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Business and Social Sciences

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CONFIRMATORY FACTOR ANALYSIS (CFA) STRUCTURAL EQUATION MODELING (SEM) ESSENTIALS

ANA ALINA TUDORAN

The purpose of this module is to provide a brief presentation of all one need to know about CFA & SEM before learning how apply SEM.

OUTLINE

PART I: FUNDAMENTALS

- What is SEM?
- Distinguishing characteristics of SEM
- Simple example
- Observable vs. Latent variables
- Exogenous vs. Endogenous variables
- Types of relationships in SEM
- Causality
- Path diagram
- Software

PART II: CFA

PART III: SEM

PART I:

FUNDAMENTALS

ANA ALINA TUDORAN

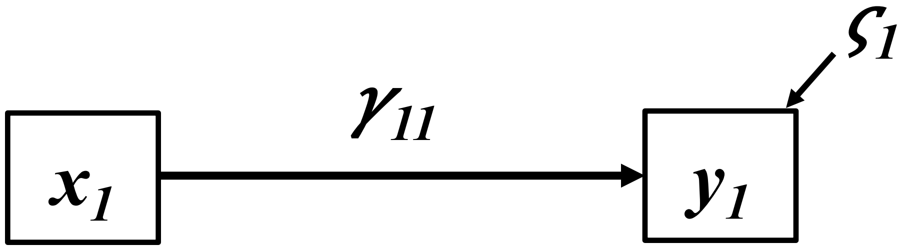
SEM essentials

1. SEM is a form of graphical modeling, and therefore a system in which relationships can be represented in either graphical or equational form.

equational form:

$$y_1 = \gamma_{11} x_1 + \zeta_1$$

graphical form:

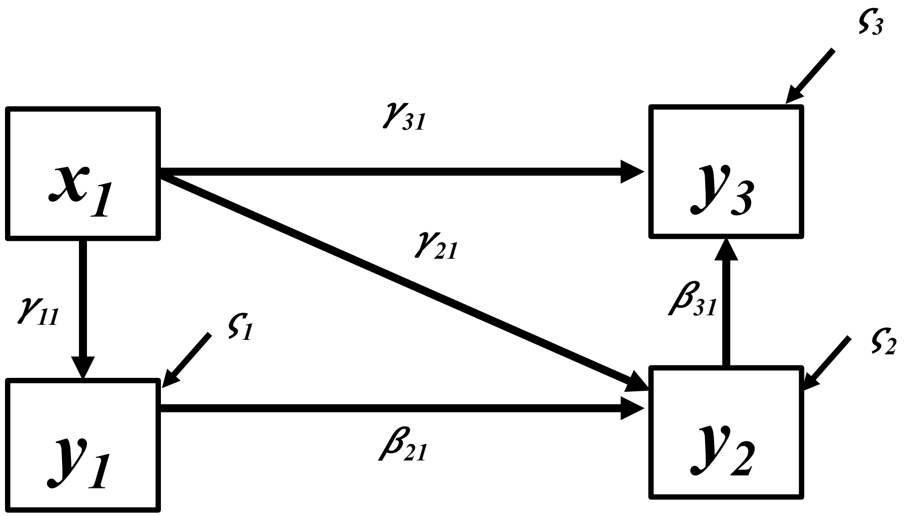


2. An equation is said to be <u>structural</u> is there exist sufficient evidence from all available sources to support the interpretation that x1 has a causal effect on y1

(adapted from Grace, 2014)

3. SEM can be defined as the use of two or more structural equations to represent complex hypotheses

Complex Hypotheses



Corresponding Equations

e.g.

$$y_1 = \gamma_{11} x_1 + \zeta_1$$
$$y_2 = \beta_{21} y_1 + \gamma_{21} x_1 + \zeta_2$$
$$y_3 = \beta_{31} y_2 + \gamma_{31} x_1 + \zeta_3$$

(adapted from Grace, 2014)

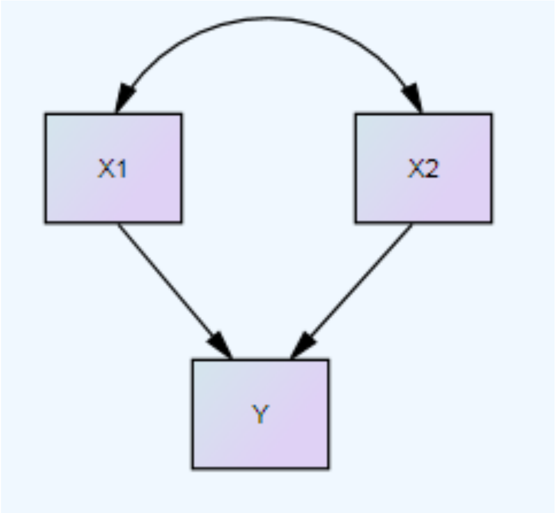
3. SEM is a process for testing a structural theory (Hair et al., 2010)

4. SEM is explicitly aimed at complex testing of theory, and superbly combines methods hitherto considered and used separately. It also makes possible the rigorous testing of theories that have until now been very difficult to test adequately.” (Kerlinger, 1977)

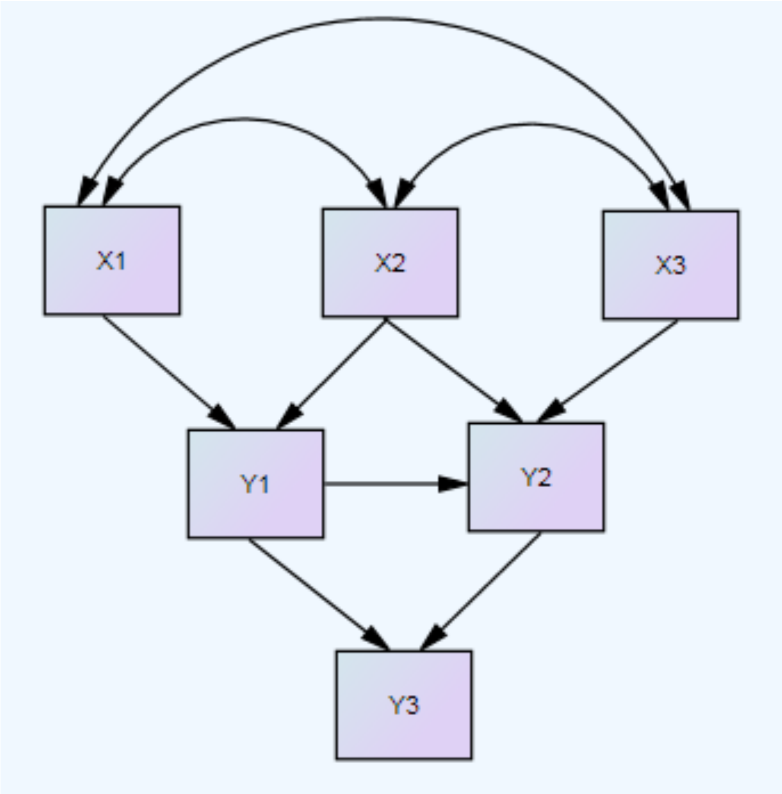
5. SEM is a framework for building and evaluating multivariate hypotheses about multiple processes. It is not depended on a particular estimation method. (Grace, 2014)

DISTINGUISHING FEATURES OF SEM

A. Ability to test complex models



Regression can examine only one dependent variable at once.



DISTINGUISHING FEATURES OF SEM

B. Multiple variables and constructs

- Variables are observable (from the questionnaire)
- Constructs are unobservable variables (abstract concepts)

The interrelationships in SEM are expressed in a series of equations, linking the variables and constructs

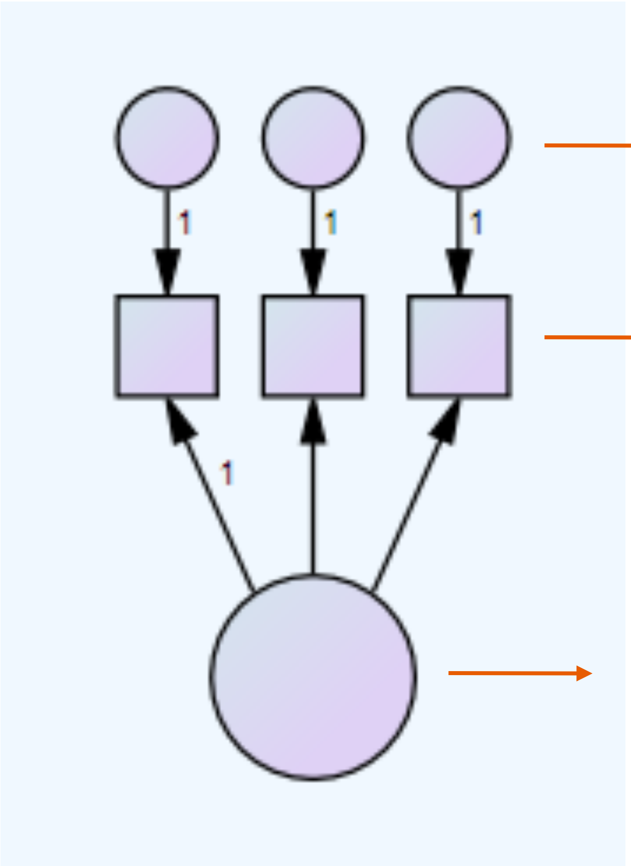
SIMPLE EXAMPLE

Constructs (not explicitly in the questionnaire)	**How employees feel about the supervisor** →	**Job satisfaction**
Observable variables (in the questionnaire)	(1) My supervisor recognizes my potential (1=disagree…7=agree) (2) My supervisor helps me solve problems at work (1=disagree…7=agree) (3) My supervisor understands the challenges of balancing work and home demands (1=disagree…7=agree) (4) …	(1) All things considered, I feel very satisfied when I think about my job (1=disagree …7=agree) (2) How satisfied are you with your current job? (1=unsatisfied …7=satisfied) (3) Indicate your satisfaction with your current job by placing the % in the blank (0% not at all, 100% highly satisfied) (4) …

WHY DO WE NEED SEVERAL OBSERVABLE VARIABLES TO ASSESS A CONSTRUCT ?

- The measurement error
  - some concepts have multi-facets
  - some may be difficult to express in only one statement
  - the individuals may interpret a question differently
  - the individuals may be unsure about how to respond to a particular question
- SEM intends to correct for this measurement error

GRAPHICAL REPRESENTATION OF OBSERVABLE AND LATENT VARIABLES

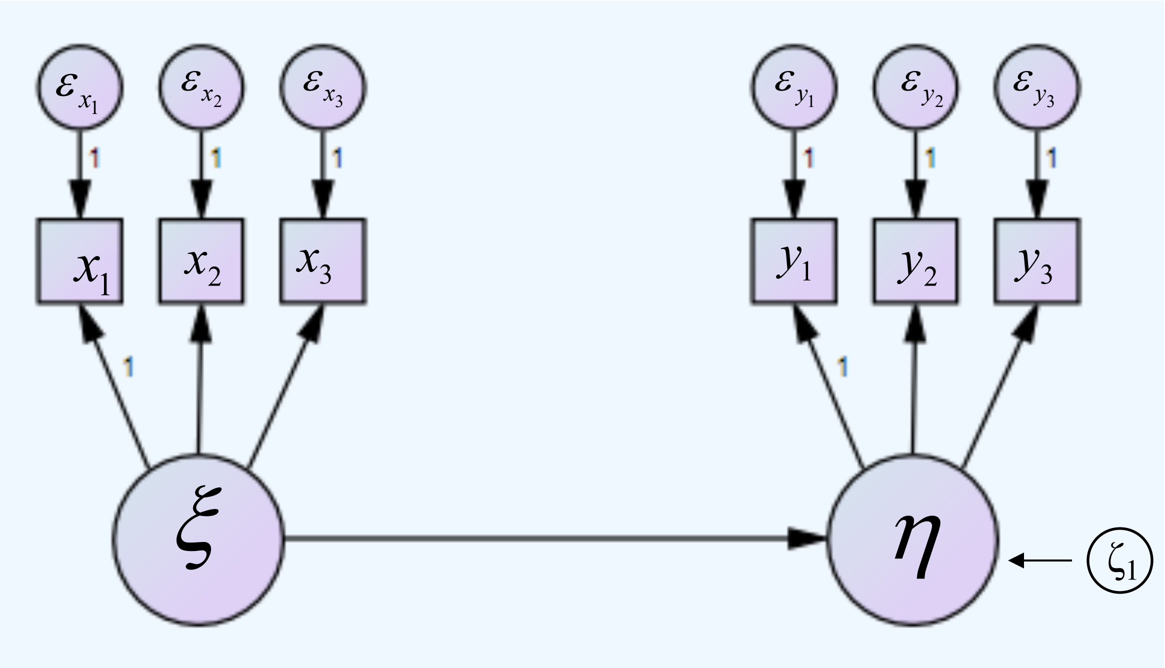


Errors of measurement

Observed variables/indicator/ manifest variables

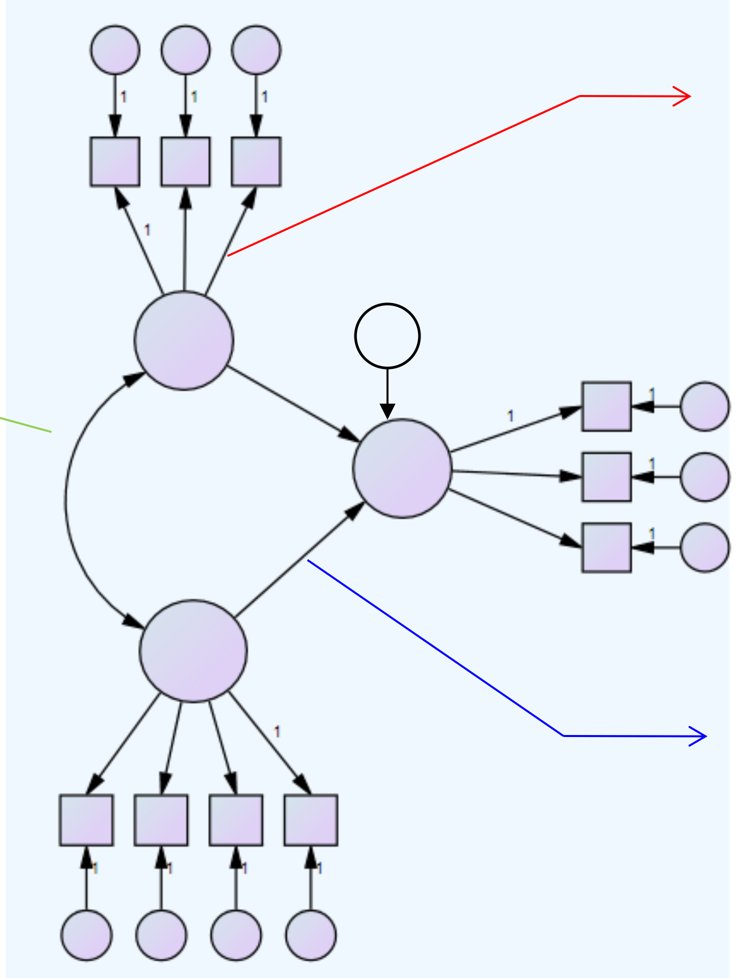
Construct/unobserved variable/latent variable/factor

EXOGENOUS AND ENDOGENOUS VARIABLES



- **Exogenous (independent) variables** send out only single-headed paths, but do not receive any
- **Endogenous (dependent) variables** have at least one single-headed path pointing toward them

TYPES OF RELATIONSHIPS INVOLVED IN SEM

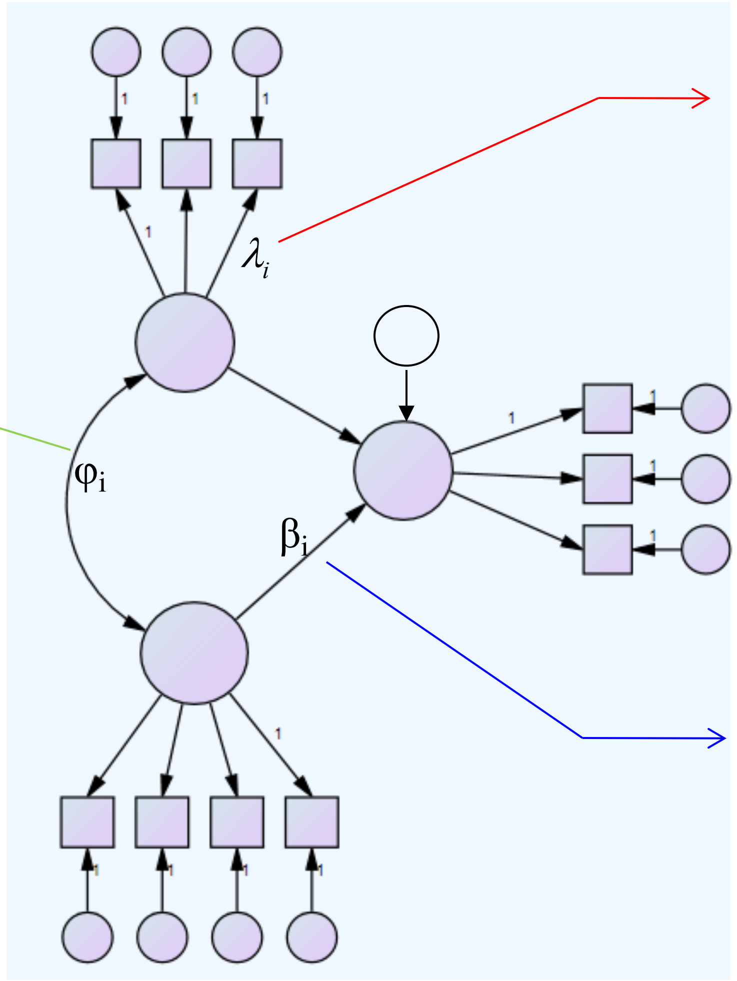


Measurement relationships between the construct and the observable variables

Correlation Relationships between two constructs

Structural Relationship between two constructs

TYPES OF ESTIMATES INVOLVED IN SEM



Loading estimate represents the relationship from constructs to variable (as in factor analysis)

Correlation coefficient

Path estimate represents the relationship between constructs (as does beta's in regression analysis)

ESTABLISHING CAUSATION

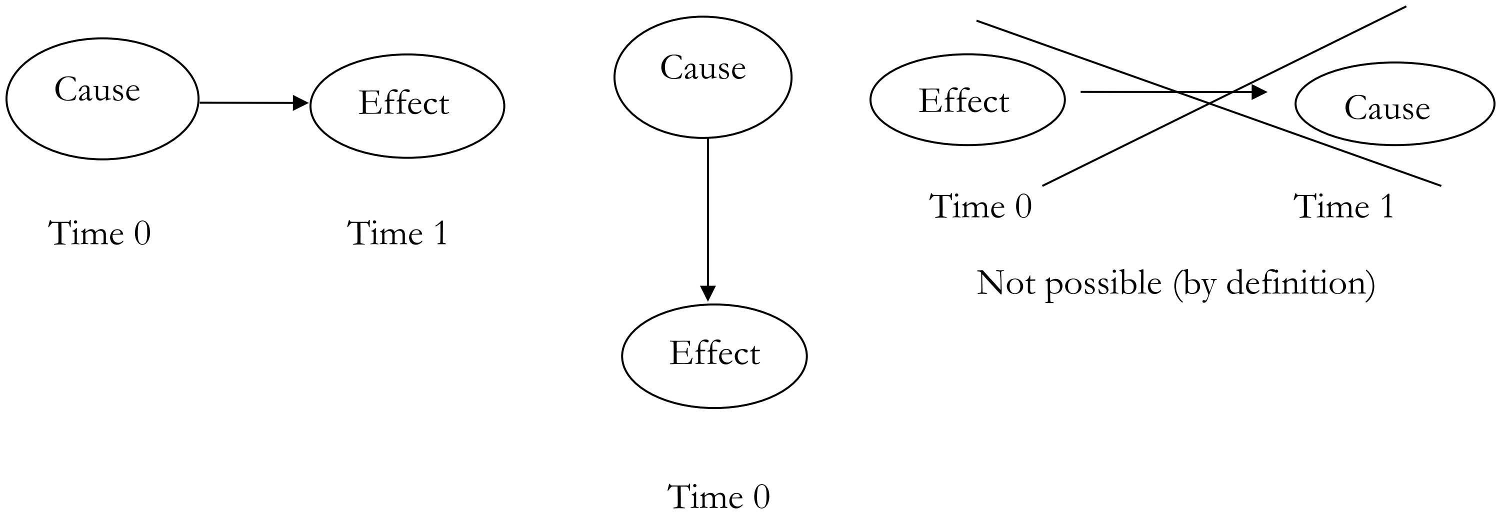
- Dependence relationships are sometimes, but not always, causal in nature
- SEM alone cannot establish causality
- SEM can however treat dependence relationships as causal if 4 types of evidence (necessary but not sufficient) are reflected in SEM:

  a. Covariation
  b. Sequence
  c. Nonspurious Covariance
  d. Theoretical Support

COVARIATION

- significant estimated paths in SEM provide evidence for covariation

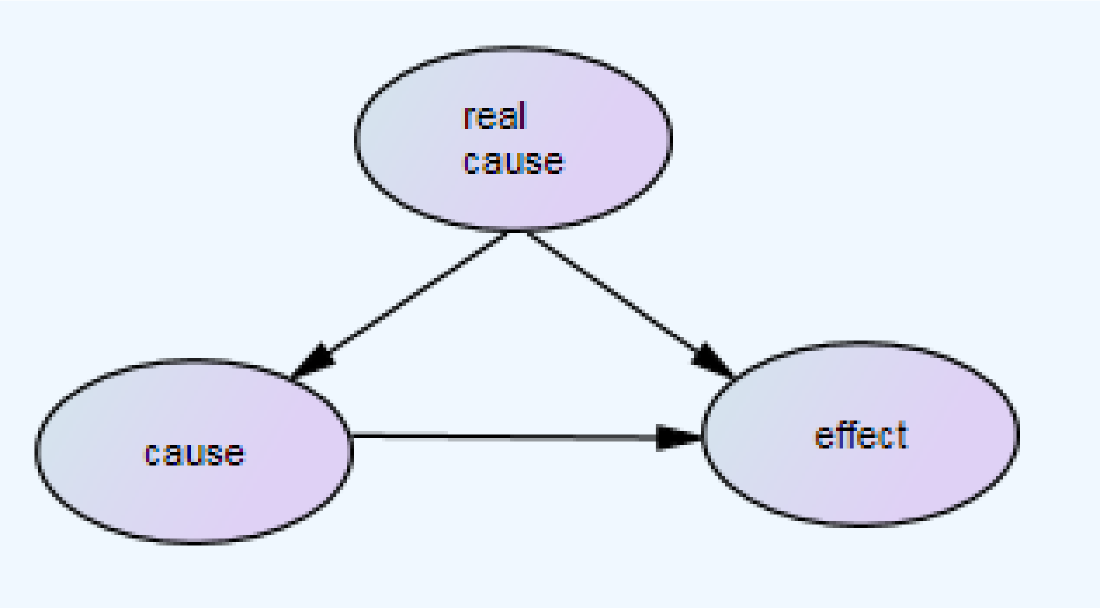
SEQUENCE



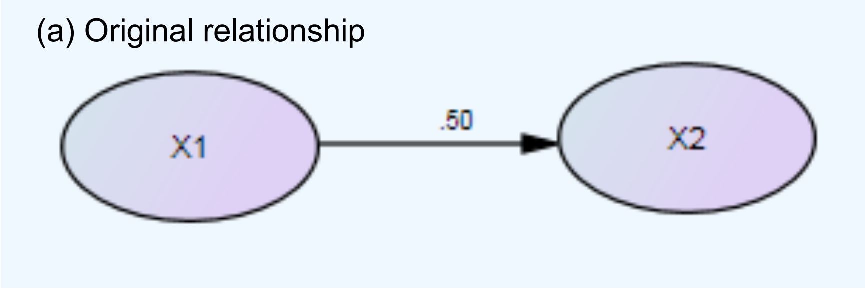
- SEM alone cannot provide this type of evidence without a research design that involves either an experimental or a longitudinal data

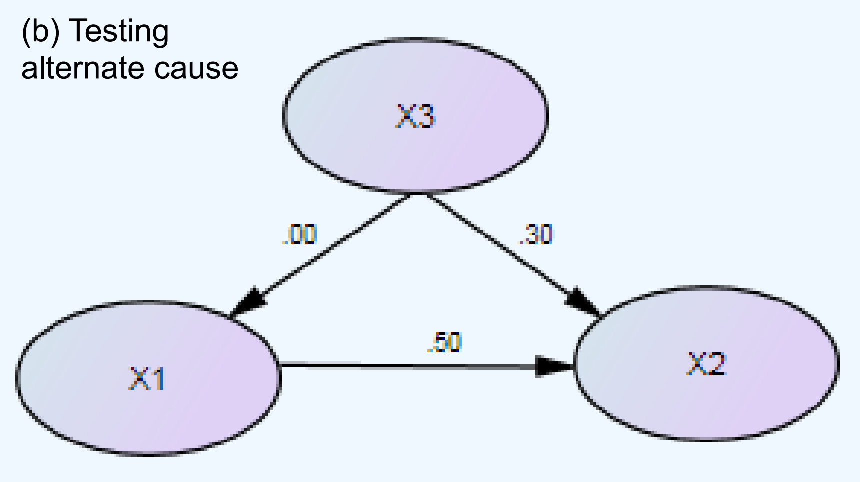
NONSPURIOUS COVARIANCE

Spurious covariance: another event (real cause) not included in the actual analysis actually explains both the cause and the effect



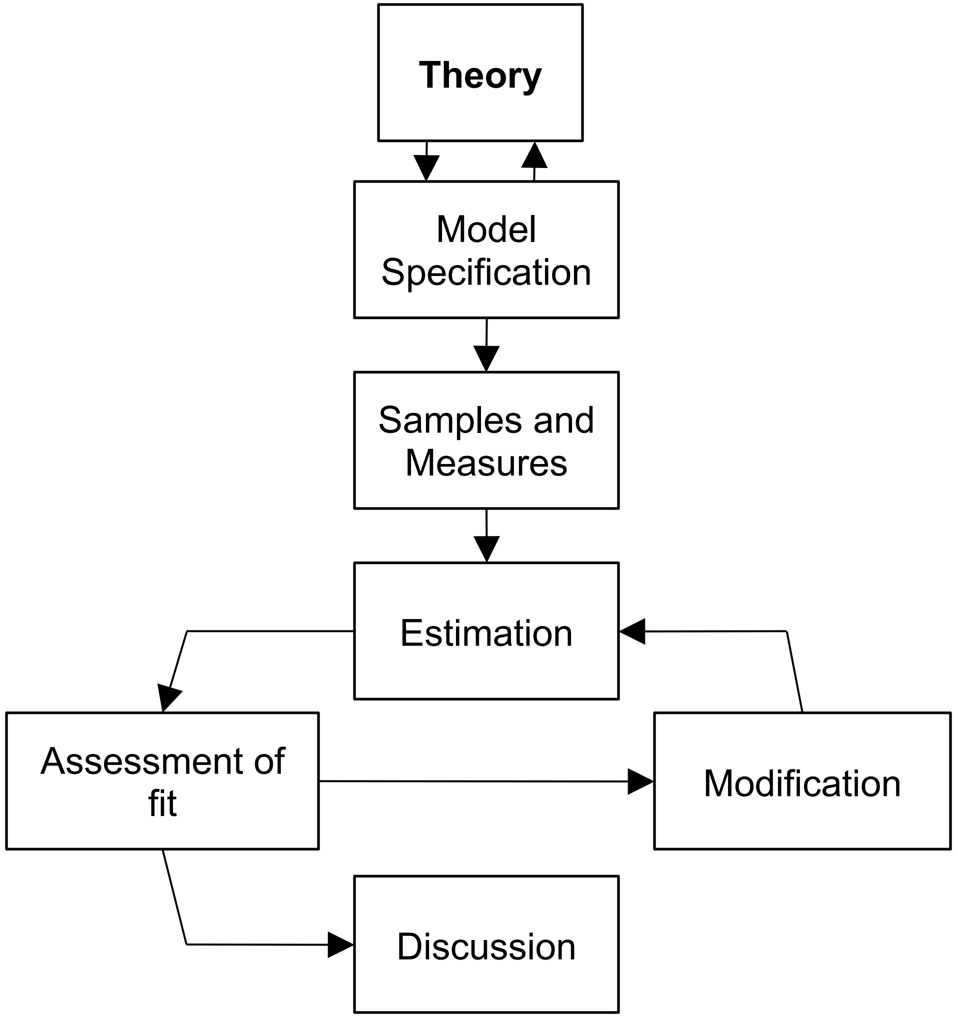
TEST FOR A NONSPURIOUS RELATIONSHIP (EXAMPLE)





Conclusion: Given the estimator of the original relationship remains unchanged, the original relationship is deemed nonspurious

THEORY SUPPORT



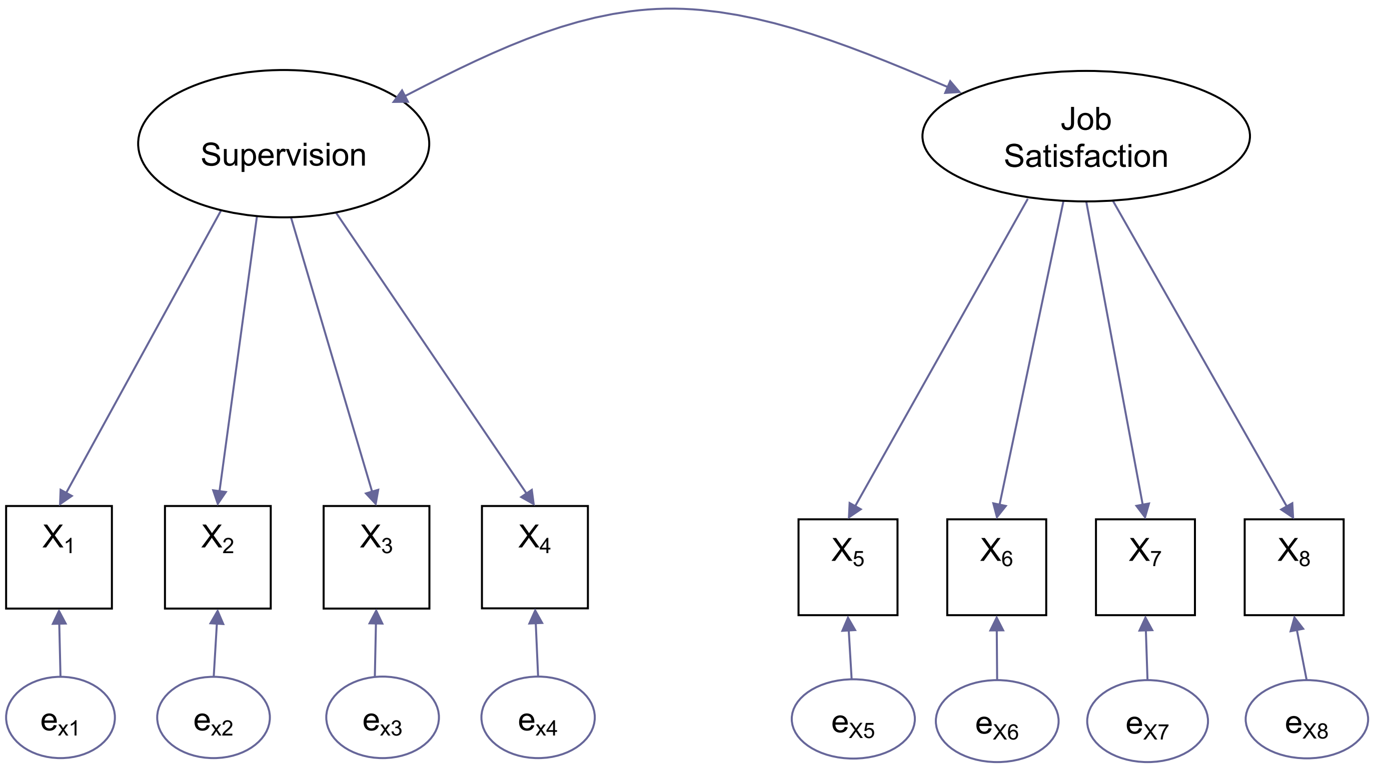
Source: Kaplan D. (2002). Structural Equation Modeling, *International Encyclopedia of the Social & Behavioral Sciences,* 15215 - 15222

MODELING STRATEGIES

- Confirmatory modeling strategy
- Competing models strategy
- Model development strategy

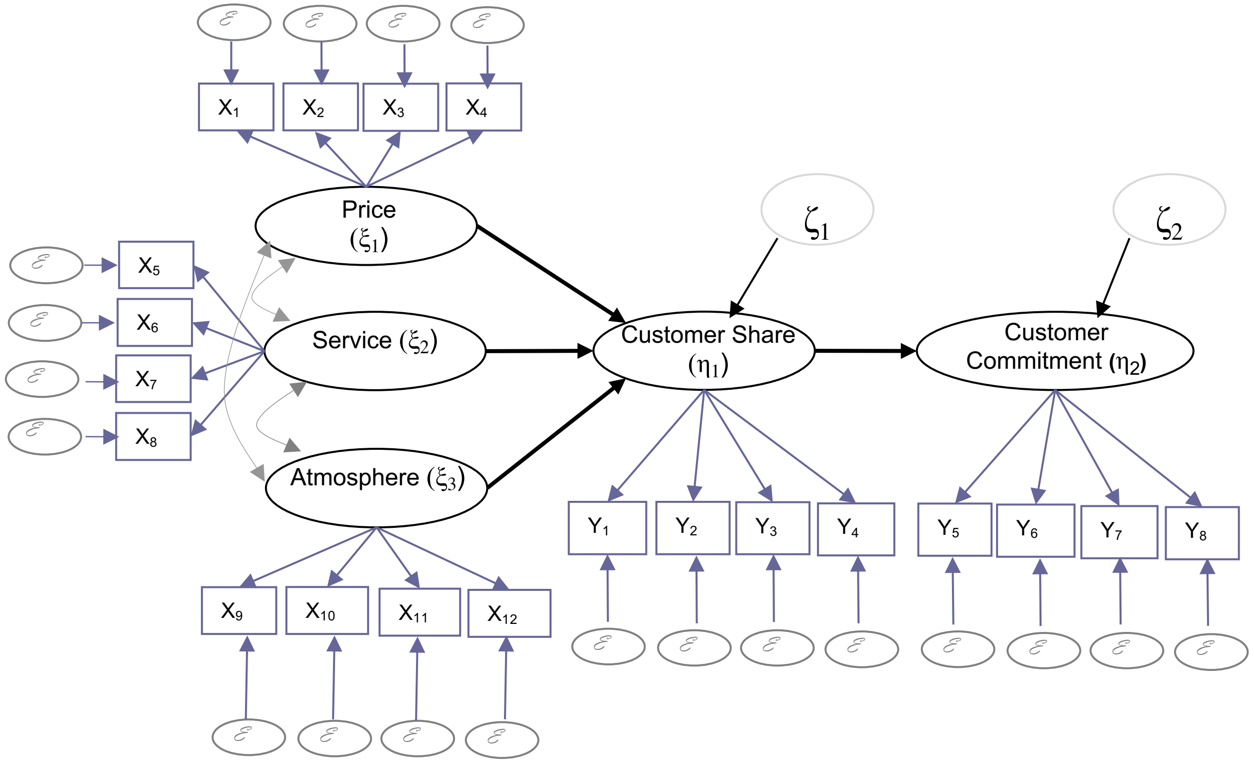
PATH DIAGRAM

EXAMPLE 1. A SIMPLE MEASUREMENT MODEL



PATH DIAGRAM

EXAMPLE 2: A MORE COMPLEX SEM MODEL



Note: Measurement model specifications are shown in gray. Structural model specifications are shown in black bold. Source: Hair et al. (2010)

SEM SOFTWARE

- LISREL (LInear Structural RELations) (http://www.ssicentral.com/)
  - PRELIS – preprocesses data
  - SIMPLIS – allows models to be specified with equations
  - LISREL – specifies models with matrices
- AMOS– Analysis of MOment Structures (IBM)
- EQS – (EQuationS)
- MPLUS (http://www.statmodel.com/)
- SAS – CALIS
- STATA
- R, package lavaan

REVIEW

- SEM framework
- The distinguishing characteristics of SEM
- Introductory example
- Observable vs. Latent variables
- Exogenous vs. Endogenous variables
- Types of relationships in SEM
- Causality
- Path diagram
- Software applications

PART II:
CONFIRMATORY FACTOR ANALYSIS (CFA)

ANA ALINA TUDORAN

The purpose of this sub-section is to provide you with knowledge on how the constructs are measured and represented in SEM. The measurement model in SEM is often referred to as Confirmatory Factor Analysis (CFA)

OUTLINE

1. EFA versus CFA
2. CFA stages
   - Stage 1: Defining Individual Constructs
   - Stage 2: Developing the Measurement Model
   - Stage 3: Designing a Study to Produce Empirical Results
   - Stage 4: Assessing the Measurement Model Fit

Remember EFA

- EFA explores the data and provides the researcher with information about how many factors are needed to best represent the data

- With EFA, all measured variables are related to <u>every</u> factor by a factor loading estimate. Simple structure results when each measured variable loads <u>highly</u> on only one factor and has smaller loadings on other factors (i.e., loadings < .40)

- The distinctive feature of EFA is that the factors are derived from statistical results, not from theory, and so they can only be named after the factor analysis is performed

- EFA can be conducted without knowing how many factors really exist or which variables belong with which constructs

CFA

- CFA is similar to Exploratory FA in some respects, but philosophically it is quite different

- In CFA the factors are derived from theory (not from statistical results as in EFA)

- Thus, with CFA, the researcher must specify *a-priori* both the number of factors that exist within a set of variables and which variables correspond (load highly) to each factor

- So, the researcher must be able to assign variables to factors *before* running the model

- CFI is then applied *to confirm* whether the pattern of factor loadings represents the actual data

STAGE 1: DEFINING INDIVIDUAL CONSTRUCTS

Operationalizing the Constructs

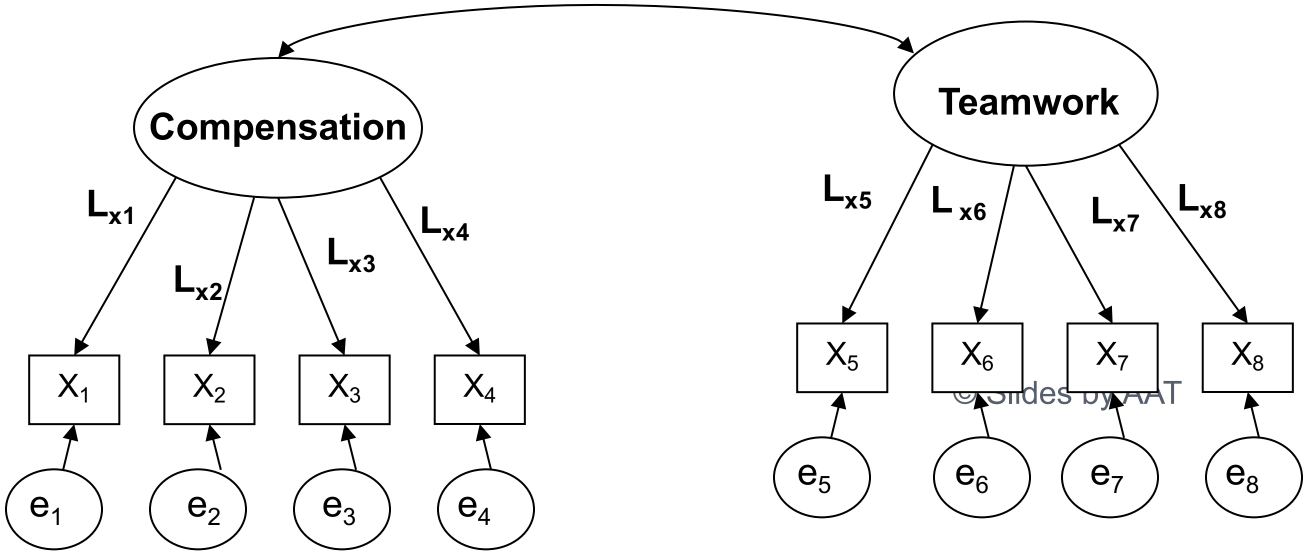
- Scales from Prior Research
- New Scale Development

Pretesting

STAGE 2: DEVELOPING THE MEASUREMENT MODEL

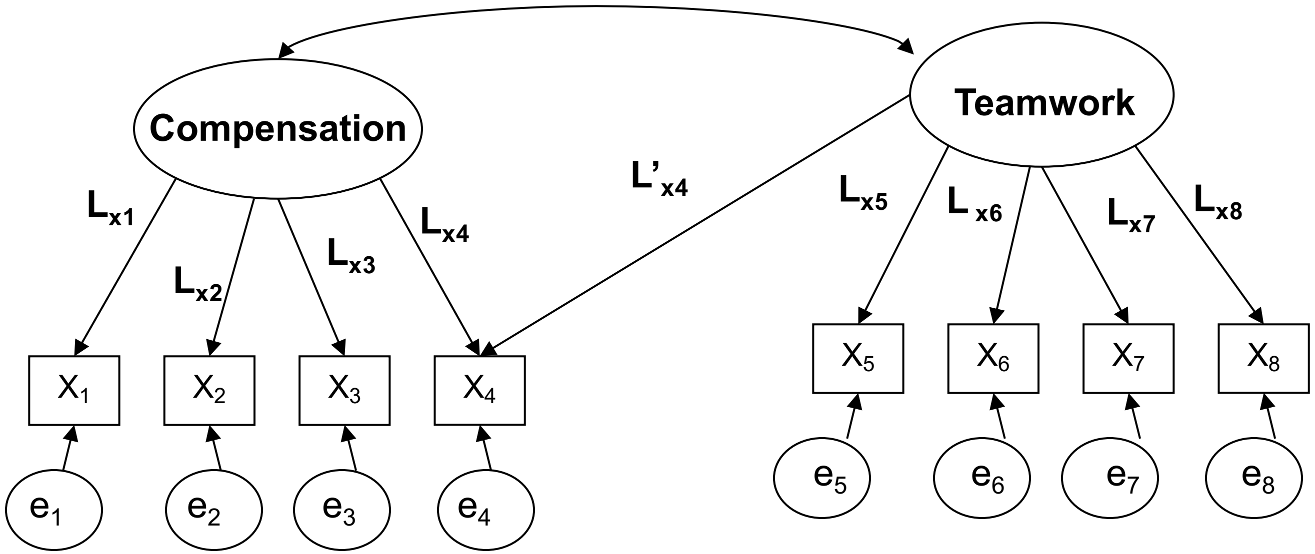
- Unidimensionality (no cross loadings)
- Uncorrelated measurement errors
- Congeneric measurement model
- # of indicators per construct
- Identification issues

UNIDIMENSIONALITY - DESIRABLE



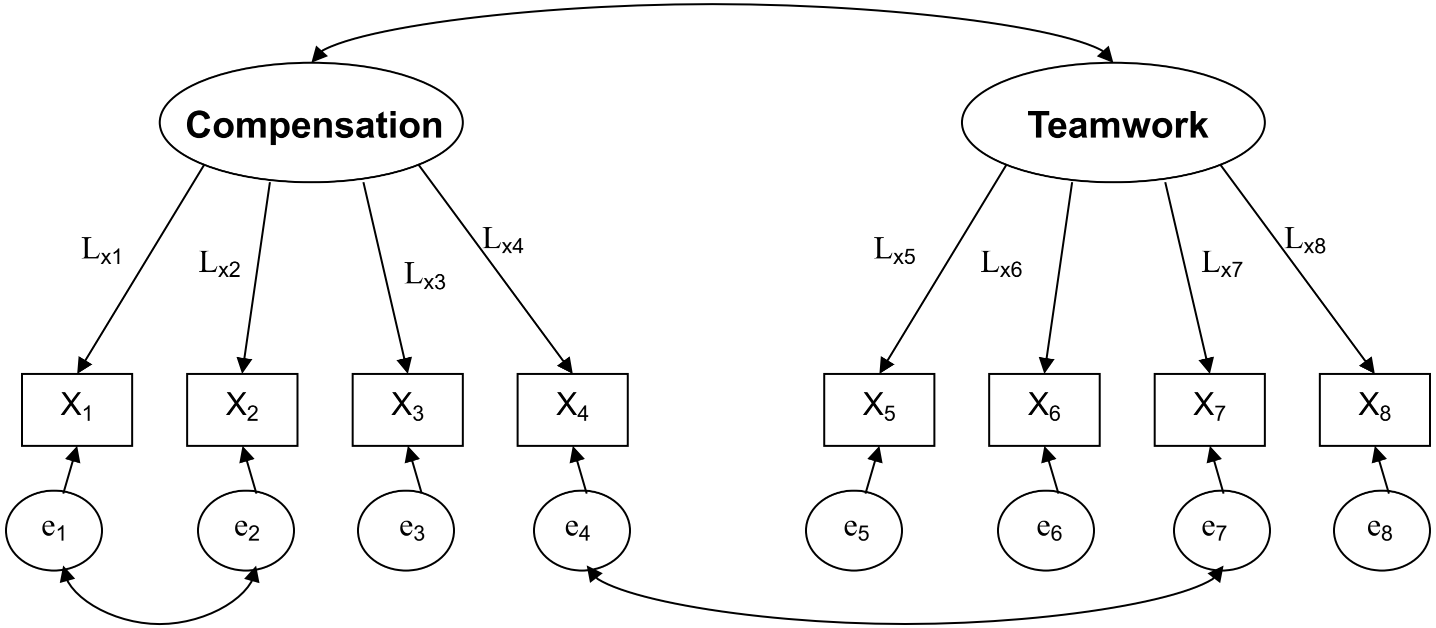
- Each measured variable is related to exactly one construct

NO-UNIDIMENSIONALITY - NOT DESIRABLE



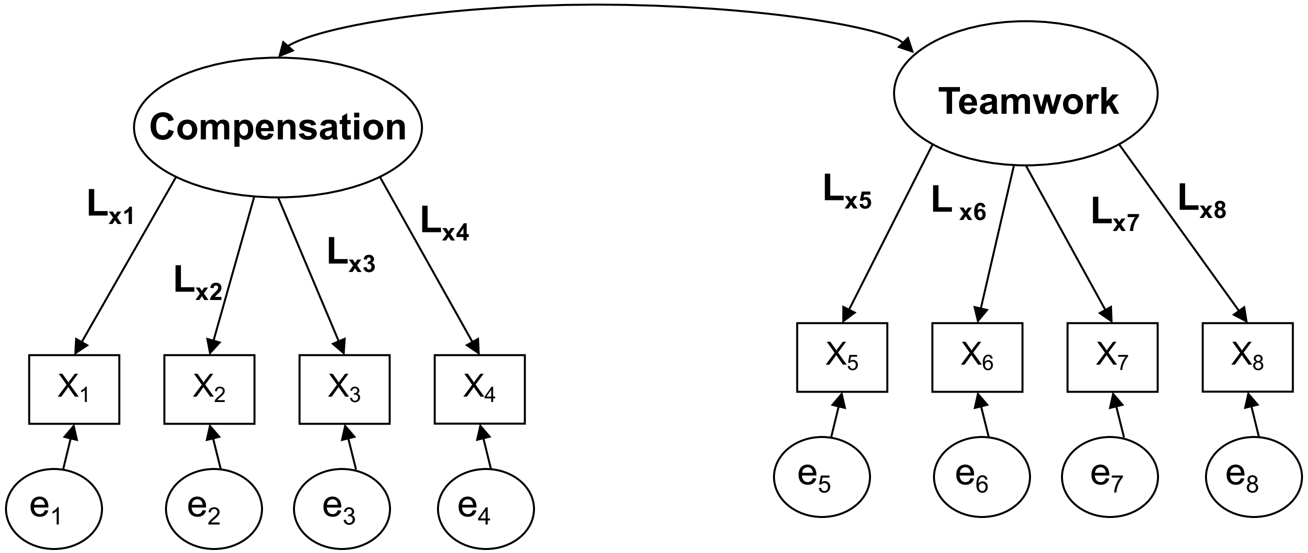
- Note that X_4 is determined by both constructs
- As a rule, we should not allow cross-loadings, because this is evidence of a lack of construct validity

CORRELATED ERROR VARIANCE – NOT DESIRABLE



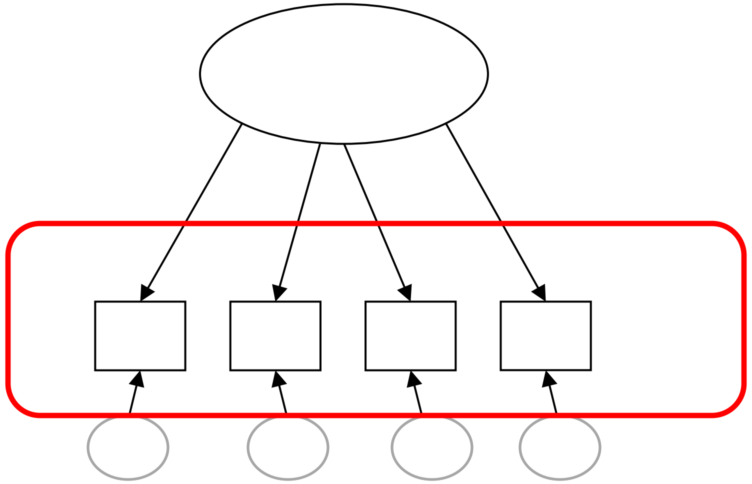
- As a rule, we should not allow correlated error variances, because this is evidence of a lack of construct validity

A CONGENERIC CFA MODEL = GOOD MEASUREMENT PRACTICE



- Each measured variable is related to exactly one construct and there are no covariances between or within construct error variances

NUMBER OF ITEMS PER CONSTRUCT



- Good practice dictates a minimum of 3-4 items per construct

IDENTIFICATION

- Enough information should exist *to identify* a solution
- Information is provided by the *sample covariance matrix*

$$1/2\left[p(p+1)\right]$$ = number of unique variance/covariances for p observable variables

- One parameter can be estimated for each unique variance and covariance in the sample covariance matrix

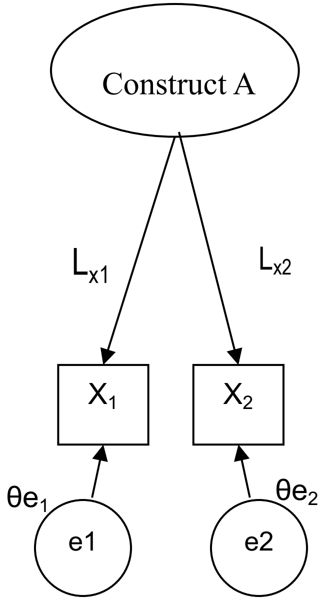
LEVELS OF IDENTIFICATION

- Unidentified
- Just-identified
- Overidentified

UNIDENTIFIED

Number of parameters to be estimated > Number of unique indicator variances/covariances (*df* is negative)

EXAMPLE



Symmetric Covariance Matrix:

	X1	X2
X1	**var(1)**	cov(1,2)
X2	**cov(2,1)**	**var(2)**

3 unique variance-covariance terms (in bold)

Loading Estimates

L_{x1}
L_{x2}

Error Variance Estimates

θe_1
θe_2

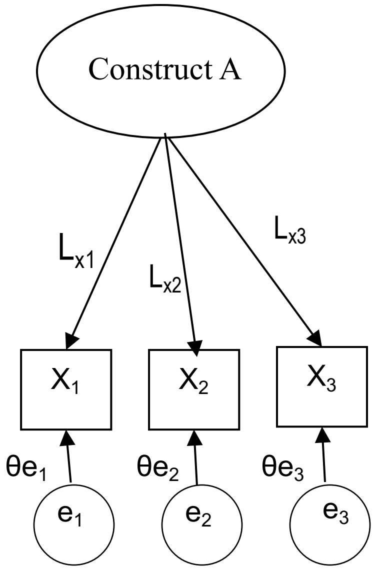
4 parameters to be estimated

Note 1: In the above example the construct variance is fixed. If one of the loadings is fixed, the construct variance would be estimated

JUST-IDENTIFIED (SATURATED)

Number of parameters to be estimated = Number of unique indicator variances/covariances (*df* = 0)

EXAMPLE



<u>Symmetric Covariance Matrix</u>:

	X1	X2	X3
X1	**var(1)**	cov(1,2)	cov(1,3)
X2	**cov(2,1)**	**var(2)**	cov(2,3)
x3	**cov(3,1)**	**(cov 3,2)**	**var(3)**

6 unique variance-covariance terms (in bold)

<u>Loading Estimates</u>	**<u>Error Variance Estimates</u>**
L_{x1}	θe_1
L_{x2}	θe_2
L_{x3}	θe_3

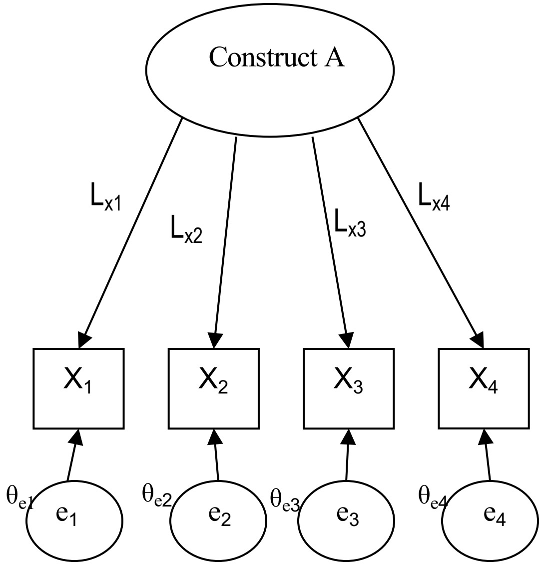
6 parameters to be estimated

See previous Note 1

OVERIDENTIFIED – OUR OBJECTIVE

Number of parameters to be estimated < Number of unique indicator variances/covariances (*df* is positive)

EXAMPLE



Model Fit:
χ^2 = 14.9
df = 2 (that is, 10-8)
p = .001
CFI = .99

Symmetric Covariance Matrix:

	X1	X2	X3	X4
X1	2.01			
X2	1.43	2.01		
X3	1.31	1.56	2.24	
X4	1.36	1.54	1.57	2.00

10 unique variance-covariance terms

Loading Estimates	Error Variance Estimates
L_{x1}=0.78	θe_1=0.39
L_{x2}=0.89	θe_2=0.21
L_{x3}=0.83	θe_3=0.31
L_{x4}=0.87	θe_4=0.24

8 parameters to be estimated

See previous Note 1

STAGE 3: DESIGNING A STUDY TO PRODUCE EMPIRICAL RESULTS

Research design

- Measurement scales
- Type of data: covariances ,correlations, raw data
- Missing data
- Sample size

Model estimation

- Model structure
- Estimation techniques

TYPE OF MEASUREMENT SCALES

- Ordinal or ratio scales
- The indicators need not be of the same scale type
- Normalization can be applied, *but it is not compulsory*

DATA

- Covariance/correlation matrix
- Raw data

SAMPLE SIZE ISSUES

1. The minimum sample size for a particular SEM model depends on several factors:

   - Variable normality
   - Estimation technique
   - Model complexity
   - Amount of missing data
   - Communalities of the items

Some guidelines:

- SEM models containing 5 or fewer constructs, each with more than 3 items (observed variables), and with high item communalities (.6 or higher), can be adequately estimated with samples as small as 100-150.
- When the number of factors is larger than 6, some of which have fewer than 3 measured items as indicators, and multiple low communalities are present, sample size requirements may exceed 500.
- The sample size must be sufficient to allow the model to run, but more important, it must adequately represent the population

DEVIATION FROM NORMALITY

If deviation from multivariate normality, then:

- Increase sample size (min.15 respondents/parameter estimated)
- Alternatives:

Robust Methods:
Satorra, A., & Bentler, P. M. (1988). Scaling corrections for chi-square statistics in covariance structure analysis. 1988 Proceedings of the Business and Economics Statistics Section of the American Statistical Association, 308-313.

Bootstrap Methods:
Bollen, K. A., & Stine, R. A. (1993). Bootstrapping goodness-of-fit measures in structural equation models. In K. A. Bollen and J. S. Long (Eds.) Testing structural equation models. Newbury Park, CA: Sage Publications.

SUGGESTIONS FOR MINIMUM SAMPLE SIZE

Minimum sample size	# of constructs	# items per construct	Communalities
100	$\leq$ 5	> 3	$\geq$ 0.6
150	$\leq$ 7	$\geq$ 3	0.50[i]
300	$\leq$ 7	< 3[i]	< 0.45[i]
500	>7	< 3[i]	0.45 - 0.50[i]

[i] For some of the constructs. Source: Hair et al. (2010)

MODEL STRUCTURE

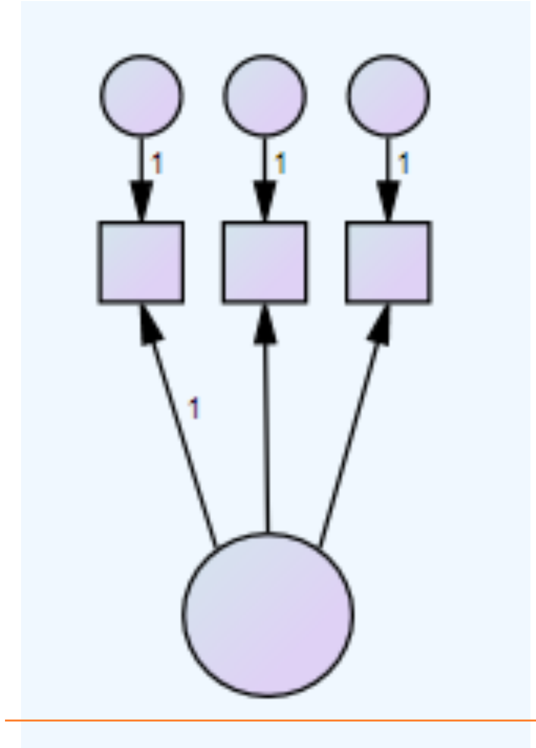
- Specifying the model structure

  Syntax, matrix notation, graphical interface

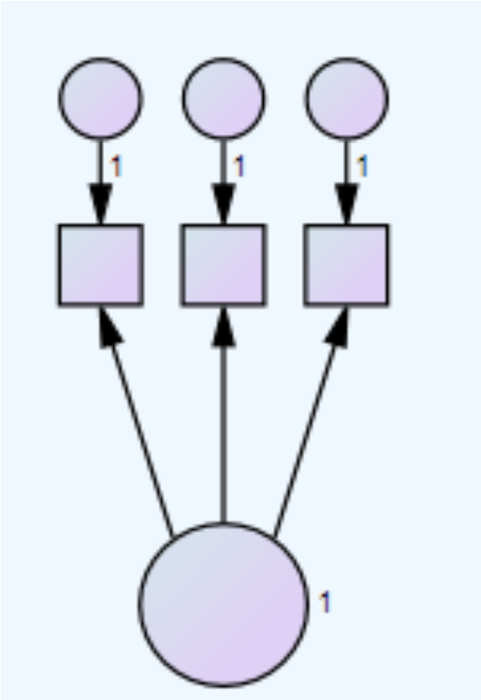
- Specifying model parameters to be estimated

  Free versus fixed parameter

SETTING THE SCALE (TWO WAYS)



Fix one of the factor loadings on each construct to a specific value (usually to 1)



Fix the value of the variance of the construct (usually to 1)

ESTIMATION TECHNIQUE

- GLS (Generalized Least Squares)
- ULS (Unweighted Least Squares)
- WLS (Weighted Least Squares)
- ML (Maximum Likelihood)
- ADF (Asymptotically Distribution Free)
- EDT (Elliptical Distribution Theory)

RECOGNIZING IDENTIFICATION PROBLEMS

- Very large standard errors
- Imposibility to invert the information matrix (no solution can be found)
- Negative error variances (Heywood cases)
- Standardized factor loadings and correlations outside the range [-1, +1]

STAGE 4: ASSESSING MEASUREMENT MODEL VALIDITY

- Model fit
- Construct validity
- Model diagnostics
  - Standardized residuals
  - Modification indices
  - Specification searches (i.e. post hoc revisions to a fitted model as determined by the modification indices)

MODEL FIT

1. Three general groups of fit indices:

- Absolute indices (X^2, RMSEA, SRMR)
- Incremental indices (NFI, CFI, TLI, IFI)
- Parsimony indices (AGFI, PNFI, AIC, CAIC)

2. Choosing among fit indices:

- CFI, TLI, IFI and RMSEA are the most frequently reported
- AIC and CAIC are helpful to use when comparing models that are NOT NESTED

CHI-STATISTIC (CMIN) (A NON-SIGNIFICANT VALUE IS DESIRED)

$$\chi^2 = f_{\min} \cdot (N-1)$$

$$df = \frac{p(p+1)}{2} - number\ of\ parameters$$

$f_{\min}$	The minimum function estimated based on the difference between the observed and the estimated covariance matrix
N	The number of individuals
p	The number of measured variables

ROOT MEAN SQUARE ERROR OF APPROXIMATION (RMSEA) (DESIRED VALUE < .08)

$$RMSEA = \sqrt{\frac{\hat{F}_0}{df_{model}}}$$

Where $$\hat{F}_0 = \frac{\chi^2_{model} - df_{model}}{N}$$

Notes: values larger than 0.10 are indicative of poor fit (Browne and Cudeck, 1993). Hu and Bentler (1999) found that in small samples the RMSEA overrejected the true model. Therefore, this index may be less preferable with small samples

ROOT MEAN SQUARE RESIDUAL (RMSR)(DESIRED VALUE < .08)

$$RMSR = \left[2 \sum_{i=1}^{q} \sum_{j=1}^{i} \frac{(s_{ij} - \hat{\sigma}_{ij})^2}{q(q+1)} \right]^{1/2}$$

NORMED FIT INDEX (NFI) (DESIRED VALUE > .95)

$$NFI = \frac{\chi^2_{indep} - \chi^2_{model}}{\chi^2_{indep}}$$

INCREMENTAL FIT INDEX (IFI) (DESIRED VALUE > .95)

$$IFI = \frac{\chi^2_{indep} - \chi^2_{model}}{\chi^2_{indep} - df_{model}}$$

TUCKER-LEWIS INDEX (TLI) (DESIRED VALUE > .95)

$$TLI = \frac{\left[\left(\frac{\chi^2_{indep}}{df_{indep}}\right) - \left(\frac{\chi^2_{model}}{df_{model}}\right)\right]}{\left[\left(\frac{\chi^2_{indep}}{df_{indep}}\right) - 1\right]}$$

COMPARATIVE FIT INDEX (CFI) (DESIRED VALUE > .95)

$$CFI = 1 - \frac{\chi^2_{\mathrm{model}} - df_{\mathrm{model}}}{\chi^2_{indep} - df_{indep}}$$

PARSIMONY FIT INDICES (I)

ADJUSTED GOODNESS OF FIT INDEX (AGFI)

$$AGFI = 1 - \frac{n(n+1)}{2df}(1 - GFI)$$

PARSIMONY NORMED FIT INDEX (PNFI)

$$PNFI = \frac{df_{\min}}{df_0} \cdot \frac{(f_0 - f_{\min)}}{f_0}$$

PARSIMONY FIT INDICES (II)

AKAIKE INFORMATION CRITERION (AIC)

$$AIC = \chi^2_{model} + 2(number\ of\ parameters)$$

CONSISTENT AKAIKE INFORMATION CRITERION(CAIC)

$$CAIC = \chi^2_{model} + (1 + \ln N)(number\ of\ parameters)$$

CONSTRUCT VALIDITY

Construct validity: is the extent to which the measured items *actually* reflect the theoretical latent construct they are designed to measure

1. Convergent validity
   - Factor loadings
   - Average variance extracted (AVE)
   - Construct reliability (CR)

2. Discriminant validity
3. Nomological validity
4. Face validity

FACTOR LOADINGS

- Standardized factor loadings should be significant and at least |.50| (ideally |.70|)
- Standardized factor loadings below |.50| are candidates for deletion

ITEM RELIABILITY

- In a congeneric model, the square of factor loading is equal to **square multiple correlation** (known as, item reliability, communality or variance extracted)
- Item reliability should be at least .50

AVERAGE VARIANCE EXTRACTED (SHOULD BE >.50)

$$AVE = \frac{\sum_{i=1}^{n} L_i^2}{n}$$

where Li represent the standardized factor loadings and n is the number of items

- AVE should be computed for each factor

CONSTRUCT RELIABILITY (SHOULD BE >.70)

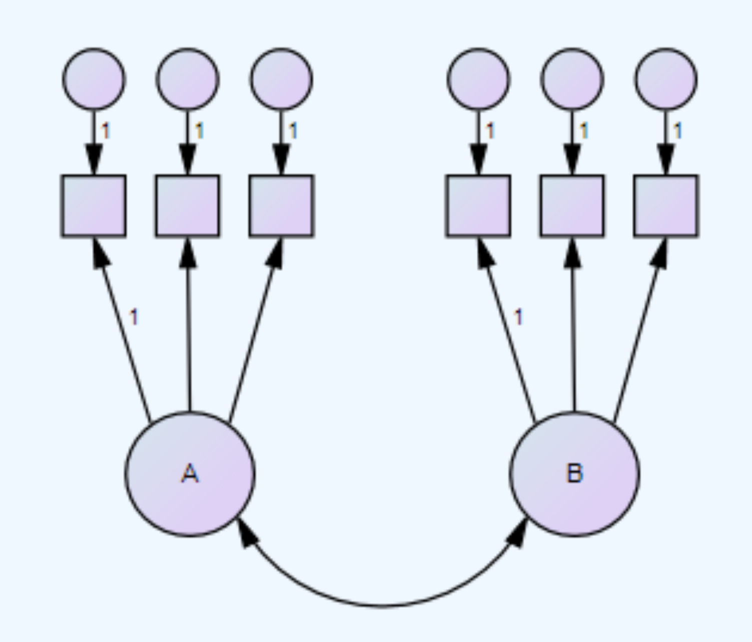
$$CR = \frac{\left(\sum_{i=1}^{n} L_i\right)^2}{\left(\sum_{i=1}^{n} L_i\right)^2 + \left(\sum_{i=1}^{n} e_i\right)}$$

where Li represent the standardized factor loadings , n is the number of items, and ei is the error variance terms for a construct

- CR should be computed for each factor

DISCRIMINANT VALIDITY (I)

- Is the extent to which a construct is truly distinct from other constructs. AVE estimates for two factors should be greater than the square of the correlation between the two factors to provide evidence of discriminant validity

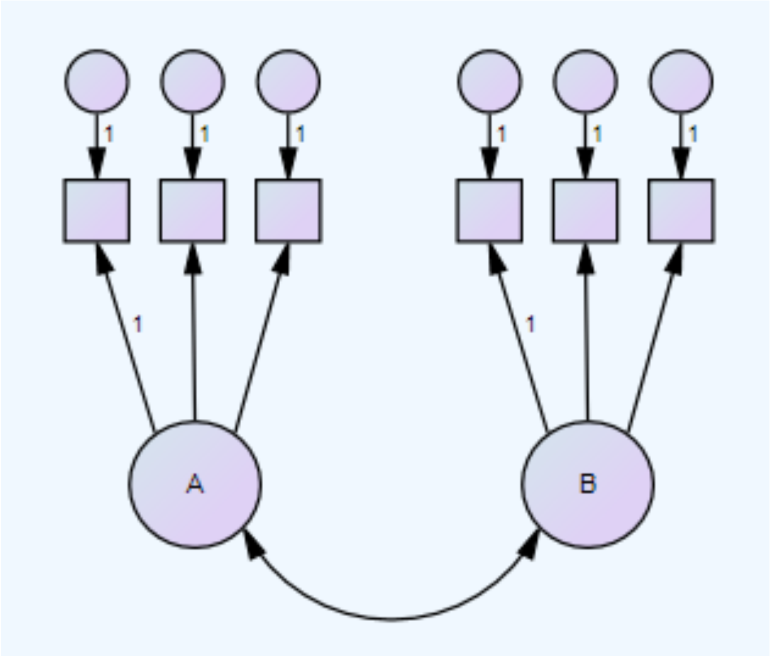


$$AVE_A > corr_{AB}^2$$

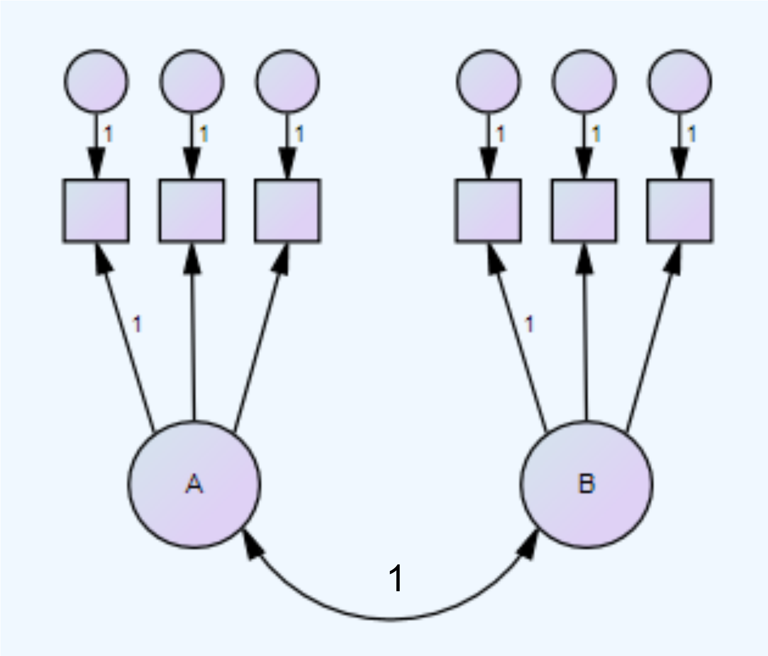
$$AVE_B > corr_{AB}^2$$

DISCRIMINANT VALIDITY (II)

Another possibility to test discriminant validity is to fix the relationships between any to constructs to 1 and then compare the fit of this model to the fit of the original model



Original model



FACE VALIDITY

- Face validity refers to the items content and meaning
- Face validity should be established prior to any theoretical testing

NOMOLOGICAL VALIDITY

- Nomological validity refers to whether the correlations among constructs in a measurement theory makes sense
- Matrix of construct correlations can be useful in this assessment

STANDARDIZED RESIDUALS

- Standardized residuals < |2.5| do not suggest a problem
- Standardized residuals > |4.0| suggest a potentially unacceptable degree of error that may call for the deletion of an offending item
- Standardized residuals between |2.5| and |4.0| deserve some attention, but may not suggest any changes to the model if no other problems are associated with those items

MODIFICATION INDICES

- A modification index is calculated for every possible relationship or path that is *not* estimated (i.e. fixed) in the model
- The index would show how much the overall model *chi-square* value would be reduced by estimating the specific path
- A value of aprox. *4.0 or greater* suggest that the fit can be improved significantly by freeing the corresponding path
- The researcher should use the modification indices only if the corresponding path that can *theoretically* be justified

DOES THE MEASUREMENT MODEL FIT WELL TO THE DATA?

No – then refine measures or design a new study

Yes – proceed to test the structural model with stages 5 & 6

APPLICATION CFA

CONTEXT

HBAT is a company who employs thousands of workers in different operations around the world. Like many firms, one of their biggest management problems is attracting and keeping productive employees. The cost to replace and retrain employees is high. Yet the average new person hired works for HBAT less than three years. In most jobs, the first year is not productive, meaning the employee is not contributing as much as the costs associated with employing him/her. After the first year, most employees become productive. HBAT management would like to understand the factors that contribute to employee retention A better understanding can be obtained if the key constructs are measured accurately. Thus, HBAT is interested in developing and testing a measurement model made up of constructs that influence employees' attitudes and opinions about remaining with HBAT

HBAT initiated a research project to study the employee retention/turnover problem. Preliminary research discovered that a large number of employees are exploring job options with the intention of leaving HBAT should an acceptable offer be obtained from another firm. Based on published literature and some preliminary interviews with employees, an employee retention/turnover study was designed focusing on 5 key constructs. The 5 constructs are defined as:

Job Satisfaction (JS) – beliefs about one's job situation
Organizational Commitment (OC) – the extent to which an employee identifies and feels part of HBAT
Staying Intentions (SI) – the extent to which an employee intends to continue working for HBAT and is not participating in activities that make quitting more likely
Environmental Perceptions (EP) – beliefs an employee has about their day-to-day, physical working conditions
Employee Attitudes toward Coworkers (AC) – attitudes an employee has toward the coworkers he/she interacts with on a regular basis

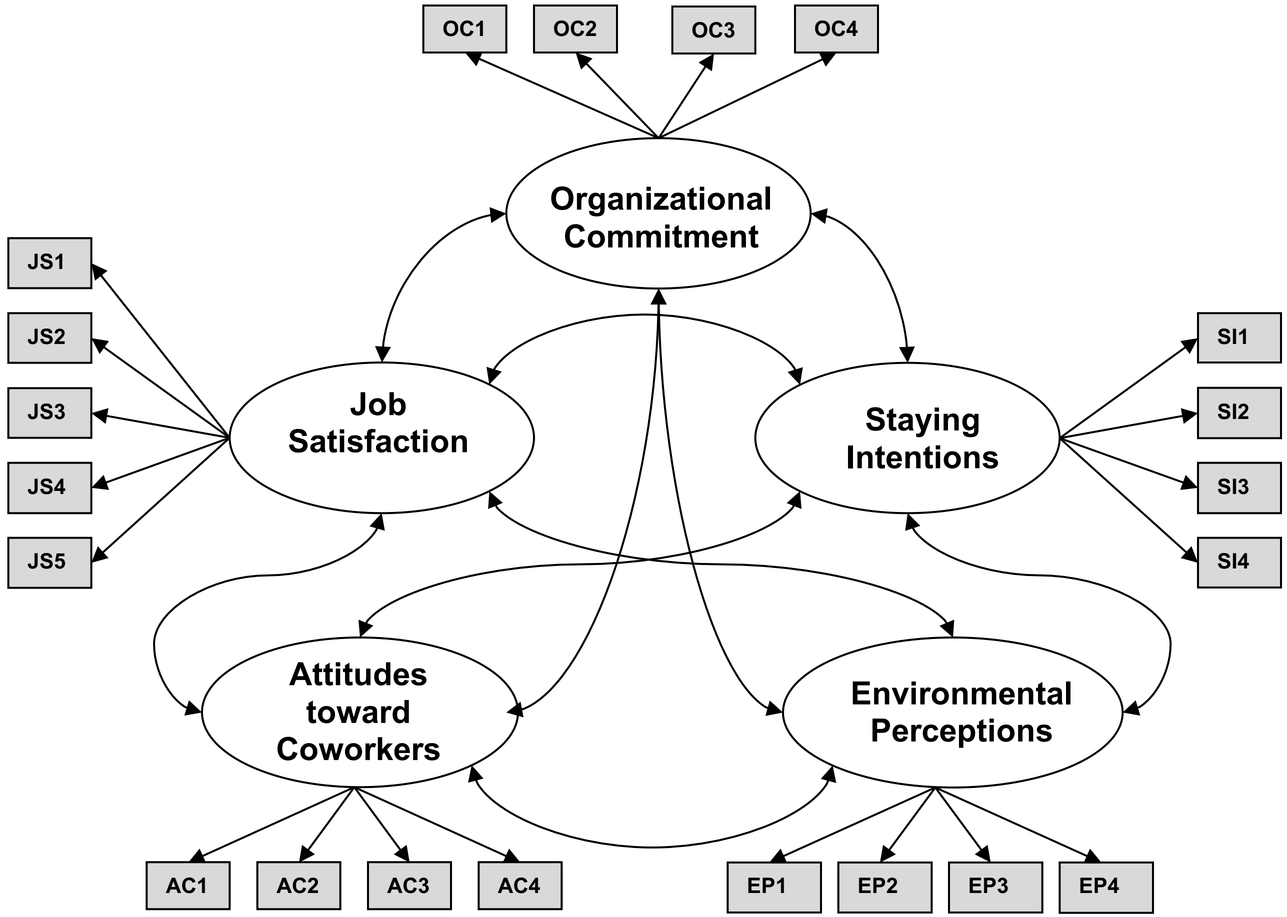
DATABASE VARIABLES

	Variable Description		Variable Type
JS1	I feel satisfied when I think about my job. (0-10, Agree-Disagree)		Metric
OC1	My work at HBAT give me a sense of accomplishment (0-10, Agree-Disagree)		Metric
OC2	I am willing to put in a great deal of effort . . to help HBAT (0-10, Agree-Disagree)		Metric
EP1	I am . . . comfortable with my . . . work environment at HBAT (0-10, Agree-Disagree)		Metric
OC3	I have a sense of loyalty to HBAT (0-10, Agree-Disagree)		Metric
OC4	I am proud to tell others that I work for HBAT (0-10, Agree-Disagree)		Metric
EP2	The place I work in is designed to help me do my job better (0-10, Agree-Disagree)		Metric
EP3	There are few obstacles to make me less productive in my workplace (0-10, Ag-Disa)		Metric
AC1	How happy are you with the work of your coworkers? (5-pt. Happy-Unhappy)		Metric
EP4	What term best describes your work environment? (7-pt. Hectic-Soothing?)		Metric
JS2	When you think of your job, how satisfied do you feel? (7-pt)		Metric
JS3	How satisfied are you with your current job with HBAT? (7-pt)		Metric
AC2	How do you feel about your coworkers? (7-pt. Unfavorable-Favorable)		Metric
SI1	I am not actively searching for another job. (5-pt. Agree/Disagree)		Metric
JS4	How satisfied are you with HBAT as an employer? (5-pt. Not vs. Very Much)		Metric
SI2	I seldom look at the job listings on Monster.com. (5-pt. Agree-Disagree)		Metric
JS5	Please indicate your satisfaction with your current job. (0-100% Satisfied)		Metric
AC3	How often do you do things with your coworkers on your days off? (5-pt. Never-Often)		Metric
SI3	I have no interest in searching for a job in the next year. (5-pt. Agree-Disagree)		Metric
AC4	Generally, how similar are your coworkers to you? (6-pt. Different-Similar)		Metric
SI4	How likely is it that you will be working at HBAT one year from today? (5-pt)		Metric
X22	Your work type – full time or part time?	(0 = Full Time/1 = Part Time)	Nonmetric
X23	Your gender – male or female?	(0 = Female/1 = Male)	Nonmetric
X24	Your geographic location – in USA or outside USA?	(0 = Outside/1 = USA)	Nonmetric
X25	Your age in years ___?		Metric
X26	How long have you worked for HBAT – years and months?		Metric
X27	Performance – as measured by their supervisor		Metric

CONSTRUCTS AND ITEMS

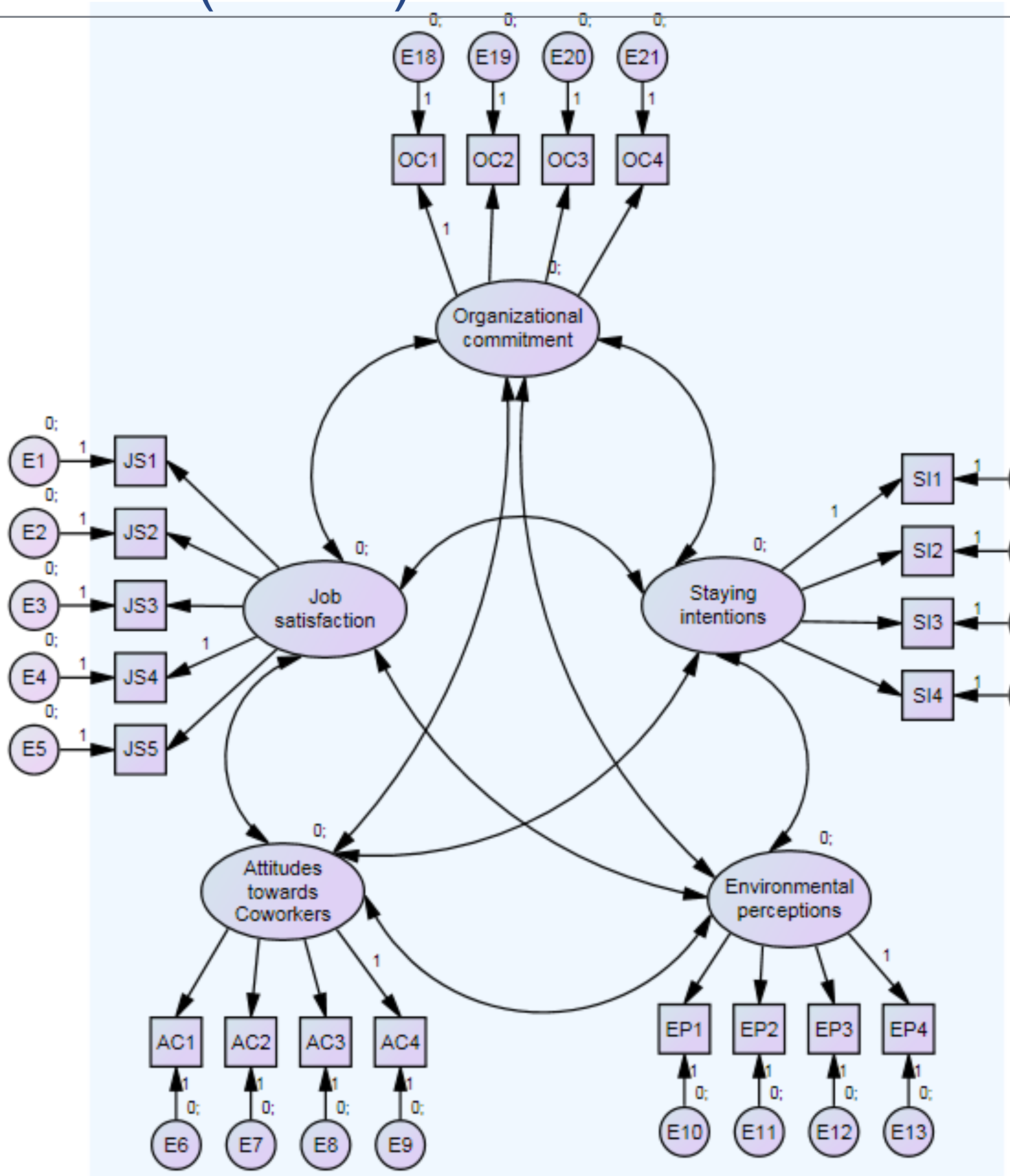
Organizational Commitment
OC1 = My work at HBAT gives me a sense of accomplishment.
OC2 = I am willing to put in a great deal of effort beyond that normally expected to help HBAT be successful.
OC3 = I have a sense of loyalty to HBAT.
OC4 = I am proud to tell others that I work for HBAT.
Staying Intentions
SI1 = I am not actively searching for another job.
SI2 = I seldom look at the job listings on monster.com.
SI3 = I have no interest in searching for a job in the next year.
SI4 = How likely is it that you will be working at HBAT one year from today?
Attitudes Towards Co-Workers
AC1 = How happy are you with the work of your coworkers?
AC2 = How do you feel about your coworkers?
AC3 = How often do you do things with your coworkers on your days off?
AC4 = Generally, how similar are your coworkers to you?
Environmental Perceptions
EP1 = I am very comfortable with my physical work environment at HBAT.
EP2 = The place I work in is designed to help me do my job better.
EP3 = There are few obstacles to make me less productive in my workplace.
EP4 = What term best describes your work environment at HBAT?
Job Satisfaction
JS1 = All things considered, I feel very satisfied when I think about my job.
JS2 = When you think of your job, how satisfied do you feel?
JS3 = How satisfied are you with your current job at HBAT?
JS4 = How satisfied are you with HBAT as an employer?
JS5 = Please indicate your satisfaction with your current job with HBAT by placing a percentage in the blank, with 0% = not satisfied at all and 100% = highly satisfied.

MEASUREMENT THEORY FOR HBAT EMPLOYEES



Note: Measured variables (21) are shown as a box with labels corresponding to those shown in the HBAT questionnaire. Latent constructs (5) are an oval. Each measured variable has an error term (not shown in the figure). The error terms are not allowed to relate to any other measured variables, and the model is congeneric. Two headed connections indicate covariance between constructs. One headed connectors indicate a causal path from a construct to an indicator (measured) variable. Source: Hair et al. (2010)

PATH DIAGRAM (AMOS)



MEASUREMENT MODEL IDENTIFICATION

Number of distinct sample moments: 231

Var, cov $$\frac{p(p+1)}{2}=\frac{21*22}{2}=231$$

Number of distinct parameters to be estimated: 52

Regression coefficients (factor loadings): (21-5) = 16
Unobserved variables Variances and Covariances: 26 + 10 = 36

Degrees of freedom: (231-52) = 179 => overidentified

MODEL FIT (AMOS)

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	52	240,14	179	,00	1,34
Saturated model	231	,00	0		
Independence model	21	4441,44	210	,00	21,15

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,95	,94	,99	,98	,99
Saturated model	1,00		1,00		1,00
Independence model	,00	,00	,00	,00	,00

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	,85	,81	,84
Saturated model	,00	,00	,00
Independence model	1,00	,00	,00

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	,41	,95	,93	,73
Saturated model	,00	1,00		
Independence model	2,36	,34	,28	,31

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	,03	,02	,04	1,00
Independence model	,22	,22	,23	,00

AIC

Model	AIC	BCC	BIC	CAIC
Default model	344,14	350,21	551,69	603,69
Saturated model	462,00	488,96	1384,03	1615,03
Independence model	4483,44	4485,89	4567,26	4588,26

Default model
Standardized RMR = ,0357

VALIDITY

TO BE CHECKED:

- FACE VALIDITY (established earlier based on the content of the corresponding items)
- CONVERGENT
- DISCRIMINANT
- NOMOLOGICAL

CONVERGENT VALIDITY – FACTOR LOADINGS SIGNIFICANCE

Estimates (Group number 1 - Default model)

Scalar Estimates (Group number 1 - Default model)

Maximum Likelihood Estimates

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
OC1	<---	Organizational_commitment	1,00				
OC2	<---	Organizational_commitment	1,31	,11	12,19	***	
OC3	<---	Organizational_commitment	,78	,08	10,31	***	
OC4	<---	Organizational_commitment	1,17	,10	11,95	***	
SI1	<---	Staying_intentions	1,00				
SI2	<---	Staying_intentions	1,07	,05	19,54	***	
SI3	<---	Staying_intentions	1,07	,07	16,03	***	
SI4	<---	Staying_intentions	1,17	,06	19,21	***	
JS4	<---	Job_satisfaction	1,00				
JS3	<---	Job_satisfaction	,99	,08	12,01	***	
JS2	<---	Job_satisfaction	1,13	,09	13,04	***	
JS1	<---	Job_satisfaction	1,10	,08	12,94	***	
AC4	<---	Attitudes_towards_Coworkers	1,00				
AC3	<---	Attitudes_towards_Coworkers	,90	,05	18,65	***	
AC2	<---	Attitudes_towards_Coworkers	1,08	,06	18,18	***	
AC1	<---	Attitudes_towards_Coworkers	,87	,05	18,23	***	
EP4	<---	Environmental_perceptions	1,00				
EP3	<---	Environmental_perceptions	,90	,05	16,50	***	
EP2	<---	Environmental_perceptions	1,13	,07	17,09	***	
EP1	<---	Environmental_perceptions	1,09	,08	14,32	***	
JS5	<---	Job_satisfaction	16,69	1,30	12,81	***	

CONVERGENT VALIDITY – STANDARDIZED FACTOR LOADINGS VALUES

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
OC1	<---	Organizational_commitment	,58
OC2	<---	Organizational_commitment	,89
OC3	<---	Organizational_commitment	,66
OC4	<---	Organizational_commitment	,84
SI1	<---	Staying_intentions	,81
SI2	<---	Staying_intentions	,86
SI3	<---	Staying_intentions	,74
SI4	<---	Staying_intentions	,85
JS4	<---	Job_satisfaction	,70
JS3	<---	Job_satisfaction	,68
JS2	<---	Job_satisfaction	,75
JS1	<---	Job_satisfaction	,74
AC4	<---	Attitudes_towards_Coworkers	,82
AC3	<---	Attitudes_towards_Coworkers	,84
AC2	<---	Attitudes_towards_Coworkers	,82
AC1	<---	Attitudes_towards_Coworkers	,82
EP4	<---	Environmental_perceptions	,82
EP3	<---	Environmental_perceptions	,78
EP2	<---	Environmental_perceptions	,80
EP1	<---	Environmental_perceptions	,69
JS5	<---	Job_satisfaction	,73

CONVERGENT VALIDITY – AVE & CR

Construct	JS	OC	SI	EP	AC
Average Variance Extracted	51.9%	56.3%	66.7%	60.3%	68.1%
Construct Reliability	0.84	0.83	0.89	0.86	0.89

Note: Based on the previous formulas of AVE and CR. See Excel file for calculations.

Conclusion:

The evidence supports the convergent validity of the measurement model

DISCRIMINANT VALIDITY

Correlations

			Est.	$Est.^2$	P
Organizational_commitment	<-->	Job_satisfaction	,21	,04	***
Organizational_commitment	<-->	Staying_intentions	,55	,30	***
Staying_intentions	<-->	Job_satisfaction	,23	,05	***
Environmental_perceptions	<-->	Staying_intentions	,56	,31	***
Job_satisfaction	<-->	Attitudes_towards_Coworkers	,05	,00	,39
Environmental_perceptions	<-->	Attitudes_towards_Coworkers	,26	,06	***
Staying_intentions	<-->	Attitudes_towards_Coworkers	,31	,10	***
Environmental_perceptions	<-->	Job_satisfaction	,24	,06	***
Organizational_commitment	<-->	Attitudes_towards_Coworkers	,31	,10	***
Environmental_perceptions	<-->	Organizational_commitment	,50	,25	***

All AVE estimates for HBAT model are greater than the corresponding interconstruct squared correlations. Therefore there are no problems with discriminant validity for the our model.

NOMOLOGICAL VALIDITY

Covariances

			Estimate	S.E.	C.R.	P
Organizational_commitment	<-->	Job_satisfaction	,28	,08	3,38	***
Organizational_commitment	<-->	Staying_intentions	,57	,08	7,18	***
Staying_intentions	<-->	Job_satisfaction	,15	,04	3,81	***
Environmental_perceptions	<-->	Staying_intentions	,46	,06	8,17	***
Job_satisfaction	<-->	Attitudes_towards_Coworkers	,06	,07	,87	,39
Environmental_perceptions	<-->	Attitudes_towards_Coworkers	,39	,09	4,31	***
Staying_intentions	<-->	Attitudes_towards_Coworkers	,29	,06	5,15	***
Environmental_perceptions	<-->	Job_satisfaction	,25	,06	3,92	***
Organizational_commitment	<-->	Attitudes_towards_Coworkers	,59	,12	4,83	***
Environmental_perceptions	<-->	Organizational_commitment	,85	,13	6,71	***

The covariance between the Job satisfaction and the Attitudes towards co-workers is positive but not significant p=0.39. Because the other covariances are consistent, this one exception is not a major concern

MODEL DIAGNOSTIC

TO BE CHECKED:

- LOADINGS ESTIMATES
- STANDARDIZED RESIDUALS
- MODIFICATION INDICES

STD. LOADINGS ESTIMATES

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
OC1	<---	Organizational_commitment	,58
OC2	<---	Organizational_commitment	,89
OC3	<---	Organizational_commitment	,66
OC4	<---	Organizational_commitment	,84
SI1	<---	Staying_intentions	,81
SI2	<---	Staying_intentions	,86
SI3	<---	Staying_intentions	,74
SI4	<---	Staying_intentions	,85
JS4	<---	Job_satisfaction	,70
JS3	<---	Job_satisfaction	,68
JS2	<---	Job_satisfaction	,75
JS1	<---	Job_satisfaction	,74
AC4	<---	Attitudes_towards_Coworkers	,82
AC3	<---	Attitudes_towards_Coworkers	,84
AC2	<---	Attitudes_towards_Coworkers	,82
AC1	<---	Attitudes_towards_Coworkers	,82
EP4	<---	Environmental_perceptions	,82
EP3	<---	Environmental_perceptions	,78
EP2	<---	Environmental_perceptions	,80
EP1	<---	Environmental_perceptions	,69
JS5	<---	Job_satisfaction	,73

As noticed before, only one estimate – 0.58 associated with OC1 – fell below the ideal loading cutoff of 0.7. It did not appear to be causing problems (the model fit remained high) so we decided to keep this item in the model.

STANDARDIZED RESIDUALS

Standardized Residual Covariances (Group number 1 - Default model)

	JS5	EP1	EP2	EP3	EP4	AC1	AC2	AC3	AC4	JS1	JS2	JS3	JS4	SI4	SI3	SI2	SI1	OC4	OC3	OC2	OC1
JS5	,00																				
EP1	,74	,00																			
EP2	-,03	,71	,00																		
EP3	1,42	-,61	-,20	,00																	
EP4	,34	-,23	-,38	,67	,00																
AC1	1,61	-,12	,06	,42	-,59	,00															
AC2	,97	,26	,12	-,66	-,21	-,02	,00														
AC3	,43	,15	-,18	-,32	-,87	,05	,06	,00													
AC4	1,72	,16	1,14	,44	,73	,00	,03	-,12	,00												
JS1	,08	-1,17	-,41	-,71	-1,17	,20	-,56	-1,05	-,23	,00											
JS2	,23	,84	,45	,33	,27	-,68	-,90	-1,13	-,43	,02	,00										
JS3	-,50	,63	-,25	,38	,26	,31	-,35	-,77	,79	,20	-,22	,00									
JS4	-,08	-,09	-,43	-,38	-,38	,35	-,32	,32	,43	-,18	-,07	,54	,00								
SI4	1,40	,87	1,25	-,20	-,05	-,26	-,20	,52	,78	-,11	,10	,90	,58	,00							
SI3	,07	,79	,23	-,49	,32	,29	-,44	,15	,16	-1,56	-,47	,91	,51	,63	,00						
SI2	,48	,66	,00	-1,04	-,61	-,37	-,53	-,25	,14	-,64	-,45	-,60	-1,00	-,18	-,26	,00					
SI1	,83	,49	-,33	-1,17	,35	,48	-,19	-,08	,05	-,48	-,33	,46	-,25	-,36	-,36	,52	,00				
OC4	,90	-,16	,83	-,65	-,42	-1,16	-,79	-,16	,67	,63	-,78	-,14	-,57	,38	-,74	-,24	,07	,00			
OC3	,80	,20	2,08	1,17	1,77	-,62	-1,49	-,93	-,07	1,12	,16	-,20	,65	-,91	-1,31	-,64	-1,31	,30	,00		
OC2	1,04	-1,01	,37	,09	-,42	,79	-,23	,86	1,29	,08	-,96	,12	-,59	,78	,00	,91	,65	-,03	-,41	,00	
OC1	-,08	-1,74	-,08	-2,01	-,13	-1,79	-,85	-1,08	-,33	-,59	-,70	-,20	-,57	-1,88	-2,02	-1,72	-1,53	-,06	1,13	,13	,00

NOTE: This std residuals are calculated with non-missing data file (AMOS does not display them with missing data).

No std. residual exceeds the benchmark interval of (-2,5; +2,5)

MODIFICATION INDICES (LAGRANGE MULTIPLIER TEST)

- Modification Indices (MI) allow you to evaluate many *potential modifications* of the model in a single analysis

- They provide suggestions for model modifications that are likely to pay off in smaller chi-square values

Limitation of using MI: It is hard to justify the particular modification on theoretical grounds even it produces an acceptable fit

MODIFICATION INDICES

- Modification indices are calculated *for* every fixed parameter (i.e. all of the possible parameters that were not estimated in the model)

- 2 sets of MIs most useful in CFA are for
  - the loadings
  - the error terms between items

MODIFICATION INDICES

Modification Indices (Group number 1 - Default model)

Covariances: (Group number 1 - Default model)

			M.I.	Par Change
E11	<-->	E10	4,99	,17
E12	<-->	E5	4,16	1,47
E13	<-->	E12	7,71	,12
E17	<-->	E11	6,60	,08
E16	<-->	E1	5,95	-,09
E16	<-->	E17	6,58	,05
E14	<-->	E13	5,95	,06
E14	<-->	E15	7,23	,04
E21	<-->	E6	7,28	-,16
E20	<-->	Environmental_perceptions	13,10	,26
E20	<-->	Staying_intentions	8,40	-,12
E20	<-->	E13	4,27	,13
E19	<-->	Attitudes_towards_Coworkers	4,21	,18
E19	<-->	Staying_intentions	8,37	,11
E19	<-->	E12	4,57	,13
E19	<-->	E6	5,55	,14
E18	<-->	Staying_intentions	6,88	-,17
E18	<-->	Organizational_commitment	4,14	,28
E18	<-->	E12	6,07	-,24
E18	<-->	E13	4,47	,21
E18	<-->	E20	4,51	,31

Variances: (Group number 1 - Default model)

	M.I.	Par Change

M.I. = Decrease in chi-square that will occur if the corresponding variables are allowed to be correlated

Par Change = Approximate estimate of how much the parameter would change if it were estimated rather than fixed to zero

PART III:

STRUCTURAL EQ. MODEL (SEM)

ANA ALINA TUDORAN

Measurement model was about how the constructs are represented.
Structural model is about how the constructs relate to each other.

SEM PROCESS

- The 1st step involved testing the fit and construct validity of the *measurement model* (stages 1-4 covered under CFA). The measurement model relates the variables to the constructs

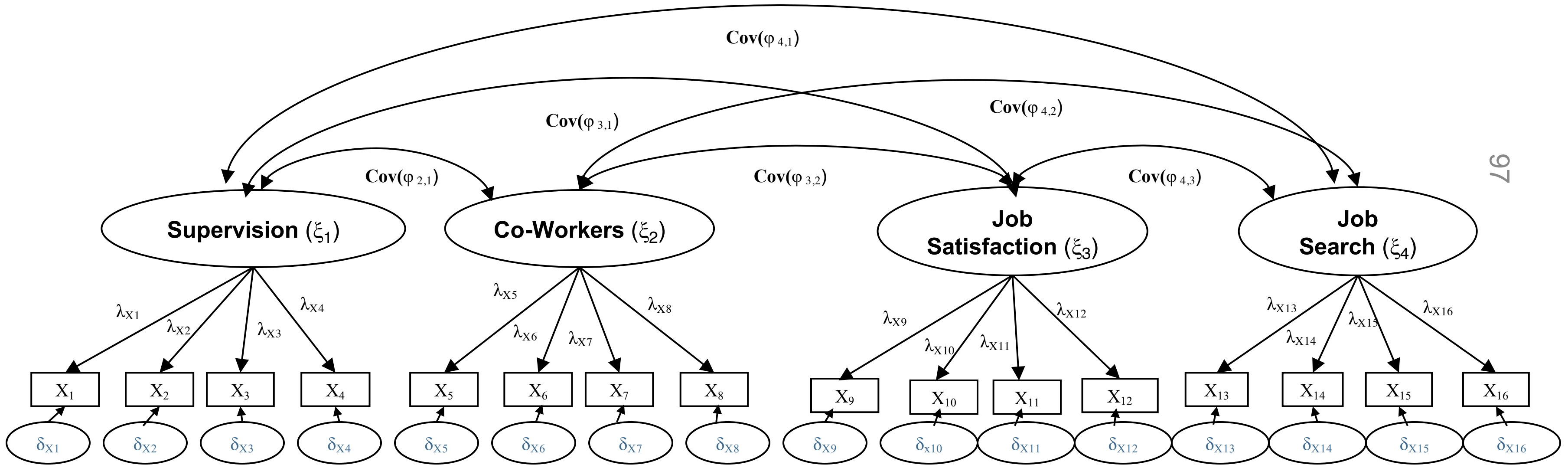
- Once a satisfactory measurement model is obtained, the 2nd step is to test the *structural model* (stages 5-6). The structural model tests a theory and relates the constructs to other constructs

STAGE 5: SPECIFYING THE STRUCTURAL MODEL

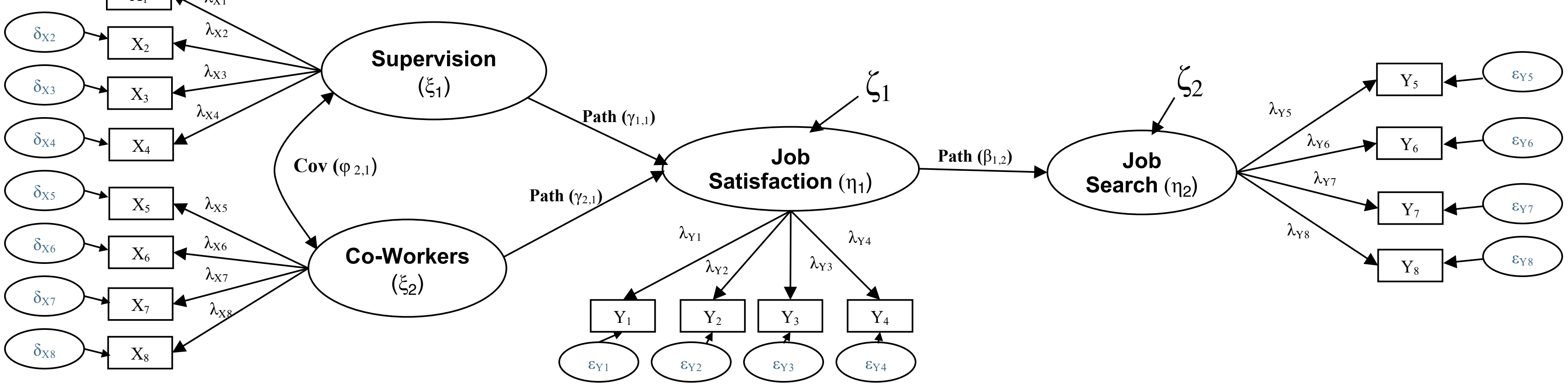
- The path diagram
- Recursive and nonrecursive models

Example of converting a measurement model into a structural model

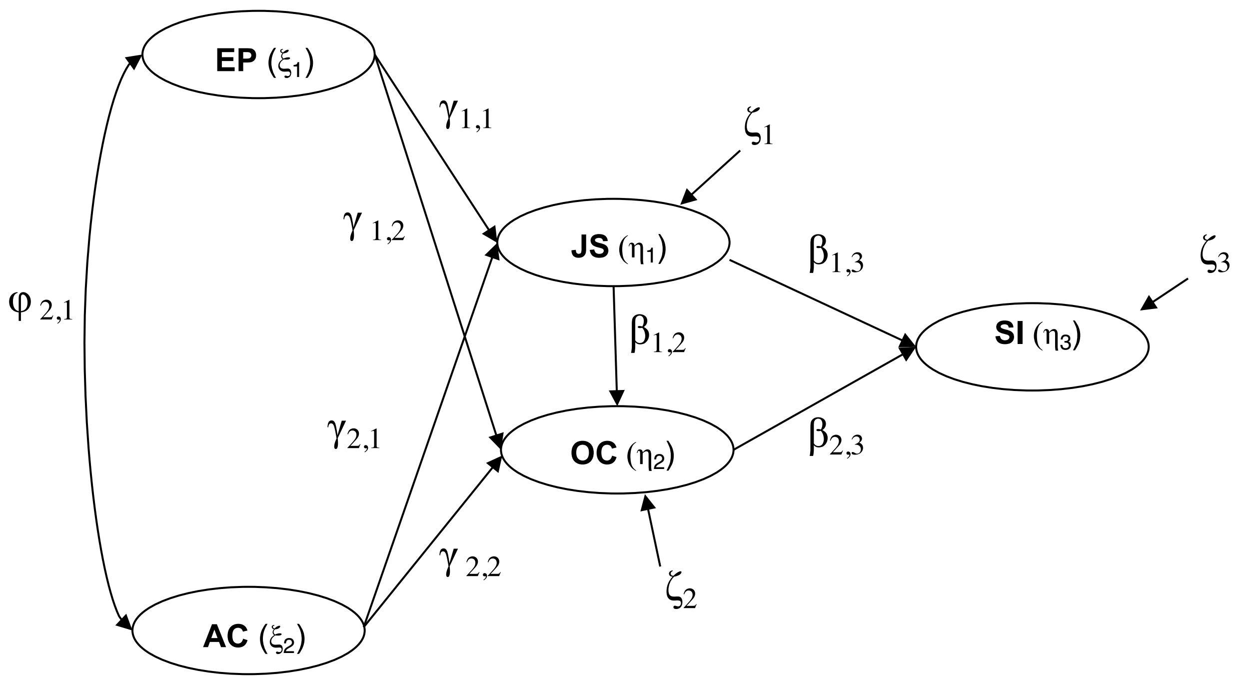
CFA Model (Example)



Structural Model (Example)

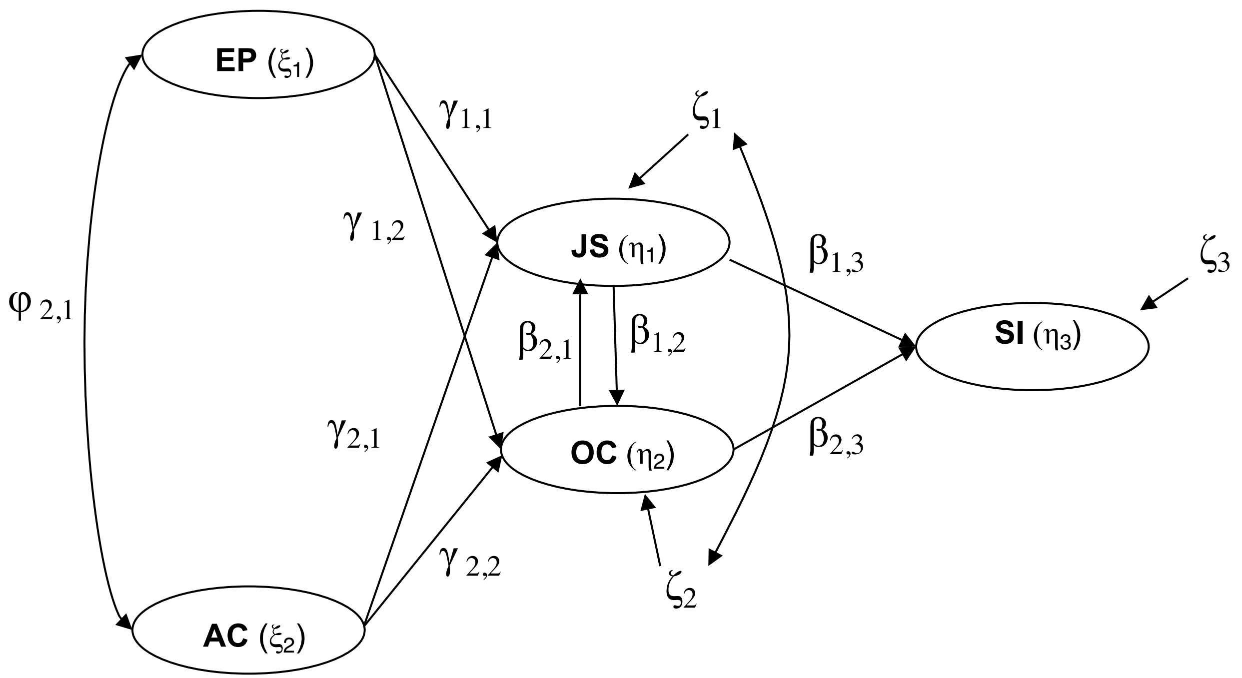


A RECURSIVE MODEL



Observable indicator variables are not shown to simplify the model

A NONRECURSIVE MODEL



Observable indicator variables are not shown to simplify the model

- Non-recursive models (feedback loops) involving cross-sectional data should be avoided in most instances
- Estimation of recursive models requires additional identification constraints

STAGE 6: THE STRUCTURAL MODEL VALIDITY

- Model fit
- Significance, direction, and size of the structural parameter estimates
- Model diagnostics and model respecification

MODEL FIT

- The structural model fit is assessed as was the CFA model fit

  - Overall χ^2 goodness-of-fit test
  - Other fit measures (RMSEA, CFI, TLI, ...)

- In addition, we may *compare* the CFA fit and structural model fit. A structural model demonstrating *an insignificant* $\Delta\chi^2$ value with its CFA model, suggests adequate structural fit (given that CFA fit was acceptable)

EXAMINING THE HYPOTHESIZED RELATIONSHIPS

- Parameter estimates should be:
  - Statistically significant and in the predicted direction
  - Nontrivial (check standardized estimates)
- Check the explained variance (R^2) for the endogenous constructs

MODEL DIAGNOSTIC

- Standardized residuals
- Modification indices
- Specification searches

Note: model diagnostic is examined in the same manner as they are for CFA model

DOES THE MODEL FIT WELL TO THE DATA?

- No – refine model and test with new data
- Yes – draw substantive conclusions and recommendations

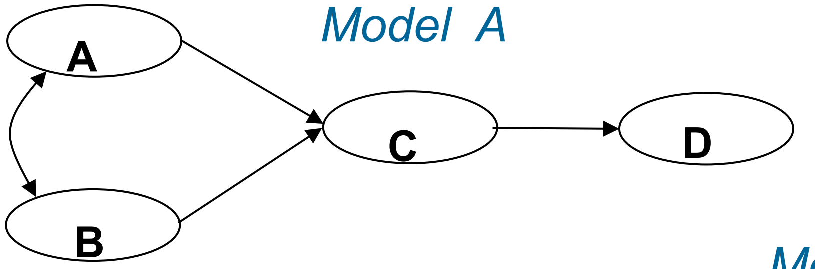
HOW TO COMPARE MODELS?

NESTED MODELS

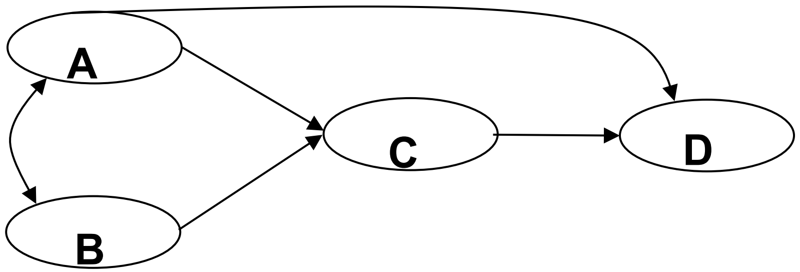
- A model is nested within another model if it contains *the same number of variables* and can be formed from the other model by altering relationships (such as changing, adding or deleting relationships) or imposing specific constraints.

Example

Model A



Model B: nested model



COMPARING NESTED MODELS

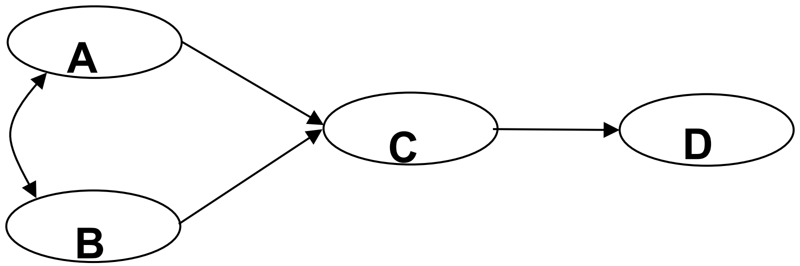
- A chi-square difference test can be used for deciding which of the two models yields to a better fit

- One of the models is estimated as a *baseline* model A. The nested model is estimated as a *target* model B.

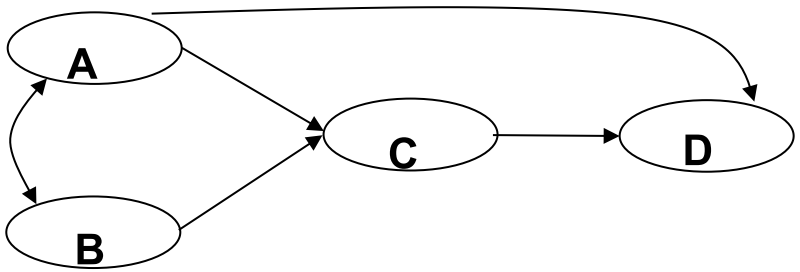
- The difference $\Delta\chi^2_{\Delta df} = \chi^2_{df(A)} - \chi^2_{df(B)}$ is χ^2 distributed with $df = df_A - df_B$

COMPARING NESTED MODELS - EXAMPLE

Model A



Model B: nested model



$$\chi^2_{df(A)} = 103.84,\ \ df = 15$$

$$\chi^2_{df(B)} = 100.00,\ \ df = 14$$

$$\Delta\chi^2_{\Delta df} = 3.84\ \ with\ \ \Delta df = 1$$

$$\Rightarrow p - value \leq 0.05$$

The model with one additional path provides a better fit based on the significant reduction in the chi-square goodness of fit.

COMPARING *NON* NESTED MODELS

- Models which are not nested *cannot* be compared by means of a chi-square difference test (as the difference in their fit values is not chi-square distributed and the sampling distribution is not known)

- Information-theoretic measures have to be used instead (e.g. the Consistent Akaike Information Criterion (CAIC), the Bayes Information Criterion (BIC))

- Of several models specified a-priori, the model yielding *the lowest* CAIC (or BIC) is selected as "the best model"

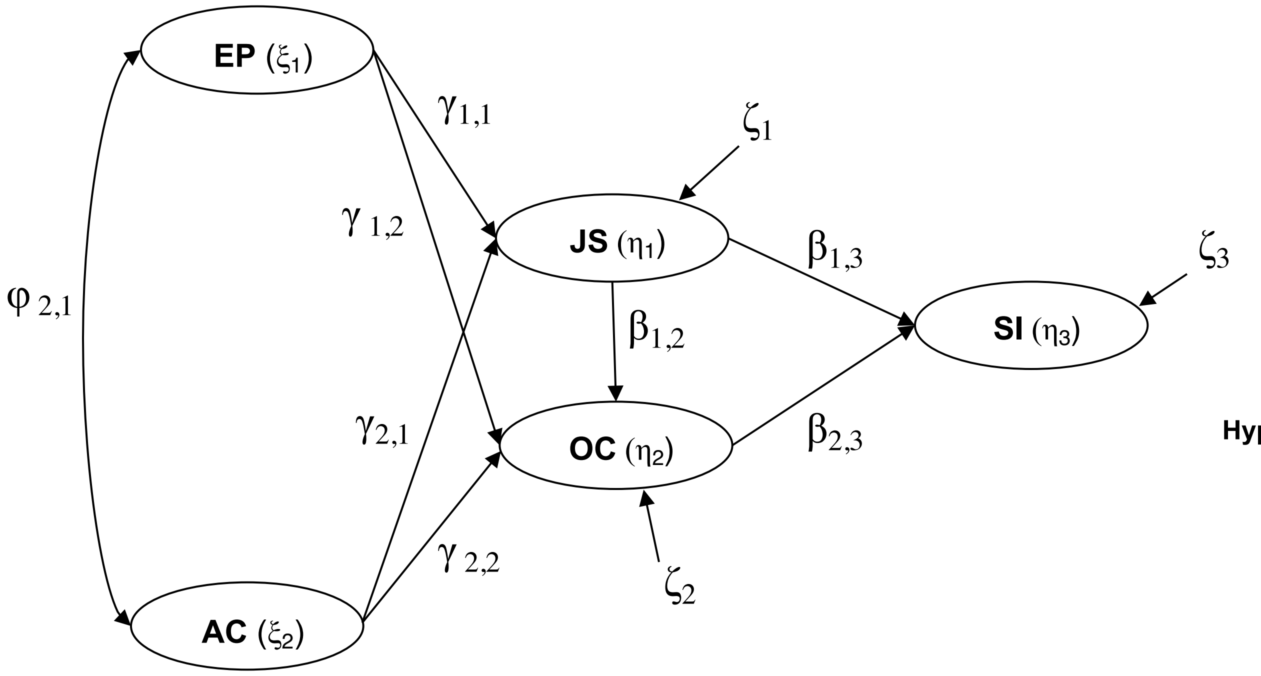
APPLICATION SEM

OBJECTIVES

- The measurement model (CFA) in Stages 1-4). The measurement model was found to have adequate fit

- Now HBAT would like to explain why some employees stay on the job longer than others. More specifically evaluate therelative importance of different determinants on satisfaction and staying intentions.

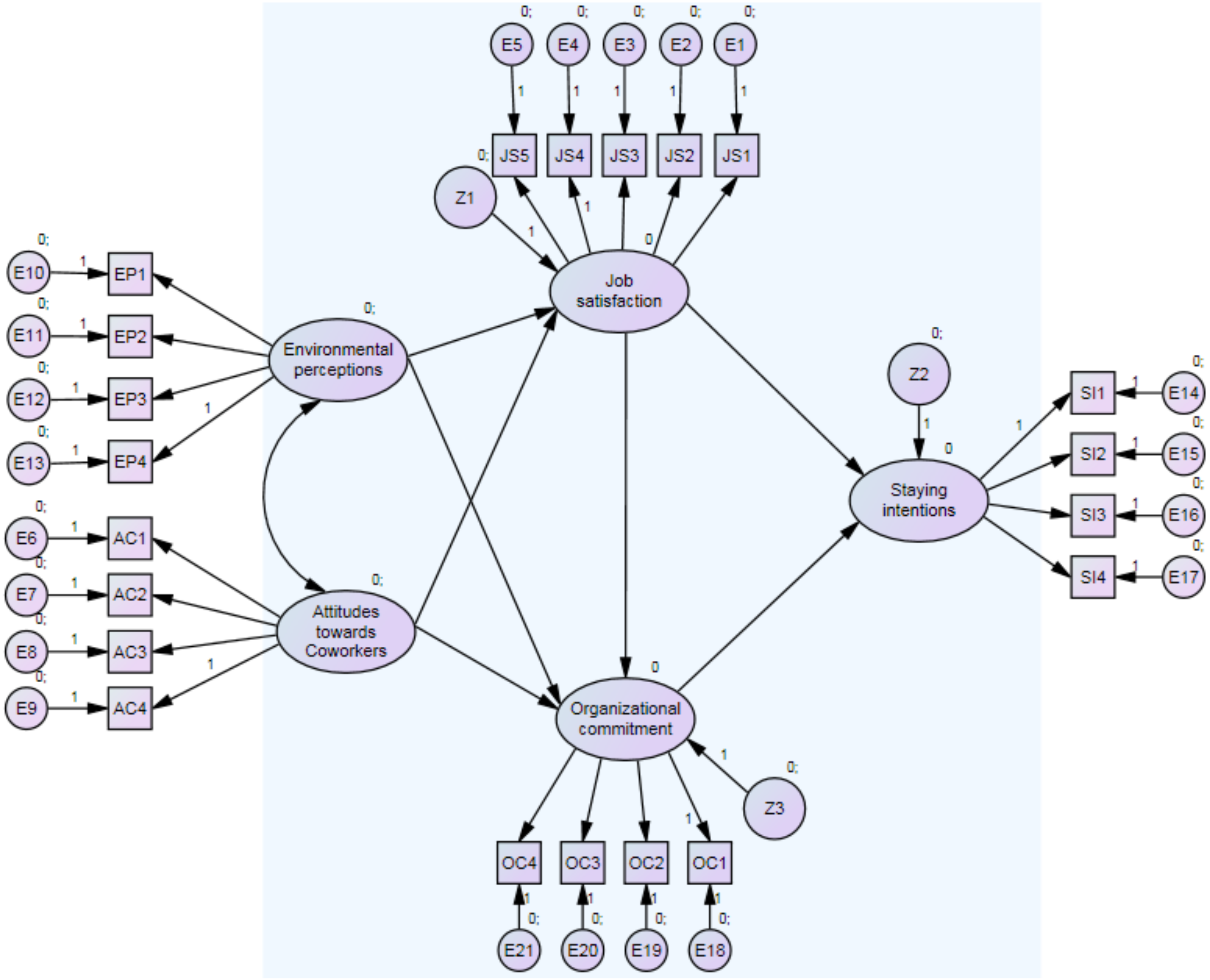
STRUCTURAL THEORY AND HYPOTHESES



Hypotheses:
H1: EP +→ JS
H2: EP +→ OC
H3: AC +→JS
H4: AC +→OC
H5: JS +→ OC
H6: JS + → SI
H7: OC +→SI

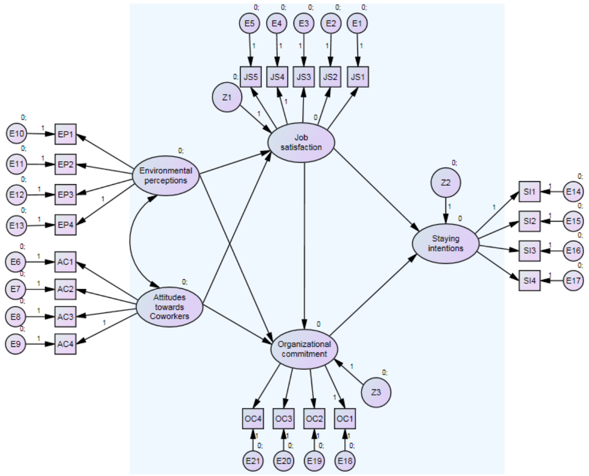
H1: Environmental perceptions (EP) are positively related to job satisfaction (JS)
H2: Environmental perceptions (EP) are positively related to organizational commitment (OC)
H3: Attitudes toward coworkers (AC) are positively related to job satisfaction (JS)
H4: Attitudes toward coworkers (AC) are positively related to organizational commitment (OC)
H5: Job satisfaction (JS) is related positively to organizational commitment (OC)
H6: Job satisfaction (JS) is related positively to staying intentions (SI)
H7: Organizational commitment (OC) is related positively to staying intentions (SI)

VISUAL DIAGRAM



STRUCTURAL MODEL IDENTIFICATION

Number of distinct sample moments: 231



Var, cov $\frac{p(p+1)}{2} = \frac{21*22}{2} = 231$

Number of distinct parameters to be estimated: 50

Regression coefficients: 16 (LOADINGS) + 7 (PATHS) = 23
Unobserved variables Variances and Covariances: 26 + 1 = 27

Degrees of freedom: (231-50) = 181 => The model is overidentified

MODEL FIT

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	71	286,46	181	,00	1,58
Saturated model	252	,00	0		
Independence model	42	4441,44	210	,00	21,15

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,94	,93	,98	,97	,98
Saturated model	1,00		1,00		1,00
Independence model	,00	,00	,00	,00	,00

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	,86	,81	,84
Saturated model	,00	,00	,00
Independence model	1,00	,00	,00

NCP

Model	NCP	LO 90	HI 90
Default model	105,46	63,33	155,52
Saturated model	,00	,00	,00
Independence model	4231,44	4018,35	4451,79

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	,72	,26	,16	,39
Saturated model	,00	,00	,00	,00
Independence model	11,13	10,61	10,07	11,16

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	,04	,03	,05	,99
Independence model	,22	,22	,23	,00

AIC

Model	AIC	BCC	BIC	CAIC
Default model	428,46	436,75		
Saturated model	504,00	533,41		
Independence model	4525,44	4530,34		

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	1,07	,97	1,20	1,09
Saturated model	1,26	1,26	1,26	1,34
Independence model	11,34	10,81	11,89	11,35

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	298	318
Independence model	22	24

SEM FIT VS. CFA FIT

$$\Delta\chi^2_{\Delta df} = 286{,}46 - 240{,}14 = 46{,}32$$

$$with \;\; \Delta df = 181 - 179 = 2$$

$$\Rightarrow p < .001$$

- Because the difference is significant, it suggests that the structural model fit is worse (chi-square for the SEM model increased significantly). It suggests that the structural model can be improved.

MODEL DIAGNOSTIC

TO BE CHECKED:

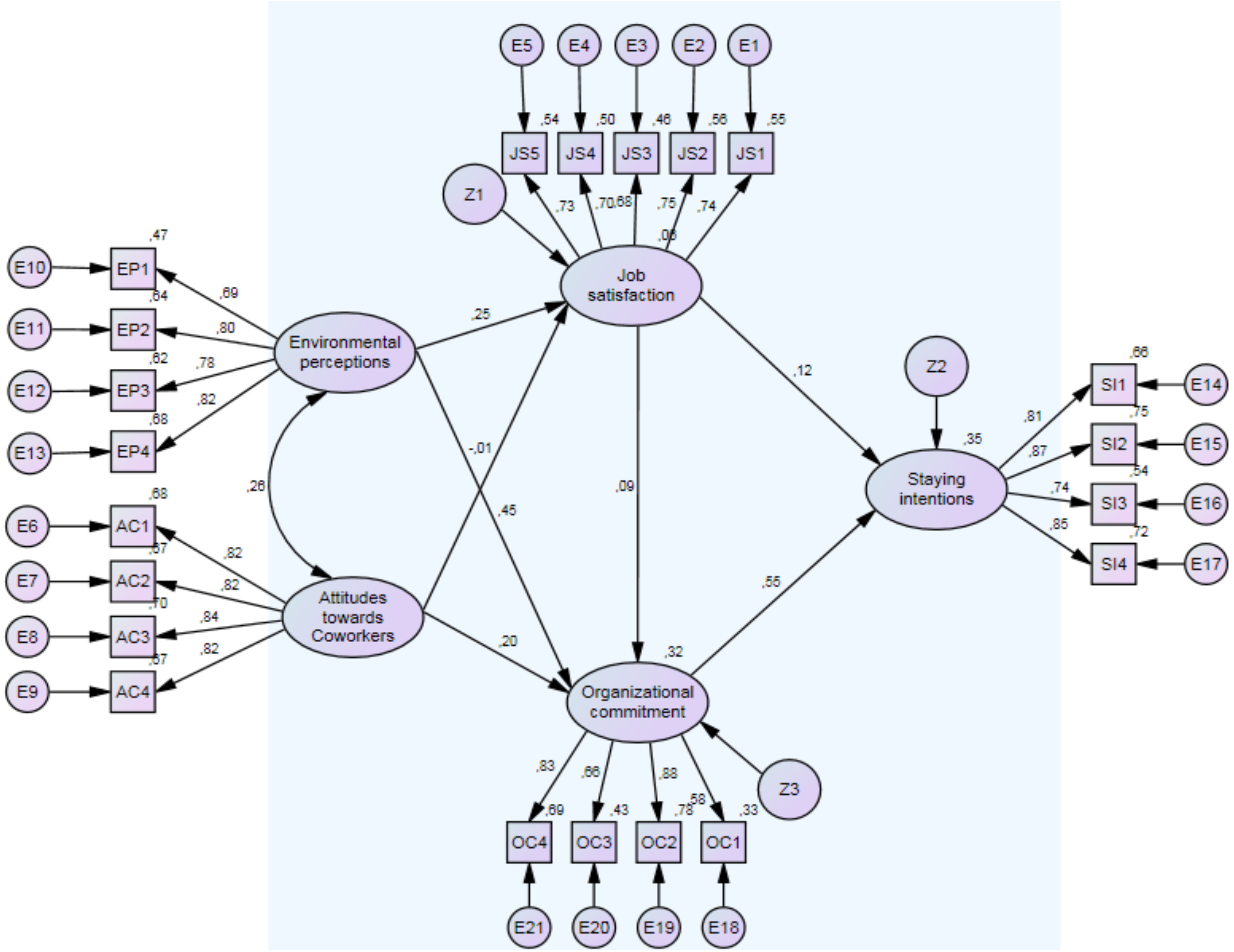
- PATH ESTIMATES
- STANDARDIZED RESIDUALS
- MODIFICATION INDICES

PATH ESTIMATES

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
Job_satisfaction	<---	Attitudes_towards_Coworkers	-,01	,04	-,19	,85	
Job_satisfaction	<---	Environmental_perceptions	,20	,05	4,07	***	
Organizational_commitment	<---	Job_satisfaction	,14	,09	1,60	,11	
Organizational_commitment	<---	Attitudes_towards_Coworkers	,22	,06	3,74	***	
Organizational_commitment	<---	Environmental_perceptions	,57	,08	6,89	***	
Staying_intentions	<---	Job_satisfaction	,10	,04	2,38	,02	
Staying_intentions	<---	Organizational_commitment	,27	,03	8,27	***	
OC1	<---	Organizational_commitment	1,00				
OC2	<---	Organizational_commitment	1,33	,11	12,07	***	
OC3	<---	Organizational_commitment	,79	,08	10,20	***	
OC4	<---	Organizational_commitment	1,17	,10	11,79	***	
SI1	<---	Staying_intentions	1,00				
SI2	<---	Staying_intentions	1,08	,05	19,64	***	
SI3	<---	Staying_intentions	1,06	,07	15,96	***	
SI4	<---	Staying_intentions	1,16	,06	19,09	***	
JS4	<---	Job_satisfaction	1,00				
JS3	<---	Job_satisfaction	,99	,08	12,02	***	
JS2	<---	Job_satisfaction	1,14	,09	13,05	***	
JS1	<---	Job_satisfaction	1,10	,08	12,92	***	
AC4	<---	Attitudes_towards_Coworkers	1,00				
AC3	<---	Attitudes_towards_Coworkers	,90	,05	18,64	***	
AC2	<---	Attitudes_towards_Coworkers	1,08	,06	18,19	***	
AC1	<---	Attitudes_towards_Coworkers	,87	,05	18,24	***	
EP4	<---	Environmental_perceptions	1,00				
EP3	<---	Environmental_perceptions	,90	,05	16,58	***	
EP2	<---	Environmental_perceptions	1,13	,07	16,95	***	
EP1	<---	Environmental_perceptions	1,08	,08	14,11	***	
JS5	<---	Job_satisfaction	16,70	1,30	12,81	***	

VISUALISING THE STANDARDIZED PATH ESTIMATES ON THE PATH DIAGRAM



EXPLAINED VARIANCE (R^2)

Squared Multiple Correlations: (Group number 1 - Default model)

	Estimate
Job_satisfaction	,06
Organizational_commitment	,32
Staying_intentions	,35
JS5	,54
EP1	,47
EP2	,64
EP3	,62
EP4	,68
AC1	,68
AC2	,67
AC3	,70
AC4	,67
JS1	,55
JS2	,56
JS3	,46
JS4	,50
SI4	,72
SI3	,54
SI2	,75
SI1	,66
OC4	,69
OC3	,43
OC2	,78
OC1	,33

STANDARDIZED RESIDUALS

Standardized Residual Covariances (Group number 1 - Default model)

	JS5	EP1	EP2	EP3	EP4	AC1	AC2	AC3	AC4	JS1	JS2	JS3	JS4	SI4	SI3	SI2	SI1	OC4	OC3	OC2	OC1
JS5	,00																				
EP1	,69	,00																			
EP2	-,11	,83	,00																		
EP3	1,31	-,60	-,25	,00																	
EP4	,25	-,15	-,37	,57	,00																
AC1	1,56	-,09	,07	,40	-,59	,00															
AC2	,93	,29	,13	-,69	-,21	-,02	,00														
AC3	,38	,19	-,16	-,34	-,87	,05	,06	,00													
AC4	1,67	,19	1,15	,41	,72	-,01	,02	-,12	,00												
JS1	,10	-1,21	-,48	-,81	-1,25	,15	-,60	-1,09	-,27	,00											
JS2	,22	,79	,37	,22	,17	-,73	-,95	-1,18	-,48	,04	,00										
JS3	-,50	,58	-,32	,29	,18	,26	-,39	-,82	,74	,22	-,23	,00									
JS4	-,09	-,13	-,50	-,48	-,46	,31	-,36	,28	,38	-,16	-,08	,54	,00								
SI4	1,33	3,77	4,59	2,93	3,28	1,48	1,54	2,30	2,52	-,17	,03	,84	,52	,00							
SI3	,01	3,31	3,10	2,24	3,25	1,81	1,07	1,70	1,66	-1,62	-,52	,86	,46	,73	,00						
SI2	,39	3,55	3,28	2,06	2,70	1,37	1,20	1,52	1,87	-,73	-,55	-,68	-1,08	-,18	-,27	,00					
SI1	,75	3,22	2,75	1,74	3,52	2,13	1,44	1,59	1,68	-,56	-,41	,38	-,33	-,33	-,34	,43	,00				
OC4	,92	-,36	,54	-,98	-,73	-1,32	-,95	-,32	,51	,66	-,76	-,12	-,55	,12	-,96	-,57	-,22	,00			
OC3	,81	,02	1,83	,87	1,50	-,76	-1,63	-1,07	-,21	1,14	,17	-,19	,66	-1,13	-1,50	-,92	-1,56	,37	,00		
OC2	1,05	-1,25	,05	-,29	-,77	,60	-,42	,67	1,10	,10	-,95	,13	-,58	,48	-,28	,52	,30	,04	-,37	,00	
OC1	-,05	-1,86	-,26	-2,22	-,32	-1,89	-,94	-1,18	-,43	-,56	-,68	-,17	-,54	-2,03	-2,15	-1,92	-1,71	,09	1,23	,24	,00

One pattern is obvious: each item of the EP construct (EP1 – EP4) has significant standardized residual with at least three of the four items in the SI construct. This indicates that it might be a substantial relationship ommited between these two constructs

At this moment, there is no direct relationship between SI and EP - only indirect relationships (EP -> JS -> SI and EP -> JS ->OC ->SI)

MODIFICATION INDICES

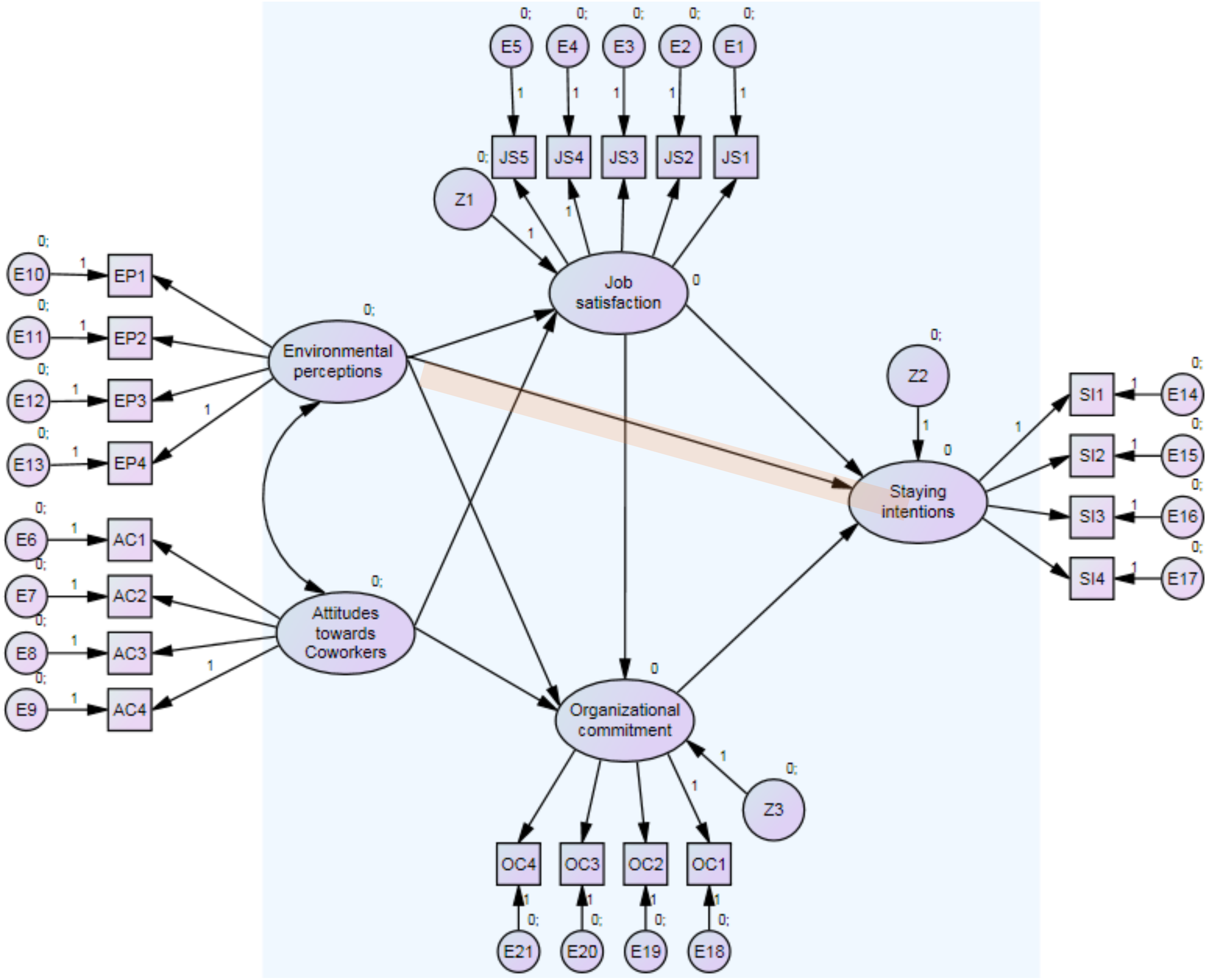
Regression Weights: (Group number 1 - Default model)

			M.I.	Par Change
Staying_intentions	<---	Attitudes_towards_Coworkers	7,75	,07
Staying_intentions	<---	Environmental_perceptions	24,87	,15
JS5	<---	Attitudes_towards_Coworkers	4,43	1,31
EP2	<---	Staying_intentions	4,23	,17
SI4	<---	Environmental_perceptions	6,25	,07
OC1	<---	Staying_intentions	7,56	-,43

- Examination of the modification indices for the direct paths EP -> SI and AC -> SI shows that both have values over 4.0, with EP -> SO value much higher

- This evidence strongly supports the addition of the EP -> SI relationship, if it can be supported theoretically

MODEL RESPECIFICATION



RESPECIFIED MODEL FIT

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	72	245,62	180	,00	1,36
Saturated model	252	,00	0		
Independence model	42	4441,44	210	,00	21,15

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	,03	,02	,04	1,00
Independence model	,22	,22	,23	,00

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,94	,94	,98	,98	,98
Saturated model	1,00		1,00		1,00
Independence model	,00	,00	,00	,00	,00

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	,86	,81	,84
Saturated model	,00	,00	,00
Independence model	1,00	,00	,00

NCP

Model	NCP	LO 90	HI 90
Default model	65,62	28,57	110,74
Saturated model	,00	,00	,00
Independence model	4231,44	4018,35	4451,79

COMPARING RESPECIFIED MODEL FIT

$$\Delta\chi^2_{\Delta df} = 286{,}46 - 245{,}62 = 40{,}84$$
$$with\ \ \Delta df = 181 - 180 = 1$$
$$=> p < .001$$

- The difference is significant; it suggests that the respecified structural model is much better than the original structural model

$$\Delta\chi^2_{\Delta df} = 245{,}62 - 240{,}14 = 5{,}48$$
$$with\ \ \Delta df = 180 - 179 = 1$$
$$=> p < .05$$

- The difference is significant; it suggests that the CFA fit is still better than the respecified structural model

ESTIMATES FOR THE RESPECIFIED MODEL

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
Job_satisfaction	<---	Attitudes_towards_Coworkers	-,01	,04	-,23	,82	
Job_satisfaction	<---	Environmental_perceptions	,19	,05	3,96	***	
Organizational_commitment	<---	Job_satisfaction	,16	,09	1,80	,07	
Organizational_commitment	<---	Attitudes_towards_Coworkers	,22	,06	3,63	***	
Organizational_commitment	<---	Environmental_perceptions	,53	,08	6,52	***	
Staying_intentions	<---	Job_satisfaction	,05	,04	1,33	$\boxed{,18}$	
Staying_intentions	<---	Organizational_commitment	,17	,03	5,77	***	
Staying_intentions	<---	Environmental_perceptions	,23	,04	6,28	***	
OC1	<---	Organizational_commitment	1,00				
OC2	<---	Organizational_commitment	1,32	,11	12,18	***	
OC3	<---	Organizational_commitment	,78	,08	10,28	***	
OC4	<---	Organizational_commitment	1,17	,10	11,92	***	
SI1	<---	Staying_intentions	1,00				
SI2	<---	Staying_intentions	1,07	,05	19,55	***	
SI3	<---	Staying_intentions	1,06	,07	16,02	***	
SI4	<---	Staying_intentions	1,17	,06	19,18	***	
JS4	<---	Job_satisfaction	1,00				
JS3	<---	Job_satisfaction	,99	,08	12,01	***	
JS2	<---	Job_satisfaction	1,13	,09	13,04	***	
JS1	<---	Job_satisfaction	1,10	,08	12,94	***	
AC4	<---	Attitudes_towards_Coworkers	1,00				
AC3	<---	Attitudes_towards_Coworkers	,90	,05	18,64	***	
AC2	<---	Attitudes_towards_Coworkers	1,08	,06	18,19	***	
AC1	<---	Attitudes_towards_Coworkers	,87	,05	18,24	***	
EP4	<---	Environmental_perceptions	1,00				
EP3	<---	Environmental_perceptions	,90	,05	16,48	***	
EP2	<---	Environmental_perceptions	1,13	,07	17,08	***	
EP1	<---	Environmental_perceptions	1,10	,08	14,32	***	
JS5	<---	Job_satisfaction	16,69	1,30	12,81	***	

Note: The path JS->SI is no longer significant (see the original model)

EXPLAINED VARIANCE (R^2)

Squared Multiple Correlations: (Group number 1 - Default model)

	Estimate
Job_satisfaction	,06
Organizational_commitment	,29
Staying_intentions	,42
JS5	,54
EP1	,48
EP2	,65
EP3	,61
EP4	,68
AC1	,68
AC2	,67
AC3	,70
AC4	,67
JS1	,55
JS2	,56
JS3	,46
JS4	,50
SI4	,72
SI3	,55
SI2	,75
SI1	,66
OC4	,70
OC3	,43
OC2	,79
OC1	,34

Note: The squared multiple correlation for SI improved from 0.35 to 0.42 with the addition of the new relationship. This findings suggest that the respecified model performs well (although not perfect)

FINAL CONSIDERATIONS

- The topic of model selection, which focuses on how you choose between competing models, is important
- Please refer to the additional references on the following slide for further consideration on this issue
- While we have glossed over several details, we hope that these fundamentals will help you get started with SEM

REFERENCES

BOOK CHAPTERS:

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- Iacobucci, D. (2009). Everything you always wnated to know about and SEM (Structural Equation Modeling) but were afraind to ask, *Journal of Consumer Psychology, 19, 673-680*