ISYS3401
IT Evaluation

Week 9 Lecture

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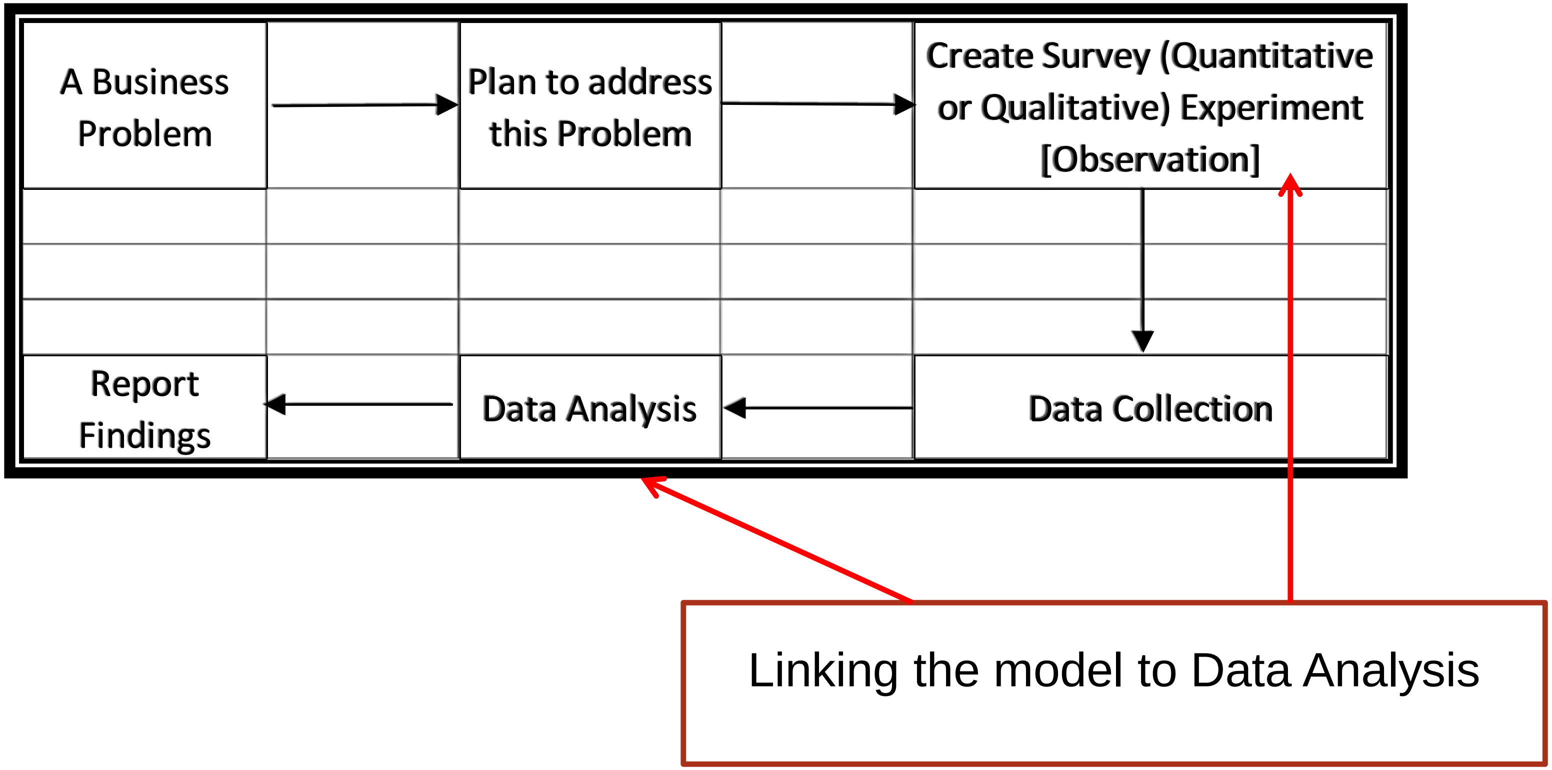
Agenda

- Reflective versus Informative Indicators
- Measurement Error
- Reliability and Validity
- Exploratory Factor Analysis
- Convergent and Discriminant Validity
- SPSS
- Class Activities

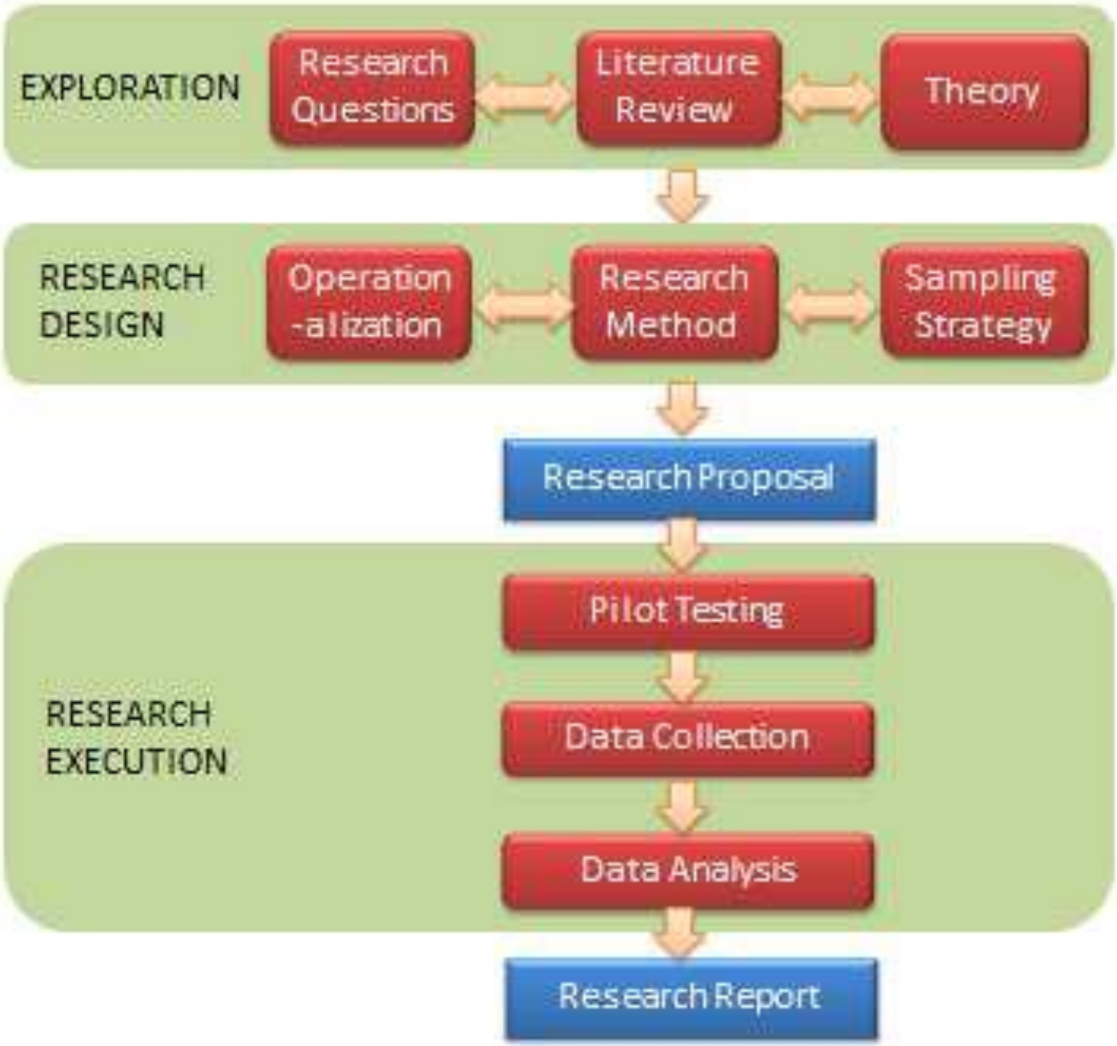
References

http://scholarcommons.usf.edu/cgi/viewcontent.cgi?article=1002&context=oa_textbooks (Chapter 6 and 7)

This week …


A Business Problem
Plan to address this Problem
Create Survey (Quantitative or Qualitative) Experiment [Observation]
Data Collection
Data Analysis
Report Findings
Linking the model to Data Analysis

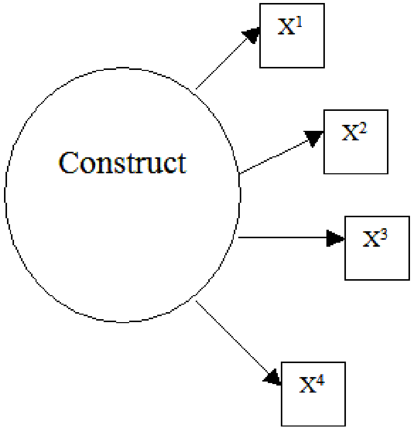
Research Process



Operationalisation of Construct

- The process of developing indicators (variables) for measuring the constructs
- Indicator
  1. Reflective Indicators (Latent Construct)
     - Indicator that “reflects” an underlying construct
     - Changes in the construct cause changes in the indicators

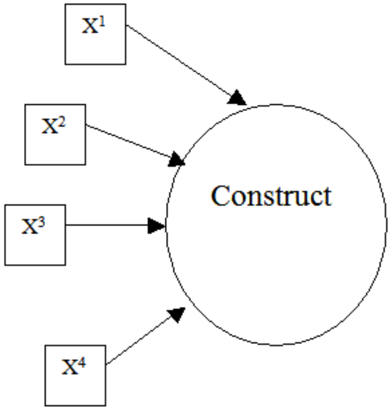
     For example, Parental Monitoring Ability:
     - Self-reported evaluation
     - Video taped measured time
     - Child’s assessment
     - External Expert
     - ➢ If a parent behaviourally increases their monitoring ability, then each indicator will increase as well



Ref: From Wynne Chin’s PLS Workshop at UNSW, 2013

Operationalisation of Construct

2. Formative (Emergent Construct)
   - Indicator that "forms" or contributes to an underlying construct
   - Changes in the indicators cause changes in the construct



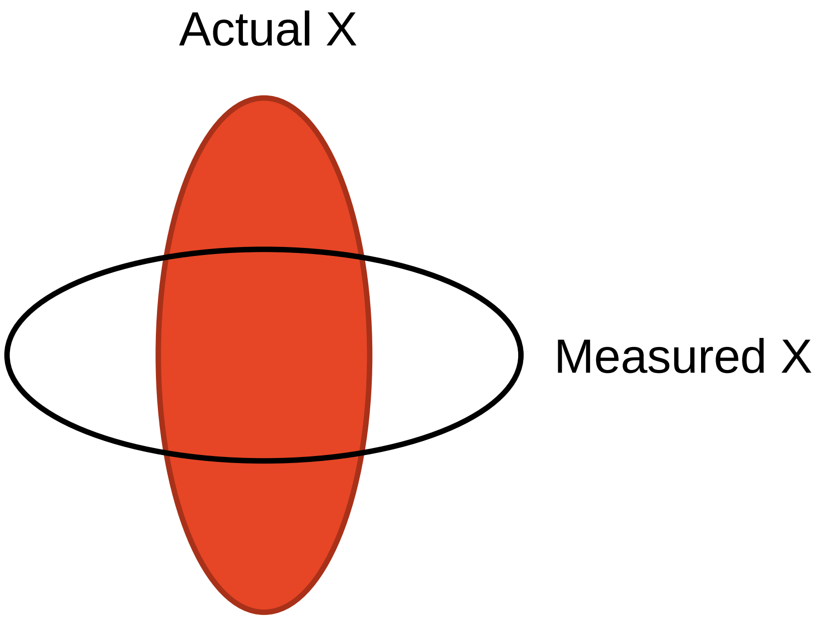
For example, Parental Monitoring Ability:

- Eyesight
- Overall Physical Health
- Number of children being monitored
- Motivation to monitor

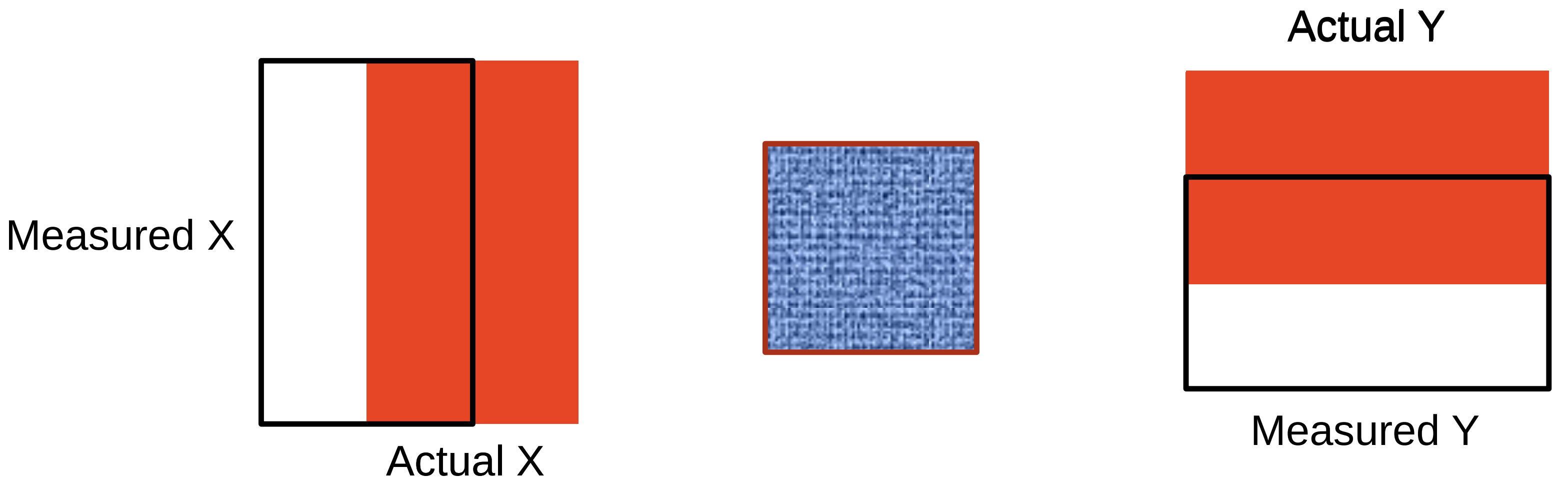
➢ A drop in health does not imply any change in number of children being monitored.

Ref: From Wynne Chin's PLS Workshop at UNSW, 2013

Measurement Error suggest that our measured variables consists of actual plus unique error (specific and noise)

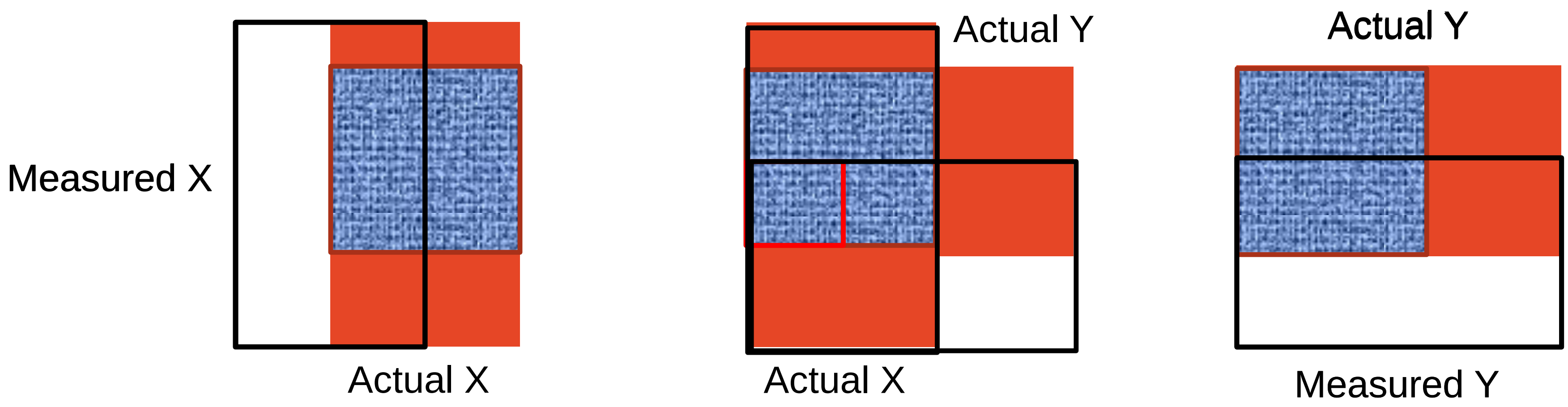


Consider the case of our measured variables X and Y



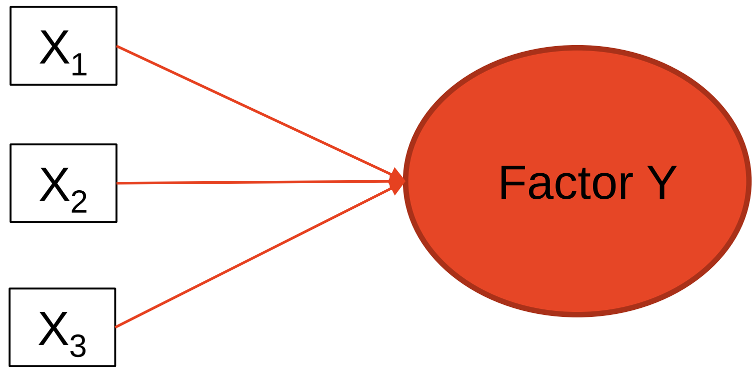
Lets assume: Actual X and Y share 50% of variance

Measurement overlap with actual 50%

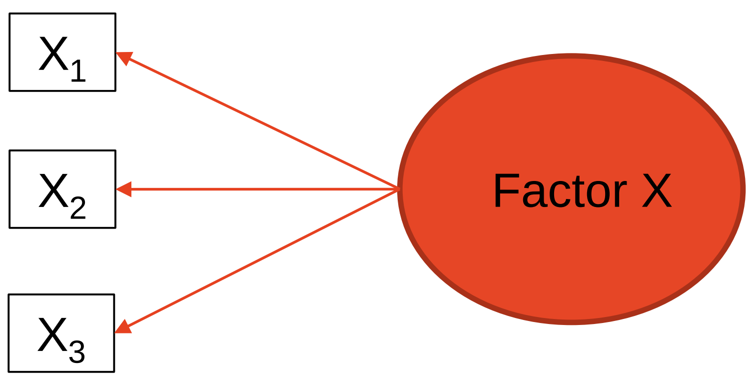


Actual shared variance
Versus
Observed shared variance at 25% actual
[Note: the Factor Loading is 0.71]

Modelling



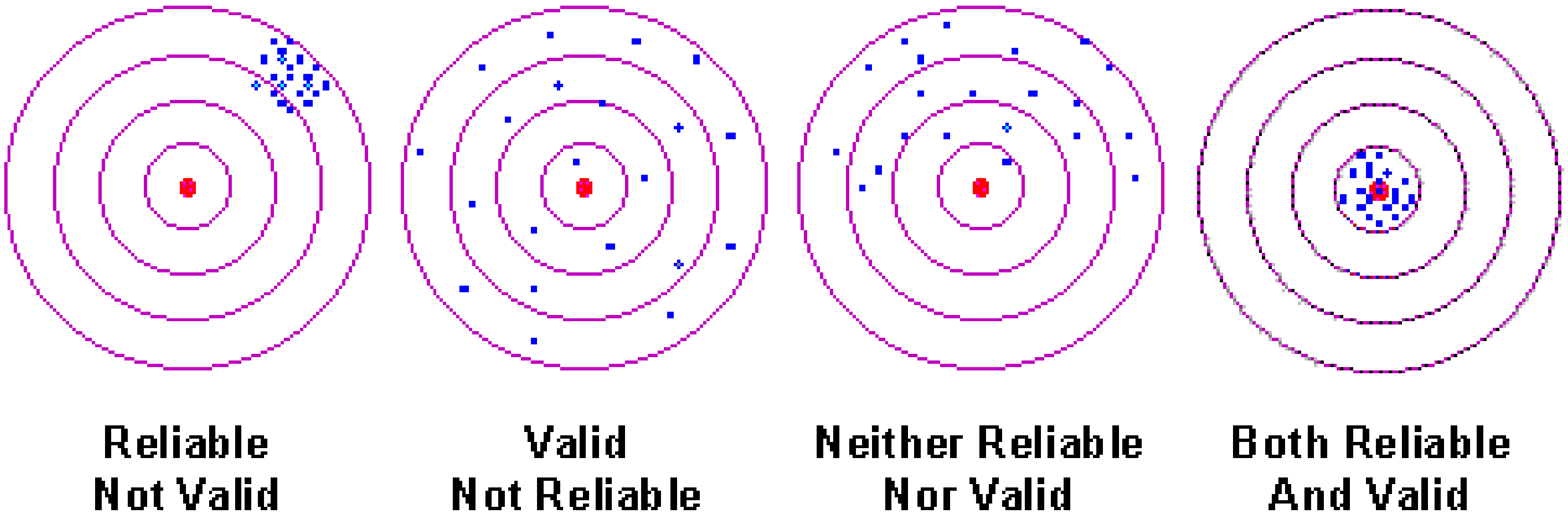
Regression Analysis:
Y is the dependent variable to be estimated



Factor Analysis
X is the Construct to be measured

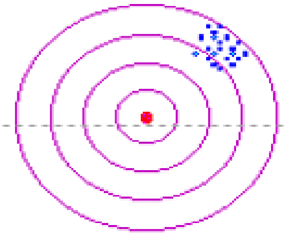
Reliability and Validity

Think of the centre of the target as the concept that you are trying to measure. Imagine that for each person you are measuring, you are taking a shot at the target. If you measure the concept perfectly for a person, you are hitting the centre of the target. If you don't, you are missing the centre.



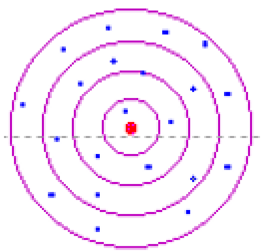
Ref: https://www.socialresearchmethods.net/kb/relandval.php

Reliability and Validity (cont')



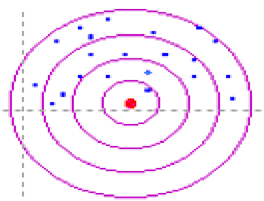
Reliable
Not Valid

You are hitting the target consistently, but you are missing the centre of the target, i.e. you are consistently and systematically measuring the wrong value for all respondents. This measure is reliable, but no valid (that is, it's consistent but wrong).



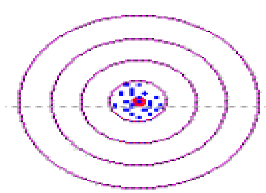
Valid
Not Reliable

You hit randomly across the target. You seldom hit the centre of the target but, on average, you are getting the right answer for the group (but not very well for individuals). You get a valid group estimate, but inconsistent. Here, you can clearly see that reliability is directly related to the variability of your measure.



Neither Reliable
Nor Valid

Your hits are spread across the target and you are consistently missing the centre. Your measure in this case is neither reliable nor valid. This is the worst case scenario.



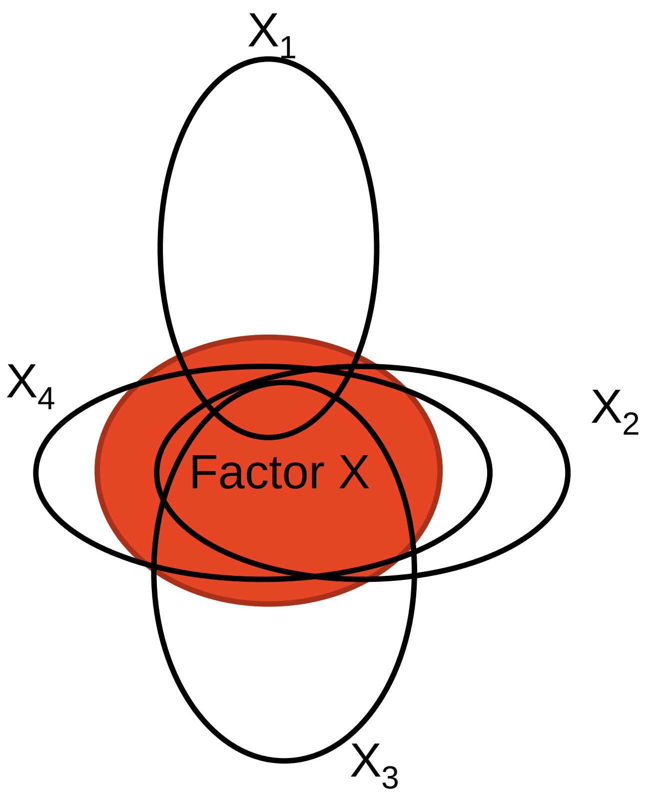
Both Reliable
And Valid

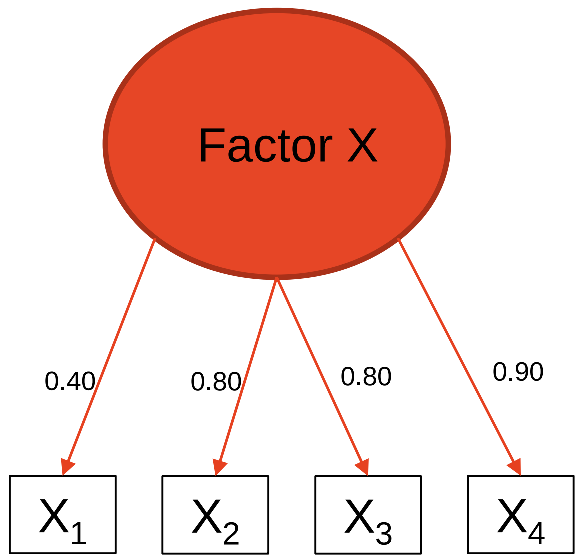
Finally, we see the "Robin Hood" scenario - you consistently hit the centre of the target. Your measure is both reliable and valid.

Psychometric Properties of Measurement Scales

- Reliability
  - The degree to which the measure of a construct is consistent or dependable
- Construct Validity
  - The extent to which a measure adequately represents the underlying construct that it is supposed to measure
  - Validity of the measurement procedures
  - Distinct from the validity of hypotheses testing procedures
    - **Internal validity** - refers to how well to which a measure adequately represents the underlying construct that it is supposed to measure.
    - **External validity** - extent to which the results of a study can be generalised to other situations and to other people

Factor analysis (more later) converges on the true variance and estimates how much each measure captures the actual variable (referring to "factor")



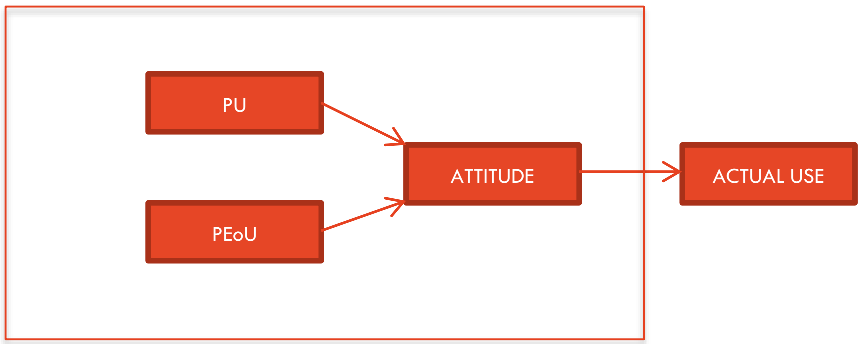


Jum Nunnally's (1978) Psychometrics text

"What a satisfactory level or reliability is depends on how a measure is being used. In the early stages of research… one saves time and energy by working with instruments that have only modest reliability, for which purpose reliabilities of .70 or higher will suffice… In contrast to the standards in basic research, in many applied settings a reliability of .80 is not nearly high enough. In basic research, the concern is with the size of correlations and with the differences in means for different experimental treatments, for which the differences in means for different measures is adequate. In many applied problems, a great deal hinges on the exact score made by a person on a test…. In such instances it is frightening to think that any [emphasis added] measurement error is permitted. Even with a reliability of .90, the standard error of measurement is almost one-third as large as the standard deviation of the test scores. In those applied settings where important decisions are made with respect to specific test scores, a reliability of .90 is the minimum that should be tolerated and a reliability of .95 should be considered desirable standard." (pp.245-246)

Recall Case for Discussion

- IT expected to be one of the important mechanism reforming the y in the future.
- An important research question in the IT domain is to study **users' Attitude** towards using the system. Based on prior researches in the IS field called Technology Acceptance Model (TAM) – Davis (1989),
- One may make the following hypotheses :
  - The attitude towards using the information system would be positively affected by Perceived usefulness (PU) of the system.
  - The attitude towards using the information system would be would be positively affected by the perceived ease of use (PEoU) of the system.
  - User's attitude towards the information system will in turn affect users' actual usage of the system.



TAM (Davis et al. 1989)

- **Perceived usefulness** (PU) – This was defined by Fred Davis as "the degree to which a person believes that using a particular system would enhance his or her job performance".
- **Perceived Ease of Use (PEoU**) – Davis defined this as "the degree to which a person believes that using a particular system would be free from effort“

From the Regression Perspective:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2$$

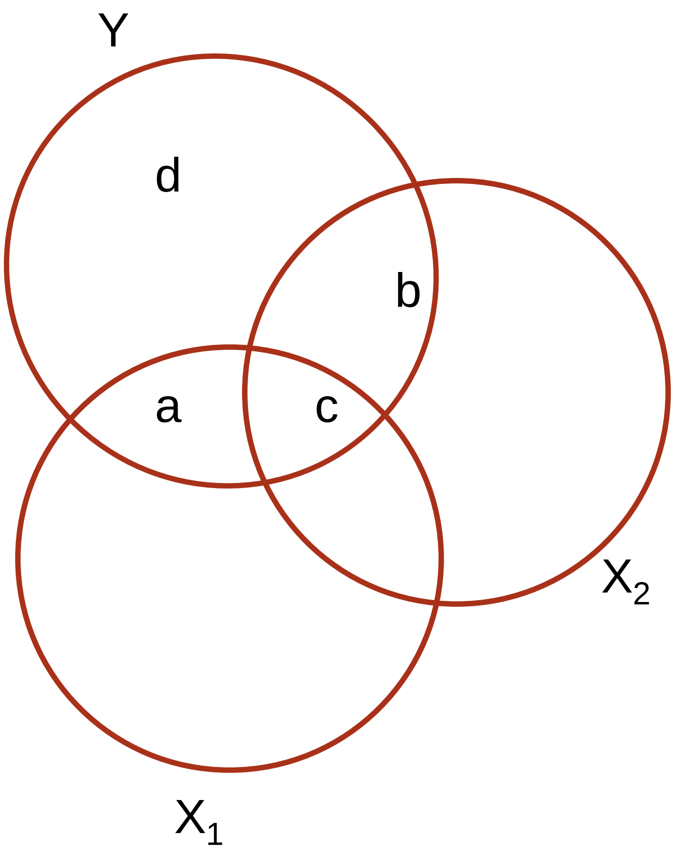
where Y: Attitude, X_1: PU, X_2: PEoU

Multiple Regression – assessing the relative importance of independent variables, Factor Analysis & Structure Equation Modelling (SEM)

Typical Equation:
$Y = a + b_1X_1 + b_1X_2 + \text{error}$

- Y is the dependent variable we wish to predict say amount of time spent on twitter annually by an individual
- X_1 & X_2 are independent variables used for predictive purposes – such as number of hours alone each day and age
- Predictiveness, in this example, is typically measured in terms of the total amount of variance in Y (R-square) that is covered by X_1 and X_2.
- Note that we are interested in determining which independent variable has more predictive impact, by how much relative to the other variables, and their total combined predictiveness.

a + b + c + d = total variance of Y



a = variance of Y uniquely explained by X_1

b = variance of Y uniquely explained by X_2

c = variance of Y jointly explained by X_1 and X_2

d = variance of Y NOT explained by X_1 or X_2

a + c = r2 between Y and X1

b + c = r2 between Y and X2

a / (a+d) = partial correlation2 of X1 controlling for X2

Represents the percentage increase in remaining R2 when X1 is added

a/{a+b+c+d} = semipartial (or part) correlation2 of X1 controlling for X2

Represents the incremental increase in R2 when X1 is added

Overall variance (R-square) can be calculated as :

$$R^2 = {r_{y1}}^2 + {sr_2}^2 = {r_{y2}}^2 + {sr_1}^2$$

Additional formulas for regression with two independent variables:
$Y = a + b_1X_1 + b_1X_2 + error$

Standardised beta: $b_1 = \frac{r_{y1} + r_{y2} * r_{12}}{1 - r_{12}^2} * \frac{SD_y}{SD_1}$

Standardised beta: $b_2 = \frac{r_{y2} + r_{y1} * r_{12}}{1 - r_{12}^2} * \frac{SD_y}{SD_2}$

Intercept: $a = M_y - (b_1M_1 + b_2M_2)$

Hierarchical Regression

- Testing whether adding additional variables to an existing regression model provides significant contribution
- $F\ distribution\ test = \frac{\frac{R_2^2 - R_1^2}{k_2 - k_1}}{\frac{1 - R_2^2}{N - k_2 - 1}}$
- $k_2 - k_1, N - k_2 - 1$ degrees of freedom

Exploratory Factor Analysis

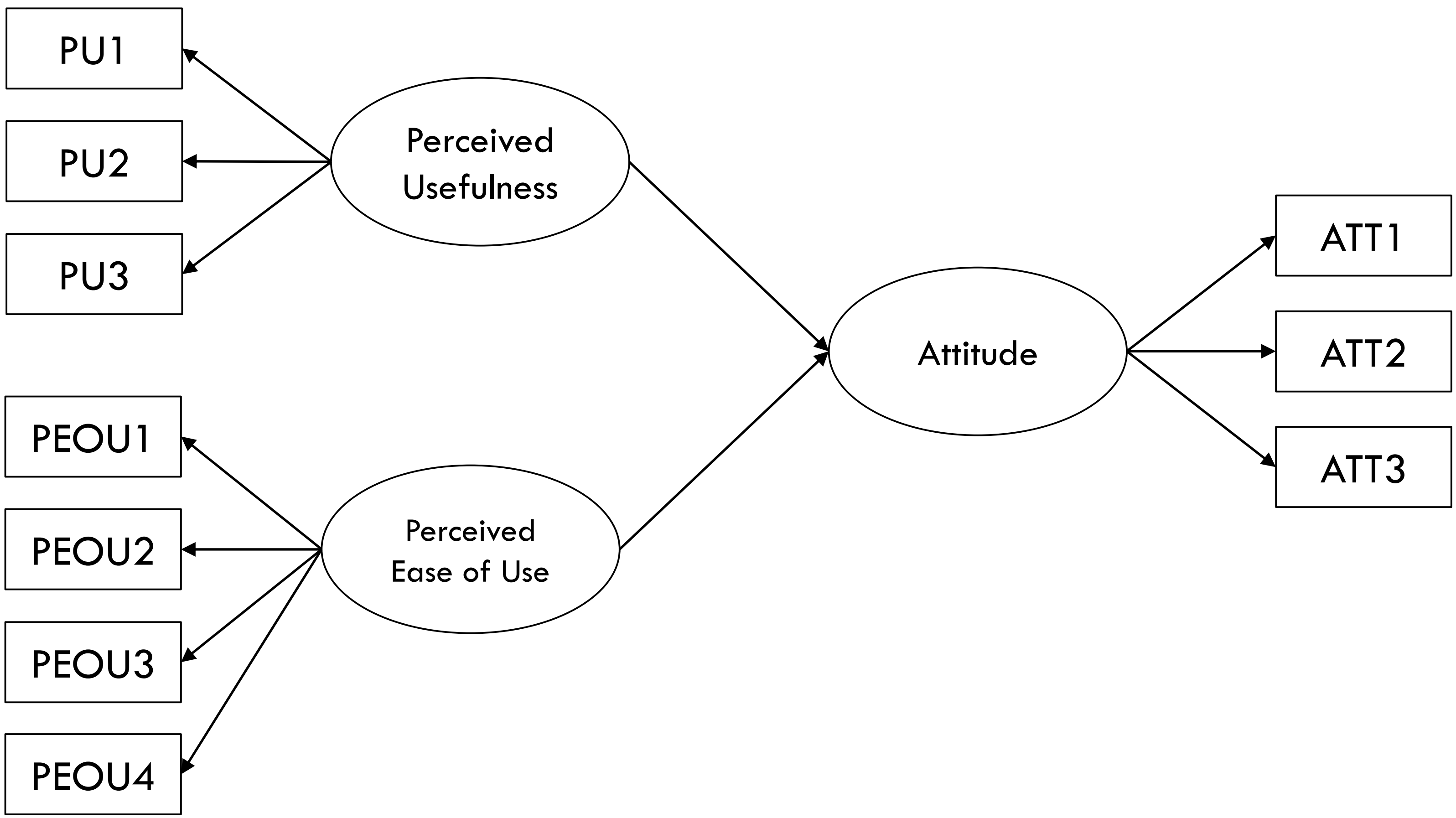
Factor Analysis

- Factor analysis is a date reduction technique whereby a large number of variables can be summarised into a more meaningful, smaller set of factors.
- Factor analysis can also be used to identify inter-relationships between variables in a dataset.
- Factor loading is the relationship between the manifest and latent variables.

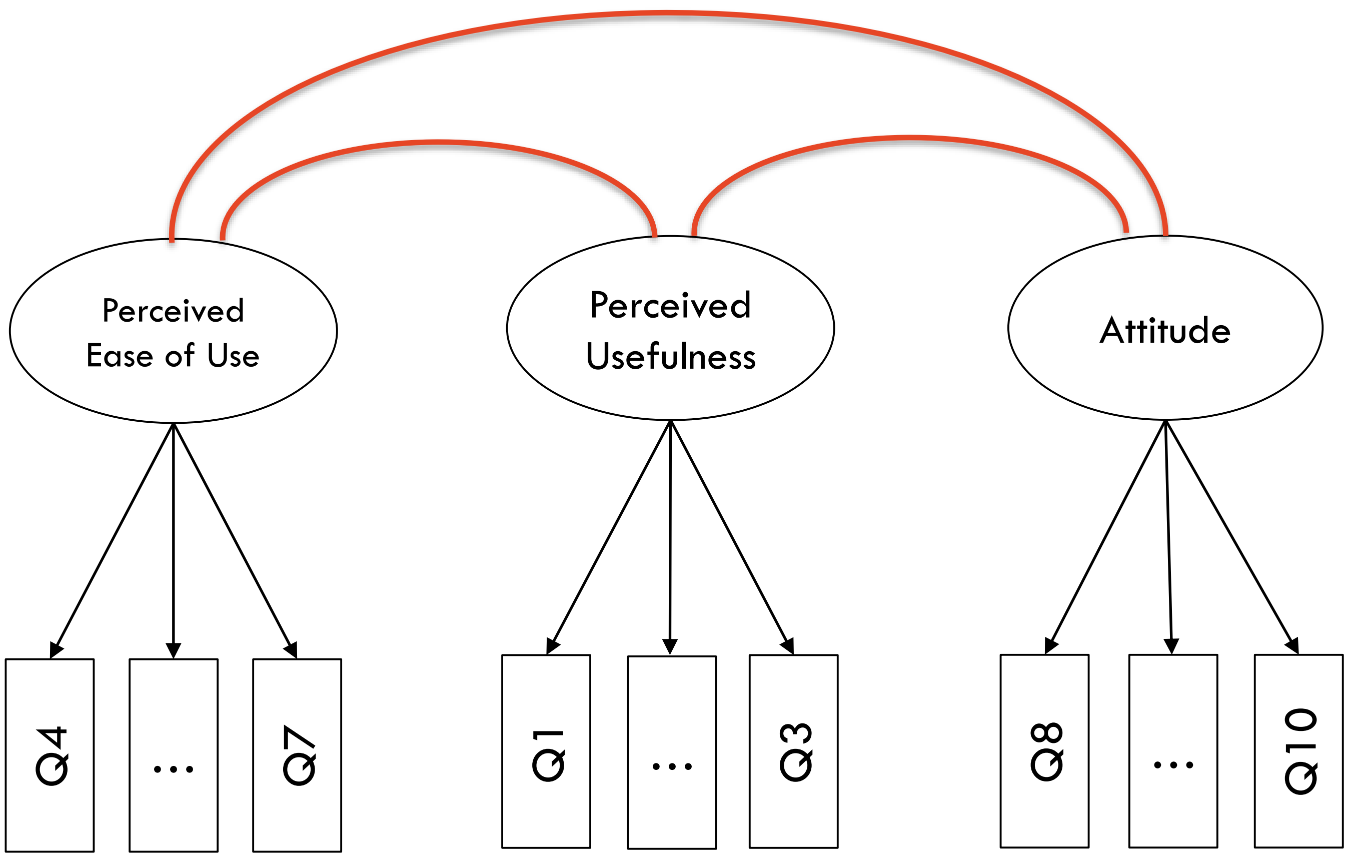
- Dataset is **ExerciseTAM data (Class).xlsx**

STRUCTURE EQUATION MODEL

Access SPSS - http://usyd.libanswers.com/faq/142268



Factor Analysis: An Example



Examine Correlations

Factor 1 Factor 2 Factor 3

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
PU1	PU2	PU3	PEOU1	PEOU2	PEOU3	PEOU4	ATT1	ATT2	ATT3
6	6	6	4	2	4	2	4	4	5
1	1	7	5	5	7	5	3	3	4
5	5	7	4	4	4	6	7	7	4
6	6	6	1	1	1	6	6	6	7
7	7	6	5	6	4	4	5	6	6
6	6	7	6	6	6	2	7	7	4
6	2	6	4	4	5	4	5	3	2
5	5	5	6	6	6	5	6	4	6
2	7	1	4	4	4	7	6	6	5
1	1	2	3	3	3	4	6	6	4
5	6	2	5	5	5	2	6	2	1
2	2	3	4	4	4	2	4	4	4
3	4	3	4	3	2	2	3	4	3
3	2	4	3	2	3	3	2	2	3
6	5	4	2	1	1	3	4	6	4
2	5	4	3	3	2	2	3	3	4
7	6	7	7	6	7	3	2	2	3
6	6	6	6	7	7	3	4	3	4
2	3	2	4	5	5	3	4	4	5
5	4	5	4	5	5	2	3	2	2
6	5	6	3	2	2	3	3	4	2

	PU1	*PU2*	*PU3*
PU1	1		
PU2	0.855252	1	
PU3	0.782688	0.730552	1

	PEOU1	*PEOU2*	*PEOU3*	*PEOU4*
PEOU1	1			
PEOU2	0.942483	1		
PEOU3	0.929468	0.943189	1	
PEOU4	0.622116	0.632097	0.622498	1

	ATT1	*ATT2*	*ATT3*
ATT1	1		
ATT2	0.760885	1	
ATT3	0.674076	0.747197	1

Created using Correlation option under Data Analysis in Microsoft Excel

Factor Analysis Example (can be complex)

Rees(2000) Examination of the Validity of the Social Support Survey

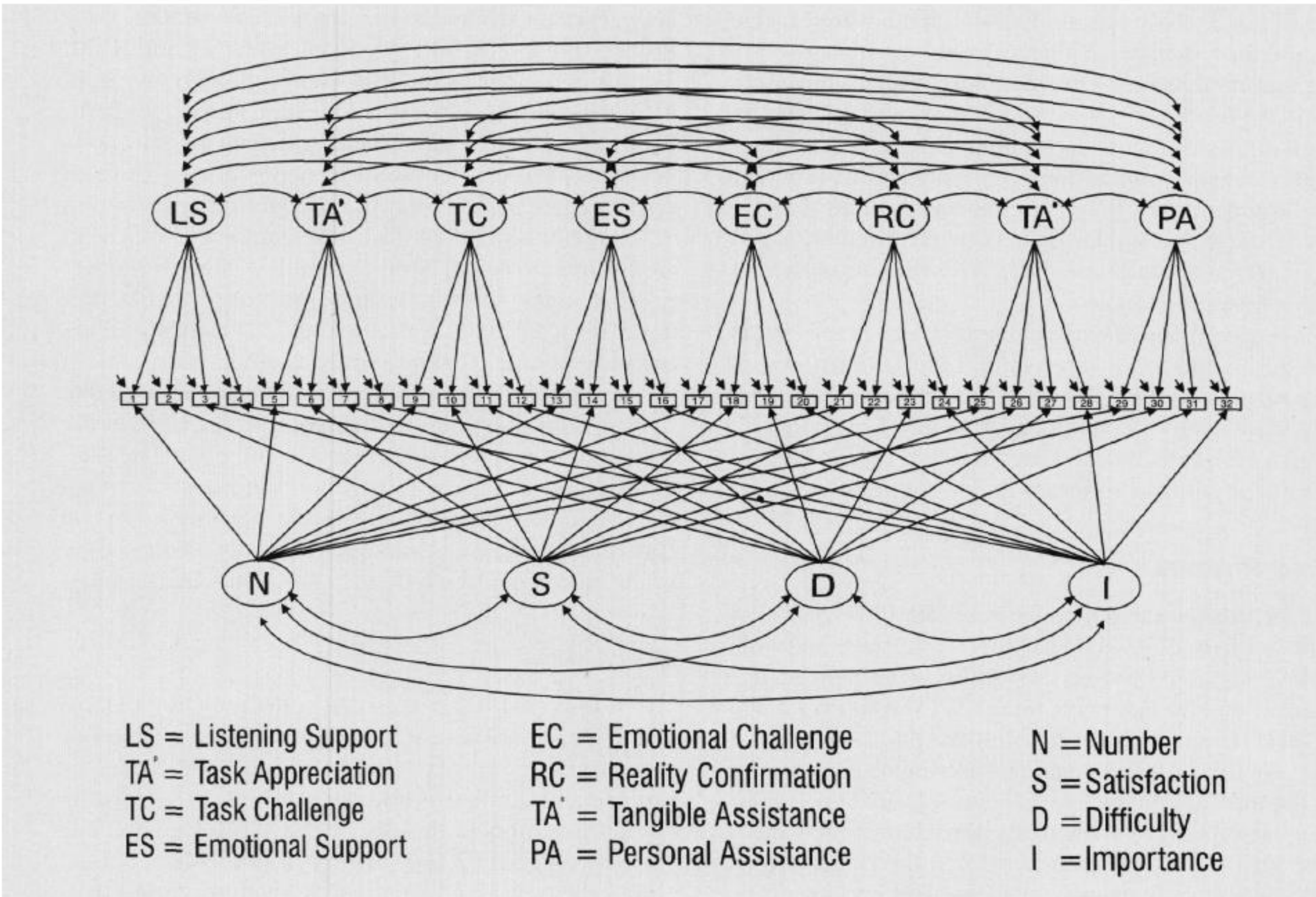
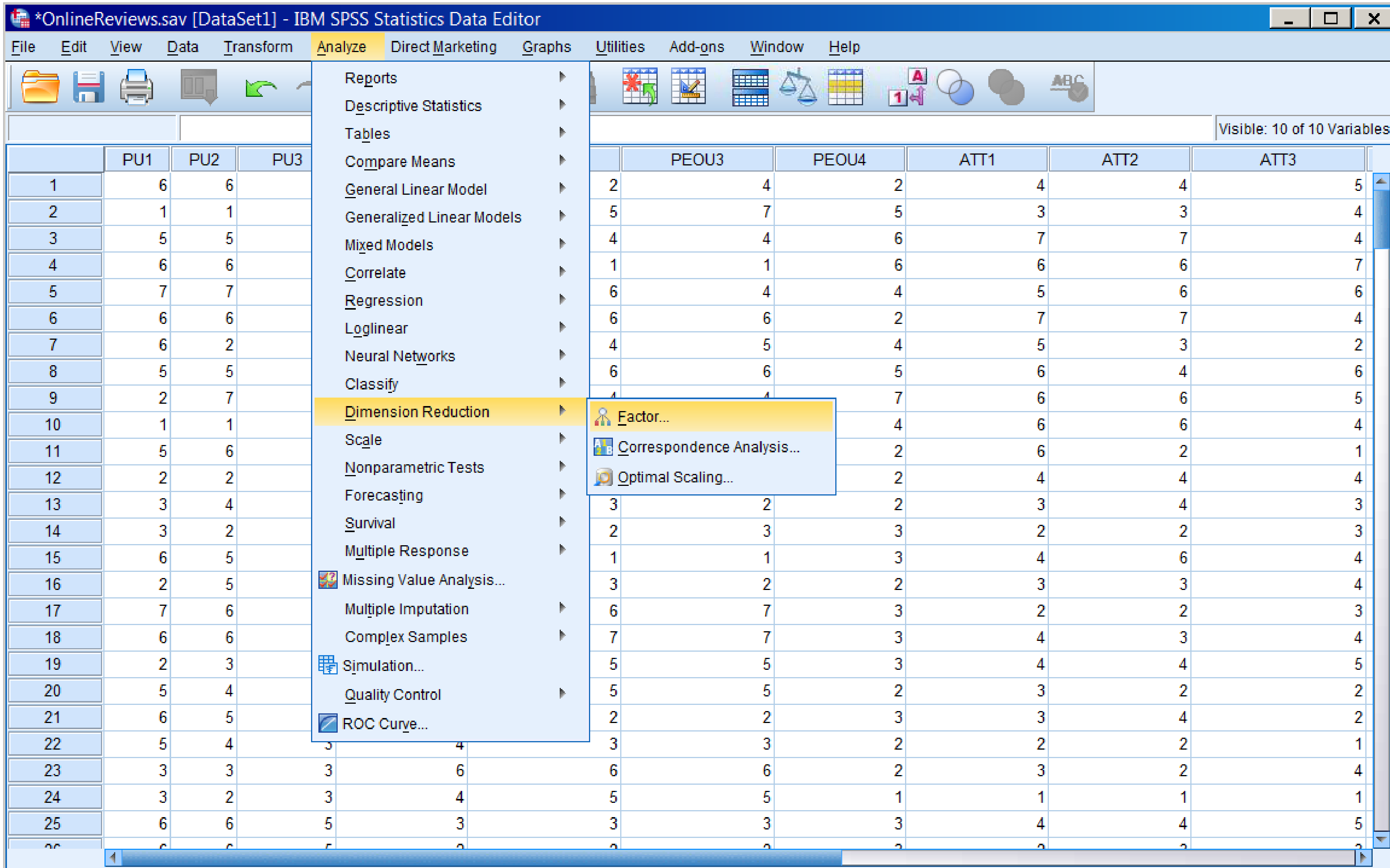


Figure 1. The multitrait-multimethod model, showing support content factors at the top (traits) and support appraisal factors below (methods).

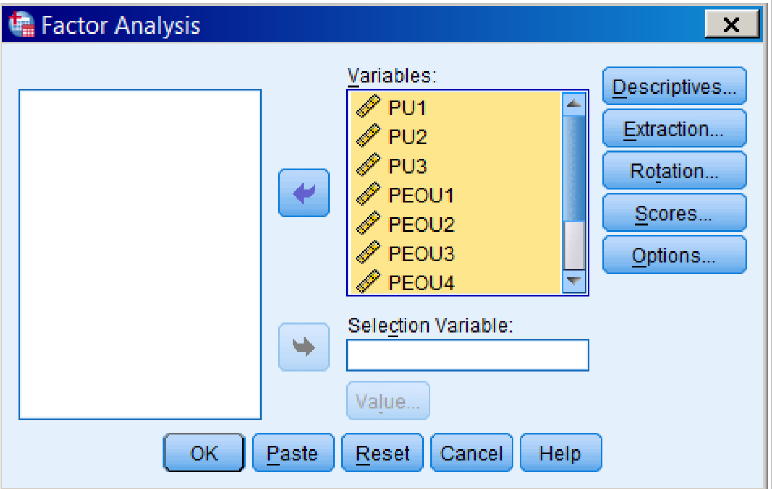
How are the factors?

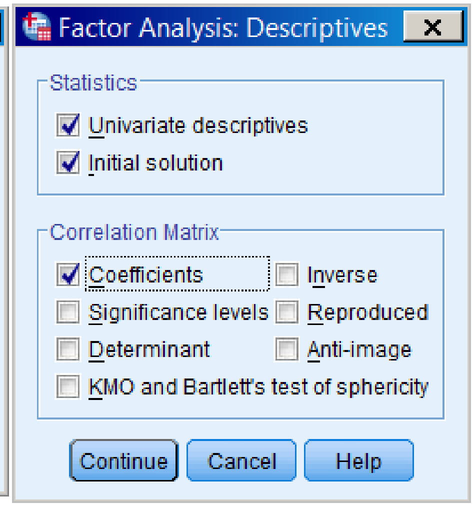
	PU1	*PU2*	*PU3*	*PEOU1*	*PEOU2*	*PEOU3*	*PEOU4*	*ATT1*	*ATT2*	*ATT3*
PU1	1									
PU2	0.855252	1								
PU3	0.782688	0.730552	1							
PEOU1	0.131461	0.12072	0.086219	1						
PEOU2	0.125735	0.123131	0.093812	0.942483	1					
PEOU3	0.088039	0.064891	0.085486	0.929468	0.943189	1				
PEOU4	0.138964	0.129545	0.108619	0.622116	0.632097	0.622498	1			
ATT1	0.323963	0.322171	0.264955	0.221999	0.233093	0.198093	0.400025	1		
ATT2	0.226749	0.250639	0.178264	-0.01219	-0.01268	-0.03209	0.265095	0.760885	1	
ATT3	0.223274	0.268959	0.20946	0.122503	0.126403	0.103926	0.400989	0.674076	0.747197	1

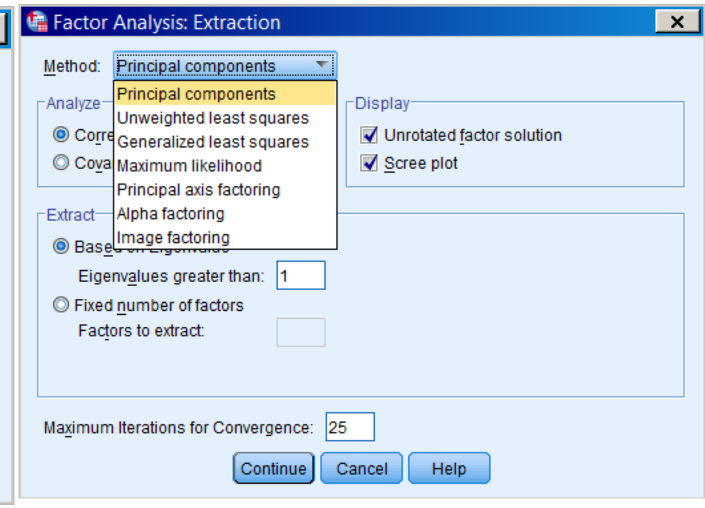
Exploratory Factor Analysis in SPSS

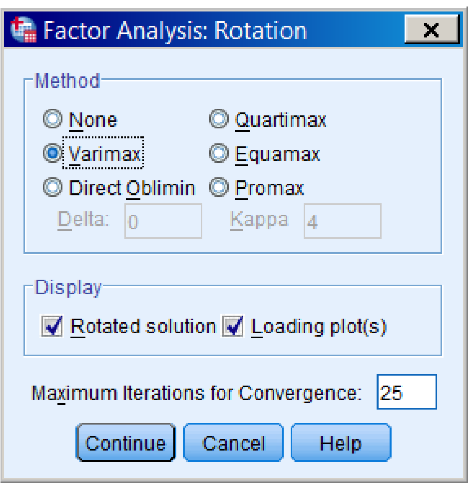


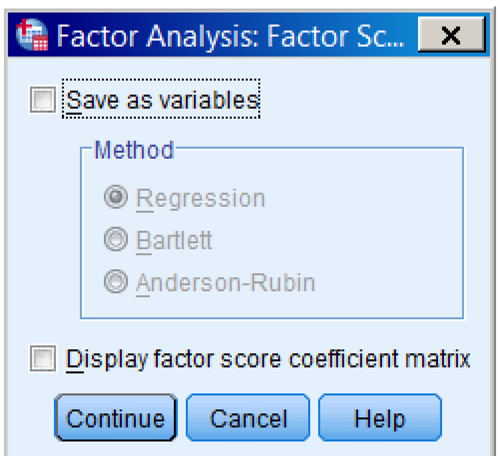
Exploratory Factor Analysis in SPSS

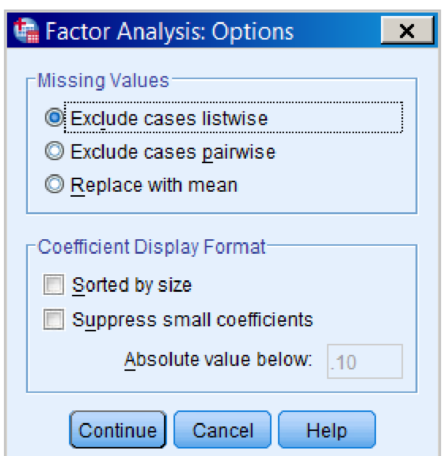










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DATASET NAME DataSet1 WINDOW=FRONT.
FACTOR
  /VARIABLES PU1 PU2 PU3 PEOU1 PEOU2 PEOU3
PEOU4 ATT1 ATT2 ATT3
  /MISSING LISTWISE
  /ANALYSIS PU1 PU2 PU3 PEOU1 PEOU2 PEOU3 P
EOU4 ATT1 ATT2 ATT3
  /PRINT UNIVARIATE INITIAL CORRELATION EXT
RACTION ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1) ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
  /ROTATION VARIMAX
  /METHOD=CORRELATION.
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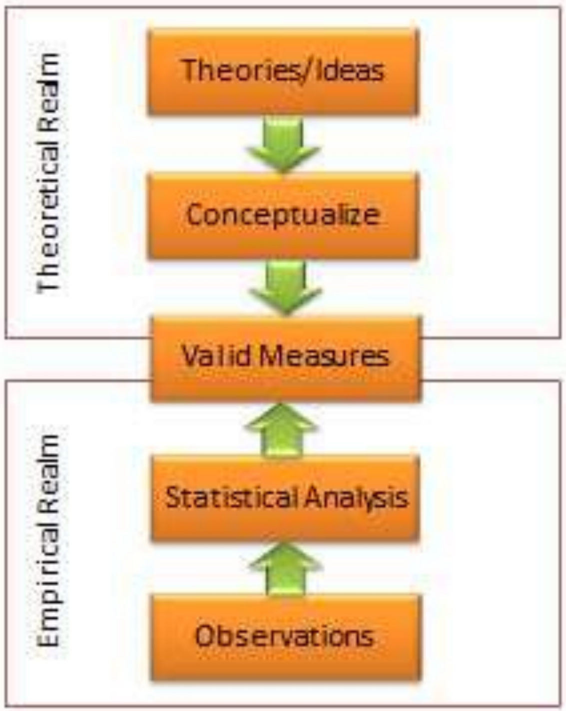
Empirical Assessment of Validity

- Criterion-related Validity
  - Examines how well a given measure relates to one or more external criterion, based on empirical observations

1. Convergent Validity
   - The closeness with which a measure relates to (or converges on) the construct that it is purported to measure
2. Discriminant Validity
   - The degree to which a measure does not measure (or discriminates from) other constructs that it is not supposed to measure
3. Predictive Validity
   - The degree to which a measure successfully predicts a future outcome that it is theoretically expected to predict
4. Concurrent Validity
   - Examines how well one measure relates to other concrete criterion that is presumed to occur simultaneously



Convergent and Discriminant Validity

– Method 1: Bivariate Correlational Analysis
  - Convergent validity
    - Comparing the observed values of one indicator of one construct with that of other indicators of the same construct
    - Demonstrating similarity (or high correlation) between values of these indicators
  - Discriminant validity
    - Demonstrating that indicators of one construct are dissimilar from (i.e., have low correlation with) other constructs

	KL1	KL2	KL3	PF1	PF2	PF3
KL1	1.00	0.83	0.79	0.23	0.21	0.19
KL2		1.00	0.75	0.11	0.20	0.03
KL3			1.00	0.03	-0.11	0.17
PF1				1.00	0.84	0.91
PF2					1.00	0.77
PF3						1.00

High correlations between items of the same construct (convergent validity)

Low correlations between items of different constructs (discriminant validity)

Exploratory Factor Analysis in SPSS

Bivariate Correlational Analysis

- Convergent validity
  - High correlations with same constructs
- Discriminant validity
  - Low correlations with other constructs

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
PU1	4.94	1.496	240
PU2	4.96	1.427	240
PU3	4.93	1.450	240
PEOU1	3.98	1.697	240
PEOU2	3.88	1.807	240
PEOU3	3.93	1.777	240
PEOU4	3.45	1.676	240
ATT1	3.95	1.298	240
ATT2	3.78	1.392	240
ATT3	3.83	1.335	240

Correlation Matrix

		PU1	PU2	PU3	PEOU1	PEOU2	PEOU3	PEOU4	ATT1	ATT2	ATT3
Correlation	PU1	1.000	.855	.783	.131	.126	.088	.139	.324	.227	.223
	PU2	.855	1.000	.731	.121	.123	.065	.130	.322	.251	.269
	PU3	.783	.731	1.000	.086	.094	.085	.109	.265	.178	.209
	PEOU1	.131	.121	.086	1.000	.942	.929	.622	.222	-.012	.123
	PEOU2	.126	.123	.094	.942	1.000	.943	.632	.233	-.013	.126
	PEOU3	.088	.065	.085	.929	.943	1.000	.622	.198	-.032	.104
	PEOU4	.139	.130	.109	.622	.632	.622	1.000	.400	.265	.401
	ATT1	.324	.322	.265	.222	.233	.198	.400	1.000	.761	.674
	ATT2	.227	.251	.178	-.012	-.013	-.032	.265	.761	1.000	.747
	ATT3	.223	.269	.209	.123	.126	.104	.401	.674	.747	1.000

Convergent and Discriminant Validity

– Method 2: Exploratory Factor Analysis (EFA)
  - – A data reduction technique which aggregates a given set of items to a smaller set of factors based on the bivariate correlation structure
  - – **Principal Components Analysis (PCA)**
    - Extract factors with eigenvalue greater than 1.0
    - Extracted factors are rotated using orthogonal (Varimax*, Quartimax, Equamax) or oblique rotation techniques (Direct Oblimin, Promax)
  - – **Convergent Validity**
    - Items belonging to a common construct should exhibit factor loadings of **0.60 or higher** on a single factor (same-factor loadings)
  - – **Discriminant Validity**
    - Items should have factor loadings of **0.30 or less** on all other factors (cross-factor loadings)

	Factor1	Factor2
KL1	0.88	0.13
KL2	0.93	0.11
KL3	0.87	0.03
PF1	0.17	0.93
PF2	-0.03	0.85
PF3	0.07	0.78

High same-factor loadings (convergent validity)

Low cross-factor loadings (discriminant validity)

Exploratory Factor Analysis in SPSS

Communalities

- Squared multiple correlation (r^2) of an indicator, taken as the dependent variable, with the extracted factors (components) treated as independent variables
- Proportion of variance in the indicator that is accounted for by the extracted factors (components)
  - E.g., 90.2% of the variance in PU1 is accounted for by the 3 extracted factors
    - 51.7% by the 1st factor (component)
    - 11.0% by the 2nd factor (component)
    - 27.5% by the 3rd factor (component)

Communalities

	Initial	Extraction
PU1	1.000	.902
PU2	1.000	.865
PU3	1.000	.814
PEOU1	1.000	.935
PEOU2	1.000	.947
PEOU3	1.000	.939
PEOU4	1.000	.670
ATT1	1.000	.800
ATT2	1.000	.873
ATT3	1.000	.801

Extraction Method: Principal Component Analysis.

Exploratory Factor Analysis in SPSS

Total Variance Explained

- Eigenvalues (λ)
  - Sum of the squared loadings of the indicators on the factor (component) with which the eigenvalue is associated
- Variance of each indicator is 1.0
- Total variance is the number of indicators (K)
- λ / K = Proportion of the total variance accounted for by the component with which the λ is associated
  - E.g., The 1st component accounts for 4.008/10=40.075% of the total variance
  - E.g., The 3 extracted components account for 18.099% of the total variance

Total Variance Explained

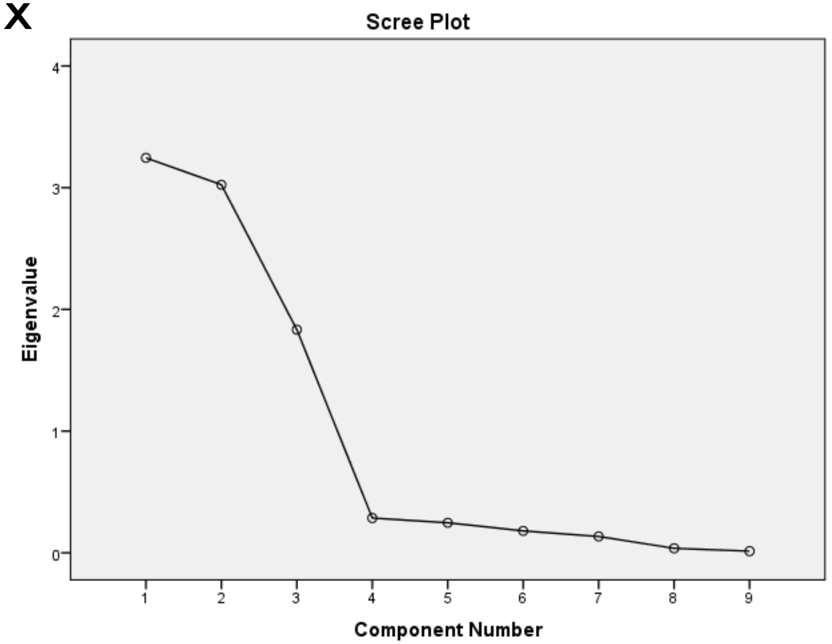
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.008	40.075	40.075	4.008	40.075	40.075	3.387	33.869	33.869
2	2.729	27.289	67.364	2.729	27.289	67.364	2.593	25.934	59.803
3	1.810	18.099	85.463	1.810	18.099	85.463	2.566	25.661	85.463
4	.428	4.279	89.742						
5	.306	3.064	92.806						
6	.283	2.833	95.638						
7	.185	1.847	97.486						
8	.134	1.343	98.829						
9	.066	.664	99.493						
10	.051	.507	100.000						

Extraction Method: Principal Component Analysis.

Exploratory Factor Analysis in SPSS

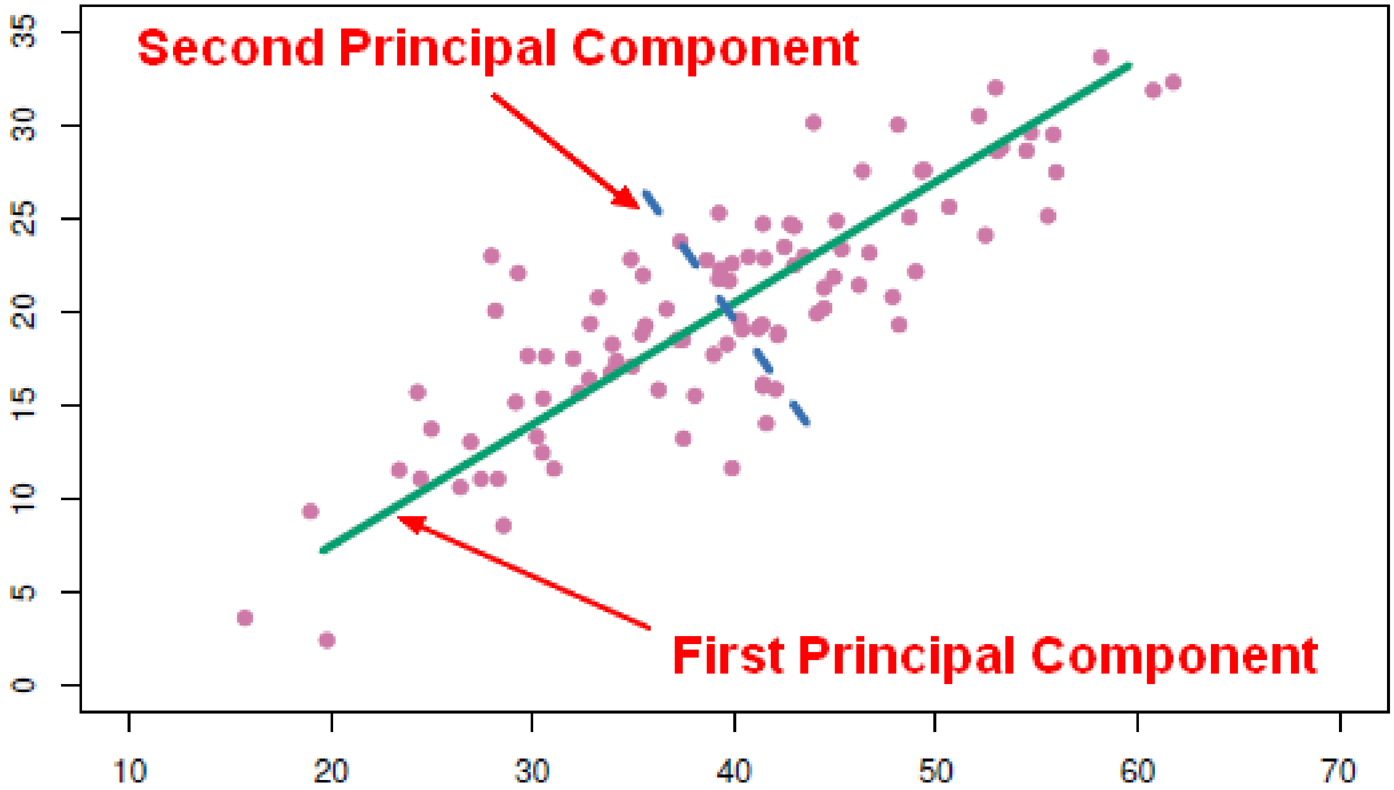
Scree Plot

- The plot of λ's in descending order of magnitude
- An aid to in determining the number of factors to be retained
- Identify a clear break, akin of an elbow, between large λ's and small ones (appearing to lie on a horizontal line)
- E.g., The scree plot confirms our expectation that **three** factors underlie the correlation matrix



Principal Component Analysis

– The most common factor extraction method that uses orthogonal linear projections to capture the underlying variance of the data



Exploratory Factor Analysis in SPSS

Component (Factor) Matrix

- Component (factor) loadings
  - Correlations between the indicator and the factor (component)
  - Square of a loading is the proportion of variance in the indicator that is accounted for by the factor
  - Row totals of squared loadings = Communalities
    - E.g., $(0.554)^2+(0.558)^2+(-0.553)^2=0.902$
  - Column totals of squared loadings = Eigenvalues
    - E.g., $(0.554)^2+(0.549)^2+\ldots+(0.578)^2=4.008$

Component Matrix[a]

	Component		
	1	2	3
PU1	.554	.558	.533
PU2	.549	.568	.491
PU3	.496	.532	.533
PEOU1	.736	-.615	.121
PEOU2	.744	-.617	.118
PEOU3	.713	-.646	.111
PEOU4	.732	-.307	-.202
ATT1	.670	.361	-.471
ATT2	.481	.511	-.617
ATT3	.578	.388	-.563

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

Exploratory Factor Analysis in SPSS

Rotated Component Matrix

- Loadings in the component matrix are hard to interpret
- Transformed (rotated) using orthogonal (Varimax*, Quartimax, Equamax) or oblique rotation techniques (Direct Oblimin, Promax)
- Indicators are remapped on rotated axes
- Improves the interpretability of the loadings
  - **Convergent validity**
    - **Same-factor loadings ≥ 0.60**
  - **Discriminant validity**
    - **Cross-factor loadings ≤ 0.30**

Component Transformation Matrix

- Matrix used to transform (rotate) the component matrix to the rotated component matrix

Rotated Component Matrix[a]

	Component		
	1	2	3
PU1	.066	.938	.138
PU2	.050	.913	.170
PU3	.041	.896	.096
PEOU1	.964	.068	.017
PEOU2	.970	.069	.022
PEOU3	.968	.033	-.001
PEOU4	.720	.028	.389
ATT1	.193	.205	.849
ATT2	-.060	.105	.926
ATT3	.099	.116	.882

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

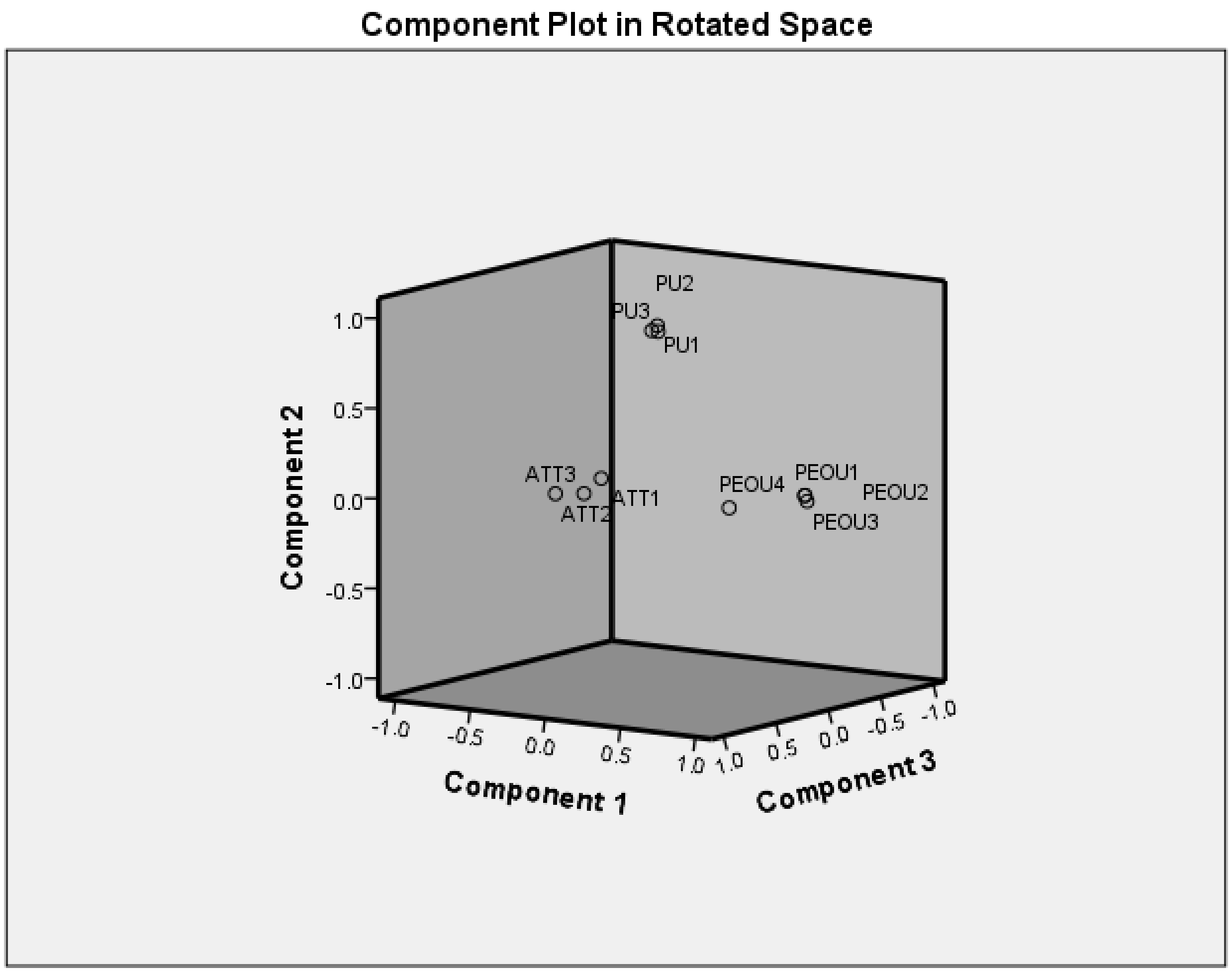
a. Rotation converged in 5 iterations.

Component Transformation Matrix

Component	1	2	3
1	.721	.466	.513
2	-.686	.578	.441
3	.091	.670	-.737

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

Exploratory Factor Analysis in SPSS



Before

Rotated Component Matrix[a]

	Component		
	1	2	3
PU1		.938	
PU2		.913	
PU3		.896	
PEOU1	.964		
PEOU2	.970		
PEOU3	.968		
PEOU4	.720		.389
ATT1			.849
ATT2			.926
ATT3			.882

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

After Excluding PEOU4

Rotated Component Matrix[a]

	Component		
	1	2	3
PU1		.938	
PU2		.912	
PU3		.897	
PEOU1	.974		
PEOU2	.978		
PEOU3	.977		
ATT1			.864
ATT2			.930
ATT3			.882

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 4 iterations.