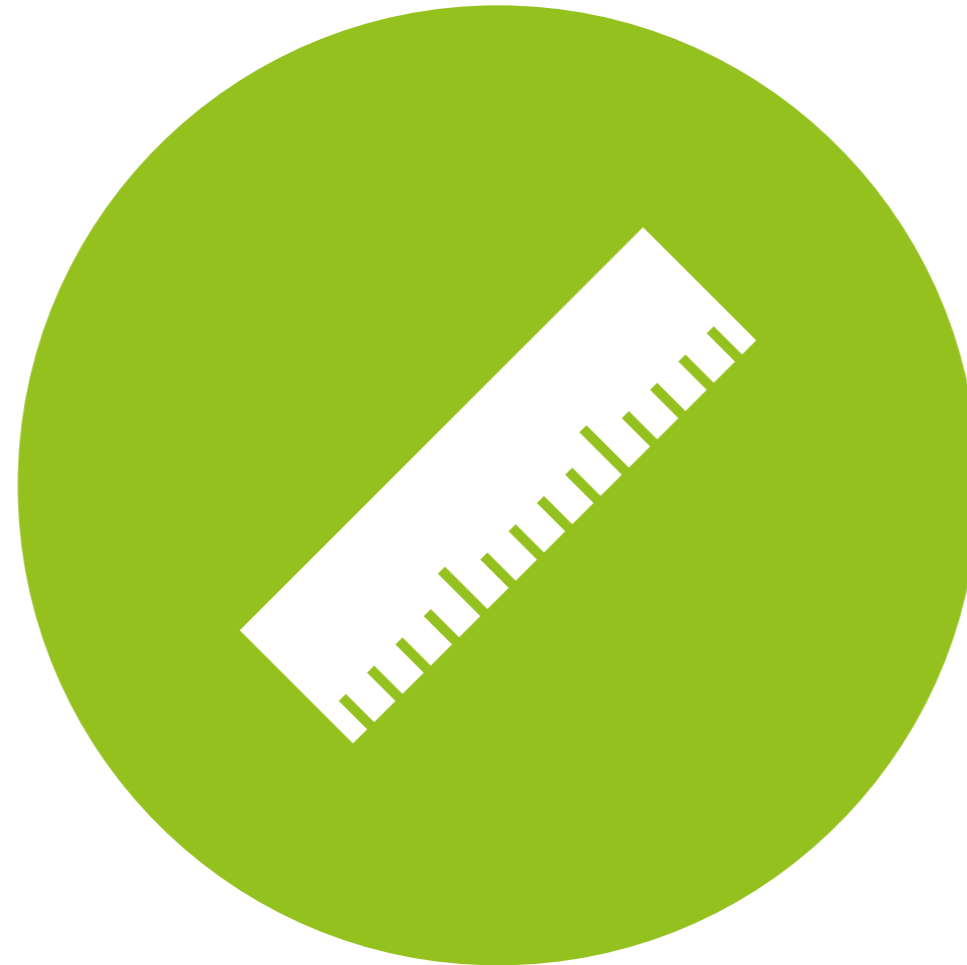
# Intro

Today's goal:

Teach the idea behind Confirmatory Factor Analysis.

Outline:

- Rationale behind CFA
- Model specification and identification
- Estimation
- Item, Factor, and Model Fit



**CFA**

Confirmatory Factor Analysis

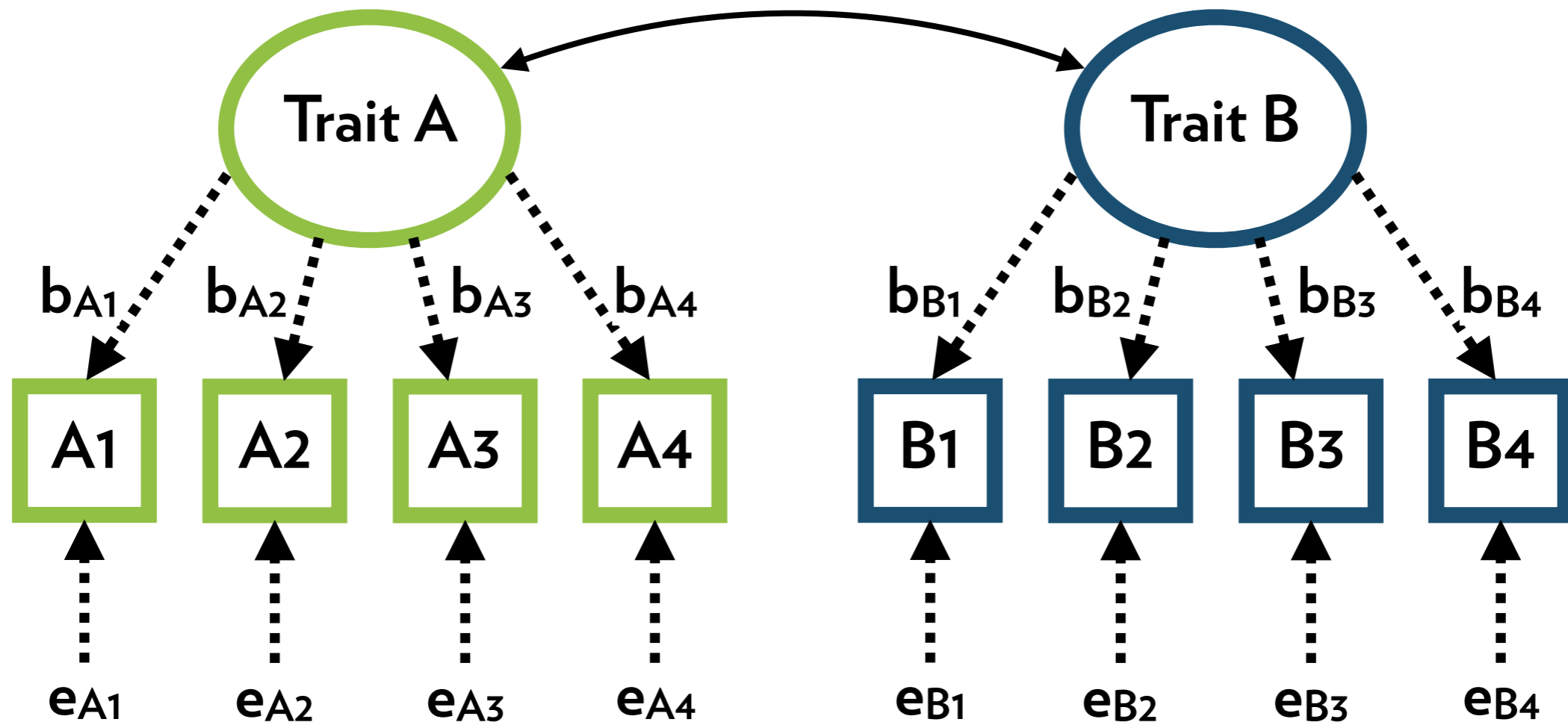


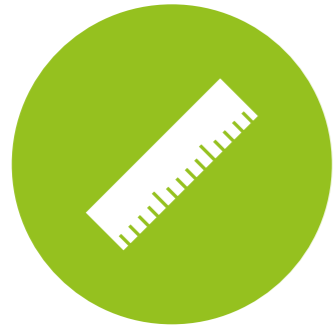
# CFA

What if the items do not have an equal correlation?

$$b_{A1} \neq b_{A2} \neq b_{A3} \neq b_{A4}$$

And what if we want to measure multiple traits?





# Why CFA?

Establish convergent and discriminant validity

CFA can suggest ways to remedy problems with the scale

Outcome is a normally distributed measurement scale

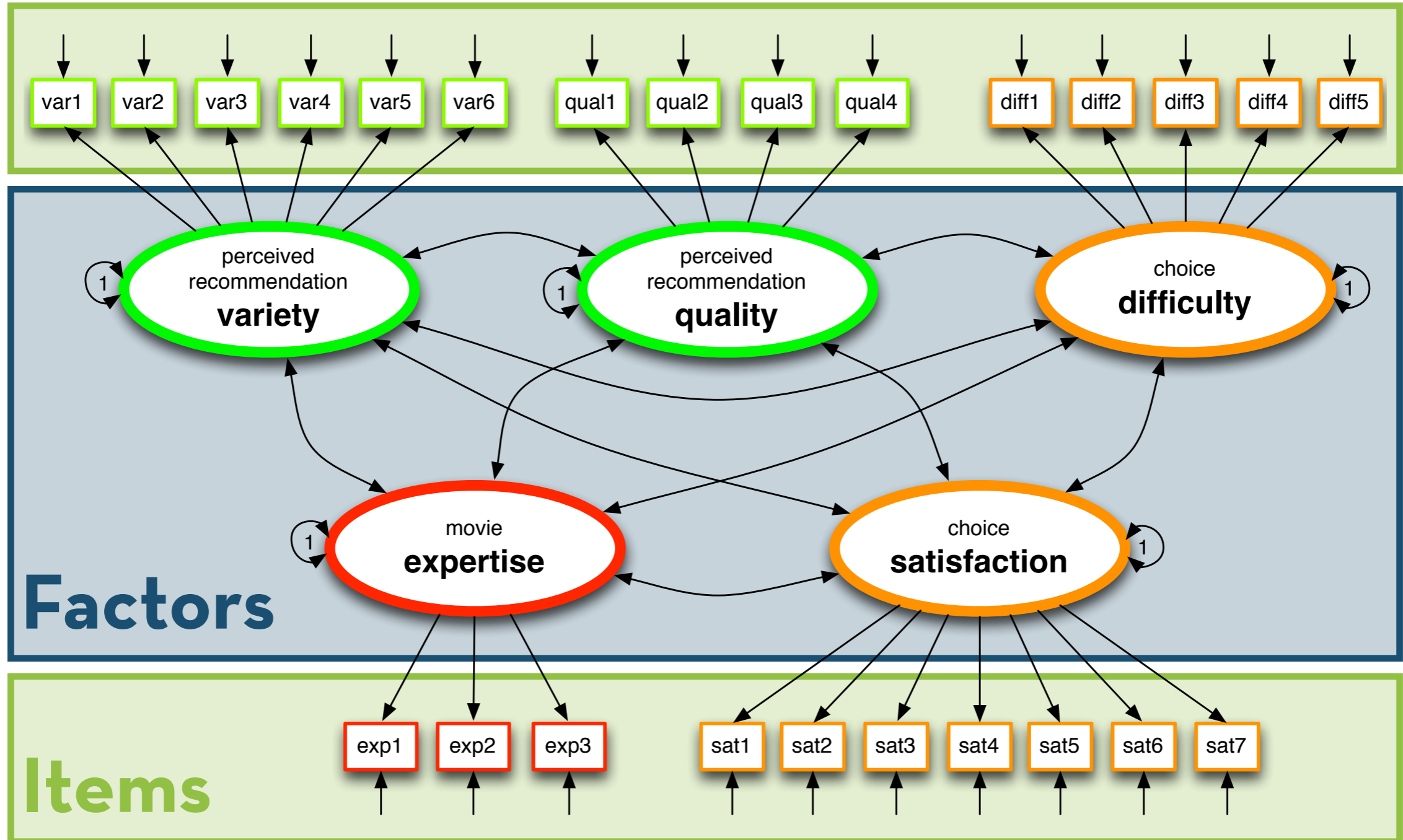
Even when the items are yes/no, 5- or 7-point scales!

The scale captures the “shared essence” of the items

You can remove the influence of measurement error in your statistical tests!

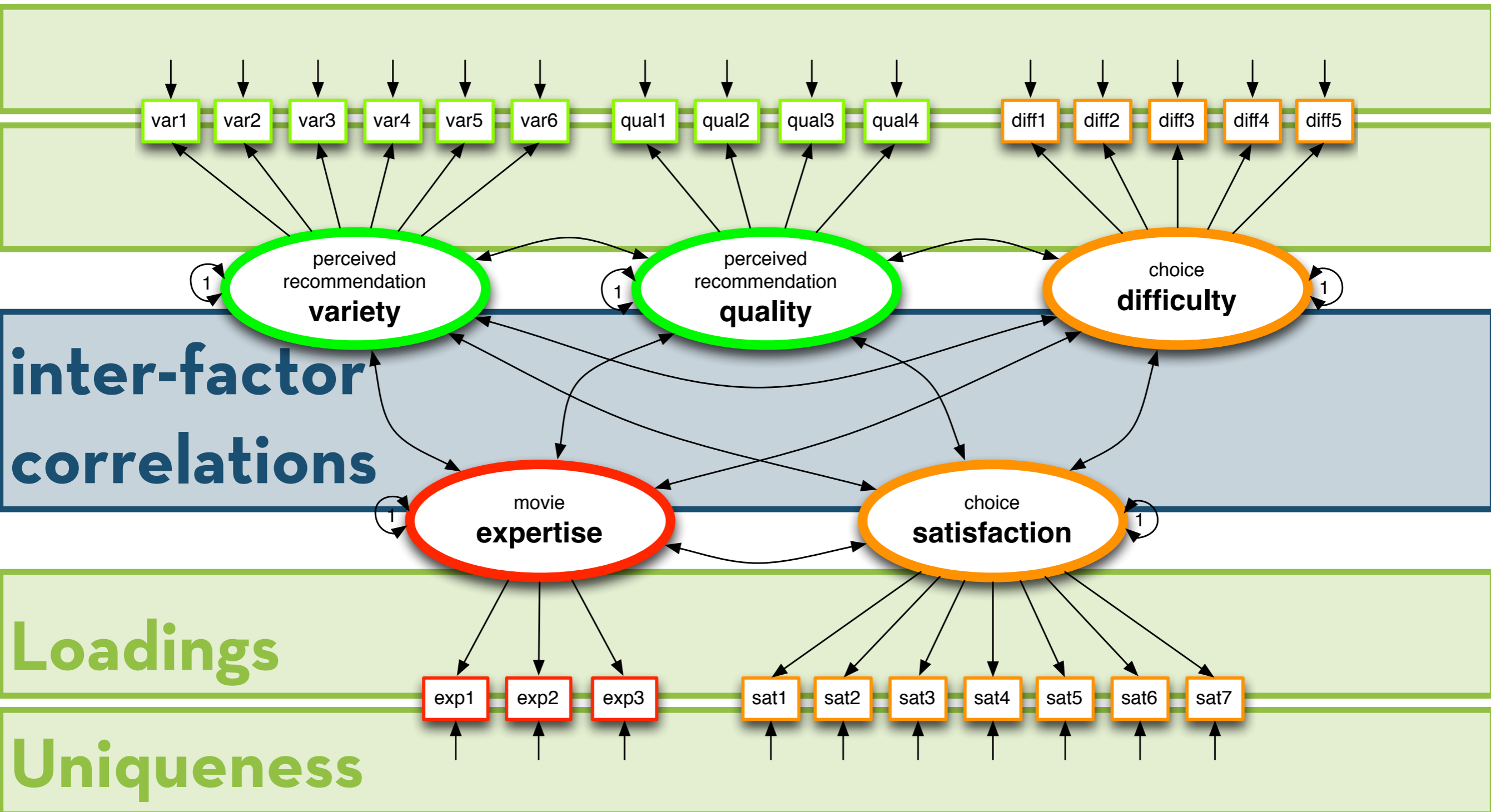


# CFA: the concept





# CFA: the concept





# CFA: the concept

Factors are **latent constructs** that represent the trait or concept to be measured

The latent construct cannot be measured directly

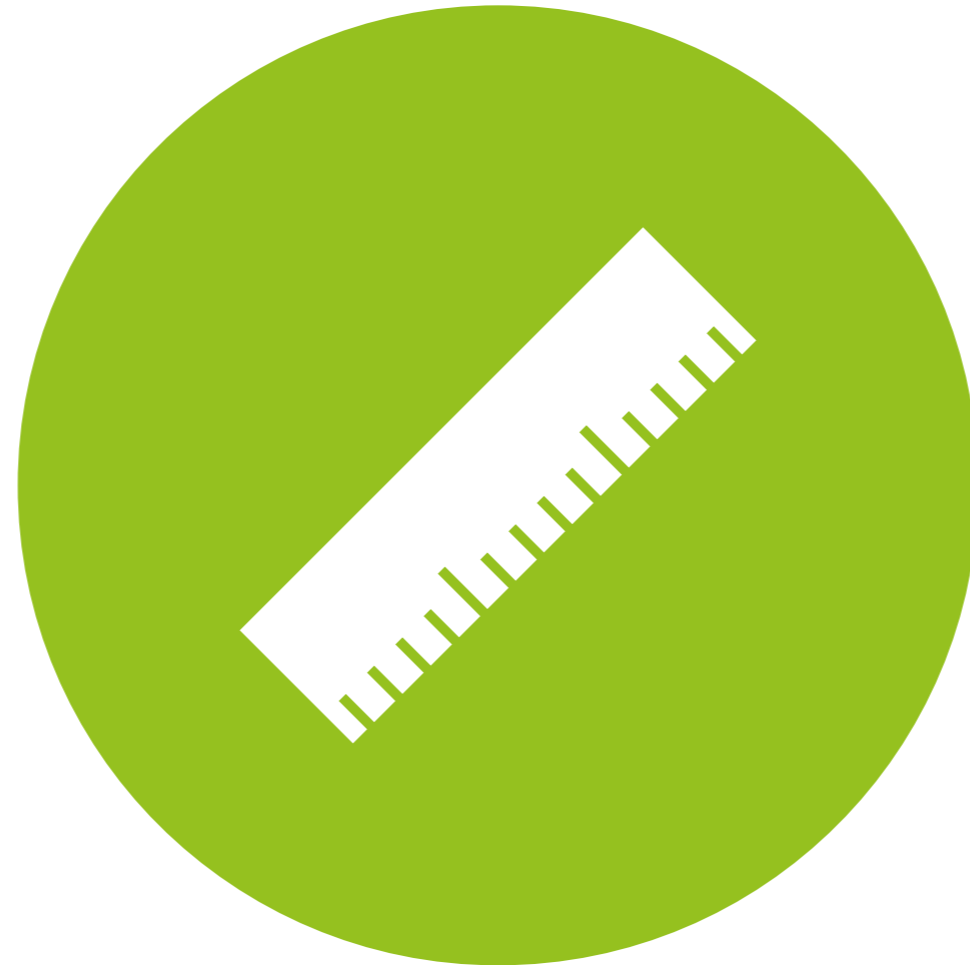
The latent construct “**causes**” users’ answers to items

Items are therefore also called **indicators**

Like any measurement, indicators are not perfect measurements

They depend on the true score (loading) as well as some measurement error (uniqueness)





# Identification

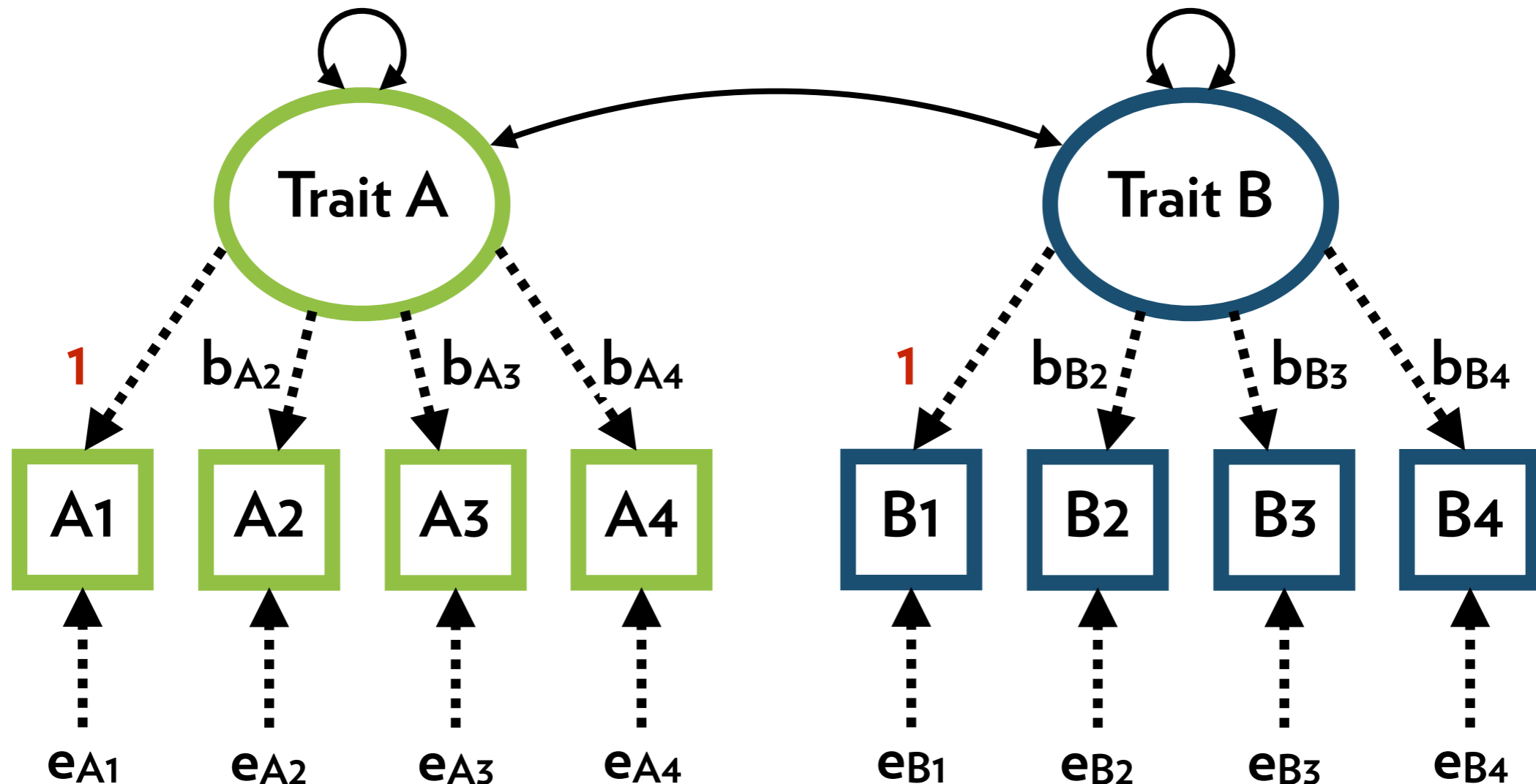
of CFA models



# Identification

Factors need to be **scaled** in order to be identified

Unit Loading Identification (ULI)

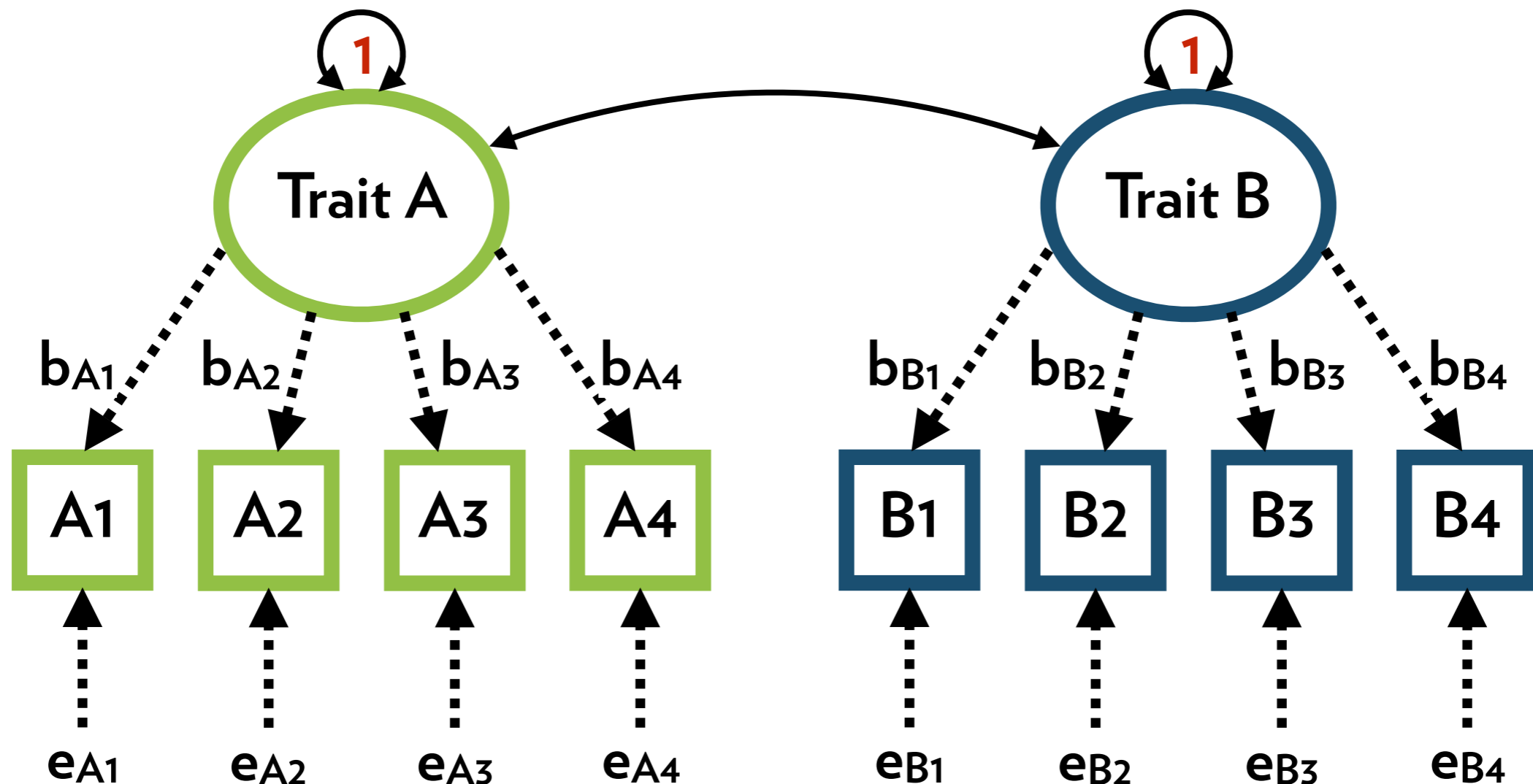




# Identification

Factors need to be **scaled** in order to be identified

Unit Variance Identification (UVI)





# How it works

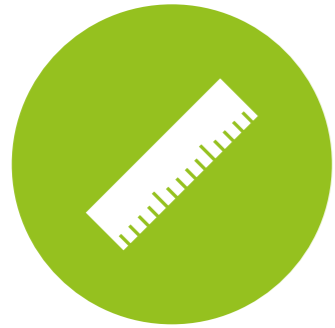
By looking at the **overlap** (covariance) between items, we can separate the measurement error from the true score!

The scale captures the “shared essence” of the items

The factor is assumed to explain **all** of this overlap

The partial correlation between  $A_1$  and  $A_2$  controlling for factor  $A$  is assumed to be zero!

There can be a **residual correlation**, but such a model will be more difficult to identify



# How it works

Each item belongs to only a **single factor**

Again, **cross-loadings** are possible, but such a model will be more difficult to identify

There still exist a relationship between A1 and factor B

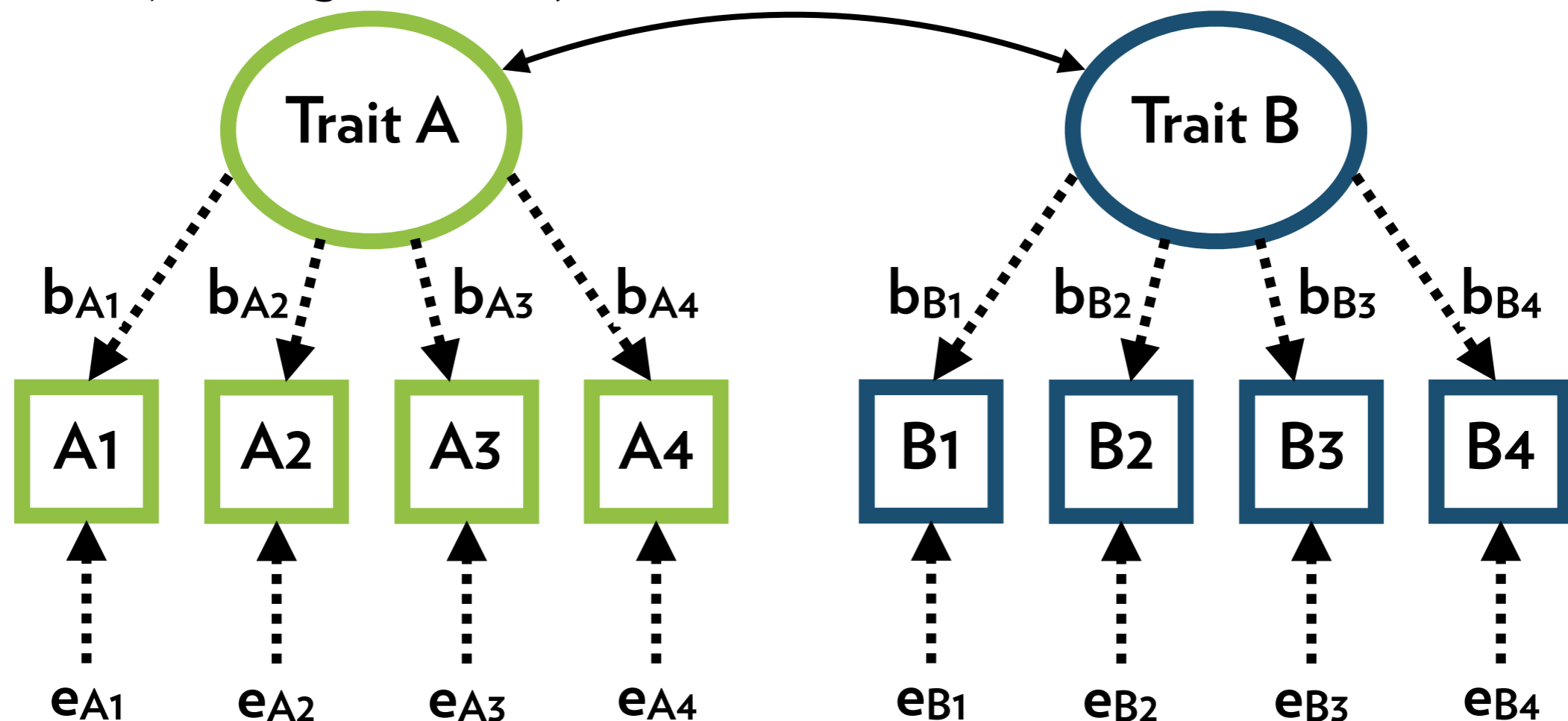
Because factor B is correlated to factor A



# Identification

A model with no residual correlations and no cross-loadings is called a **unidimensional model**

It is identified if each factor has at least 2 items (3 if it is only a single factor)

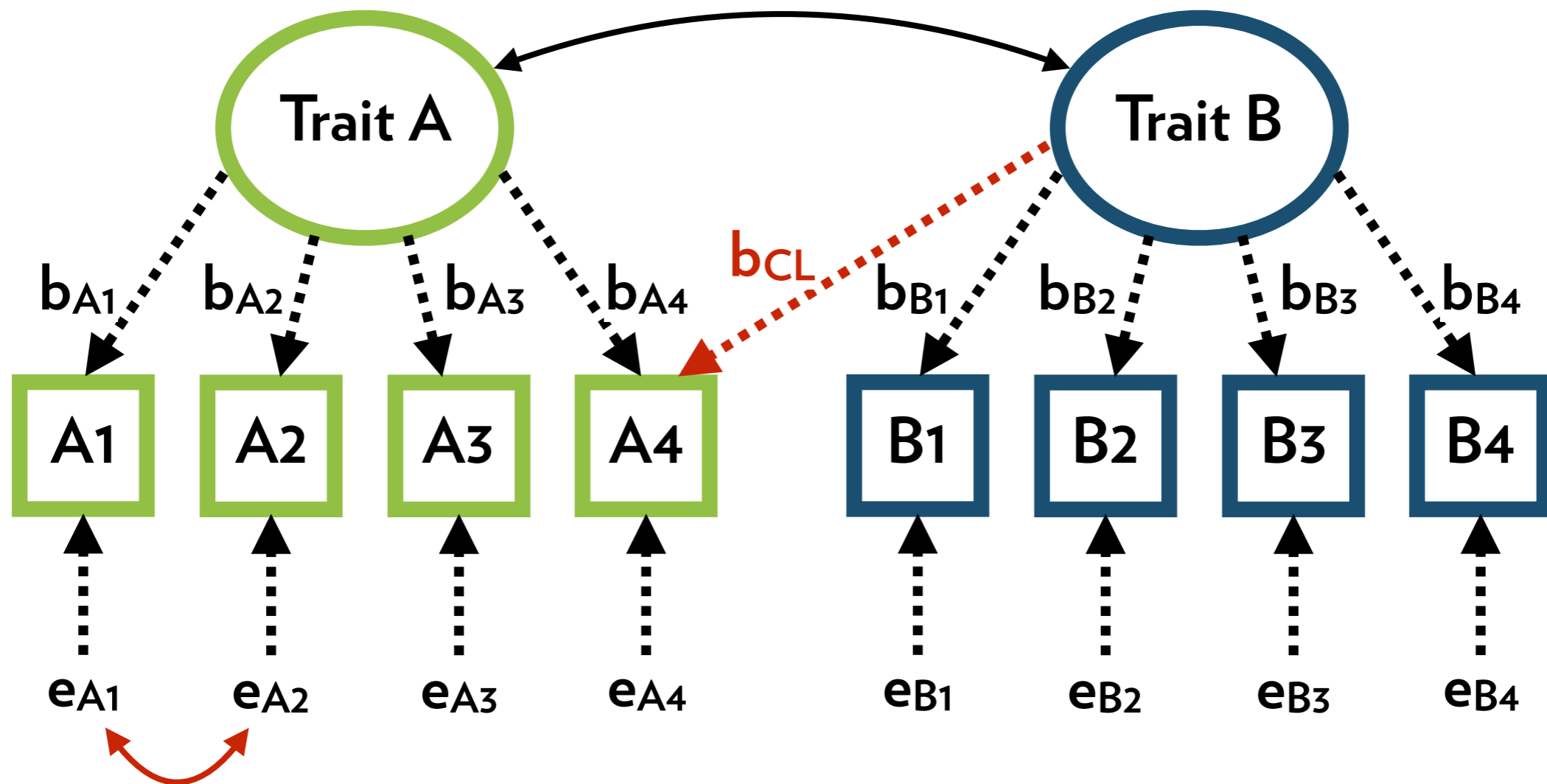


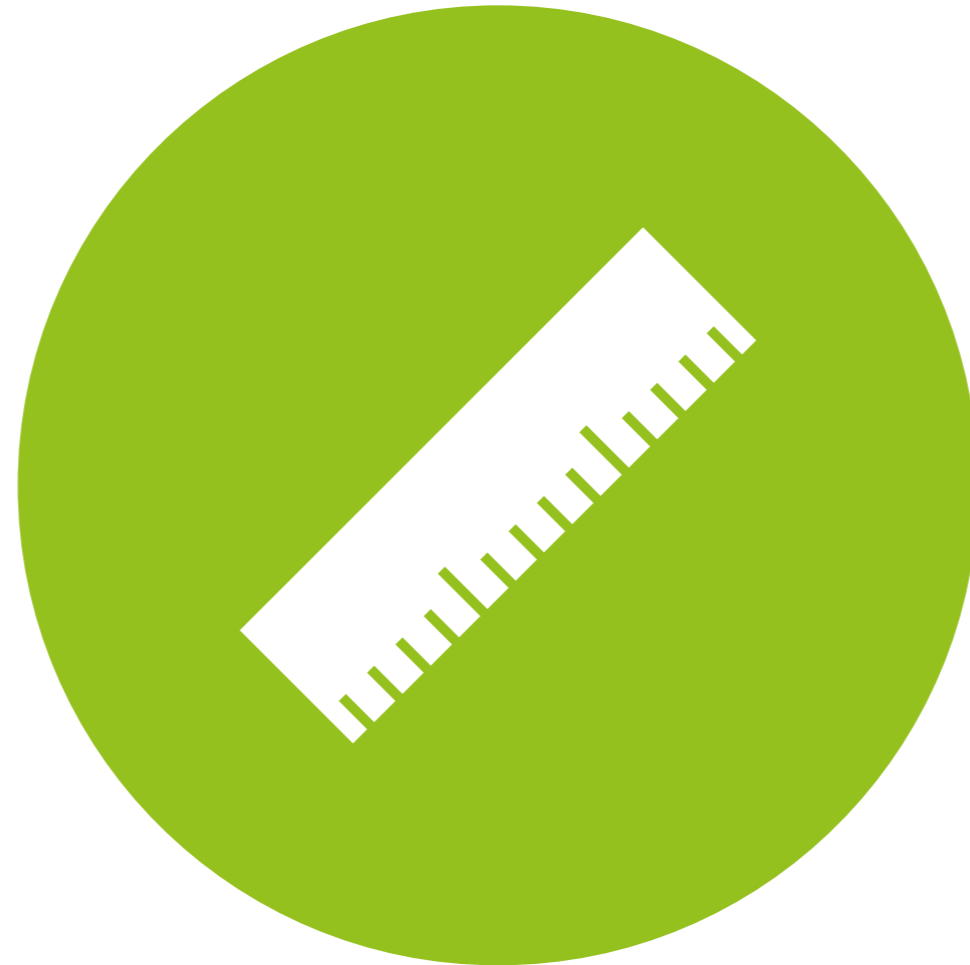


# Identification

Example model with residual correlations and cross-loadings

Try to avoid this as much as possible

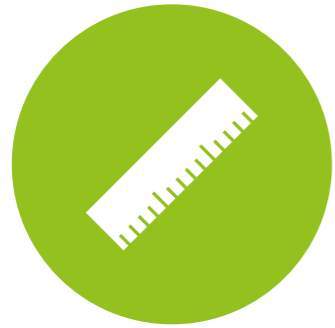




# Estimation

of CFA models





# How it works

The basis for Factor Analysis is the item correlation matrix

Or the covariance matrix (which is a little more complex)

How do we determine the loadings etc?

By **modeling** the correlation matrix as closely as possible!

This is the job of that wizard in your computer...



# Observed

	A	B	C	D	E	F
A	1.00	0.73	0.71	0.34	0.49	0.34
B	0.73	1.00	0.79	0.35	0.32	0.32
C	0.71	0.79	1.00	0.29	0.33	0.35
D	0.34	0.35	0.29	1.00	0.74	0.81
E	0.49	0.32	0.33	0.74	1.00	0.75
F	0.34	0.32	0.35	0.81	0.75	1.00

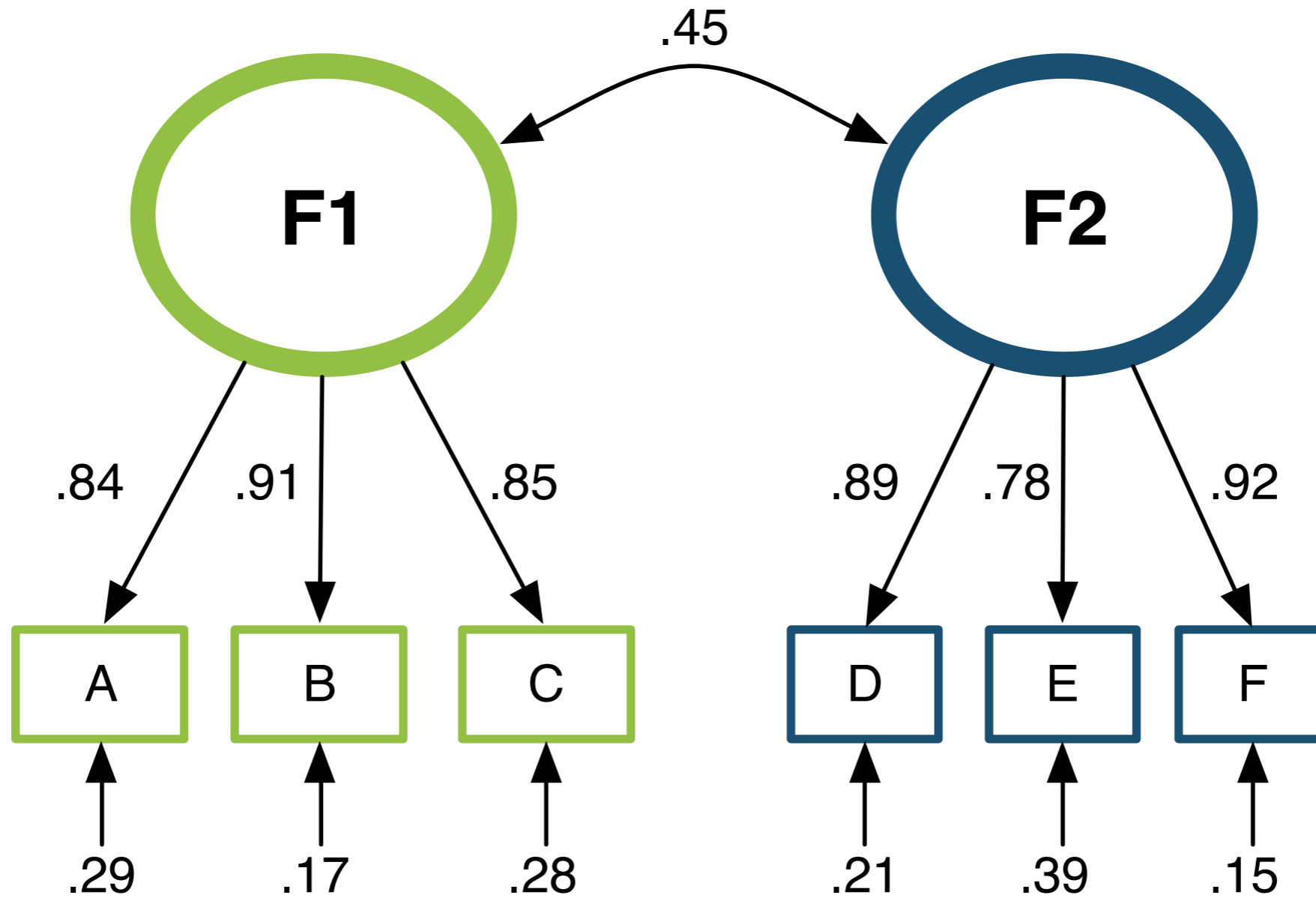


# Observed

	A	B	C	D	E	F
A	1.00	0.73	0.71	0.34	0.49	0.34
B	0.73	1.00	0.79	0.35	0.32	0.32
C	0.71	0.79	1.00	0.29	0.33	0.35
D	0.34	0.35	0.29	1.00	0.74	0.81
E	0.49	0.32	0.33	0.74	1.00	0.75
F	0.34	0.32	0.35	0.81	0.75	1.00



# Model





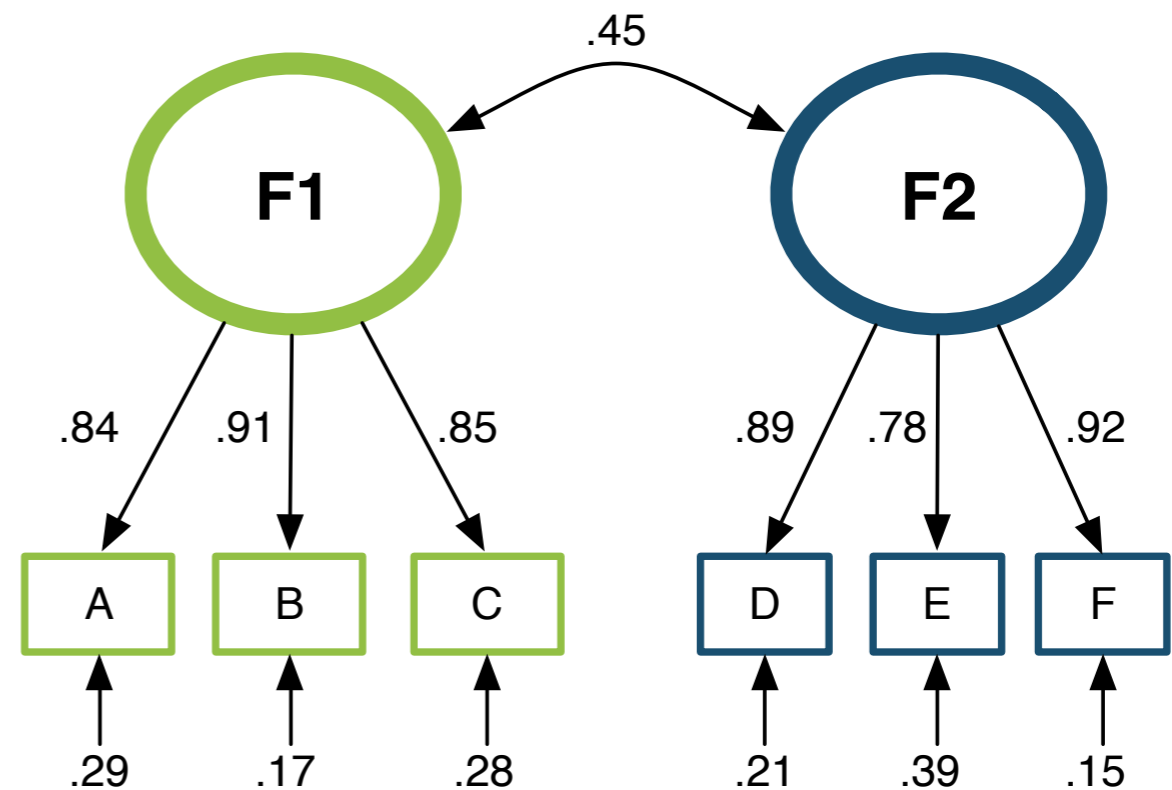
# Estimation

Estimate the correlation matrix:

$$r_{AB} = .84 * .91 = .76$$

$$r_{AD} = .84 * .45 * .89 = .34$$

etc.





# Estimated

	A	B	C	D	E	F
A	0.71	0.76	0.71	0.34	0.29	0.35
B	0.76	0.83	0.77	0.36	0.32	0.38
C	0.71	0.77	0.72	0.34	0.30	0.35
D	0.34	0.36	0.34	0.79	0.69	0.82
E	0.29	0.32	0.30	0.69	0.61	0.72
F	0.35	0.38	0.35	0.82	0.72	0.85



# Estimated

	A	B	C	D	E	F
A	1.00	0.73	0.71	0.34	0.49	0.34
B	0.73	1.00	0.79	0.35	0.32	0.32
C	0.71	0.79	1.00	0.29	0.33	0.35
D	0.34	0.35	0.29	1.00	0.74	0.81
E	0.49	0.32	0.33	0.74	1.00	0.75
F	0.34	0.32	0.35	0.81	0.75	1.00

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	A	B	C	D	E	F
A	0.71	0.76	0.71	0.34	0.29	0.35
B	0.76	0.83	0.77	0.36	0.32	0.38
C	0.71	0.77	0.72	0.34	0.30	0.35
D	0.34	0.36	0.34	0.79	0.69	0.82
E	0.29	0.32	0.30	0.69	0.61	0.72
F	0.35	0.38	0.35	0.82	0.72	0.85

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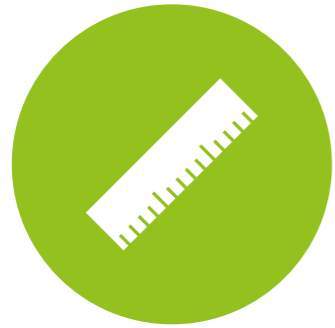
	A	B	C	D	E	F
A	0.29	-0.03	0.00	0.00	0.20	-0.01
B	-0.03	0.17	0.02	-0.01	0.00	-0.06
C	0.00	0.02	0.28	-0.05	0.03	0.00
D	0.00	-0.01	-0.05	0.21	0.05	-0.01
E	0.20	0.00	0.03	0.05	0.39	0.03
F	-0.01	-0.06	0.00	-0.01	0.03	0.15



# Residual

	A	B	C	D	E	F
A	0.29	-0.03	0.00	0.00	0.20	-0.01
B	-0.03	0.17	0.02	-0.01	0.00	-0.06
C	0.00	0.02	0.28	-0.05	0.03	0.00
D	0.00	-0.01	-0.05	0.21	0.05	-0.01
E	0.20	0.00	0.03	0.05	0.39	0.03
F	-0.01	-0.06	0.00	-0.01	0.03	0.15





# How it works

Covariance matrix, estimate variables to fit

ML, WLS

Use estimates and misfit in item-, factor-, and model-fit metrics

Item-fit: Loadings, communality, residuals

Factor-fit: Average Variance Extracted

Model-fit: Chi-square test, CFI, TLI, RMSEA



# Item, factor & model fit

of CFA models



# Item-fit metrics

Variance extracted (squared standardized loading):

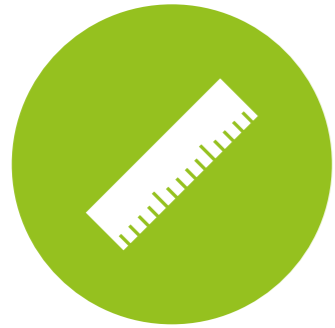
- Regression  $R^2$ , which is the amount of variance explained by the factor (1-uniqueness)
- Should be  $> 0.50$  (although some argue 0.40 is okay)

In lavaan output: r-squared



# Variance extracted

	A	B	C	D	E	F
A	0.29	-0.03	0.00	0.00	0.20	-0.01
B	-0.03	0.17	0.02	-0.01	0.00	-0.06
C	0.00	0.02	0.28	-0.05	0.03	0.00
D	0.00	-0.01	-0.05	0.21	0.05	-0.01
E	0.20	0.00	0.03	0.05	0.59	0.03
F	-0.01	-0.06	0.00	-0.01	0.03	0.15



# Item-fit metrics

Residual correlations:

- The observed correlation between two items is significantly higher (or lower) than predicted

In lavaan output: modification indices

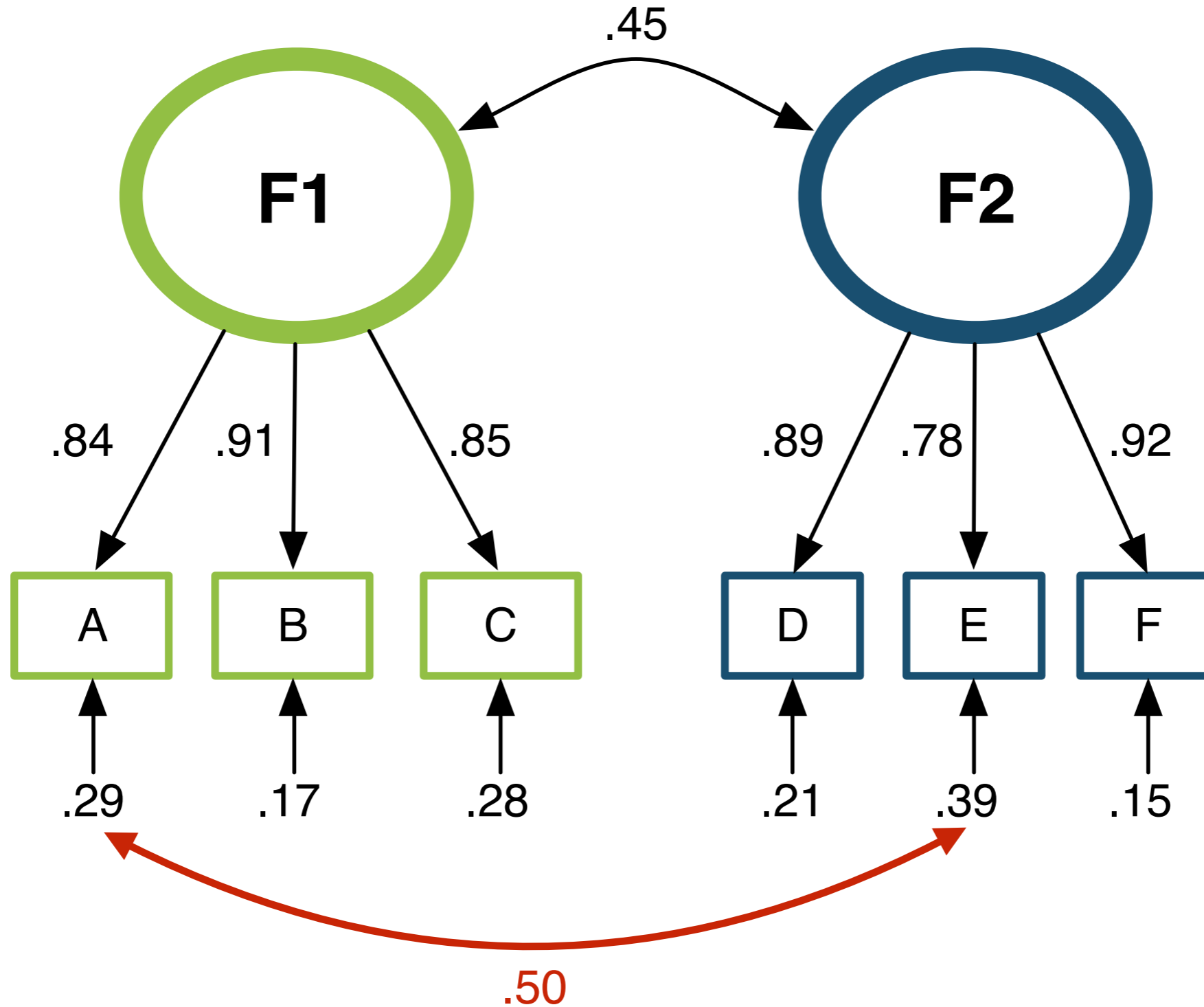


# Residual...

	A	B	C	D	E	F
A	0.29	-0.03	0.00	0.00	0.20	-0.01
B	-0.03	0.17	0.02	-0.01	0.00	-0.06
C	0.00	0.02	0.28	-0.05	0.03	0.00
D	0.00	-0.01	-0.05	0.21	0.05	-0.01
E	0.50	0.00	0.03	0.05	0.39	0.03
F	-0.01	-0.06	0.00	-0.01	0.03	0.15



# Solution





# Split factors...

If you have lots of residuals, it might mean that factors should be split up!

E.g., “satisfaction” turns out to be “satisfaction” and “intention to use”

In lavaan: low r-squared, many high modification indices





# Split factors...

	A	B	C	D	E	F
A	0.59	0.29	0.24	-0.27	-0.23	-0.30
B	0.29	0.47	0.19	-0.20	-0.19	-0.31
C	0.24	0.19	0.58	-0.31	-0.25	-0.28
D	-0.27	-0.23	-0.30	0.51	0.30	0.18
E	-0.20	-0.19	-0.31	0.30	0.69	0.25
F	-0.31	-0.25	-0.28	0.18	0.25	0.45



# Item-fit metrics

## Cross-loadings:

- When the model suggest that the model fits significantly better if an item also loads on an additional factor
- Could mean that an item actually measures two things

In R: modification indices

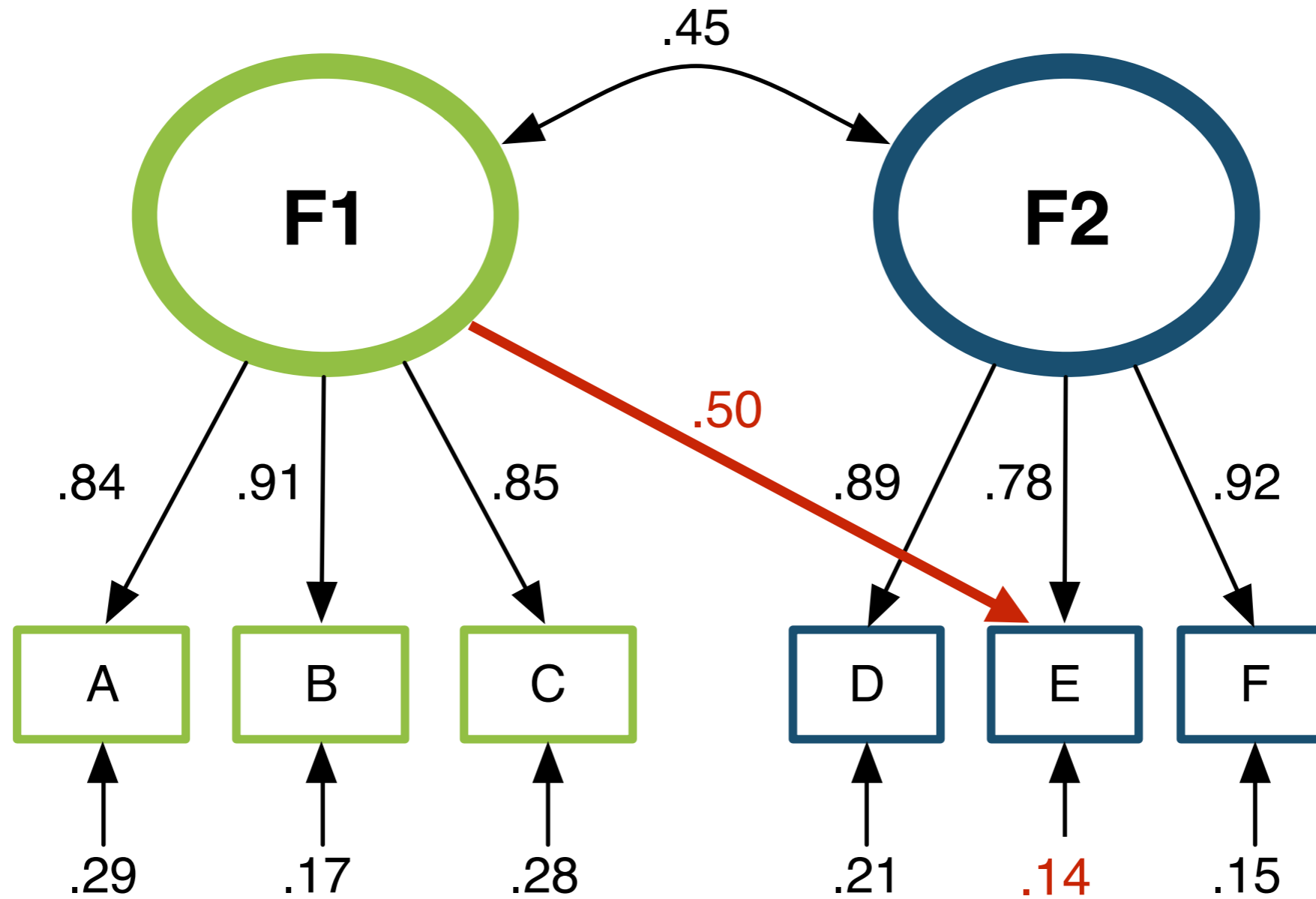


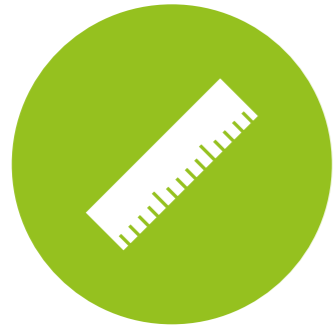
# Cross-loadings...

	A	B	C	D	E	F
A	0.29	-0.03	0.00	0.00	0.20	-0.01
B	-0.03	0.17	0.02	-0.01	0.00	-0.06
C	0.00	0.02	0.28	-0.05	0.03	0.00
D	0.00	-0.01	-0.05	0.21	0.05	-0.01
E	0.34	0.36	0.36	0.05	0.39	0.03
F	-0.01	-0.06	0.00	-0.01	0.03	0.15



# Solution





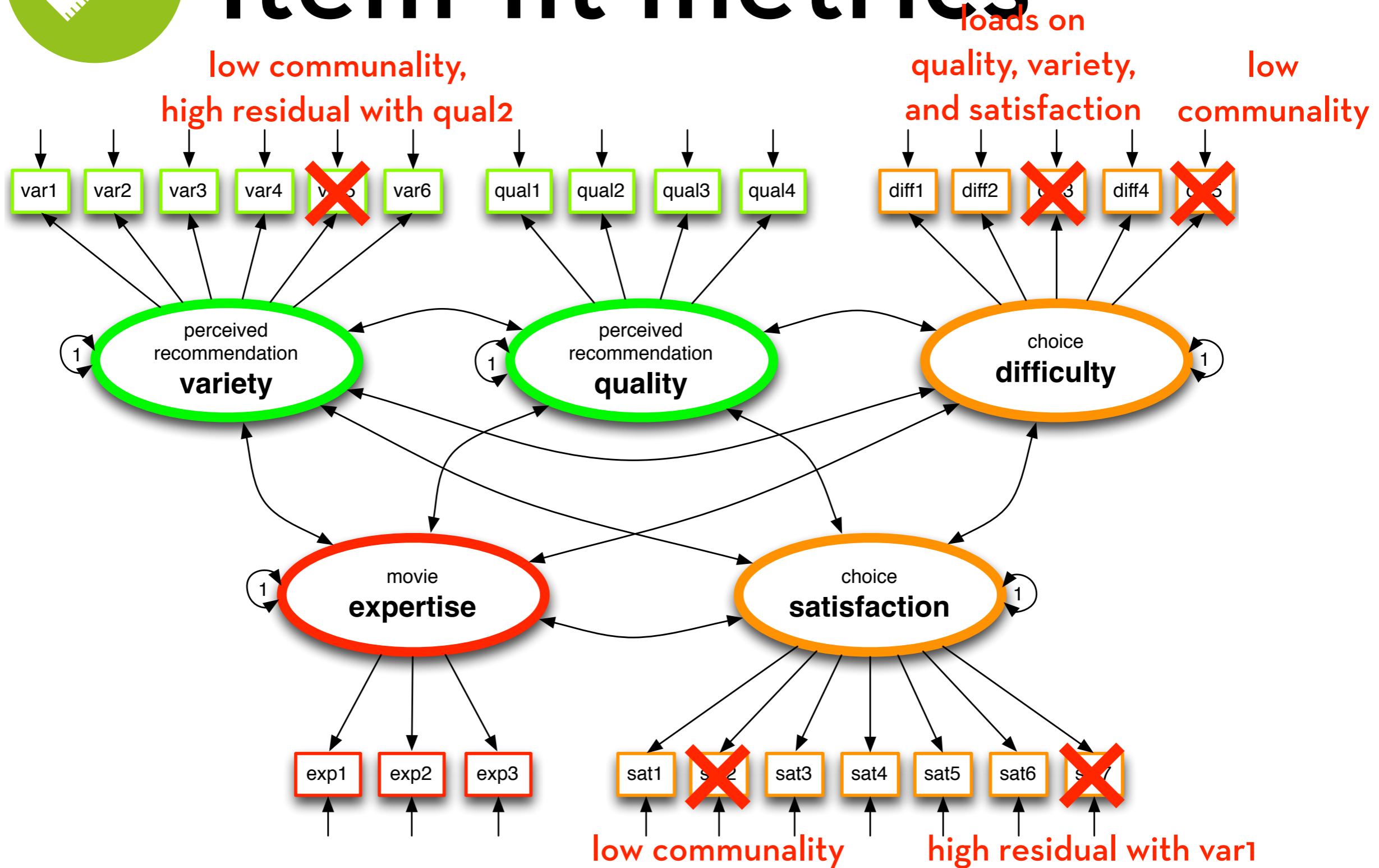
# Item-fit metrics

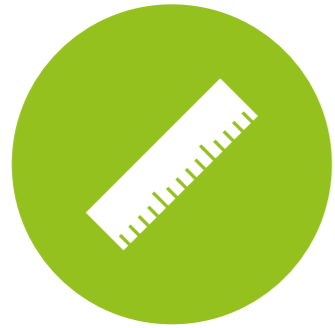
For all these metrics:

- Remove items that do not meet the criteria, but be careful to keep at least 3 items per factor
- One may remove an item that has values much lower than other items, even if it meets the criteria



# Item-fit metrics





# Factor-fit metrics

AVE (average variance extracted, over all items per factor)

- In lavaan: average r-squared of items per factor

A value  $> 0.50$  indicates convergent validity

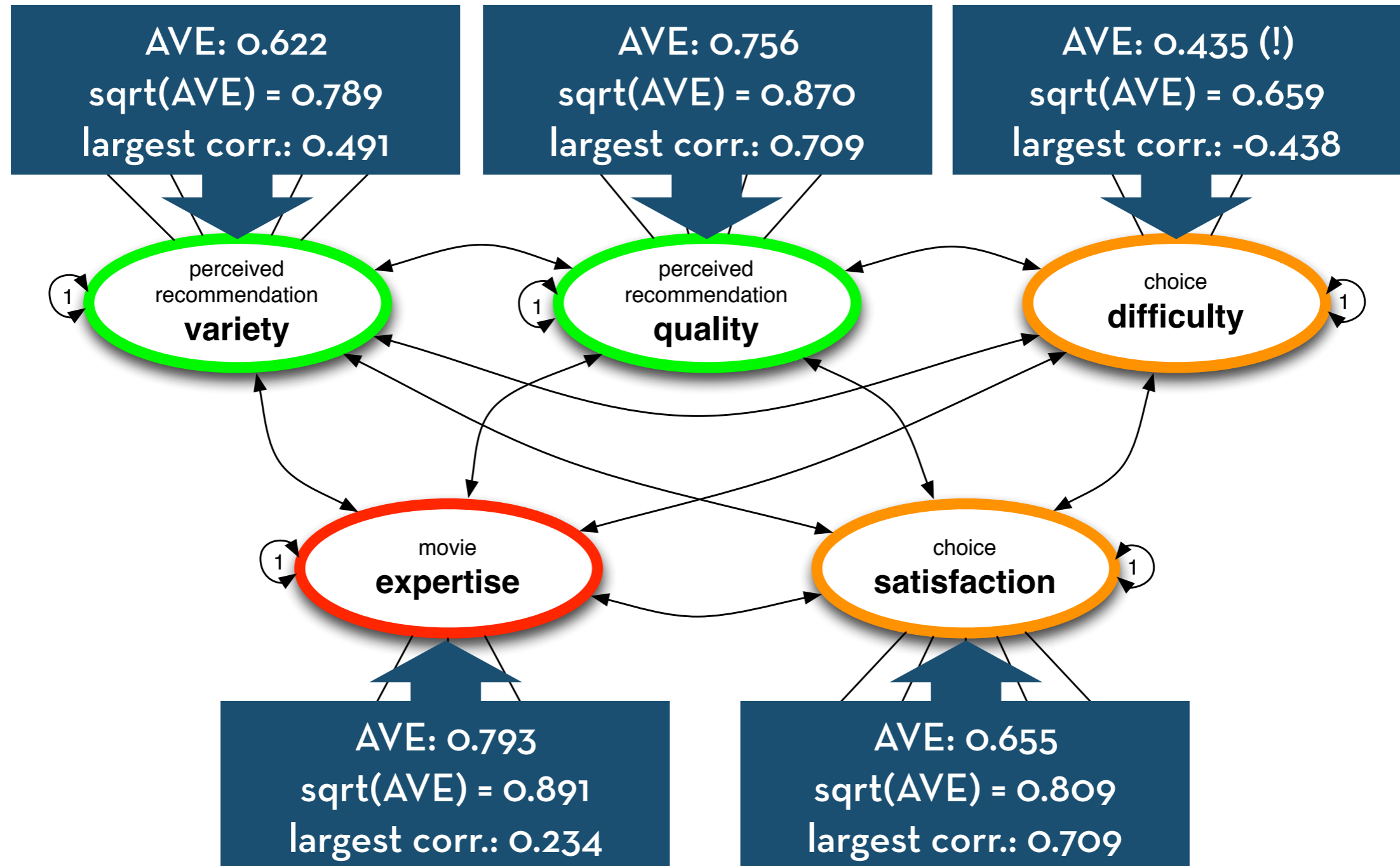
- Otherwise, remove worst-fitting items

Also, the square root of the AVE of a factor should be higher than its highest correlation with other factors

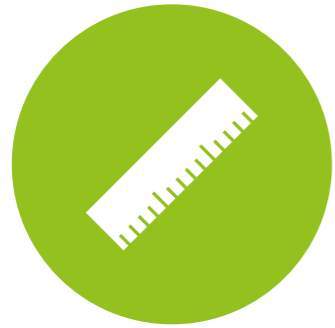
- This indicates discriminant validity
- Otherwise, the factors may as well be combined



# Factor-fit metrics







# Model-fit metrics

Chi-square test of model fit:

- Tests whether there any significant misfit between estimated and observed correlation matrix
- Often this is true ( $p < .05$ ); factor models are rarely perfect!
- Alternative metric:  $\chi^2 / df < 3$  (good fit) or  $< 2$  (great fit)



# Model-fit metrics

## CFI and TLI:

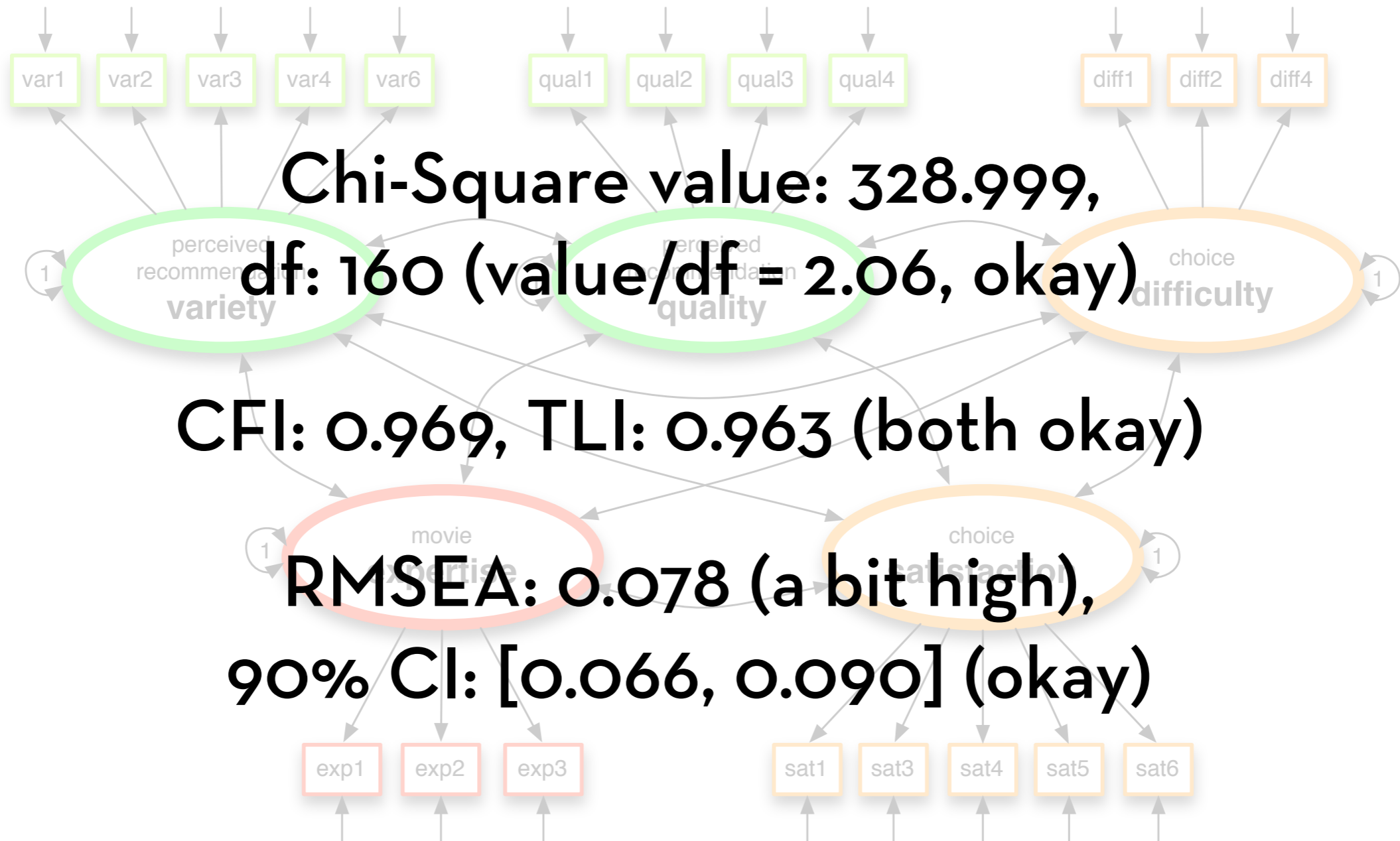
- Relative improvement over baseline model; ranging from 0.00 to 1.00
- CFI should be  $> 0.96$  and TLI should be  $> 0.95$

## RMSEA:

- Root mean square error of approximation
- Overall measure of misfit
- Should be  $< 0.05$ , and its confidence interval should not exceed 0.10.



# Model-fit metrics



**“It is the mark of a truly intelligent person  
to be moved by statistics.”**



**George Bernard Shaw**