

# Measuring if things group the way I intended: Factor analysis

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## Problem of depending on single variables

- ▶ Lack of reliability in measurement with single variable
  - Objective demographic variables can probably be measured accurately with single prompt—
    - e.g., SEX, AGE, ETHNICITY?
  - Opinion/Attitude Proficiency/Ability variables highly susceptible with single measure
    - How overcome?: Multiple measures of same thing
    - How do we know they are the same?: Factor Analysis



## Logic of Factor Analysis

- ▶ If an opinion is real and stable
  - the mathematical pattern of responses to items related to the opinion should be highly correlated
  - there should be little Noise or Error or Residual unexplained after the pattern is found
  - Correlations between items of same factor should be higher than their correlations with items they are not related to
- Note the similarity to reliability theory in CTT



## Effect of a Factor

- ▶ The factor simplifies the data
  - Data reduction
  - Instead of reporting multiple items, we report one factor score and improves confidence in interpretations
- ▶ The weight of multiple measures ensures better estimation of opinion or attitude or ability
  - The factor reduces chance effects
  - The factor reduces error



## Getting to a Factor

- ▶ Direct observation/measurement
  - Answers to test questions
  - Response to rating statements
  - Measures of volume, mass, area
- ▶ Indirect inference about latent trait or ability
  - Factors that are derived from the statistical interaction of directly observable measures
  - *Is it real, if it cannot be directly observed?*
    - Is evolution not real just because it happens on a time scale too difficult for us to observe?



## Factors

- ▶ Latent
  - derived from variables that group in common;
  - not directly observed
- ▶ Efficient—one value instead of multiple values
- ▶ Increased Accuracy—multiple measures reduce error

## Factors—Spearman (approx 1900)



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- ▶ Means of simplifying data by examining the commonalities in a matrix of data
- ▶ Values for response can be different for cases
- ▶ Pattern of responses across number of variables detected show pools of variables

	Variables			
Case	A	B	C	D
a	8	7	5	8
b	4	3	2	4
c	7	6	4	7
d	3	2	1	3

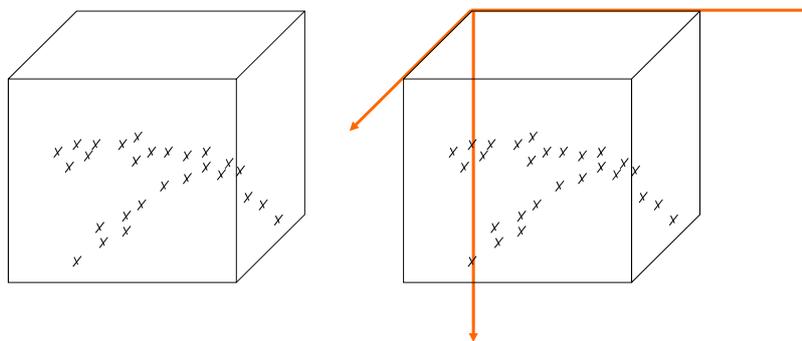
We expect A, B, & D to be in same factor

## Factors



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- ▶ Vectors through  $n$ -dimensional space
  - Angles that meet at the ceiling of a square room are vectors perfectly orthogonal ( $90^\circ$  to each other)



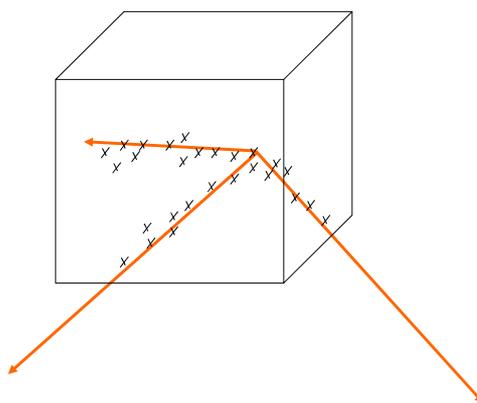
**NB:** Correlation of factors  $r = 0.00$  when orthogonal

## Factors



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- ▶ Rotation—we find a point from which we can see the vectors along which the variables group, minimise difference to lines (similar to regression)

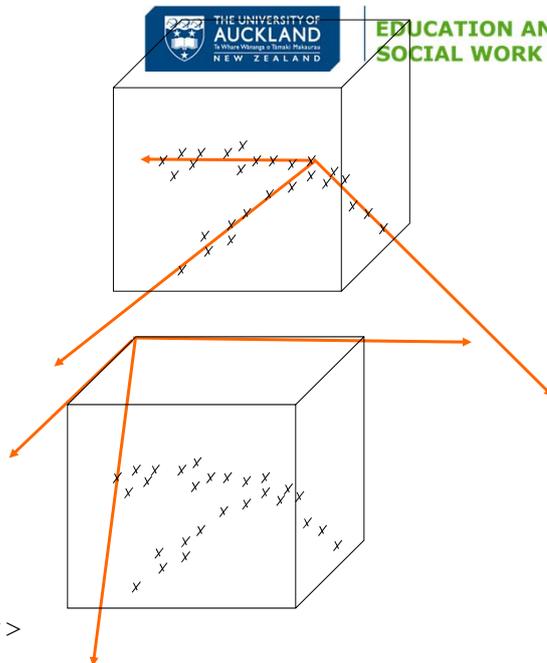


## Factors

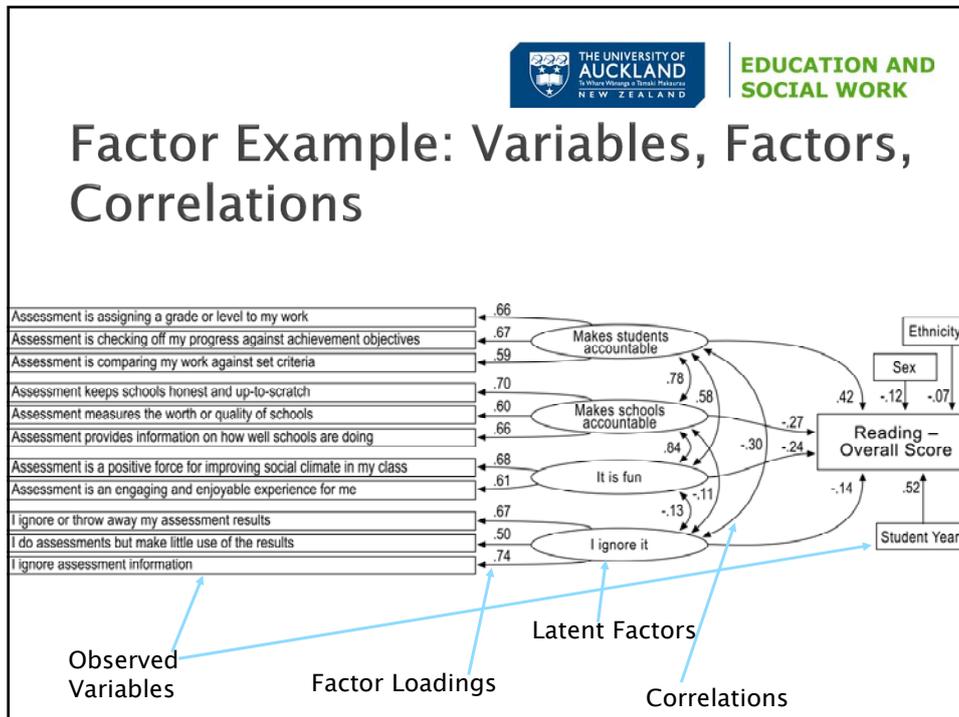


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- ▶ Correlated—psychological artefacts are likely to be oblique or connected with each other unlike an orthogonal room



**NB:** Correlation of factors  $r > 0.00$  when oblique




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## Best Factor Analysis

- ▶ **Maximum Likelihood Estimation (MLE)**
  - Best estimate of population values
  - Not principal components which includes error
- ▶ **Oblique Rotation**
  - Not orthogonal
- ▶ **At least 3 items per factor**
  - Loading > .30
- ▶ **At least 5 cases per item**
  - Preferably 15
  - But if large numbers of items in a factor, number of cases can be low: 12 items ↔ 50 cases

Bandalos, D. L., & Finney, S. J. (2010). Factor analysis: Exploratory and confirmatory. In G. R. Hancock & R. O. Mueller (Eds.), *The reviewer's guide to quantitative methods in the social sciences* (pp. 93–114). New York: Routledge.

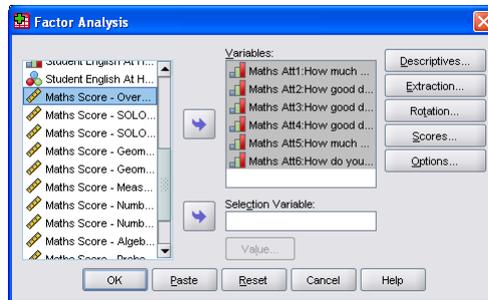
Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment Research & Evaluation, 10*(7).

# Math attitudes



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- ▶ 6 items too many. Can they be reduced to a smaller number of meaningful categories?
- ▶ Analyse > Dimension Reduction > Factor Analysis
  - Options:
    - Extraction MLE; eigenvalues > 1
    - Rotation Oblimin



Total Variance Explained							
Factor	Initial Eigenvalues			Extraction Sums of Squared Multiple Correlations			
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	2.948	49.134	49.134	2.469	41.143	41.143	2.060
2	1.036	17.263	66.397	.549	9.147	50.290	2.134
3	.643	10.710	77.107				
4	.516	8.603	85.710				
5	.460	7.665	93.375				
6	.397	6.625	100.000				

Extraction Method: Maximum Likelihood.  
a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

**Factors are only real when they have strong theoretical and statistical evidence.**

Are these 2 factors interpretable? What shall we call them?

Chi-Square	df	Sig.
51.159	4	.000

Factor	1	2
1	1.000	.611
2	.611	1.000

Extraction Method: Maximum Likelihood.  
Rotation Method: Oblimin with Kaiser Normalization.

	Factor	
	1	2
Maths Att1:How much do you like doing maths at school?	.824	.026
Maths Att5:How much do you like doing maths in your own time (not at school)?	.692	-.068
Maths Att6:How do you feel about doing things in maths you haven't tried before?	.489	.111
Maths Att3:How good does your teacher think you are at maths?	-.019	.731
Maths Att4:How good does your Mum or dad think you are at maths?	-.028	.700
Maths Att2:How good do you think you are at maths?	.103	.696

Extraction Method: Maximum Likelihood.  
Rotation Method: Oblimin with Kaiser Normalization.  
a. Rotation converged in 7 iterations.

## How many factors?



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- ▶ **Optimal Coordinate**
  - Measures gradients associated with eigenvalues and their preceding coordinates
- ▶ **Acceleration Factor**
  - Determines coordinate where the slope of the curve changes most abruptly
- ▶ **Velicer's Minimum Average Partial (MAP)**
  - average squared correlations after partialling out previous components
  - use polychoric correlations for ordinal variables
- ▶ **Horn's Parallel Analysis**
  - takes into account the proportion of variance resulting from sampling error
- ▶ **Ruscio & Roche's Comparison Data**
  - multiple datasets with known factorial structures are analyzed to determine which best reproduces the profile of eigenvalues for the actual data
- ▶ **Kaiser's eigenvalue-greater-than-one rule (K1)**
  - PCA not FA
  - Tends to overestimate number of factors
- ▶ **Cattell's (1966) scree test**
- ▶ **eye-ball scree plot of eigenvalues for a break, hinge, or "elbow"**
  - Highly subjective, low inter-rater reliability
- ▶ **Very Simple Structure**
  - Only if very few factors in data

Strong

Weak

## Number of Factors



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- ▶ **SPSS + R plug-in to calculate**
- ▶ Courtney, M. G. R. (2013). Determining the number of factors to retain in EFA: Using the SPSS R-Menu v2.0 to make more judicious estimations. *Practical Assessment Research & Evaluation, 18(8)*, Available online: <http://pareonline.net/getvn.asp?v=18&n=18>.

Table 1. Summary of Modern Techniques for Determining Number of Factors to Retain in EFA

Modern Technique	Standard for all Data Types	% Accuracy	Bias in simulation	Recommended version for ordinal data
CD	CD <sub>r</sub>	87.14	Slight under-extraction	CD <sub>r</sub>
PA	PA-PCA <sub>rm</sub>	76.42	Unbiased	PA-PCA <sub>pm</sub>
OC	OC <sub>r</sub>	74.03	Slight under-extraction	Not established
MAP	MAP <sub>r</sub> <sup>2</sup>	59.6	Moderate under-extraction	MAP <sub>p</sub> <sup>2</sup>
AF	AF <sub>r</sub>	45.91	Substantial under-extraction	Not established

Note: Accuracy and Bias estimates taken from Ruscio & Roche's (2012) simulation study (p. 289). Although the OC and AF procedures may be carried out with Spearman or polychoric correlations in the SPSS R-menu v2.0, such modifications are not established.

## Number of factors



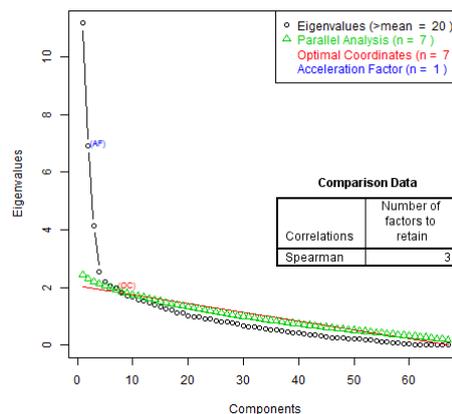
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- ▶ 67 items from 2 inventories, total 8 starting factors
- ▶ Possibly 1–7 factors
  - All options between 3–7 tested
  - 4 was most interpretable in terms of item content per factor

Velicer's Minimum Average Partial Test

	Velicer's Minimum	
	Minimum	Components to retain
Squared MAP	.013	4
4th power MAP	.001	4

Parallel analysis on data permutation



## Once you have a factor....



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- ▶ How can you be sure it is right?
- ▶ What evidence can we use?
  - Maximum likelihood estimation permits tests as to whether the observed result fits the data
- ▶ Confirmatory factor analysis tests EFA result by setting all off-paths to ZERO

## Mathematical Test of Model



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- ▶ CFA is a sophisticated correlational–causal mathematical testing of a model against a data set
- ▶ Does the model even solve properly?
- ▶ How close are they? Does the model fit the data?
  - Models are rejected if they do NOT have close fit to the data
    - the data can't be wrong esp. if it is a representative and large sample—it's the reality we are trying to model
  - Models are NOT accepted if they have close fit to the data
    - They are NOT YET DISCONFIRMED—Popper
    - Multiple models can fit equally well the same data
    - Fit could be attributable to chance factors in the data we collected

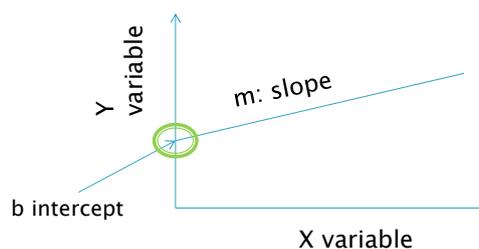
## The linear relationship



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- ▶ Changes in XXX cause a linear change (increase or decrease) in YYY
- ▶ Formula:  

$$Y = m \cdot X + b$$
  - $m$  = slope [standardised beta = a proportion of standard deviation]
  - $b$  = intercept [starting point of equation; represents tendency to respond]
- ▶ Multiple predictors
  - $y = b_0 + b_1X_1 + b_2X_2 \dots$  (just keep adding an X for each new variable)



### Interpretations:

1. For every 1 *SD* change in X, you will get  $m \cdot SD$  change in Y.
2. This relationship explains  $x\%$  of variance in Y

## Looking Under the Hood: Components of CFA and SEM models

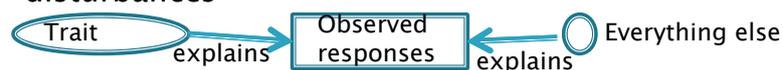
### ▶ Variables

- Manifest [observed behaviours, usually dependent, rectangles]
- Latent [unobserved, explanatory, ovals]
- Residual [unobserved, unexplained, ovals]



### ▶ Manifest variables are predicted by both Latent traits and residuals

- Goal to have large proportion of variance in manifest explained by latent rather than residual disturbances



## Looking Under the Hood: Components of CFA and SEM models

### ▶ Paths

- **Fixed:** equations require SEED values to solve; 1 is the conventional seed. All latent traits must have one path to their predicted manifest variables with a fixed value. All other values are estimated relative to the seed value.
- **Free:** All other paths are allowed to be estimated freely based on the data provided to the model; they may be stronger than the fixed path, but better to make the strongest path in a factor the fixed path.
- **Zero:** Paths not required by the model are forced to be non-existent. This contrasts to EFA where all paths have some freely estimated value.



## Estimation

- ▶ Maximum likelihood (most common)
  - The parameter values in the data set (a sample) are the most likely values in the population (not present, but to which we wish to generalise)
  - Hence, procedure attempts to maximise the input values when estimating the solution
    - means, standard deviations, covariances
  - Hence, it matters that the sample reflects the population and is sufficiently large that parameters are likely to apply to population
  - Valid if response categories are defensibly continuous (i.e.,  $\geq 5$  ordinal categories)



## Model Evaluation: Fit to Data

- ▶ Because of MLE, it is possible to evaluate the fit of the model relative to the data by comparing the distributions
  - The chi-squared ( $\chi^2$ ) test is the fundament of model evaluation
  - $\chi^2$  test: difference between Observed (model) and Expected (Data) adjusted by number of parameters and cases (degrees of freedom)
  - However,  $\chi^2$  penalises **falsely** large  $N$  (i.e.,  $> 100$ ) and large number of manifest variables
  - So it is a poor test, notwithstanding vehement objections by some researchers



## Evaluating Results: Which Fit indices & What Values?

Decision	Goodness of Fit		Badness of fit	
	$p$ of $\chi^2/df$	CFI gamma hat	RMSEA	SRMR*
Good	>.05	>.95	<.05	≈.06
Acceptable	>.05	>.90	<.08	<.08
Marginal	>.01	.85–.89	<.10	
Reject	<.01	<.85	>.10	>.08

**Note.**

Report multiple indices but beware.....

CFI punishes **falsely** complex models (i.e., >3 factors)

RMSEA rewards **falsely** complex models with mis-specification

See Fan & Sivo, 2007

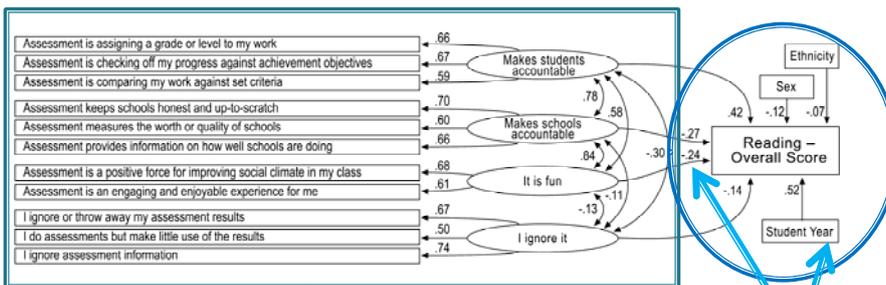
\*AMOS only generates SRMR if NO missing data;

**thus**, important to clean up missing values prior to any analysis.

Recommend expectation maximization (EM) procedure

## CFA + SEM

(Brown & Hirschfeld, 2008)



CFA: Measurement Model—4 correlated factors

**Note.** Accurate measurement models are also needed for reading score, year, sex, & ethnicity

**Note.**

If measurements of each construct are **NOT** robust, do **NOT** use them for anything!!!

**Structural model:** multiple predictors of performance



## What is Confirmation in CFA?

- ▶ Most studies follow this process
  - An inventory is developed using theory
  - The validity of the questionnaire may be explored
  - EFA identifies a plausible model within a data set
  - CFA tests the fit of the EFA model to the data
  - CFA refines the EFA model with the same data
  - This process is better considered Restrictive analysis not CFA
- ▶ True confirmation comes when an existing model is TESTED with an independent sample
  - Requires that 2<sup>nd</sup> sample is drawn from the same population
  - No EFA needed
  - Just run the model, does it fit?
  - If NOT, then EFA must begin again...



## Application to testing

- ▶ Do all the items belong to one dimension? Is the test unidimensional?
  - An advanced form of discrimination checking
  - If yes, IRT analysis appropriate
  - If not, then determine dimensionality and test robustness and validity with CFA and IRT
  - report dimension scores
- ▶ If you planned sub-tests then you want multiple dimensions. But did you get the dimensions you wanted? As many as you planned? In the types you planned?
  - Test with CFA for the desired structure
  - If robust, then report sub-test scores

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