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Measurement in social sciences

Direct measurement

You measure exactly the thing you want to measure

- What would we like to measure?

Weight

- Measurement instrument

Indirect measurement

You measure the thing you want to measure through measuring something else

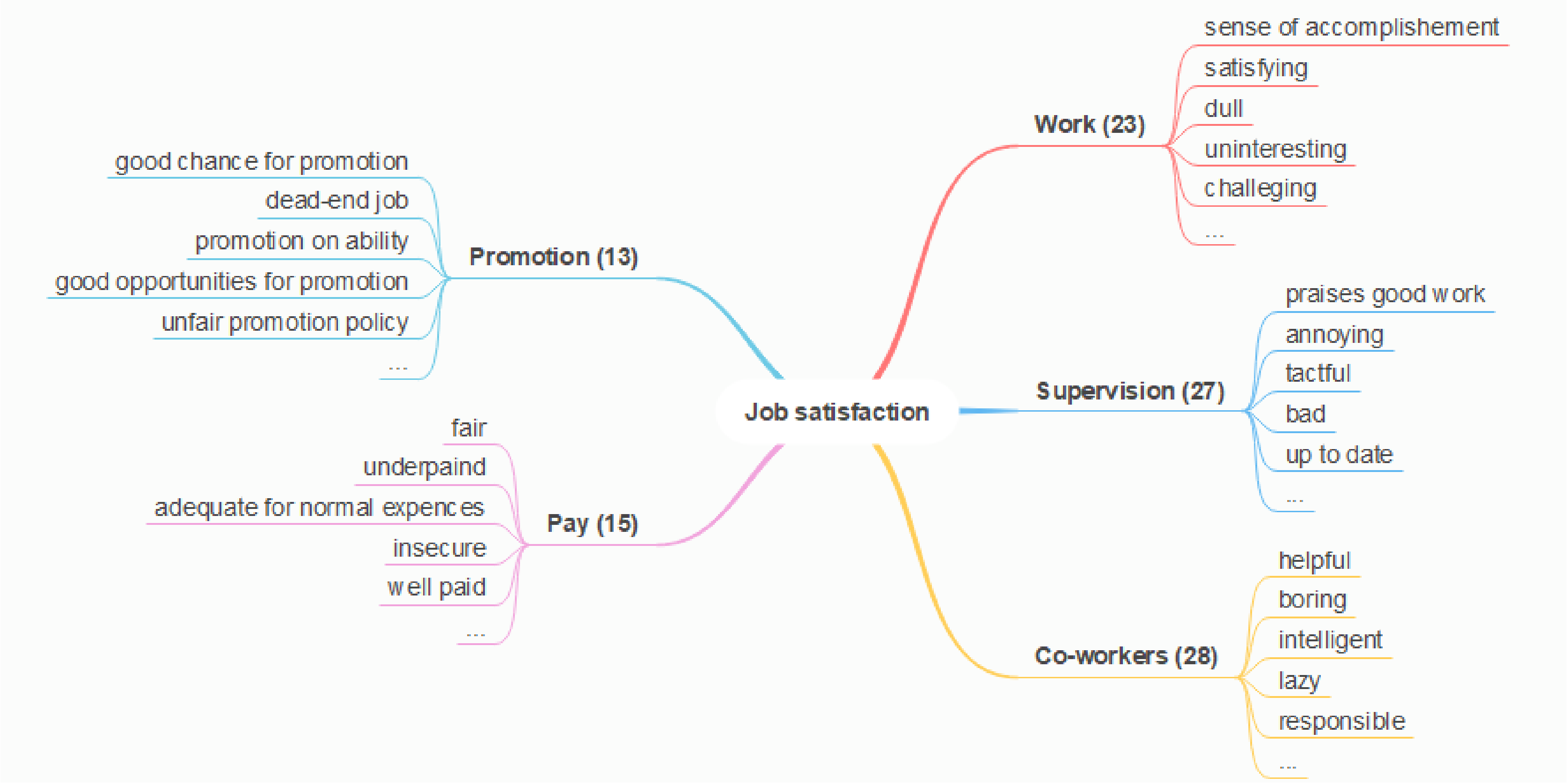
- What would we like to measure?

Work satisfaction

- Measurement instrument

Job satisfaction

- Definition?
- Which dimensions (facets)?
- Which questions/items?



Smith, P.C., Kendall, L., Hulin, C.L. (1969). *Job Descriptive Index – JDI*

Measurement process

Conceptualization

- Theoretical definition of the concept and its dimensions
- Literature review
- Existing measurement instruments?

Operacionalization

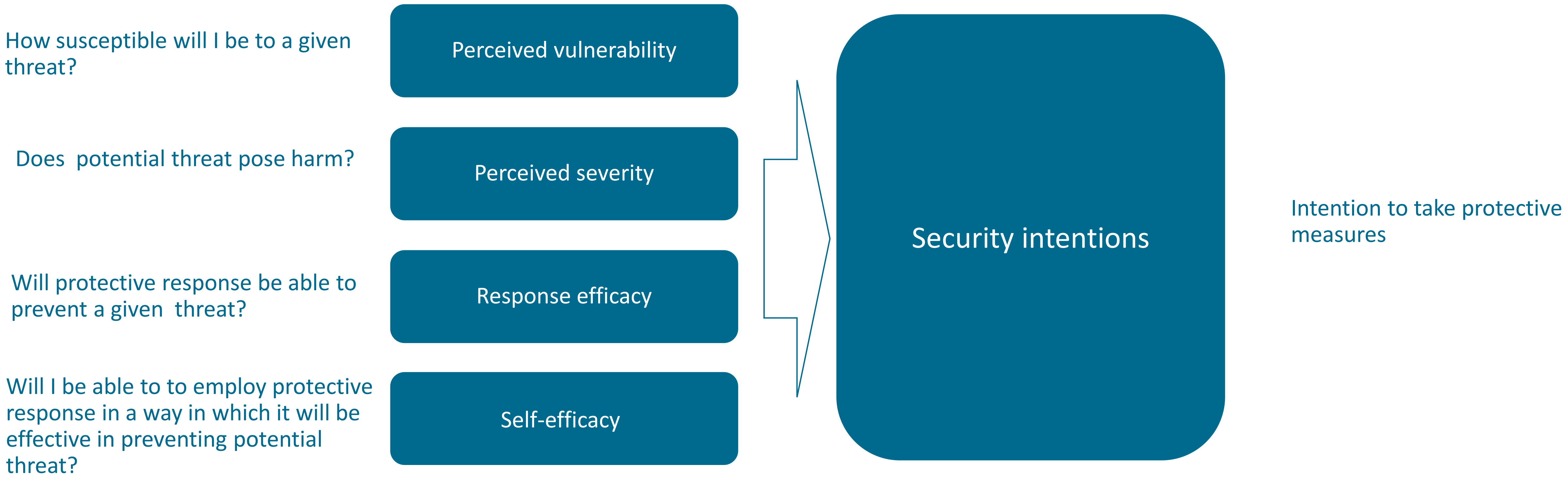
- Questions, items in a questonnaire
- Pilot testing

Measurement quality

- Validity
- Reliability

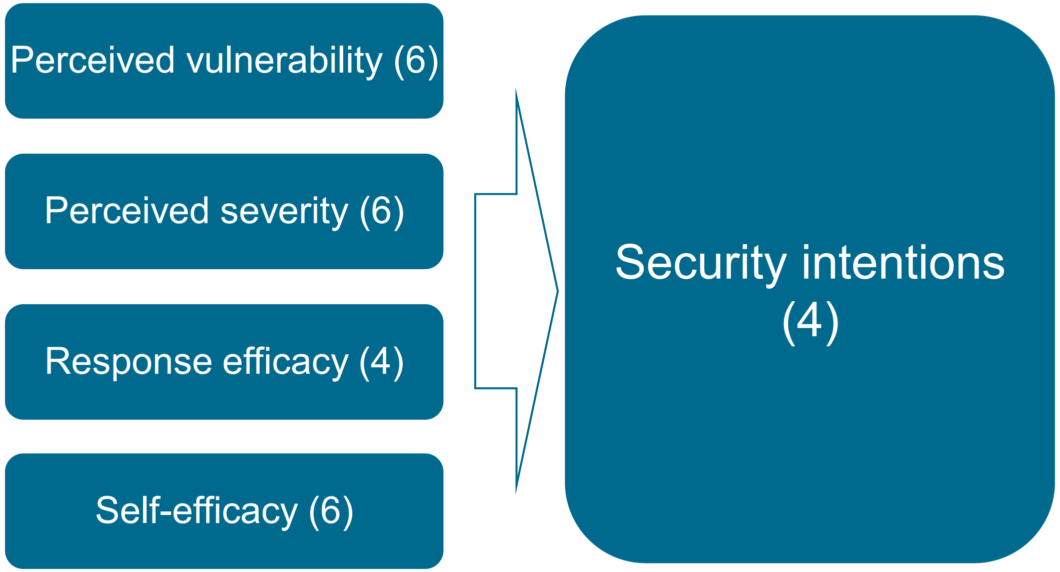
Conceptualization: protection motivation theory (Rogers, 1975)

- Explores social and cognitive processes leading to self-protection behaviour.



Operacionalization - example

- Operationalized by Thompson, McGill, Wang (2018)
- Adjusted for smart phone users
- Translation – back-translation
- 26 items
- 5-point Likert scale



“Security begins at home”: Determinants of home computer and mobile device security behavior (Thompson, Wang, McGill, 2017)

To ensure validity and reliability of the items used to measure the model constructs, we selected items that had been validated in relevant behavioral security research studies wherever possible.

Security intentions (Adapted from Taylor & Todd, 1995)	I am likely to take security measures on my *device* It is possible that I will take security measures to protect my *device* I am certain that I will take security measures to protect my *device* It is my intention to take measures to protect my *device*

Operacionalization: perceived vulnerability

CONSTRUCT

Synonims:
Latent variable
Factor

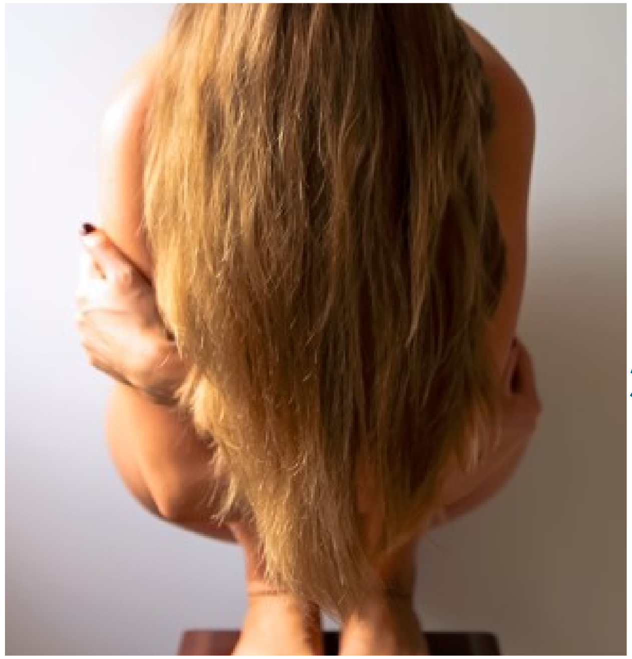


Photo by Ava Sol on Unsplash

INDICATORS

Synonims:
Manifest variables
Observed variables

- My smart phone could be a target to a serious information security threat
- By using a smart phone I am facing more and more information security threats
- I think that my smart phone could be vulnerable to a security threat
- It is likely, that my smart phone will be subject to a successful online attack
- Information and data on my smart phone are vulnerable to security breaches
- I could become victim to a malicious attack if I would not follow good security practices

Operacionalization: perceived severity

CONSTRUCT

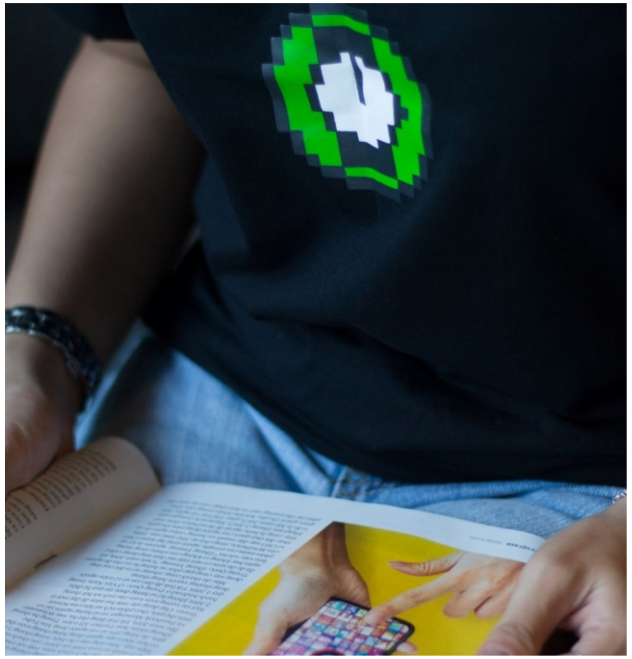


Photo by Hacker Noon on Unsplash

INDICATORS

- A security breach on my smart phone would be a serious problem for me
- It would be serious problem for me, if I lose my information because of hacking
- If someone accessed without my knowledge or my consensus my confidential information on my smart phone, it would be serious problem for me
- If someone successfully attack and damage my smart phone, it would be very problematic for me
- I view information security attacks on me as harmful
- I think that protection of information is important on my smart phone

Operacionalization: response efficacy

CONSTRUCT

INDICATORS

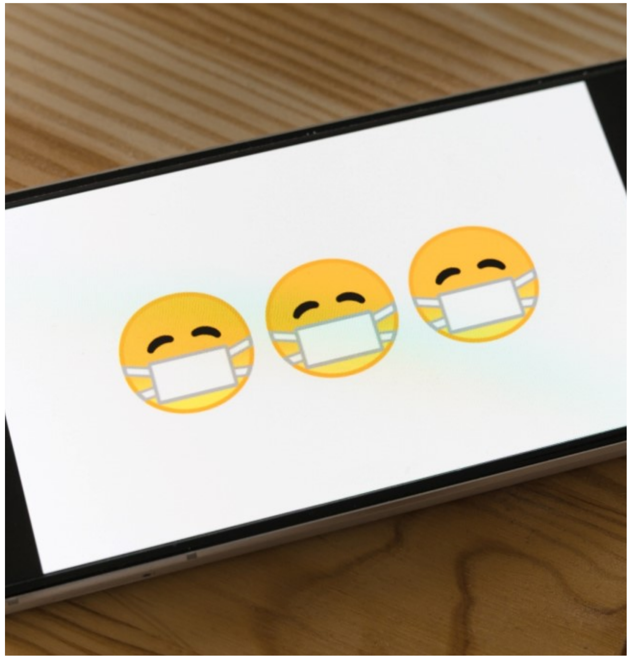


Photo by Markus Winkler on Unsplash

- Technical security measures on smart phones help preventing security breaches
- Implementing security measures on my smart phone is effective for preventing security breaches
- Enabling technical security measures would prevent hackers to steal personal information from smart phones
- Preventive measures that are available are effective to stop people from getting confidential data from smart phones

Operacionalization: self-efficacy

CONSTRUCT

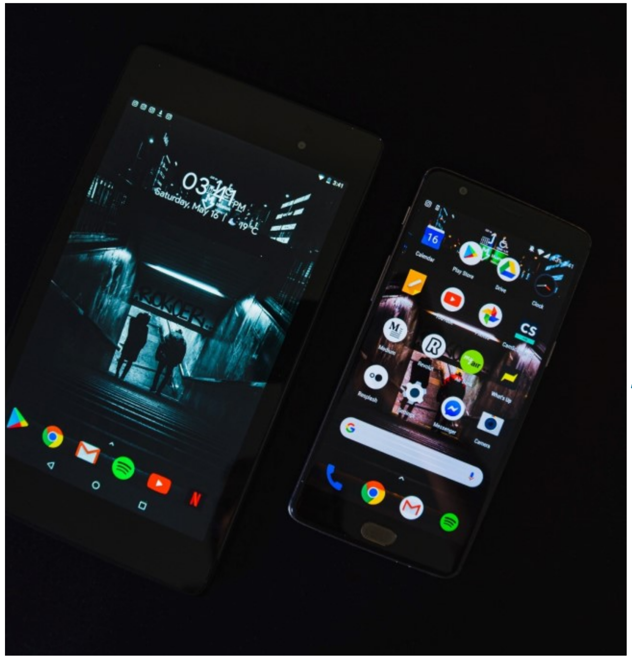
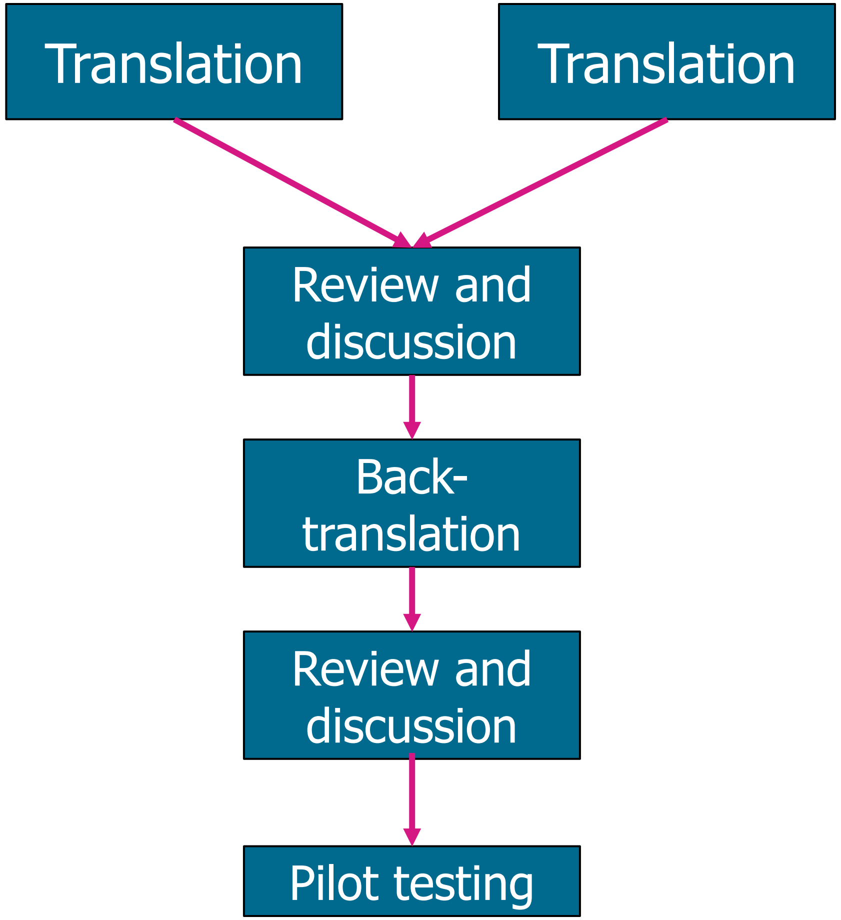


Photo by The Average Tech Guy on Unsplash

INDICATORS

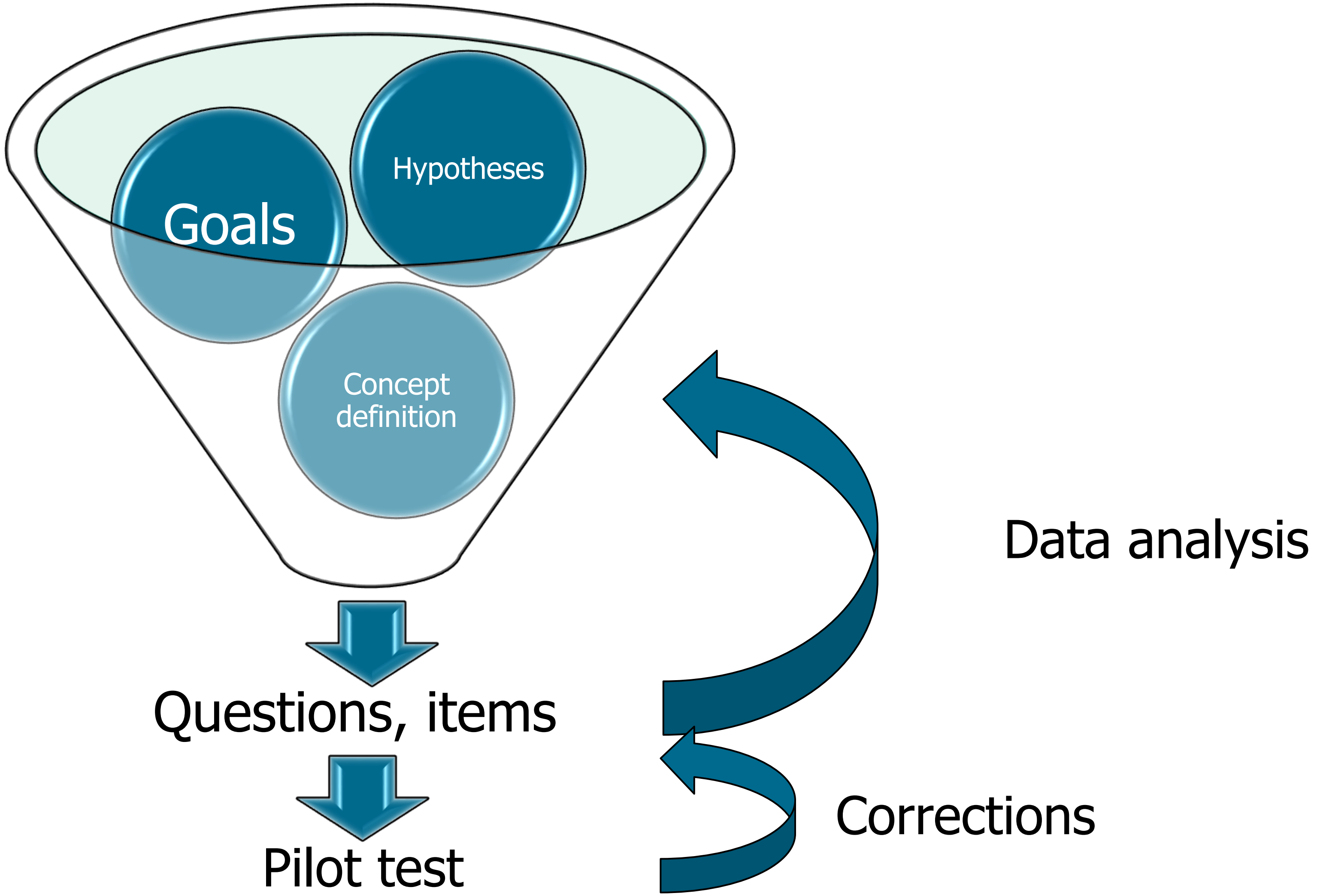
- I have no problems taking measures for security of my smart phone
- Taking necessary security measures is entirely under my control
- I have resources and the knowledge to take the necessary security measures
- Taking necessary security measures is simple
- I know how to protect my smartphone by myself
- I know how to enable security measures on my smart phone

Translation of questionnaire used abroad



WHO: https://terrance.who.int/mediacentre/data/WHODAS/Guidelines/WHODAS%202.0%20Translation%20guidelines.pdf

Make your own questionnaire



„Good“ questionnaire

- Valid and reliable
- A good question should adress three key aspects (Groves et al., 2004):
  - Content (questions ask after the right content).
  - Cognitive (all respondents understand a question in the same way).
  - Usefulness (fill in questionnaire easily and enables the use of the predicted statistical tests).

Measurement validity – questionnaire testing

- Does a questionnaire measure what it is suppose to measure?

Content

- Do questions adress all dimensions of a concept?
  - Expert assessment
  - Face validity = non-expert assessment

Criterion

- Predictive
- Between-group difference
- Correlation with existing questionnaire

Construct

- Do questions measure the concept they are suppose to measure?
  - Factor analysis

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Content validity

Face validity

- To what extent does it seem that the questions measure what they are suppose to measure.
- A questionnaire has face validity when also non-professionals are able to identify the content the questionnaire is adressing.

- **Example**: a researcher prepares a questionnaire to measure depression and asks a colleague to see if he or she finds the questions valid (to measure depression).
- **Example:** A larger number of respondents evaluate the validity on the Likert scale (1 - the questionnaire is completely unsuitable for measuring a certain concept up to 5 - the questionnaire is completely appropriate ..)

Expert validity

- The extent to which the questions measure what they should measure is judged by the experts in the field.
- They can also state what each question is measuring.
- The researcher reviews their answers.

- Example: a questionnaire on depression is reviewed by psychiatrists to assess the extent to which each question actually measures depression (for example, through various symptoms)

Criterion validity

Predictive validity

- Predict an event or situation (criterion variable) on the basis of a current variable.
- **Example**: do results on a final exam (graduate examination) at the end of the high school predict the success of the study at university

Concurrent validity

- Variable correlates highly with an existing valid criterion variable
- **Example**: are strong religious beliefs associated with attendance of religious services?

Known groups validity

- Choosing different groups of people for which it is known they differ in a measured concept, which validity we want to assess

- **Example**: Validity of new scale measuring the extent of a political conservatism is assesed by deploying it to the conservative and liberal associations/organizations.. in

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Construct validity – exploratory factor analysis

Objectives

- Test construct validity
  - Do indicators really measure the concept they are supposed to measure?
- Reduce the number of variables
  - Can we reduce the number of variables in the data?

When?

- Big enough sample size
- Continous variables (Likert type variables also allowed)
- Normally distributed variables
- Strong correlations between variables measuring the same construct and weak between variables measuring a different construct.

What is a big enough sample size?

Photo by Owen Cannon on Unsplash

- **Number of subjects per variable**
  - 10 subjects per variable (Nunnally, 1978)
  - 5 subjects per variable or 100 subjects (Hatcher, 1994)
  - 2 subjects per variable (Kline, 1994)
- **Total sample size**
  - 100 subjects, when clear structure (Kline, 1994)
  - 300 subjects, high correlations among variables → fewer than 300 (Tabachnik and Fidell, 2001)

Factor analysis (FA) – can relationships between variables be explained by a lower number of factors?

CONSTRUCT or LATENT VARIABLE or FACTOR (F)

Indicator or manifest or observed variable 1 (x_1)

Indicator or manifest or observed variable 2 (x_2)

Indicator or manifest or observed variable 3 (x_3)

Strong correlations between variables

Factor model:

$$x_1 = \lambda_1 F + E_1$$

$$x_2 = \lambda_2 F + E_2$$

$$x_3 = \lambda_3 F + E_3$$

Common factor

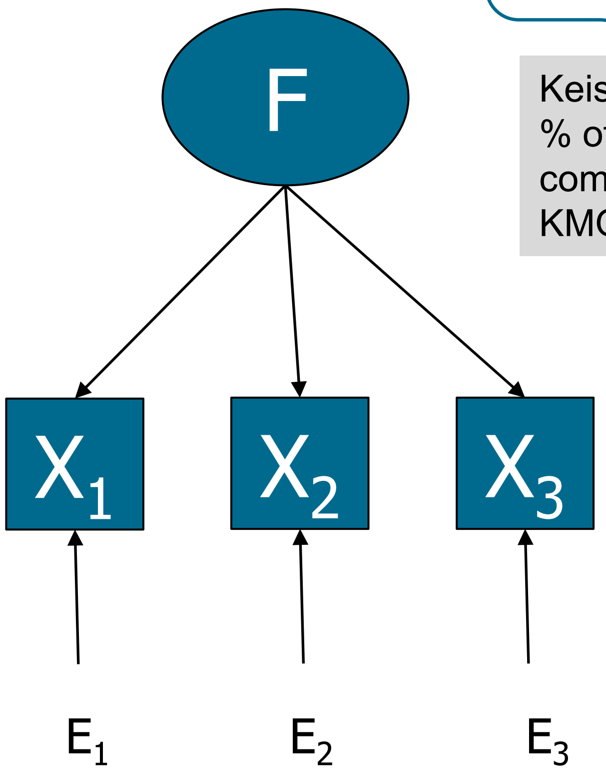
Factor weights (correlations between each variable and factor)

Specific factor (effect only specific variable)

Assumptions:
Common and specific factors are independent.
Specific factors are independent.
Common factors are independent.

Graphical presentation

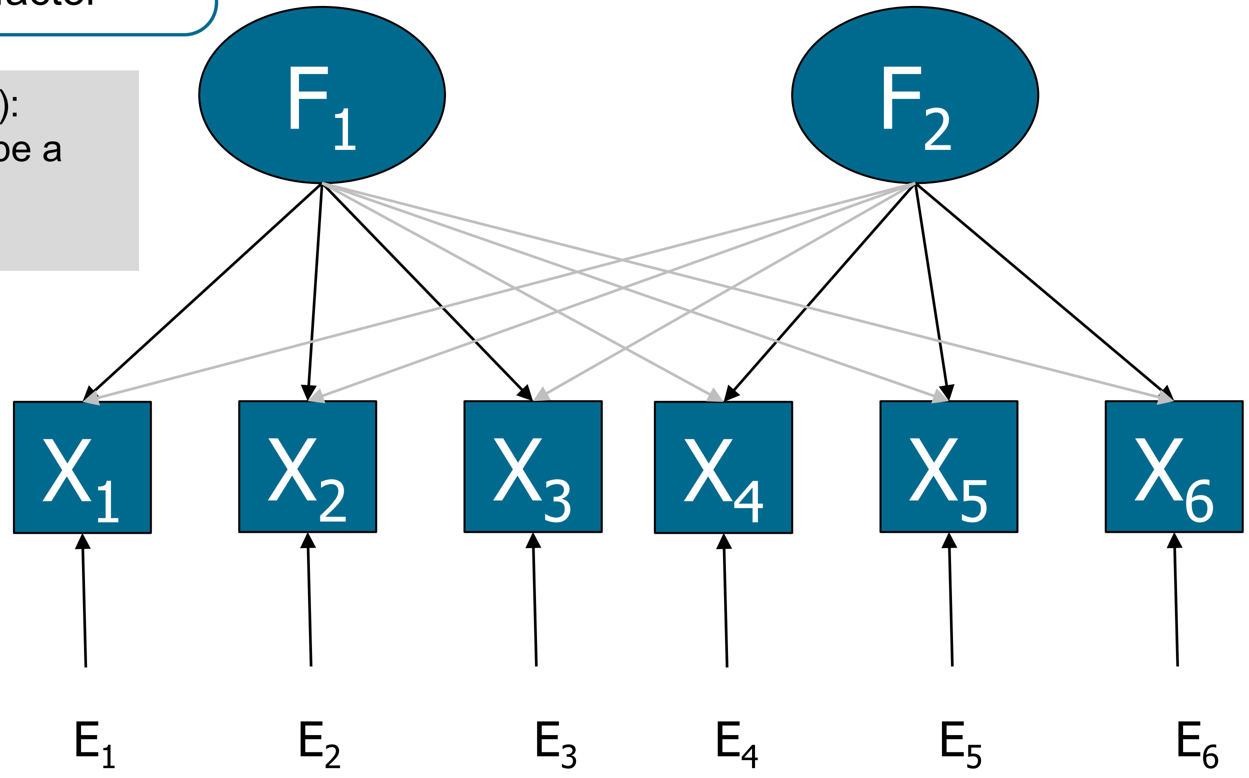
1 FACTOR



Main aim is to explain as much variance among variables as possible by a common factor

Keiser-Meier-Olkin (KMO):
% of variance that might be a common variance
KMO > 0.50 adequate

2 FACTORS



Revisiting PMT (KMO = 0,87)

- PERCEIVED VULNERABILITY (PV)

- My smart phone could be a target to a serious information security threat (PV1)
- By using a smart phone I am facing more and more information security threats (PV2)
- I think that my smart phone could be vulnerable to a security threat (PV3)
- It is likely, that my smart phone will be subject to a successful online attack (PV4)
- Information and data on my smart phone are vulnerable to security breaches (PV5)
- I could become a victim to a malicious attack if I would not follow good security practices (PV6)

- SECURITY INTENTIONS (SI)

- I will probably take security measures on my smart phone (SI1)
- It is possible that I will take security measures to protect my smart phone (SI2)
- I am certain that I will take security measures to protect my smart phone (SI3)
- I am planning to take measures to protect my smart phone (SI4)

Examining correlation matrix

Bartlett test of sphericity:
Is a correlation matrix an identity matrix?
Should be significant!

PMT
Bartlett's Test of Sphericity
χ^2 (45) =1755.3; $p < 0.001$

	PV1	PV2	PV3	PV4	PV5	PV6	SI1	SI2	SI3	SI4
PV1	--									
PV2	0.63**	--								
PV3	0.74**	0.65**	--							
PV4	0.53**	0.46**	0.57**	--						
PV5	0.60**	0.53**	0.67**	0.56**	--					
PV6	0.53**	0.44**	0.51**	0.41**	0.44**	--				
SI1	0.20**	0.10	0.16**	0.03	0.11	0.31**	--			
SI2	0.20**	0.09	0.13*	0.04	0.08	0.31**	0.84**	--		
SI3	0.20**	0.09	0.15**	0.07	0.07	0.27**	0.75**	0.71**	--	
SI4	0.19**	0.10	0.14*	0.05	0.06	0.34**	0.70**	0.70**	0.74**	--

% of item variance explained by each common factor

Correlation matrix

Eigenvalues

Eigenvectors

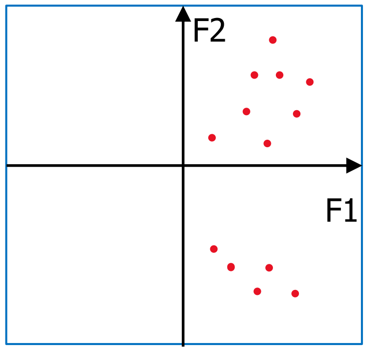
Factor weights = correlation between each variable and the common factor

Different methods, most common:

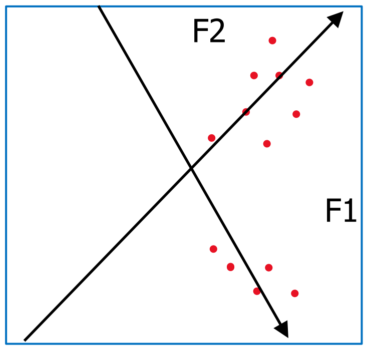
- Principal axis factoring (PAF)
- Maximum likelihood (ML)

Factor rotation – enhance interpretability

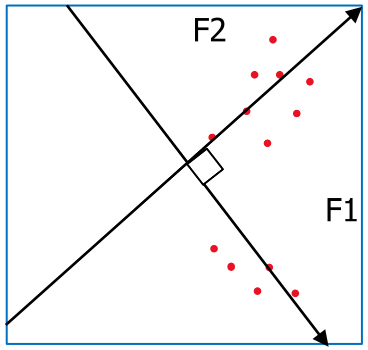
- Oblique
  - Factors are correlated (for example different dimensions of work satiskaction)
  - First step.
- Orthogonal
  - Factors are independent, uncorrelated (for example job satisfaction and body height)
  - After oblique rotation the correlations between factors are low (< 0.32)



No rotation



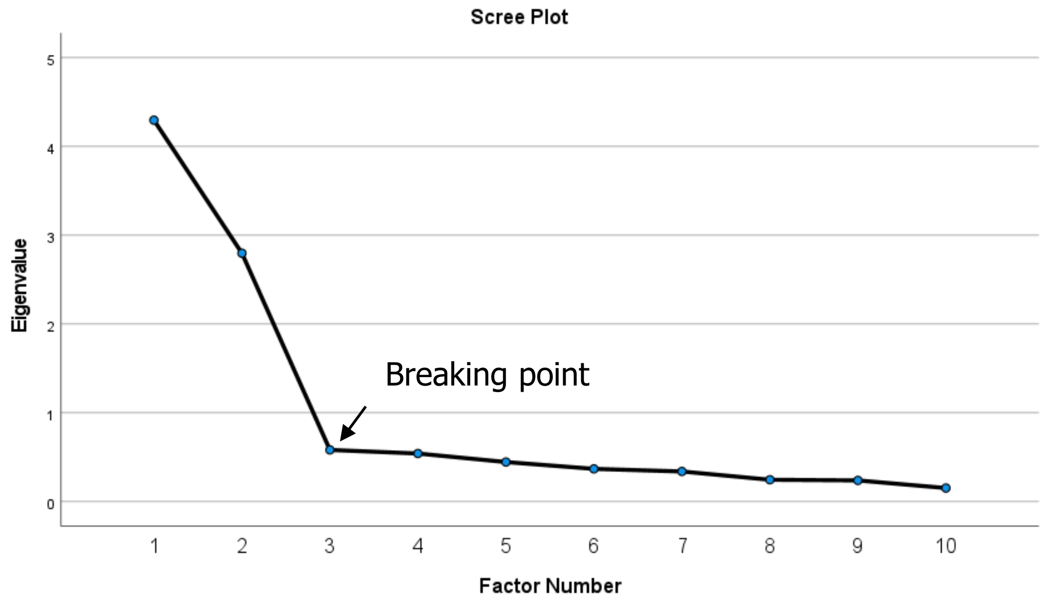
Oblique rotation



Orthogonal rotation

How many factors to extract?

- Scree plot (elbow diagram)
  - Graphical presentation of the share of variance, explained by each common factor.
  - Breaking point → number of factors preceding it



How many factors to extract?

After oblique rotation % of variance explained by each factor can‵t be calculated

- Keiser-Guttman criteria
  - Number of factors with eigenvalues > 1
  - Eigenvalues → calculation of the % of variance of items explained by each coomon factor

Factor	Initial Eigenvalues			Eigenvalues after rotation			
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	4.3	43.0	43.0	3.9	39.5	39.5	3.5
2	2.8	28.0	70.9	2.5	24.9	64.4	3.2
3	0.6	5.8	76.7				
4	0.5	5.4	82.1				
5	0.4	4.4	86.6				
6	0.4	3.7	90.3				
7	0.3	3.4	93.7				
8	0.2	2.5	96.1				
9	0.2	2.4	98.5				
10	0.2	1.5	100.0				

How much variance of an item is explained by common factors?

Communalities	Initial	Extraction
My smart phone could be a target to a serious information security threat	0.63	0.70
By using a smart phone I am facing more and more information security threats	0.48	0.52
I think that my smart phone could be vulnerable to a security threat	0.68	0.78
It is likely, that my smart phone will be subject to a successful online attack	0.42	0.45
Information and data on my smart phone are vulnerable to security breaches	0.53	0.58
I could become a victim to a malicious attack if I would not follow good security practices	0.40	0.43
I will probably take security measures on my smart phone	0.76	0.81
It is possible that I will take security measures to protect my smart phone	0.73	0.77
I am certain that I will take security measures to protect my smart phone	0.67	0.71
I am planing to take measures to protect my smart phone	0.64	0.69

Extraction Method: Principal Axis Factoring.

Factor weights

	Factor	
	PV	SI
My smart phone could be a target to a serious information security threat (PV1)	0.82	0.07
By using a smart phone I am facing more and more information security threats (PV2)	0.73	-0.04
I think that my smart phone could be vulnerable to a security threat (PV3)	0.89	-0.02
It is likely, that my smart phone will be subject to a successful online attack (PV4)	0.68	-0.07
Information and data on my smart phone are vulnerable to security breaches (PV5)	0.77	-0.07
I could become a victim to a malicious attack if I would not follow good security practices (PV6)	0.55	0.25
I will probably take security measures on my smart phone (SI1)	-0.01	0.90
It is possible that I will take security measures to protect my smart phone (SI2)	-0.02	0.88
I am certain that I will take security measures to protect my smart phone (SI3)	0.01	0.84
I am planning to take measures to protect my smart phone (SI4)	0.00	0.83

Crossloadings?
Low factor weights?

FACTOR SCORE: $PV = 0.82 \cdot PV1 + 0.73 \cdot PV2 \ldots + 0 \cdot SI4$

$SI = 0.07 \cdot PV1 - 0.04 \cdot PV2 \ldots + 0.83 \cdot SI4$

Reduction of observed variables

- Calculate factor score for each factor from factor equation
- Calculate aritmetic mean of item scores, measuring each factor (so called composite variable) → more common

Assess measurement reliability of factors

- Is measurement consistent?

Nunnally's (1978) rule of thumb: 0.70.

Test -retest

- Questionnaire filled in by the same person twice after a short period of time (14 days)
- Measure:
  - Correlation coefficient.

Internal consistency

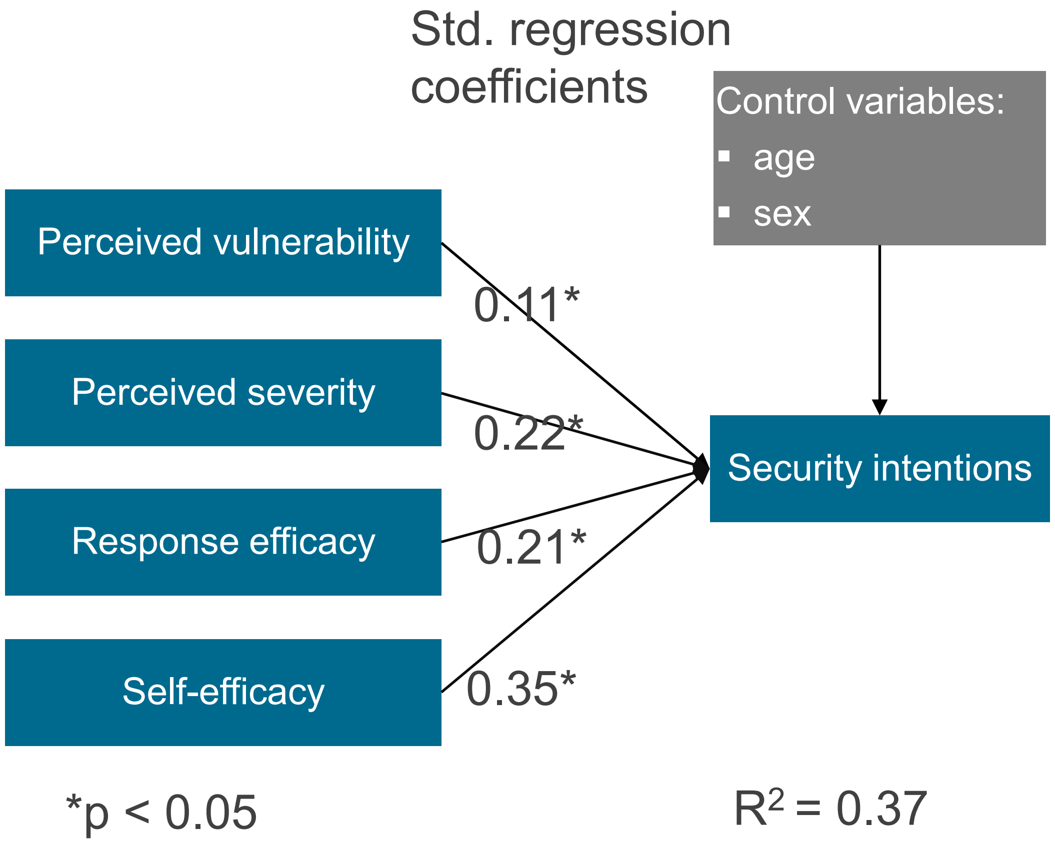
- Similar answers provided on items measuring the same construct
- Measure:
  - Cronbach coefficient α

Use of new variables in the analysis

- As dependent/independent variables in linear regression analysis
- As independent variables in discriminant analysis
- As dependent variables in t-test and ANOVA
- etc.

Testing the PMT model

- Composite variables are included in multiple regression analysis.



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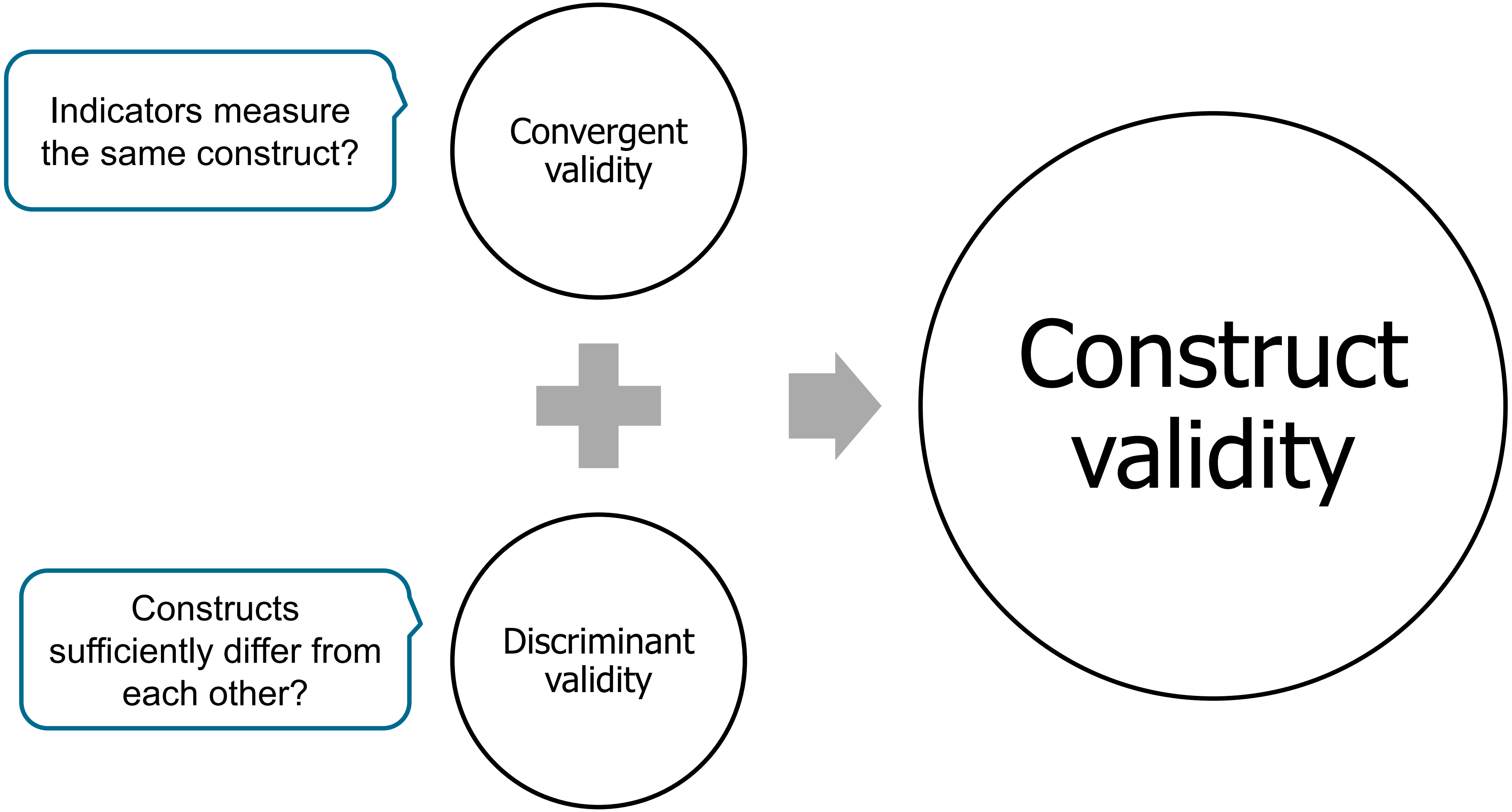
Construct validity – confirmatory factor analysis

„Subdimensions“ of construct validity



Confirmatory factor analysis (CFA)

- Part of Structural Equation Modeling (SEM) – **first step**
- Specifies indicators, constructs and their interrelationships.

EFA

- Underlying structure derived from data
- Crossloadings allowed
- Orthogonal rotation permitted

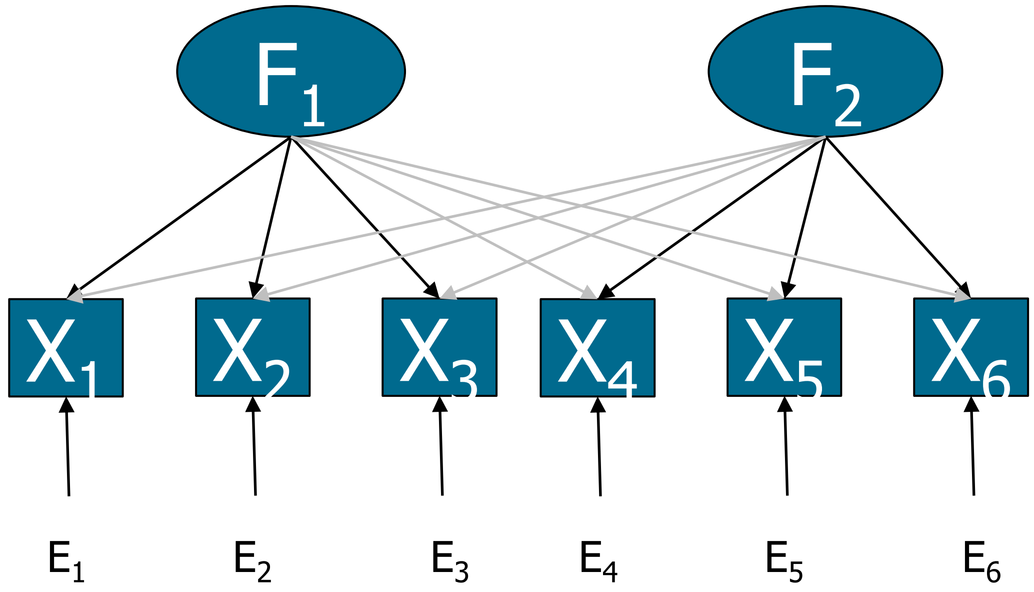
CFA

- Underlying structure based on theory
- Crossloadings not allowed
- Oblique rotation assumed

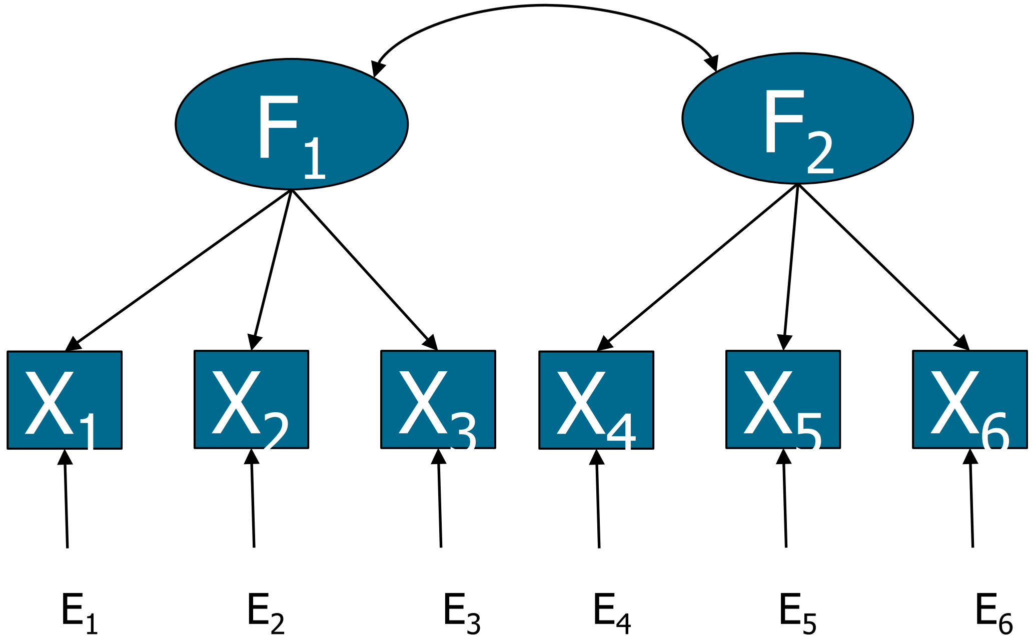
EFA

CFA

2 FACTORS



2 FACTORS



CFA and SEM

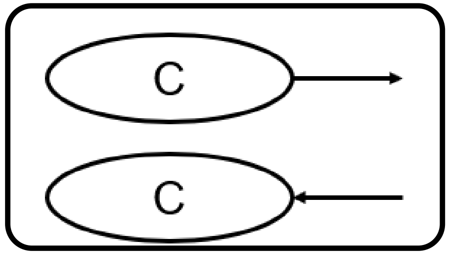
1. Step CFA – measurement model

a visual representation that specifies the model's constructs, indicator variables, and interrelationships. CFA provides quantitative measures of the reliability and validity of the constructs.

2. Step SEM – structural model

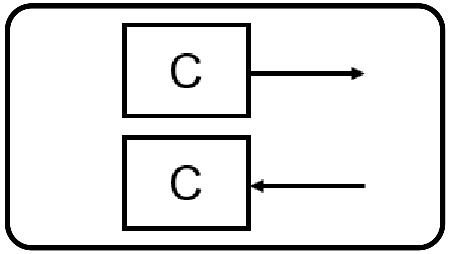
a set of dependence relationships linking the hypothesized model's constructs. SEM determines whether relationships exist between the constructs – and along with CFA enables one to accept or reject one's theory.

Basic elements of CFA model (and SEM)



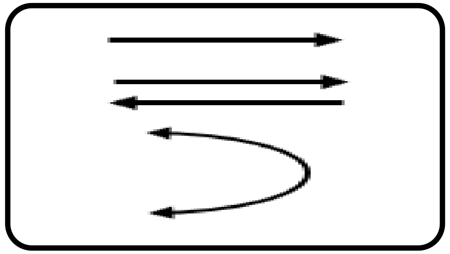
Constructs

- Exogenous
- Endogenous



Indicators

- Formative
- Reflective



Relationships

- Recursive
- Nonrecursive
- Correlational

Reflective vs. formative measurement theory and CFA

REFLECTIVE

- Factors cause the indicator
- Error = inability of the latent construct to fully explain the indicators
- Arrows from construct to indicator

FORMATIVE

- Indicators cause the construct
- Error = inability of the indicators to fully explain the construct
- Arrows from indicator to construct

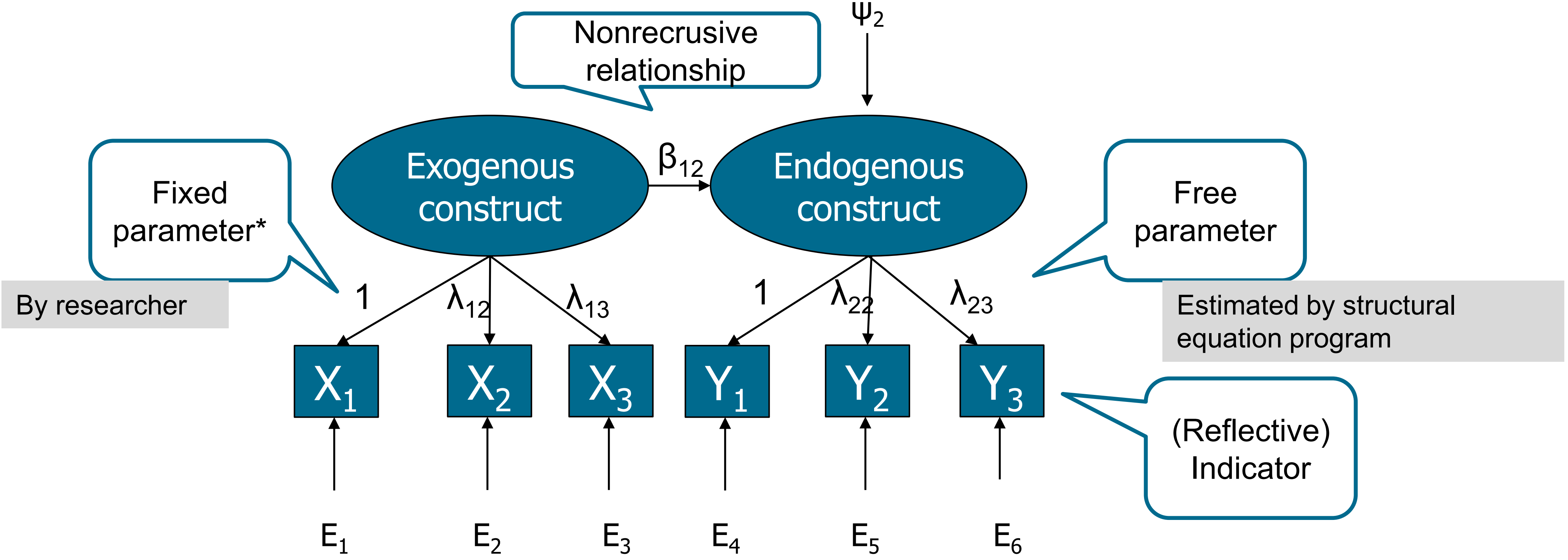
EXAMPLE: STRESS

Blood pressure, anxiety, perspiration, nervousness, sleeplessness, increased heart rate, shallow breading, nausea…

Gender, personality, age, family-work balance, work load, disliked boss, customer mistreatement, illness…

Path diagram

The difference between CFA and SEM: the later presupposes relationships (directed arrows) between constructs.



The logic behind CFA and SEM

Each element of covariance matrix is expressed by a structural and measurement equations (a function of the model parameters (relationships, variances, errors)).

Parameter estimates obtained by the used estimation method → maximum likelihood estimation (MLE) most commonly used (minimizes differences between the observed and estimated covariance matrices).

Examine goodness-of-fit → how well a model reproduces covariance matrix of the indicators.

Examine construct validity and reliability of the specified measurement model.

Three types of goodness-of-fit measures

ABSOLUTE	INCREMENTAL	PARSIMONY
How well your estimated model reproduces the observed data?	How well your estimated model fits relative to some alternative baseline model (usually the one in which all observed variables are uncorrelated)	Can your model be improved by specifying fewer estimated parameter paths (specifying a simpler model).

(Some) goodness-of-fit measures (indices)

Fit index	Description	Cut-off
χ^2	The difference btw the two covariance matrices	$p > 0.05$
χ^2/df	χ^2 sensitive to sample size	1 - 3
RMSEA	The degree to which lack of fit is due to misspecification of the model tested vs being due to sampling error	< 0.08
NNFI	How much better the hypothesized model fitted a null model that did not specify any relationships between the variables (adjusted for degrees of freedom)	>0.90
IFI	Adjusts the Normed Fit Index (NFI) for sample size and degrees of freedom	>0.90
CFI	Comparison btw proposed and baseline model (no relationships between variables), adjusted for the degrees of freedom	>0.90
SRMR	The square-root of the difference between the residuals of the sample covariance matrix and the hypothesized model	< 0.08

Construct validity – convergent validity

- Examine:
  - (Standardized) factor loadings (>0.50 and statistically significant)
    - Each indicator should load substantially and statistically significantly on the construct it is supposed to measure.
  - Average variance extracted (AVE) (>0.50)
    - How much variance in the items can be explained by the construct.

$$AVE = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum_i \mathrm{var}(\varepsilon_i)}$$

  - Composite reliability (CR) (>0.70 or >0.60)
    - Is a measure of internal consistency in scale items, much like Cronbach's alpha. It can be thought of as being equal to the total amount of true score variance relative to the total scale score variance.

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + (\sum \epsilon_i)}$$

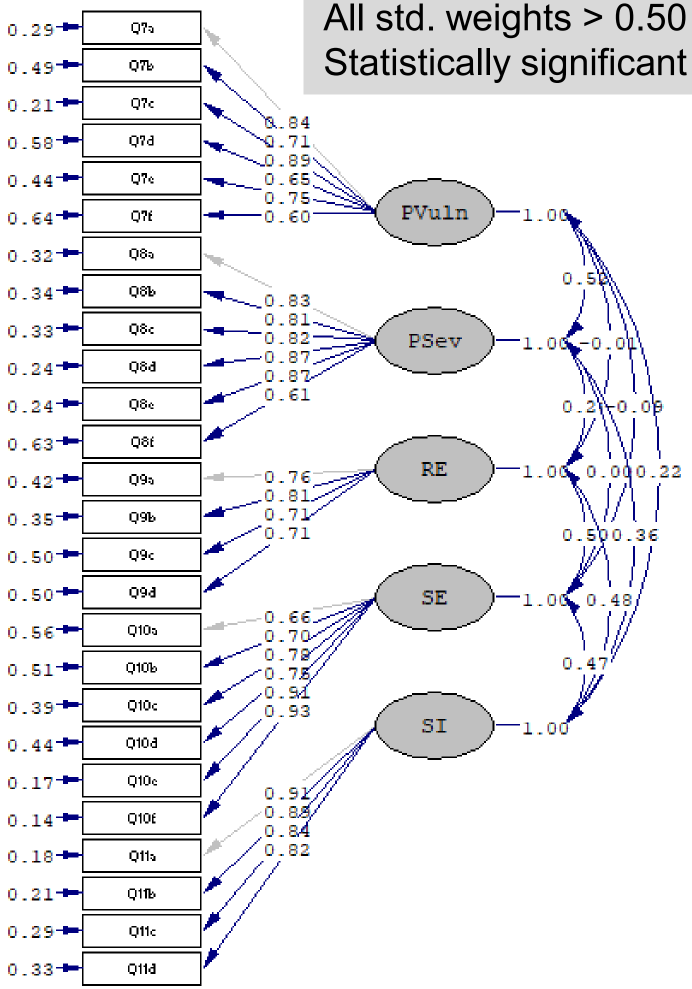
Poor fit of the model, next steps

- Identify problems with model fit
  - Examine standardized residuals (standardized differences between estimated and observed covariance matrices)
  - Examine modification indices (the program proposes changes to be made in the model):
    - Add error covariances
    - Add paths (relationships) between variables in the model
  - Modify the model:
    - Omit indicators (one change at a time)
    - Add or remove paths (relationships) between constructs

Construct validity – discriminant validity

- Examine:
  - Correlations between factors ($r < 0.85$)
  - 95% confidence interval of the correlation coefficients (the upper limit should not include 1)
  - All AVE larger than squared interconstruct correlation estimates.
  - Better fit of the model without restricted correlation coefficients between constructs to 1.

PMT revisited – fitting CFA model – convergent validity



Chi-Square=694.99, df=289, P-value=0.00000, RMSEA=0.071

All std. weights > 0.50
Statistically significant (not shown)

AVE > 0.50
CR > 0.7

$$\mathrm{AVE}_{\mathrm{PV}} = \frac{0.84^2+0.71^2+\cdots+0.60^2}{(0.84^2+0.71^2+\cdots+0.60^2)+((1-0.84^2)+(1-0.71^2)+\cdots.(1-0.60^2))} = 0.56$$

$$\mathrm{CR}_{\mathrm{PV}} = \frac{(0.84+0.71+\cdots+0.60)^2}{(0.84+0.71+\cdots+0.60)^2+((1-0.84)+(1-0.71)+\cdots.(1-0.60))} = 0.88$$

	AVE	CR
PS	0.65	0.92
RE	0.56	0.84
SE	0.63	0.91
SI	0.75	0.92

PMT revisited – fitting CFA model – goodness of fit

$\chi^2 = 694.9$; df = 289; $p < 0.001$	Significant
$\chi^2/df = 2.4$	1 - 3
RMSEA = 0.071	< 0.08
NNFI = 0.96	> 0.90
IFI = 0.96	> 0.90
CFI = 0.96	> 0.90
SRMR = 0.07	< 0.08

```
Goodness of Fit Statistics

Degrees of Freedom = 289
Minimum Fit Function Chi-Square = 674.992 (P = 0.0)
Normal Theory Weighted Least Squares Chi-Square = 694.989 (P = 0.0)
Estimated Non-centrality Parameter (NCP) = 405.989
90 Percent Confidence Interval for NCP = (332.618 ; 487.056)

Minimum Fit Function Value = 2.455
Population Discrepancy Function Value (F0) = 1.476
90 Percent Confidence Interval for F0 = (1.210 ; 1.771)
Root Mean Square Error of Approximation (RMSEA) = 0.0715
90 Percent Confidence Interval for RMSEA = (0.0647 ; 0.0783)
P-Value for Test of Close Fit (RMSEA < 0.05) = 0.000

Expected Cross-Validation Index (ECVI) = 2.978
90 Percent Confidence Interval for ECVI = (2.711 ; 3.273)
ECVI for Saturated Model = 2.553
ECVI for Independence Model = 37.943

Chi-Square for Independence Model with 325 Degrees of Freedom = 10382.330
Independence AIC = 10434.330
Model AIC = 818.989
Saturated AIC = 702.000
Independence CAIC = 10554.460
Model CAIC = 1105.454
Saturated CAIC = 2323.761

Normed Fit Index (NFI) = 0.935
Non-Normed Fit Index (NNFI) = 0.957
Parsimony Normed Fit Index (PNFI) = 0.831
Comparative Fit Index (CFI) = 0.962
Incremental Fit Index (IFI) = 0.962
Relative Fit Index (RFI) = 0.927

Critical N (CN) = 142.719

Root Mean Square Residual (RMR) = 0.0796
Standardized RMR = 0.0748
Goodness of Fit Index (GFI) = 0.837
Adjusted Goodness of Fit Index (AGFI) = 0.802
Parsimony Goodness of Fit Index (PGFI) = 0.689
```

Standardized residuals and modification indices

Standardized Residuals

	Q7a	Q7b	Q7c	Q7d	Q7e
Q7a	- -				
Q7b	1.177	- -			
Q7c	0.525	0.685	- -		
Q7d	-0.885	-0.305	-0.948	- -	
Q7e	-1.298	-0.357	0.048	2.794	- -
Q7f	1.011	-0.201	-1.281	-0.254	-0.753
Q8a	1.188	0.193	0.736	-0.426	1.707
Q8b	-2.023	-3.516	-1.502	-1.436	-1.912
Q8c	-1.681	-2.020	-1.404	-1.339	-0.932
Q8d	-2.575	-2.374	-1.137	-0.032	-0.660
Q8e	0.985	-0.595	2.296	0.119	1.407
Q8f	3.503	0.819	4.100	2.054	3.112
Q9a	1.578	1.797	1.709	-1.064	0.267
Q9b	-0.684	1.240	-0.969	-1.892	-1.564
Q9c	0.827	0.095	-0.908	-1.100	-0.089

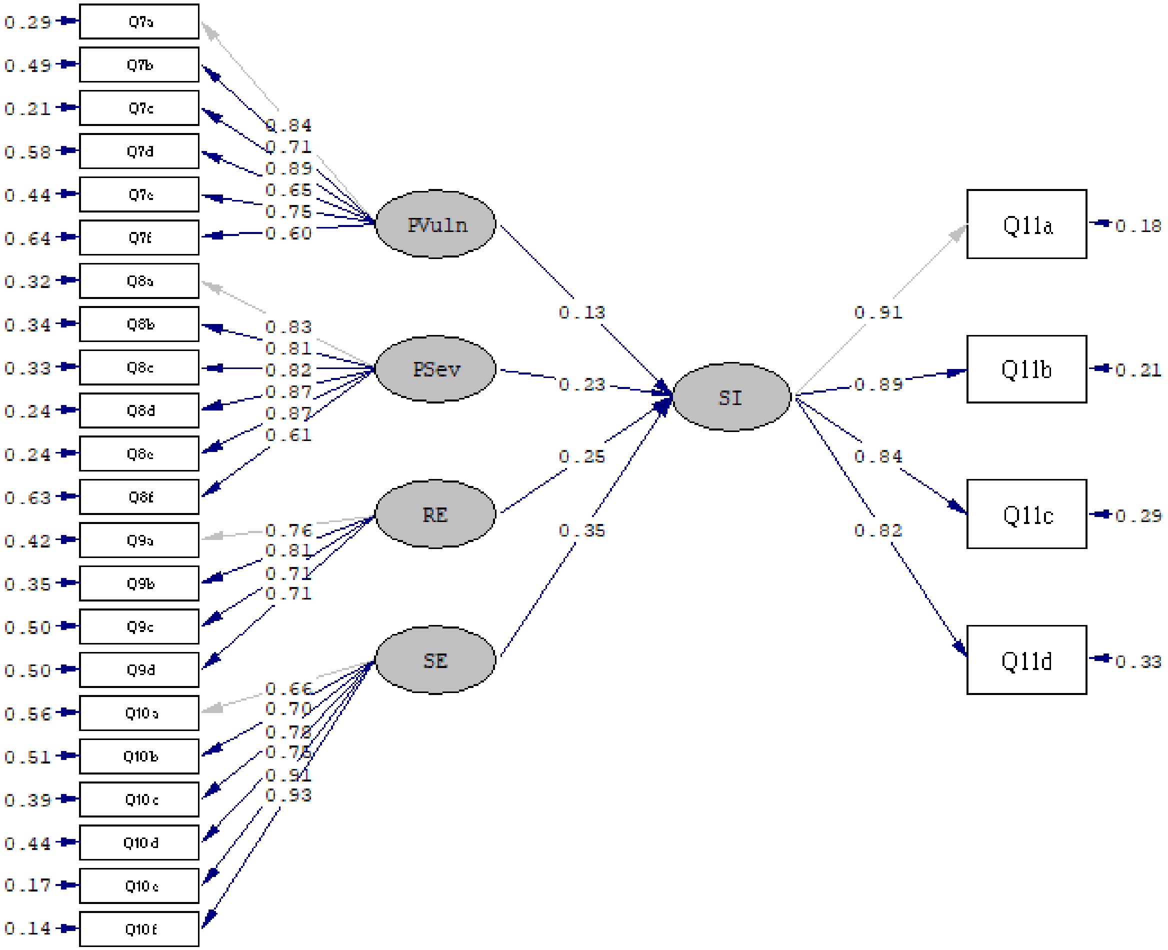
The Modification Indices Suggest to Add the

Path to	from	Decrease in Chi-Square	New Estimate
Q7f	PSev	10.1	0.24
Q7f	RE	14.4	0.35
Q7f	SE	9.0	0.28
Q7f	SI	25.6	0.35
Q8f	PVuln	18.8	0.24
Q8f	SI	26.4	0.27
Q10a	PSev	9.5	0.15
Q10a	RE	34.4	0.50
Q10a	SI	24.2	0.30
Q10b	RE	8.5	0.28
Q10f	RE	12.4	-0.22
Q11b	RE	8.6	-0.16
Q11b	SE	14.5	-0.21
Q11c	SE	17.3	0.27

The Modification Indices Suggest to Add an Error Covariance

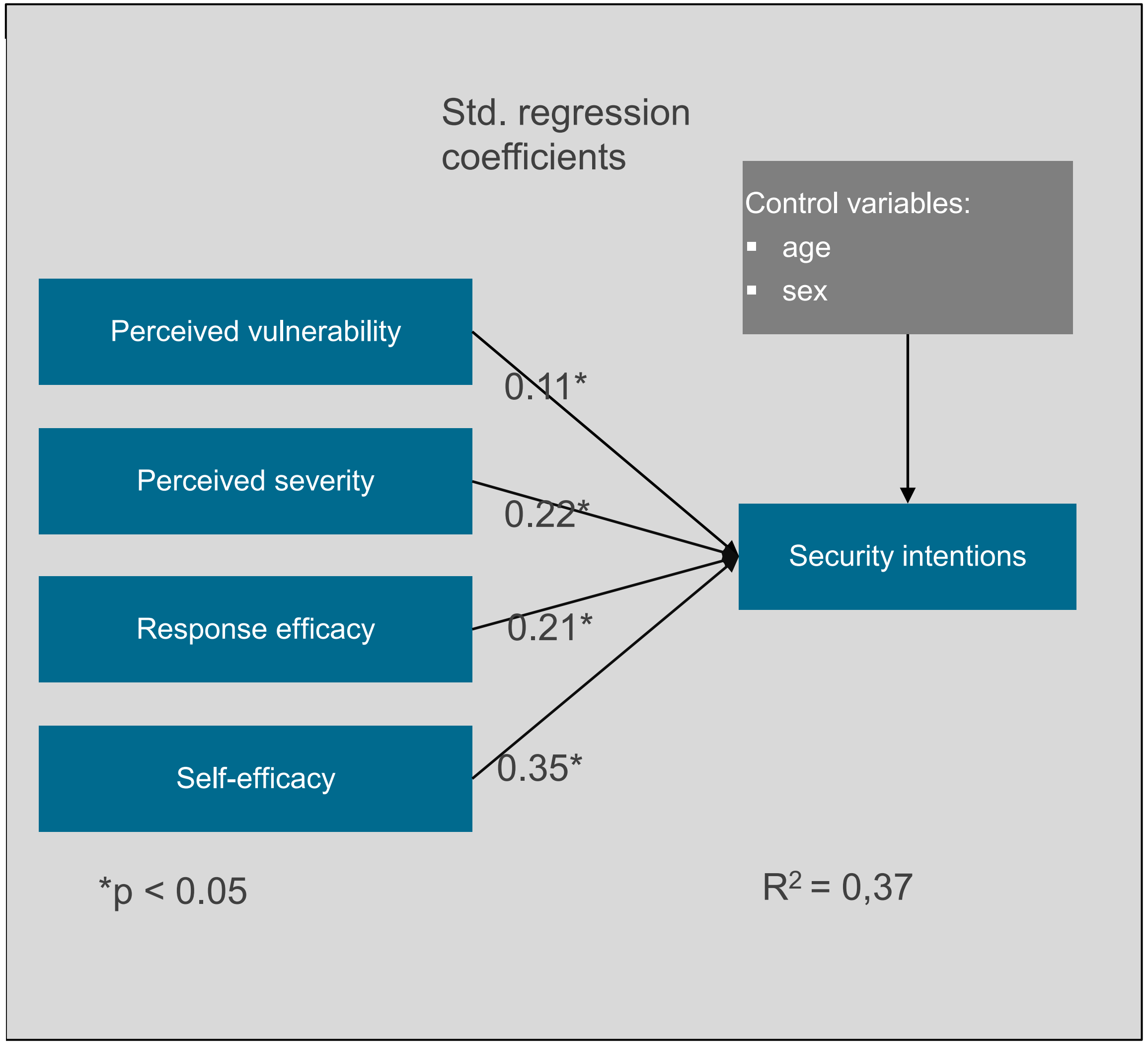
Between	and	Decrease in Chi-Square	New Estimate
Q8b	Q8a	16.2	0.15
Q8d	Q8a	13.4	-0.11
Q8e	Q8d	9.8	0.09
Q9b	Q9a	9.2	0.11

PMT revisited: SEM vs. multiple linear regression

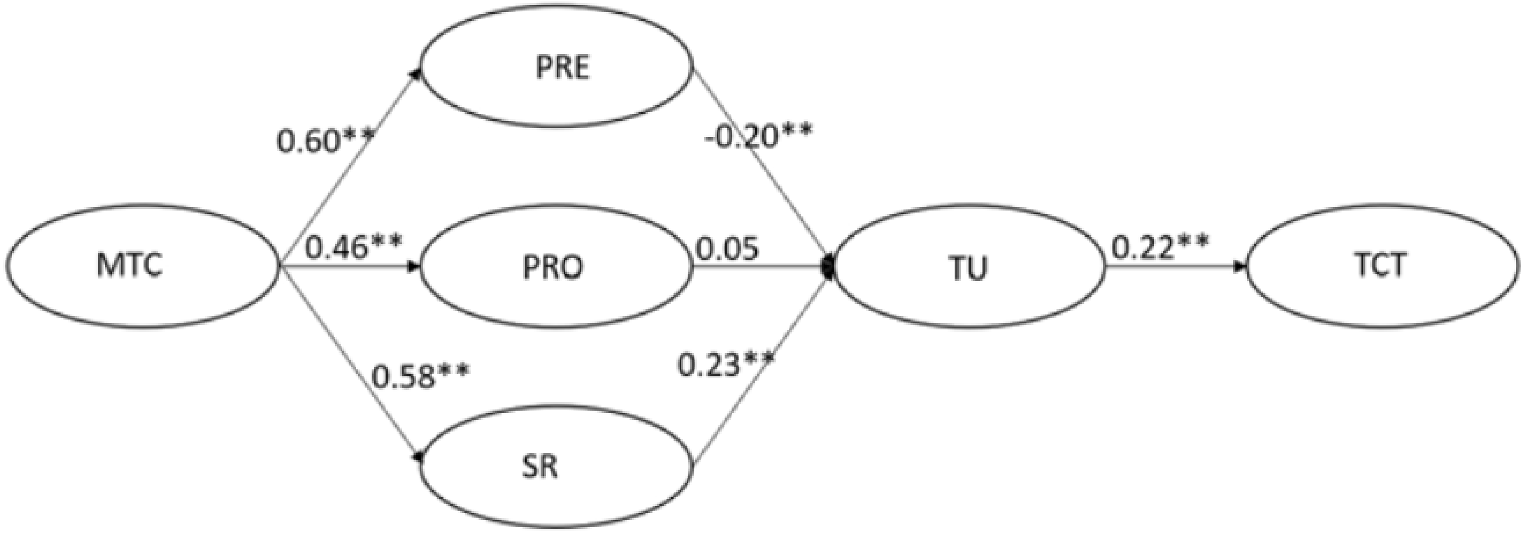


Chi-Square=694.99, df=289, P-value=0.00000, RMSEA=0.071

χ^2/df = 2,4; CFI = 0.96; IFI = 0.96; NNFI = 0.96; SRMR = 0.075



Advantage of SEM: testing indirect relationships – proposed model



Note: indicators are not shown to simplify the model.

CFA:
SB χ2 = 35.02; df = 31; p = 0.283; SB χ2/df = 1.1;RMSEA = 0.059; NFI = 0.97; NNFI = 0.99; CFI = 0.99; IFI = 0.99;SRMR = 0.04; GFI = 0.96

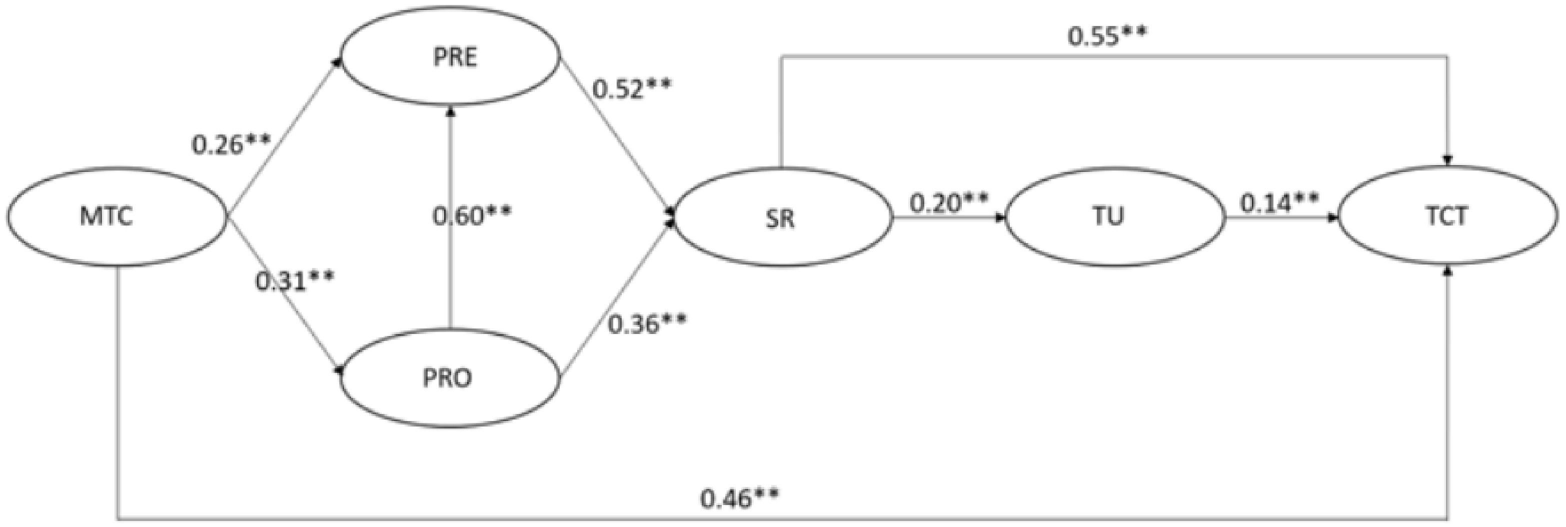
SEM:
SB χ2 = 113.5;df = 8; p < 0.001; SB χ2/df = 14.2; RMSEA = 0.45; NFI = 0.77;NNFI = 0.58; CFI = 0.78; IFI = 0.78; SRMR = 0.27; GFI = 0.63

*$p < 0.05$; ** $p < 0.01$*

Fig. 2. Structural equation model (standardised regression coefficients are shown; MTC = maintenance in transport companies; PRE = preventive behaviour; PRO = proactive behaviour; SR = small repairs; TCT = technical condition of the truck; TU = truck utilisation)

https://www.researchgate.net/publication/342143492_Maintenance_of_heavy_trucks_an_international_study_on_truck_drivers

Advantage of SEM: testing indirect relationships – modified model



Note: indicators are not shown to simplify the model.

*p < 0.05; ** p < 0.01

Fig. 3. Modified structural equation model (standardised regression coefficients are shown; MTC = maintenance in transport companies; PRE = preventive behaviour; PRO = proactive behaviour; SR = small repairs; TCT = technical condition of the truck; TU = truck utilisation)

SEM:
SB $\chi 2$ = 8.6; df = 6; p < 0.200;SB $\chi 2$/ df = 1.4; RMSEA = 0.083; NFI = 0.98; NNFI = 0.99; CFI =0.99; IFI = 0.99; SRMR = 0.04; GFI = 0.98)

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