Student Counselling Group

Next Meeting: 9am Wednesday, 21st May '08 – Bldg 21D (Student Services)

Street Theatre

<u>We Need:</u>

People to ‘act’ and help out at our Street Theatre Production (no talking involved!)

Happy People for Making Props at our Craft Day (Free Lunch! Music! Giveaways!) – 30th May 9am -3pm

Active audience members to have a great time on the days we perform (O’Week – Semester 2) ☺

<u>Why Should You Do It?</u>

To Help People

To receive Valuable experience working for a student counselling group at UQ

To get to know your fellow Psychology Students and Network!

For Free ‘Help’ Training* and Workshops* for Student Counsellors & A cool FREE* T-shirt!

*Only free if you become a permanent member

Email

Jess: **s4117173@student.uq.edu.au** or Lizzy: **s4079787@student.uq.edu.au** or Eranthi: **s4098537@student.uq.edu.au**

if you have any questions!

Hope to see you at the next meeting!

Moving objects can alter your consciousness

Tom Wallis

Wednesday, 21 May 2008 from 12-1pm
McElwain Building, Room 317

Light hits the retina, where it is transduced from an electromagnetic into an electrochemical signal. Then a highly complicated and poorly understood process occurs, and we perceive the world around us in a seemingly consistent and stable way. I will discuss a situation in which the consistent and stable representation of the world appears to break down. Motion-induced blindness (MIB; Bonneh, Cooperman, & Sagi, 2001) occurs when stationary objects (dots) disappear intermittently from awareness when surrounded by motion signals (moving dots), despite remaining physically persistent on the retina. I will present data pertaining to some low-level visual determinants of MIB. This data suggests that MIB may be a striking example of a functional mechanism, motion deblurring, acting in a dysfunctional (but really cool) way when exposed to unnatural input.

Interpretation of Common Factor Analysis

Adequacy of factor solution: Percentage of variance

Total Variance Explained

Factor	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	8.194	18.623	18.623	7.586	17.240	17.240	6.072	13.800	13.800
2	5.154	11.713	30.335	4.561	10.365	27.605	5.607	12.743	26.543
3	2.590	5.887	36.223	1.931	4.389	31.994	2.399	5.451	31.994

Extraction Method: Principal Axis Factoring.

%Total Variance

% of Total Variance that is common

Consider the %Total Variance accounted for. About 30% is a minimum and 65% or above is excellent. The difference between the %Total Variance and the % of Total Variance that is common indicates the Amount of Unique Variance.

Total variance = Common variance + Specific variance (unique + error)

DATA = MODEL + RESIDUAL

Interpretation of Common Factor Analysis

Adequacy of factor solution: Percentage of variance

Total Variance Explained

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	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.194	18.623	18.623	7.586	17.240	17.240	6.072	13.800	13.800
2	5.154	11.713	30.335	4.561	10.365	27.605	5.607	12.743	26.543
3	2.590	5.887	36.223	1.931	4.389	31.994	2.399	5.451	31.994

Extraction Method: Principal Axis Factoring.

T&F (p. 667) discuss the use of Sums of Squared Loadings (SSLs) from the orthogonally rotated factor matrix as an indicator of the importance of each factor in accounting for the variance and the covariance. The SSL/p gives the proportion of variance for a factor (p = number of variables) and $SSL/\sum SSLs$ gives the proportion of covariance (or common variance) for a factor.

	Factors 1	Factors 2	Factors 3
SSL	6.072	5.607	2.399
Percent of Variance	13.80%	12.74%	5.45%
Percent of Covariance	43.13%	39.83%	17.04%

Percent of Covariance is a measure of the 'relative strength' of the factors (they sum to 100%).

Interpretation of Common Factor Analysis

Adequacy of factor solution: Percentage of variance

Total Variance Explained

Factor	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	8.194	18.623	18.623	7.586	17.240	17.240	6.072	13.800	13.800
2	5.154	11.713	30.335	4.561	10.365	27.605	5.607	12.743	26.543
3	2.590	5.887	36.223	1.931	4.389	31.994	2.399	5.451	31.994

Extraction Method: Principal Axis Factoring.

With an oblique solution the SSLs are not used because their values are influenced by the correlations among the factors. However, the number of high loading variables on a factor gives an indication of the relative importance of the factors. This is called the ‘factor saturation’. For orthogonal solutions this is reflected in the size of the SSL.

Total Variance Explained

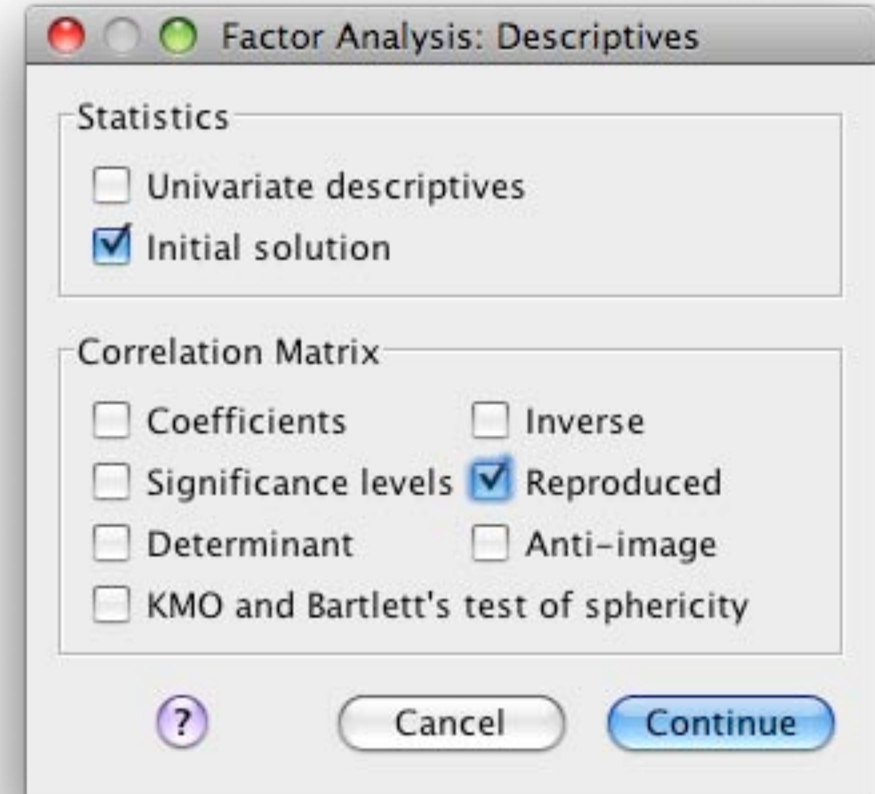
Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	8.194	18.623	18.623	7.586	17.240	17.240	6.376
2	5.154	11.713	30.335	4.561	10.365	27.605	5.961
3	2.590	5.887	36.223	1.931	4.389	31.994	2.674

Extraction Method: Principal Axis Factoring.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

Interpretation of Common Factor Analysis

Adequacy of factor solution: Residual Correlation Matrix

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		HELPFUL	self reliant	defend beliefs	YIELDING
Reproduced Correlation	HELPFUL	.283[b]	.264	.211	.084
	self reliant	.264	.400[b]	.178	.017
	defend beliefs	.211	.178	.234[b]	-.007
	YIELDING	.084	.017	-.007	.129[b]
Residual[a]	HELPFUL		.073	.027	.030
	self reliant	.073		-.032	-.029
	defend beliefs	.027	-.032		-.071
	YIELDING	.030	-.029	-.071	

Extraction Method: Principal Axis Factoring.

a. Residuals are computed between observed and reproduced correlations. There are 291 (30.0%) nonredundant residuals with absolute values greater than 0.05.

b. Reproduced communalities

The actual reproduced/residual correlation matrix is enormous, so it's impractical for a large number of variables.

Considering the residual correlation matrix can indicate whether the factor extraction is adequate, (values 0.1). If not, more factors may be needed.

Interpretation of Common Factor Analysis

Adequacy of factor solution: Communalities

Communalities

	Initial	Extraction
helpful	.374	.283
reliant	.461	.400
defbel	.417	.234
yielding	.230	.129
cheerful	.492	.244
indpt	.538	.449
athlet	.258	.083
shy	.325	.157
assert	.538	.439
strpers	.593	.511
forceful	.566	.459
affect	.553	.456
flatter	.296	.149
loyal	.391	.297
analyt	.242	.116
feminine	.358	.152
sympathy	.453	.325
moody	.381	.213
sensitiv	.486	.292
undstand	.617	.421
compass	.649	.483
leaderab	.763	.576
soothe	.435	.378
risk	.422	.260
decide	.489	.378
selfsuff	.633	.625
conscien	.399	.338
dominant	.562	.537
masculin	.316	.184
stand	.573	.431
happy	.536	.273
softspok	.402	.272
warm	.615	.602
truthful	.356	.150
tender	.605	.512
gullible	.297	.194
leadact	.761	.529
childlik	.296	.182
individ	.379	.237
foullang	.113	.020
lovchil	.284	.125
compete	.465	.251
ambitiou	.459	.230
gentle	.580	.501

Extraction Method: Principal Axis Factoring.

The initial communalities are the squared multiple correlations, and tell you how much of the variance of a variable is accounted for by all of the factors.

Extraction communalities are estimates of the variance in each variable accounted for by all the factors.

$$Z_j \leftarrow F_1 F_2 \ldots F_m$$

Small values (< 0.1) indicate that a particular variable does not fit well with the factor solution, and should possibly be dropped from the analysis.

athletic	0.258	0.083
use foul language	0.113	0.020

Small values are a concern

self sufficient	0.633	0.625
WARM	0.615	0.602

Large values are good

A checklist for interpretation of factor analysis

1. Determine model (FA via PCA or CFA)
2. Check Assumptions
   - factorability
   - linearity, outliers, skewness, multicollinearity
3. Choose the number of factors
   - initial estimates via
     - eigenvalues > 1
     - scree plot
     - parallel analysis test
   - compare several solutions
   - final decision via
     - best simple structure
     - theoretical/conceptual reasons

A checklist for interpretation of factor analysis

4. Choose the type of rotation

- compare both solutions (orthogonal and oblique)
- final decision via
  - best simple structure
  - factor correlations > 0.3
  - theoretical/conceptual reasons

5. Interpretation

- Overall importance of solution
  - % total variance explained
  - % variance that is common (for CFA only)
- Number of factors retained
  - depends on the interpretability and purpose of research.
- Importance of each factor (for orthogonal solutions)
  - % variance for each factor SSL/p
  - % covariance for each factor $SSL/\sum SSLs$

A checklist for interpretation of factor analysis

5. Interpretation (continued)

- Importance of each factor (for oblique solutions)
  - report the number of high loadings for each factor which gives a measure of the factor saturation.
- Labelling of each factor
  - specify cut-off for high loadings.
  - provide a label which reflects high-loading variables.
- Correlations between factors
  - used to decide which rotation to report.
  - report and interpret for oblique rotation only.

6. Checks of adequacy of the factor solution

- if some final communalities are small (eg < 0.1), the variable is not well explained by the factors.
- consider:
  - retaining more factors
  - removing the variable(s) from interpretation

A checklist for interpretation of factor analysis

6. Checks of adequacy of the factor solution

- if some variable loadings are split between factors, the variables are not well explained by any single factor,
- consider:
  - changing number of factors
  - changing type of rotation
  - removing the variable(s) from interpretation
- if the number of variables in each factor is low, the factor is not well defined by the variables,
- consider:
  - adding/removing variable(s) in future research
  - retaining fewer factors
- if elements in residual correlation matrix are not very small, the retained factors are not adequately modelling the data.
- consider:
  - retaining more factors
  - using an oblique rotation

Reporting the factor solution

Ford et al (1986) provide a good set of recommendations regarding the factor analytic techniques and their presentation. The evaluation of the limitations as explained by T&F is important.

- Technique
  - Default options of computer packages avoided unless justified by the researcher.
  - Factor analysis methodology is described completely with accurate terminology.
  - The factor model is related to the goal of the research.
  - Oblique solution is used unless the orthogonality assumption is tenable.
  - Multiple solutions are examined prior to the decision on factor retention.
  - Factors are interpreted based on a knowledge of the variables and an examination of all factor loadings.

Ford, J.K., MacCallum, R.C., & Tait, M. (1986). The application of exploratory factor analysis in applied psychology: A critical review and analysis. *Personnel Psychology*, *39*, 291–314. [download from the course webpage]

Reporting the factor solution

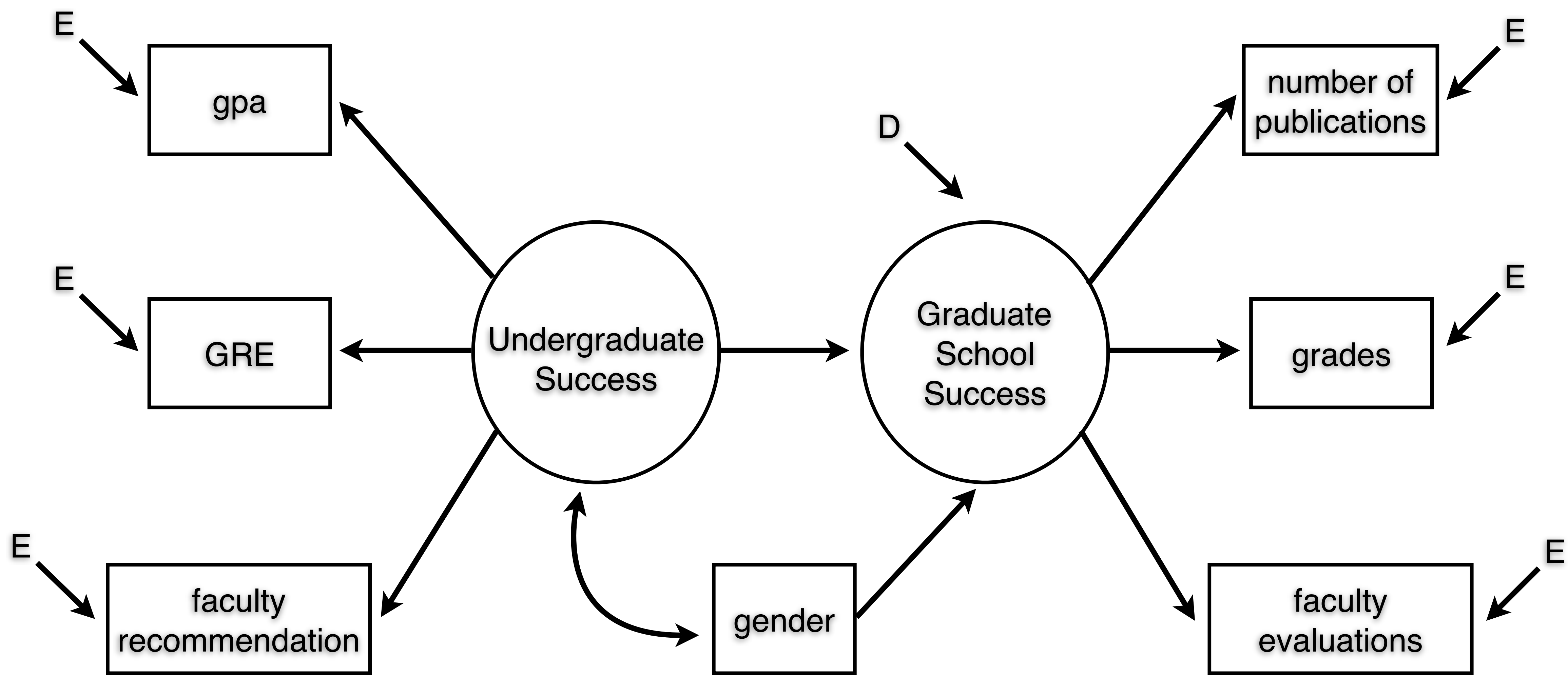
Ford et al (1986) provide a good set of recommendations regarding the factor analytic techniques and their presentation. The evaluation of the limitations as explained by T&F is important.

- Presentation
  - Information about factor analytic procedures are presented clearly in enough detail for informed review, replication, and cumulation of knowledge.
  - Information to be presented includes:

- sample size
- factor model;
- method of estimating communalities (if applicable);
- method of determining the number of factors to retain;
- rotational method;
- strategy of interpreting factors;
- eigenvalues for all the factors (if applicable);
- percentage of variance accounted for (if using orthogonal rotation);
- complete factor loading matrix for orthogonal rotation
- complete pattern matrix and interfactor correlations when oblique rotation is used.
- descriptive statistics and correlation matrix if the number of variables is small;
- computer program package;
- method for computation of factor scores;

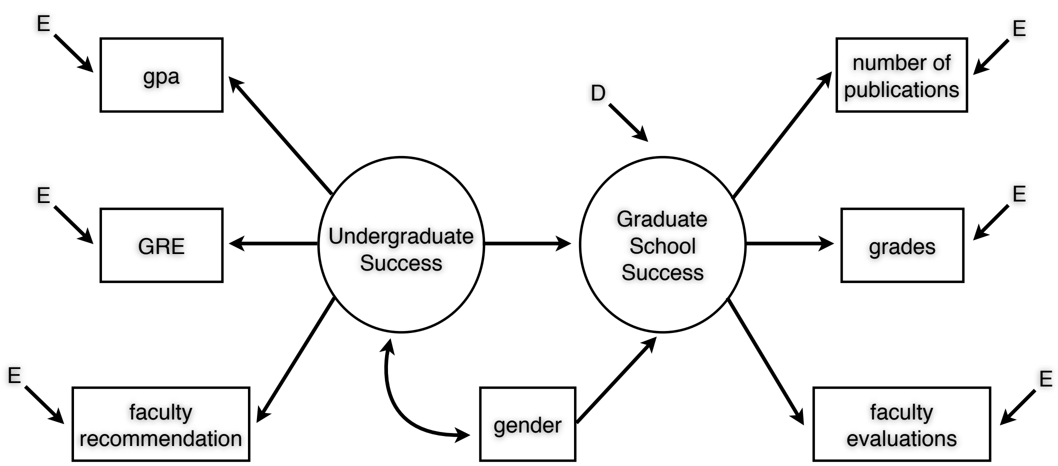
Ford, J.K., MacCallum, R.C., & Tait, M. (1986). The application of exploratory factor analysis in applied psychology: A critical review and analysis. *Personnel Psychology*, *39*, 291–314. [download from the course webpage]

Structural Equation Modelling



...a very brief introduction

Structural Equation Modelling



- Introduction
- Exploratory vs Confirmatory FA
- General purpose and process of statistical modelling

Structural Equation Modelling

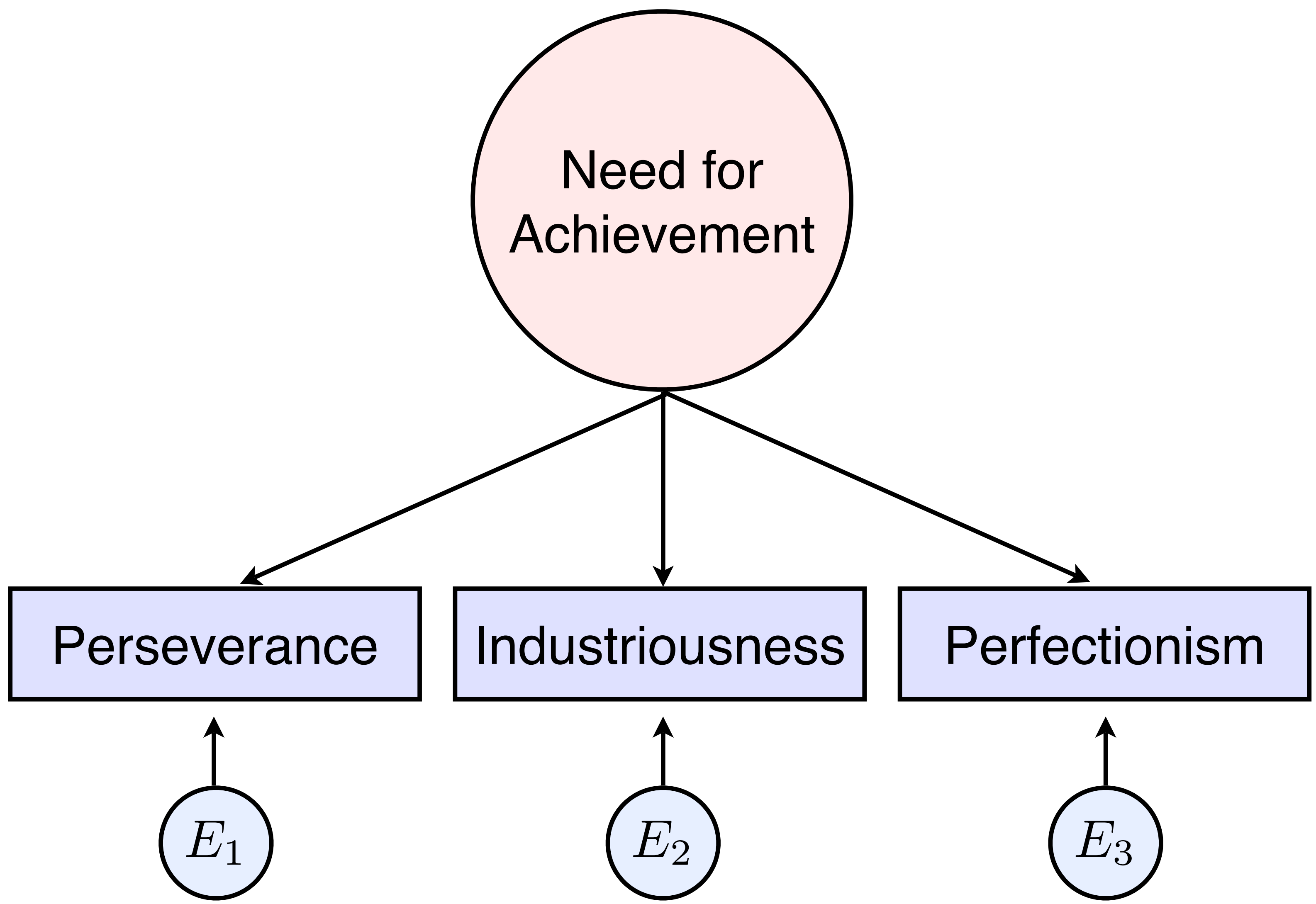
Introduction

- Structural equation modelling is a collection of statistical techniques that takes a confirmatory (i.e., hypothesis testing) approach to the structure bearing on some phenomenon.
- This theory represents "causal" processes that generate observations on multiple variables.
- There are two important aspects of the procedure:
  a. the causal processes are represented by a series of structural equations.
  b. these structural relations can be modelled pictorially to enable a clearer conceptualisation of the theory.
- The hypothesised model can then be tested statistically in a simultaneous analysis of the entire system of variables to determine the extent to which it's consistent with the data.

Structural Equation Modelling

Exploratory vs Confirmatory Factor Analysis

- In factor analysis, you examine the covariation among a set of observed variables in order to gather information on their underlying latent constructs (i.e., factors).



Structural Equation Modelling

Exploratory vs Confirmatory Factor Analysis

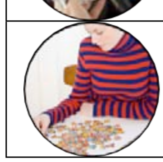
- There are two basic types of factor analysis:
  a. exploratory
  b. confirmatory
- *Exploratory FA* is designed for the situation where links between the observed and latent variables are uncertain. The analysis thus proceeds in an exploratory mode to determine how and to what extent the observed variables are linked to their underlying factors.
  - Typically you want to identify the minimal number of factors that underlie (or account for) covariation among the observed variables. These relations are represented by the factor loadings.

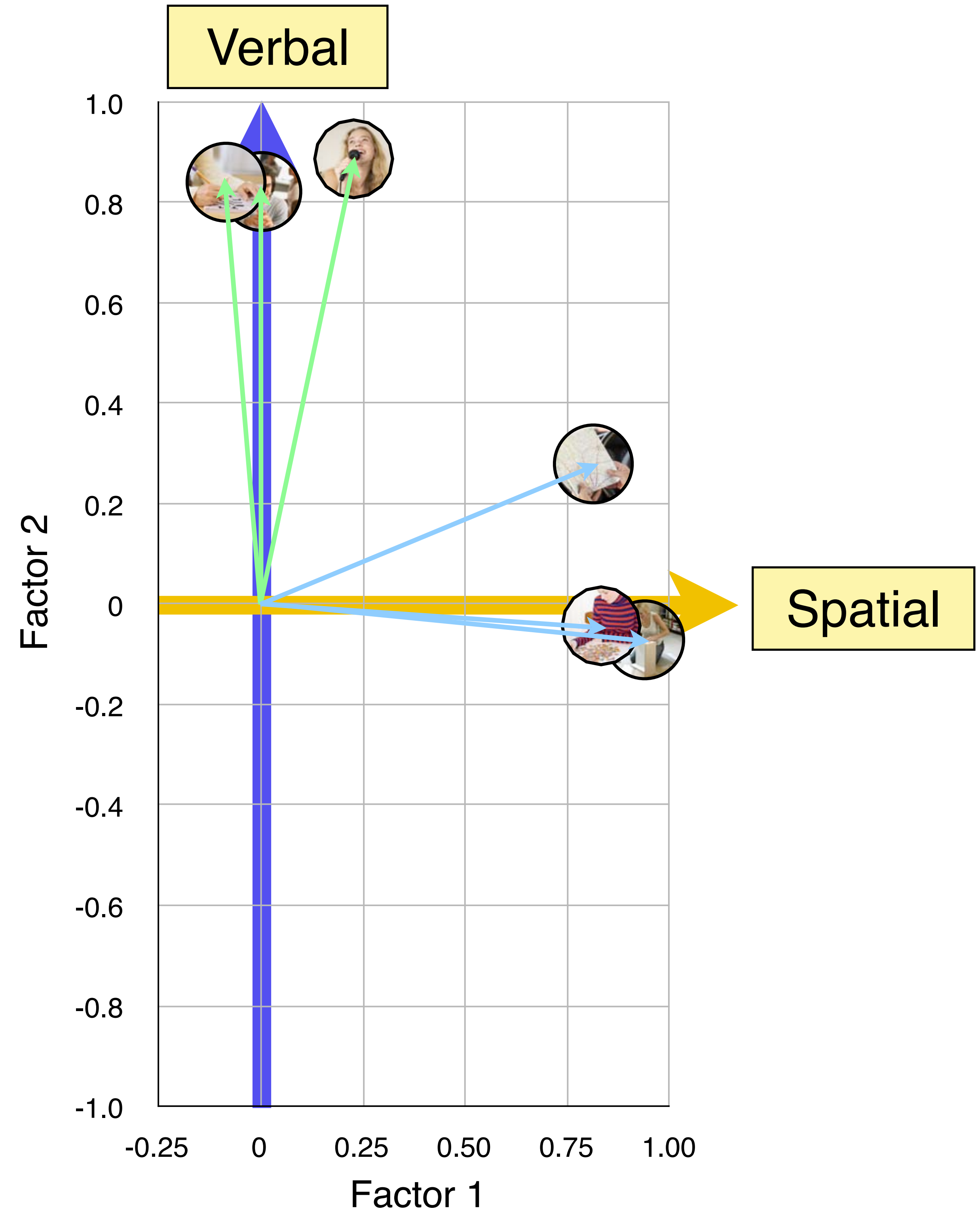
Structural Equation Modelling

Exploratory vs Confirmatory Factor Analysis

For example, you would hope that items designed to measure, say, verbal ability exhibit high loadings on that factor and low or negligible loadings on the other factor(s).

$\mathbf{A}_{\mathbf{rotated}}$

	1	2
	0.23	0.88
	0.00	0.83
	-0.08	0.84
	0.94	-0.07
	0.82	0.28
	0.84	-0.04



This approach is exploratory in the sense that you have no prior knowledge whether the items will, indeed, measure the intended factors.

Structural Equation Modelling

Exploratory vs Confirmatory Factor Analysis

- *Confirmatory FA* on the other hand, is used when you have some knowledge of the underlying latent variable structure. Based on your knowledge of the theory, previous empirical research, or both, you postulate relations between the observed measures and the underlying factors and then test this hypothesised structure statistically using a goodness-of-fit test.
    - So the factor analytic model (exploratory and confirmatory) focuses solely on how, and the extent to which, the observed variables are linked to their underlying latent factors. More specifically, it's concerned with the extent to which the observed weights are generated by the underlying latent factors, and the strength of the regression paths from the factors to the observed variables (the factor loadings) are of primary interest.

We have (and will be) only considering the Exploratory FA in any detail.

Structural Equation Modelling

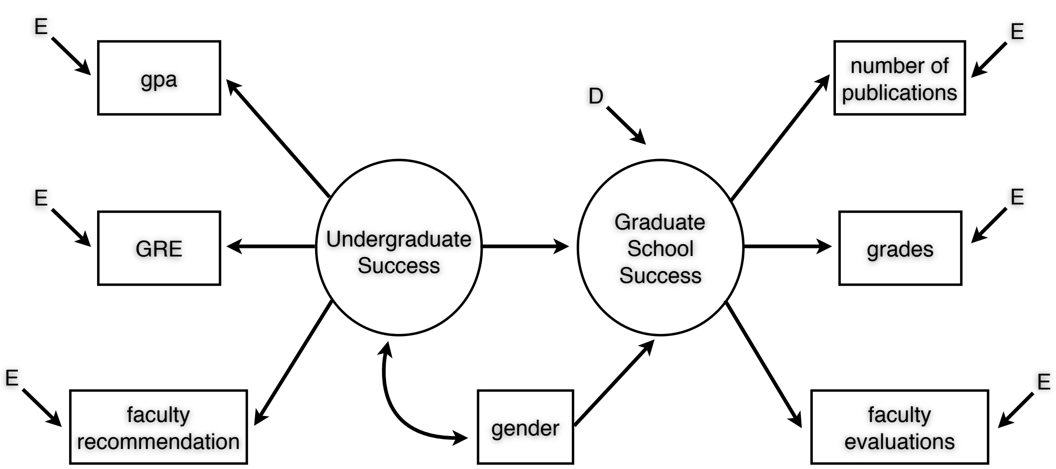
Exploratory vs Confirmatory Factor Analysis

Factor Correlation Matrix

Factor	1	2	3
1	1.000	.143	−.106
2	.143	1.000	−.177
3	−.106	−.177	1.000

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

However, while the interfactor relations are of interest (as revealed in the factor correlation matrix), any regression structure among them is not considered in the factor-analytic model.



In contrast, more sophisticated models (like the "full latent variable" model) allows for the specification of regression structure among the latent variables (i.e., factors). That is to say, the researcher can hypothesise the impact of one latent construct on another in the modelling of causal direction. This model is "full" because it depicts both the links between and among the factors and variables.

Structural Equation Modelling

General Purpose and Process of Statistical Modelling

- Typically, you would postulate a statistical model based on your knowledge of the theory, on empirical data in the area of study, or some combination of both.
- Once you’ve specified the model, you test its plausibility based on sample data that comprise all the observed variables in the model.
  - The goal here is to determine the goodness of fit between the hypothesised model and the sample data.
  - So you’re imposing the structure of the hypothesised model on to the sample data, the then testing how well the observed data fit this restricted structure.

Structural Equation Modelling

General Purpose and Process of Statistical Modelling

- Because it's highly unlikely that a *perfect* fit will exist between the observed data and the hypothesised model, there will necessarily be a differential between the two; this differential is the residual. The model-fitting process can therefore be summarised as:

score measurements related to the observed variables	=	hypothesised structure linking the observed variables to the latent variables	+	discrepancy between the hypothesised model and the observed data
DATA	=	MODEL	+	RESIDUAL

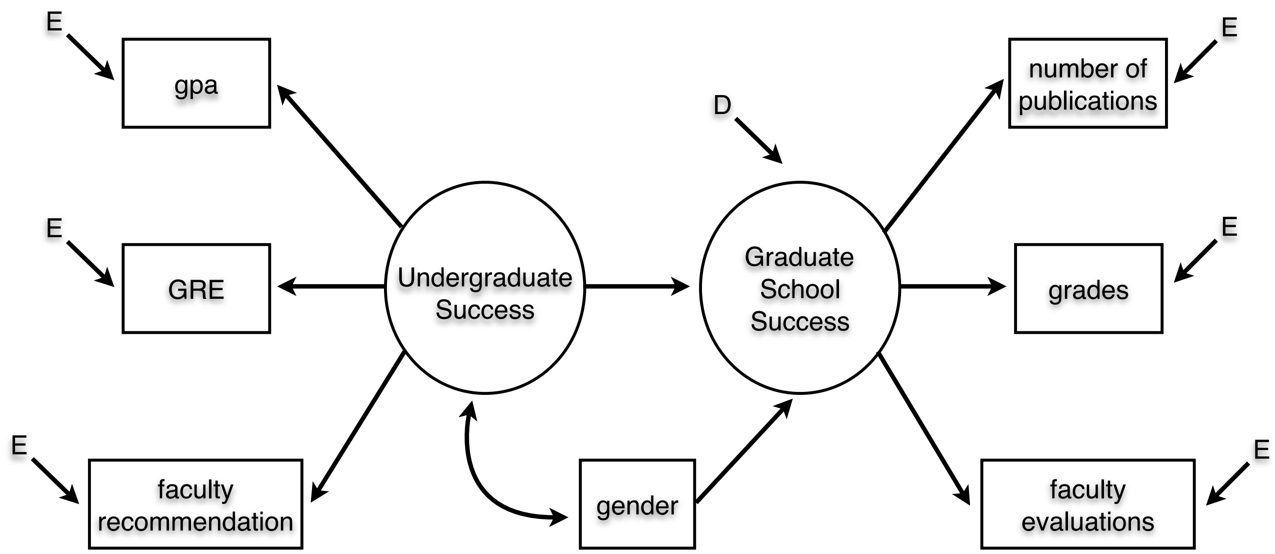
Structural Equation Modelling
General Purpose and Process of Statistical Modelling

- Joreskog (1993) distinguished among three scenarios:
  1. *Strictly confirmatory (SC)*
     - you postulate a single model based on theory, collect the appropriate data, and then test the fit of the hypothesised model to the sample data. From the results of this test, you either reject or fail to reject the model.
  2. *Alternative models (AM)*
     - you propose several alternative (competing) models, all of which are grounded in theory. Following analysis of a single set of data, you select one of the models as the most appropriate in representing the sample data.
  3. *Model generating (MG)*
     - having postulated and rejected a theoretically derived model on the basis of its poor fit to the sample data, you proceed in an exploratory (rather than confirmatory) fashion to modify and re-estimate the model. The primary focus here is to locate the source of misfit in the model and to determine a model that better describes the data.

Joreskog, K. G. (1993). Testing structural equation models. In Bollen, K. A. and Long, J. S. (Eds) *Testing Structural Equation Models*, Sage, Beverly Jills, CA, pp. 294-316.

Structural Equation Modelling

The General SEM Model



Structural equations are schematically portrayed using configurations of four geometrical symbols:

- circles (or ellipses) represent unobserved latent factors.
- squares (or rectangles) represent observed variables.
- single headed arrows (→) represent the impact of one variable on another.
- double headed arrows (↔) represent covariances or correlations between pairs of variables.

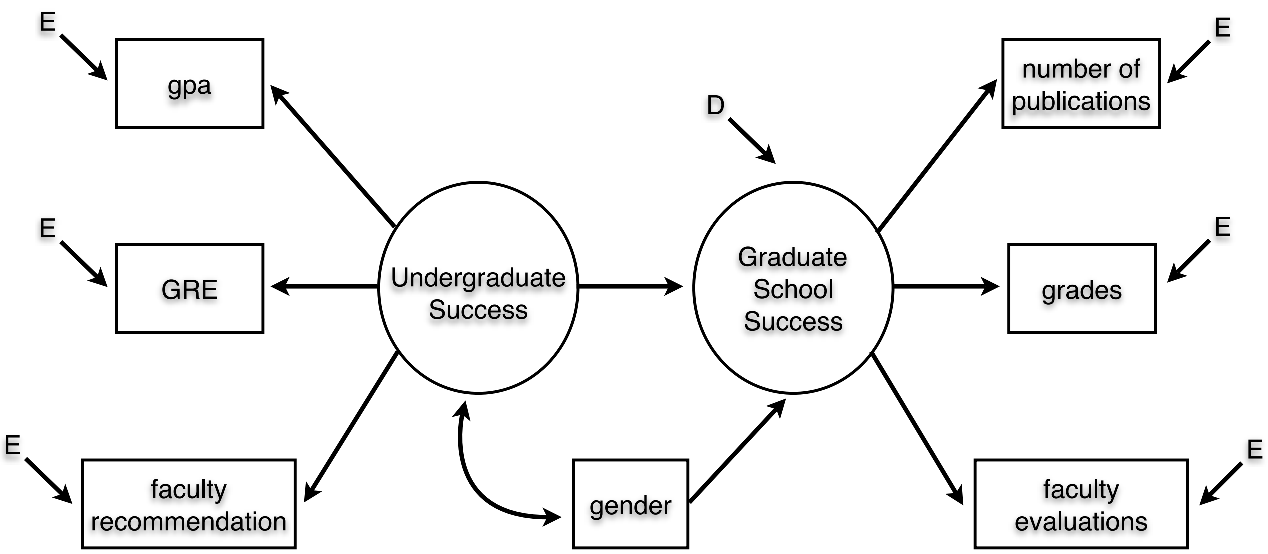
These symbols are used within the framework of four basic configurations:

- path coefficient for regression of an observed variable onto an unobserved variable (or factor).
- path coefficient for regression of one factor onto another factor.
- measurement error associated with an observed variable.
- residual error (or disturbance) in the prediction of an unobserved factor.

Schematic representations of models are *path diagrams* because they provide a visual portrayal of relations among the variables under study.

Structural Equation Modelling

The General SEM Model



The line with two arrows connecting Undergraduate Success and gender makes no claim about causal direction.

However, gender (along with Undergraduate Success) are thought to predict Graduate School Success.

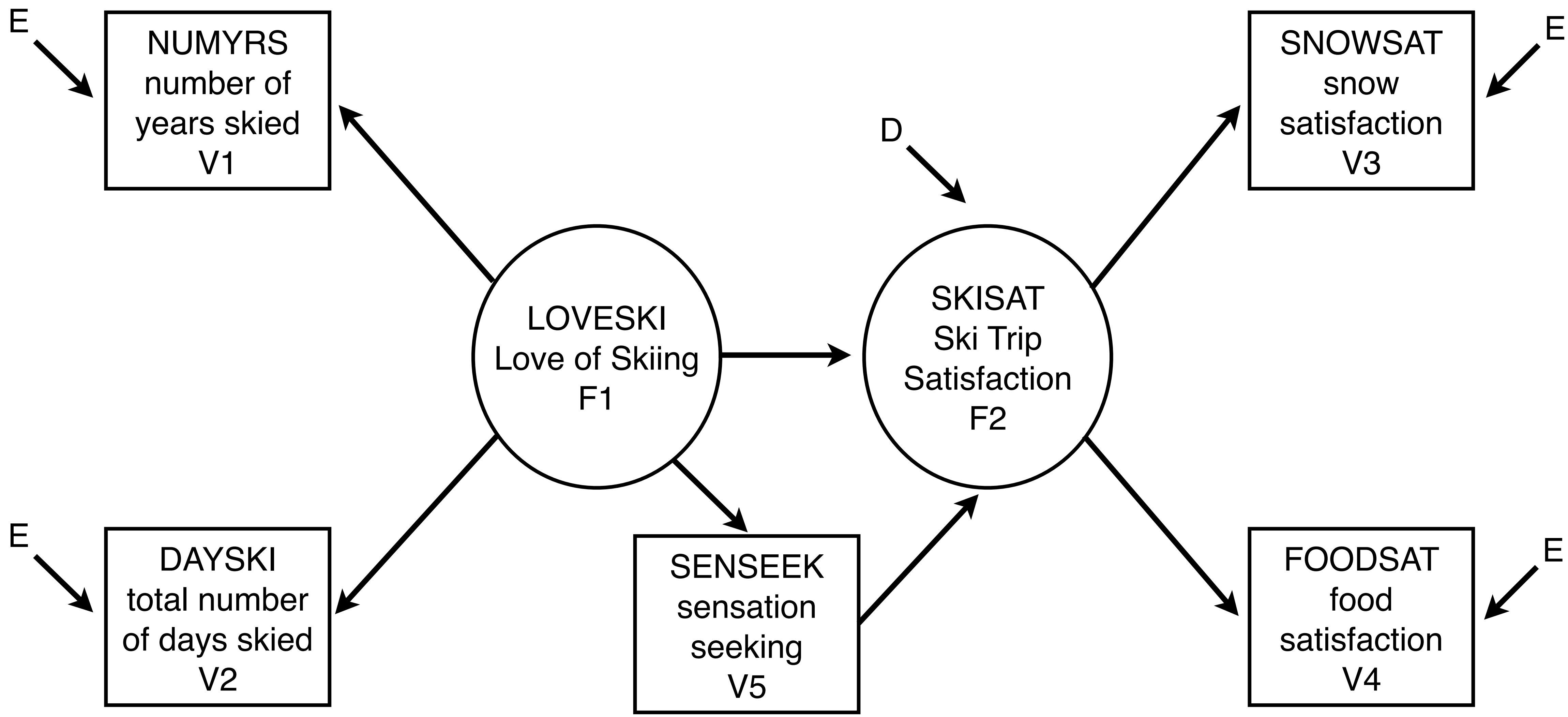
The *measurement model* describes how the factors relate to the observed variables, and is represented by arrows that flow from factors to the observed variables.

The *structural model* describes how the latent variables are related to one another, and is represented by the arrows among the factors.

In the path diagram from T&F (p. 677), we see that there are two unobserved latent factors: Undergraduate Success and Graduate School Success, and seven observed (measured) variables; three are considered to measure Undergraduate Success (i.e., gpa, GRE, faculty recommendation), and three to measure Graduate School Success (i.e., number of publications, grades, and faculty evaluations.

Structural Equation Modelling

Hypothesised Model Example



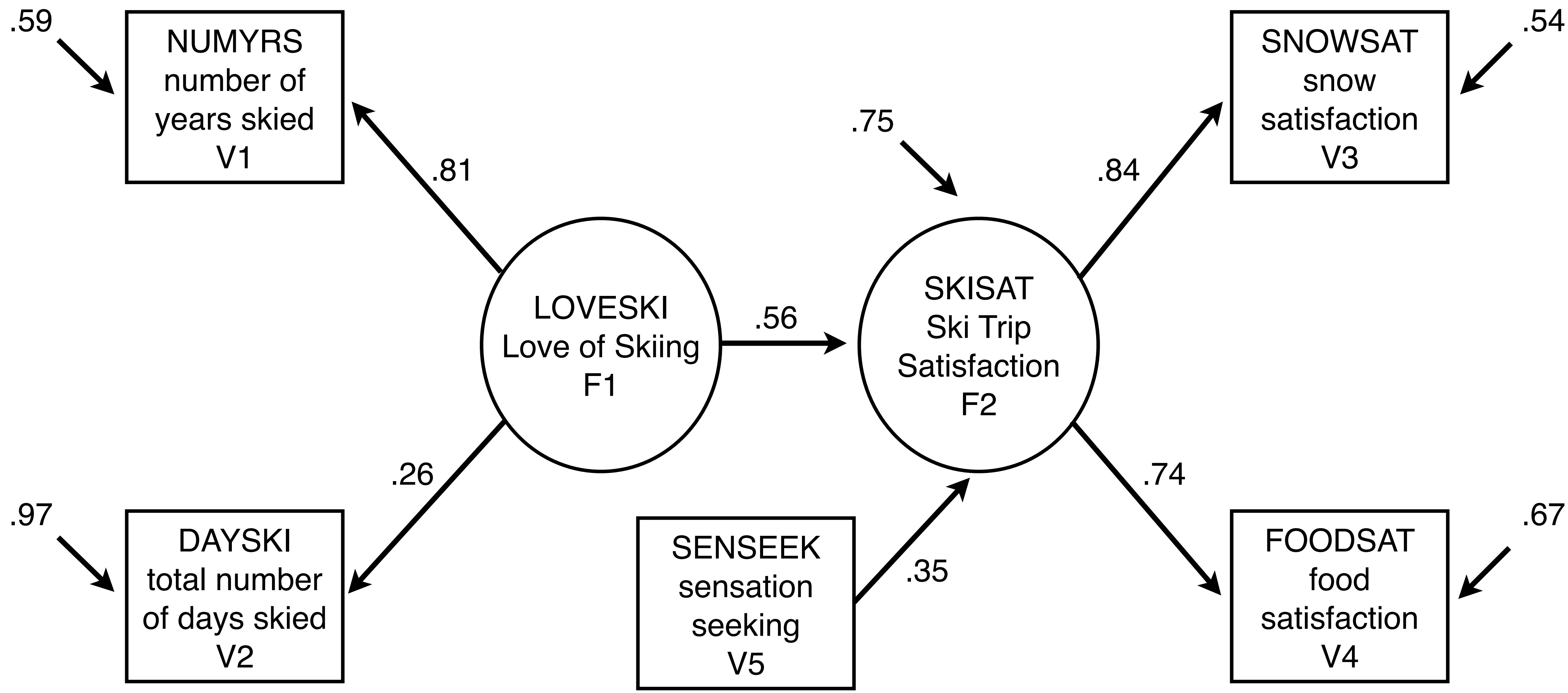
Covariance Matrix

	NUMYRS	DAYSKI	SNOWSAT	FOODSAT	SENSEEK
NUMYRS	1.00				
DAYSKI	0.70	11.47			
SNOWSAT	0.62	0.62	1.87		
FOODSAT	0.44	0.44	0.95	1.17	
SENSEEK	0.30	0.21	0.54	0.38	1.00

This covariance matrix represents the observed covariances that we're comparing the model to.

Structural Equation Modelling

Model Evaluation

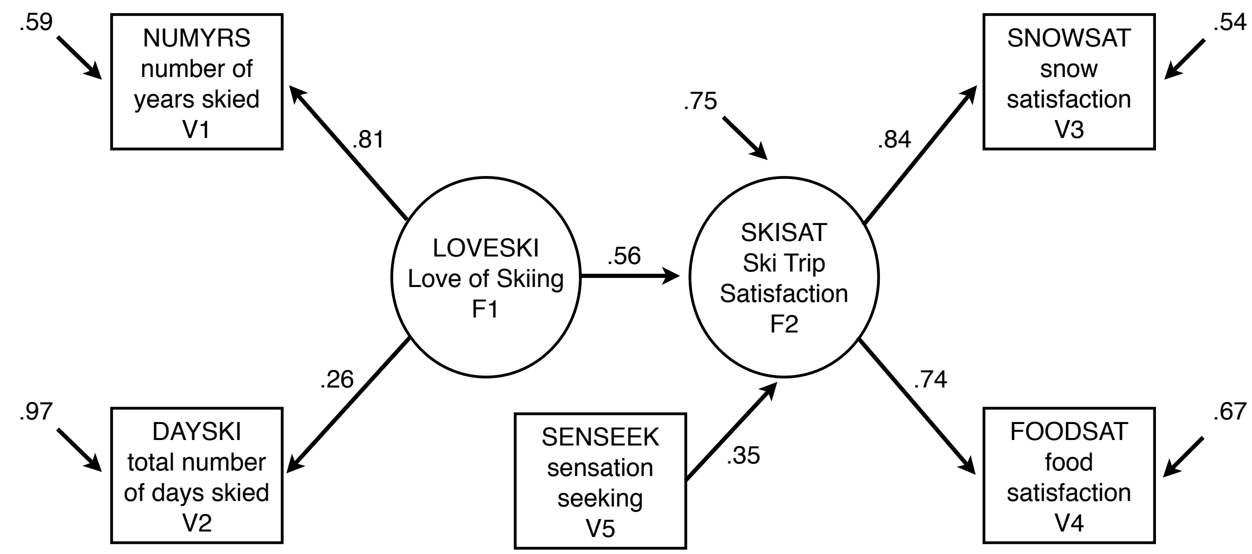


After estimation, the set of parameters imply a covariance matrix which should reproduce the sample covariance if the equations describing the theory are reasonable.

The paths from the factors to the variables are simply the standardised factor loadings. For example, the number of years that skied (NUMYRS) is a strong indicator of Love of Skiing (LOVESKI); the greater the Love of Skiing, the more number of years skied.

Structural Equation Modelling

Model Evaluation



Because the goal is to develop a model that fits the data, a *nonsignificant* chi square is desired. In this example, $\chi^2 = 9.337$, $p = .053$, which is not significant.

In most hypothesis tests, the null hypothesis specifies there is no relationship among variables (or no difference between groups). In such a scenario, we want to reject the null hypothesis and conclude that there is a statistically significant relationship (or difference).

In SEM, the logic is reversed: When chi-square is statistically significant, we reject the null hypothesis that the difference between the observed covariance matrix and the model implied covariance matrix is likely to be due to mere sampling error.

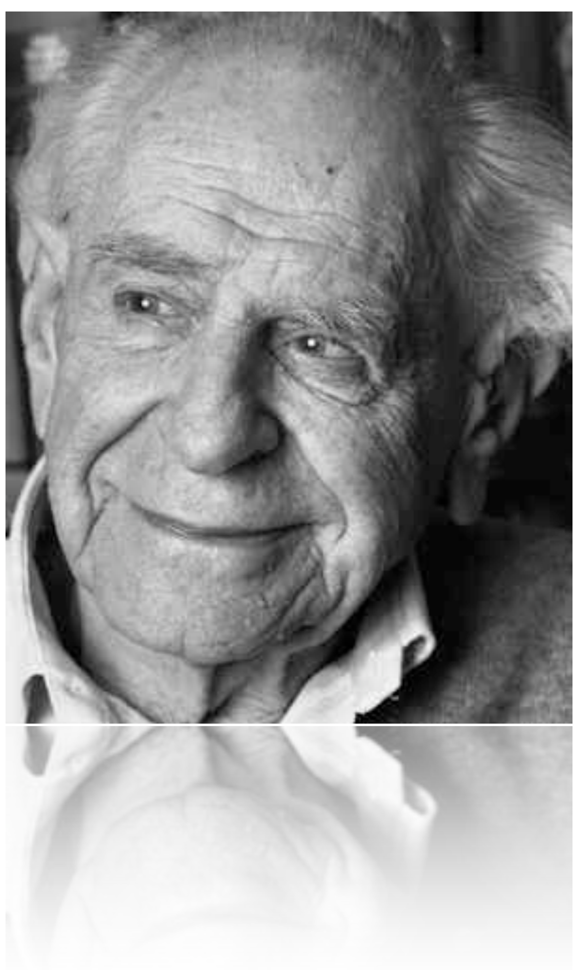
So what does a nonsignificant χ^2 allow you to conclude?

Structural Equation Modelling
Model Evaluation

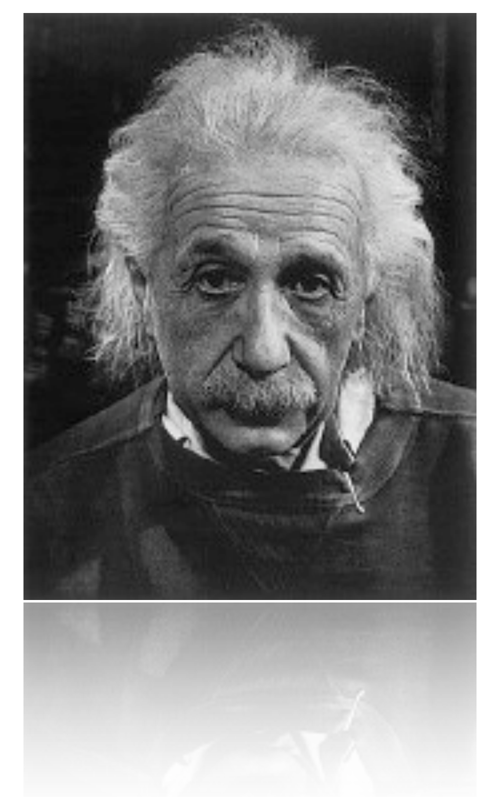
A nonsignificant χ^2 indicates simply that the model ‘fits’ the data. There are *no* grounds for concluding that such a ‘fit’ implies that ‘the model is true’.

There are *no* grounds for concluding that such a ‘fit’ implies that ‘the model is true’.

Karl Popper
1902 - 1994



“The criterion of the scientific status of a theory is its falsifiability, or refutability, or testability.”



“No amount of experimentation can ever prove me right; a single experiment can prove me wrong.”

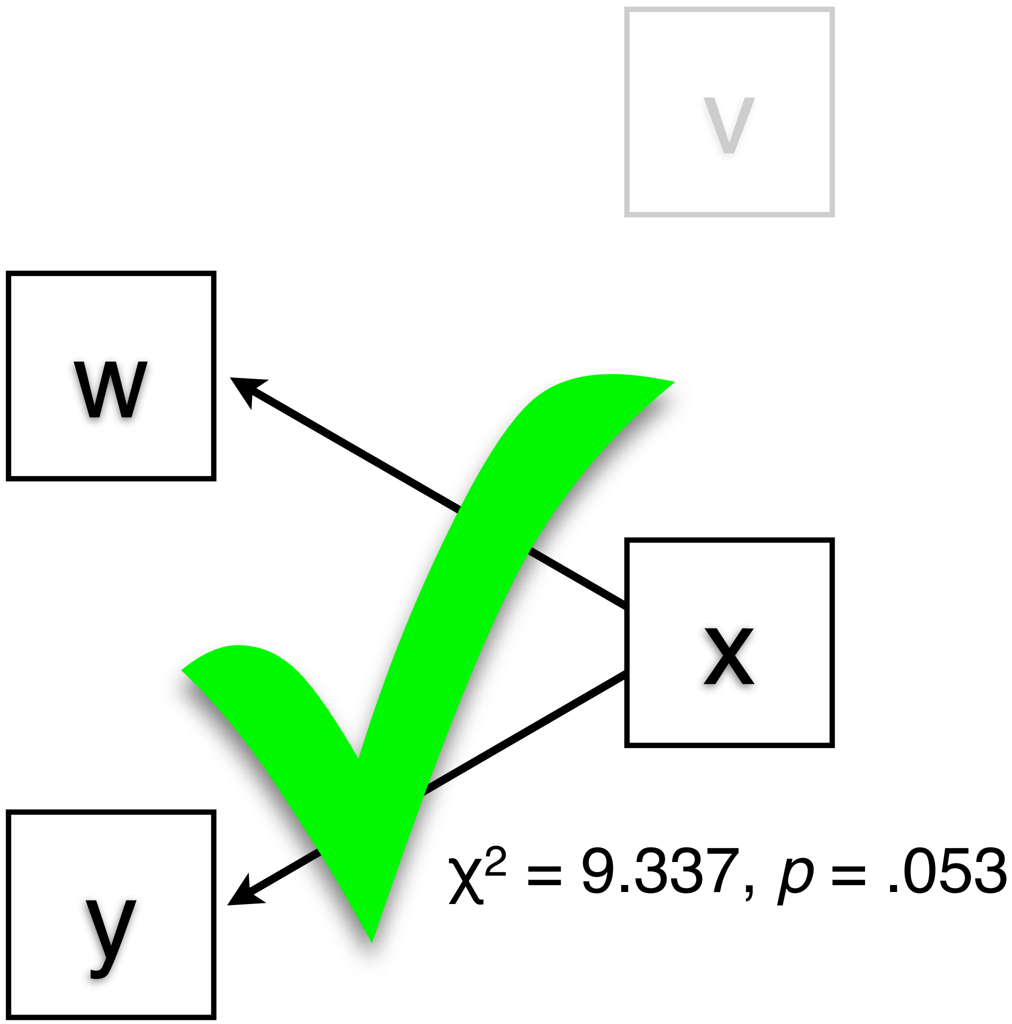
Four Basic Principles of Scientific Inference

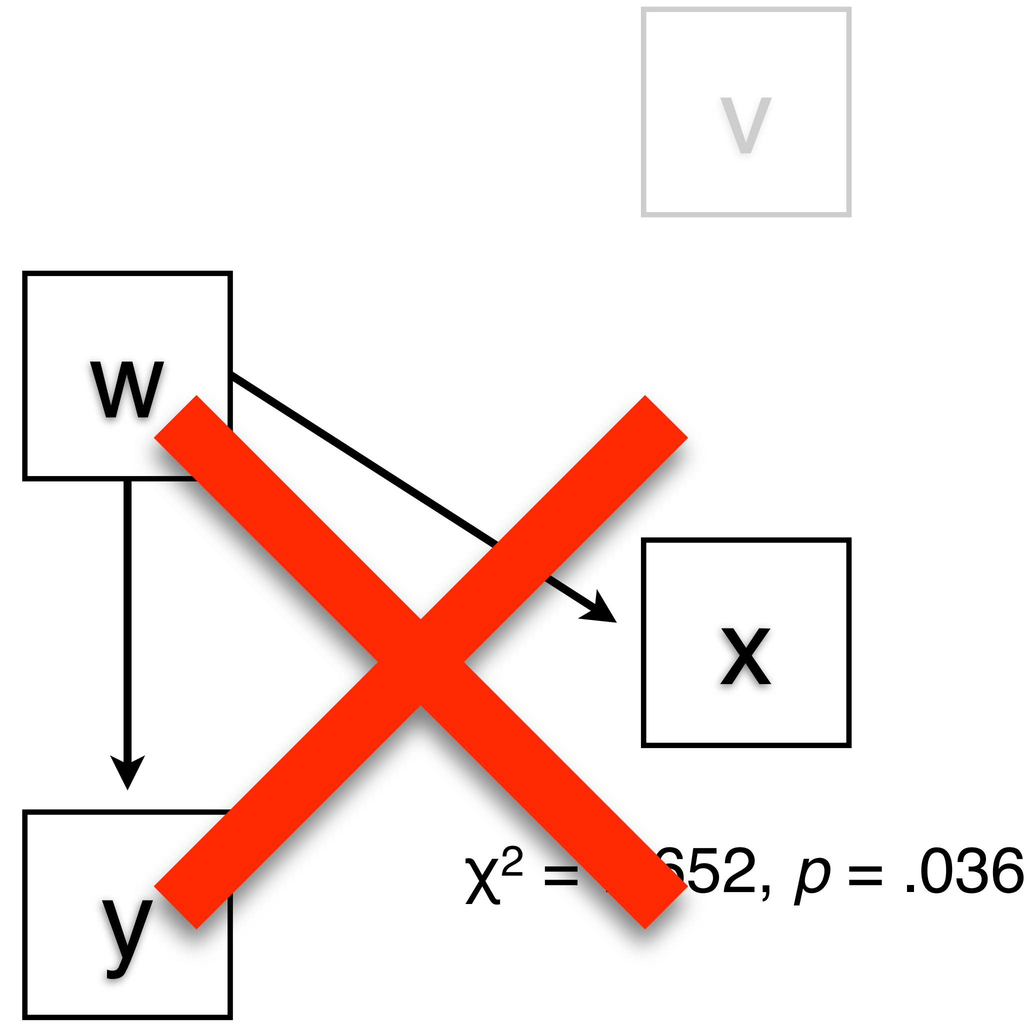
1. *Data do not confirm a model, they only fail to disconfirm it.*
   - When data fail to disconfirm a model, there are many other models that are not disconfirmed either.
2. *Post hoc does not imply propter hoc.*
   - If *a* and *b* are related, and *a* followed *b* in time, it is not necessarily true that *b* caused a.
3. *Just because we name something does not mean that we understand it, or even that we named it correctly.*
4. *Ex post facto explanations are untrustworthy.*
   - The unreliability of hindsight.

Cliff, N. (1983). Some cautions concerning the application of causal modeling methods. *Multivariate Behavioral Research*, *18*, 115–126. [download from the course webpage]

Four Basic Principles of Scientific Inference

1. Models are not confirmed by data





"It is somehow felt that the model is confirmed by the data. It is not. It is just not disconfirmed. A model involving *v* is not disconfirmed either, and until someone gets the data and does disconfirm it, the status of this model is just as good as the one involving *x*. These programs are not magic. They cannot tell the user what is not there."

Cliff, N. (1983). Some cautions concerning the application of causal modeling methods. *Multivariate Behavioral Research*, *18*, 115–126. [download from the course webpage]

Four Basic Principles of Scientific Inference

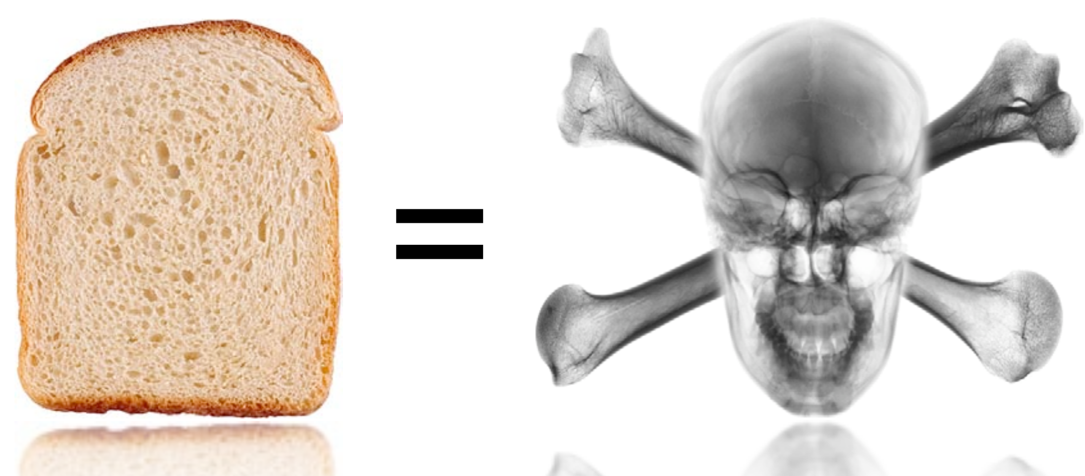
2. *Post hoc* does not imply *propter hoc*
After this does not imply *because of this*

From Attacking Faulty Reasoning by T. Edward Damer, Third Edition p. 131:

“I can't help but think that you are the cause of this problem; we never had any problem with the furnace until you moved into the apartment.” The manager of the apartment house, on no stated grounds other than the temporal priority of the new tenant’s occupancy, has assumed that the tenant's presence has some causal relationship to the furnace's becoming faulty.”

From With Good Reason by S. Morris Engel, Fifth Edition p. 165:

“More and more young people are attending high schools and colleges today than ever before. Yet there is more juvenile delinquency and more alienation among the young. This makes it clear that these young people are being corrupted by their education.”



Cliff, N. (1983). Some cautions concerning the application of causal modeling methods. *Multivariate Behavioral Research*, *18*, 115–126. [download from the course webpage]

Four Basic Principles of Scientific Inference

2. *Post hoc* does not imply *propter hoc*

“This is to say that the most satisfactory, almost the *only* satisfactory, method for demonstrating causality is the active *control* of variables, so that the complexity of the relations among them may be simplified, at least temporarily. With correlational data, it is not possible to isolate the empirical system sufficiently so that the nature of the relations among the variables can be unambiguously ascertained.”

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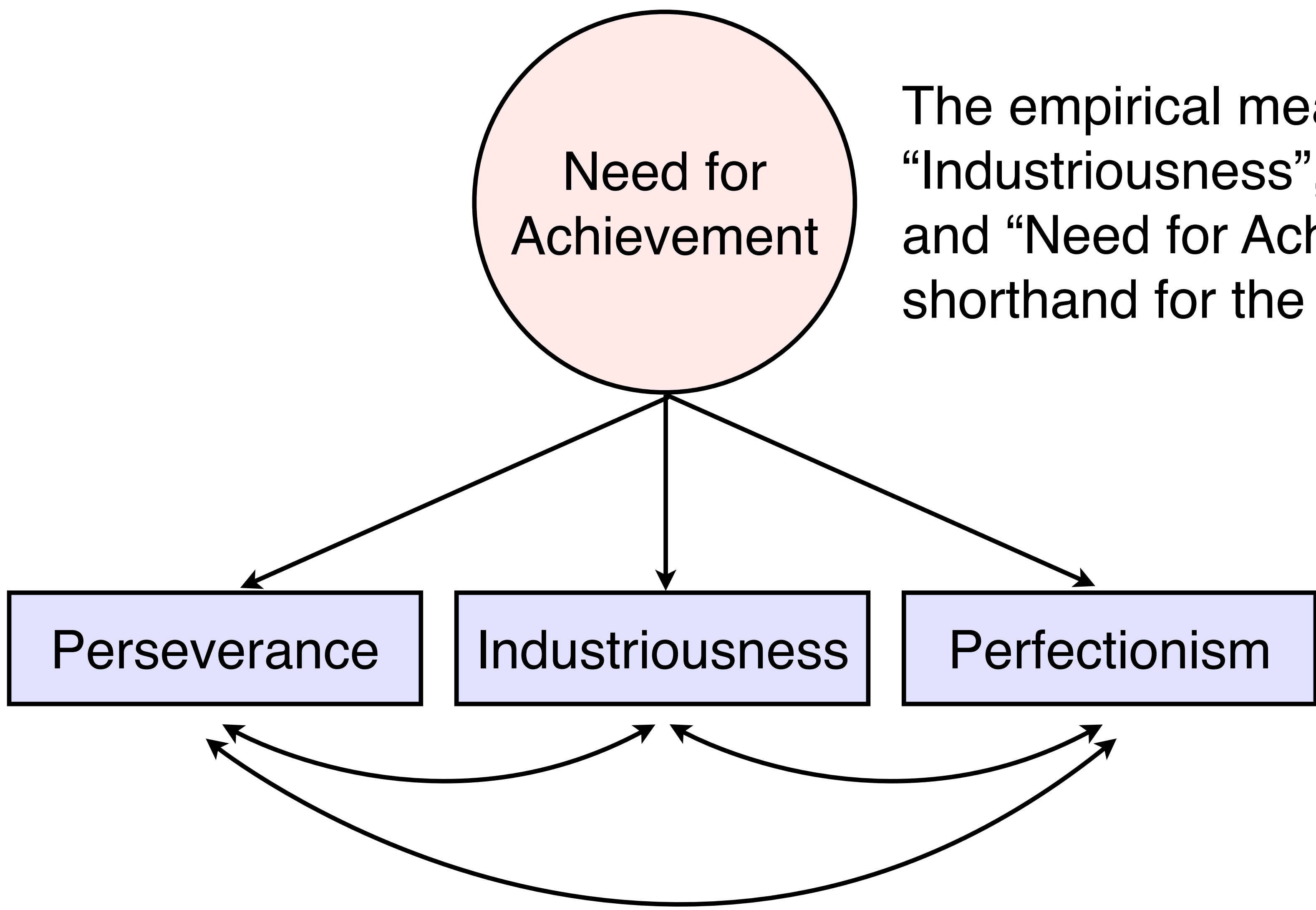
Four Basic Principles of Scientific Inference
3. The Nominalistic Fallacy

If we name something, this doesn't mean that we understand it.



The empirical meaning is only that "Perseverance", "Industriousness", and "Perfectionism" correlate, and "Need for Achievement" is nothing more than a shorthand for the observation of the correlations.

In SEM and "confirmatory" factor analysis, it's not the nature of the factors that's confirmed; the only thing that's confirmed is that the observed covariance matrix is not *inconsistent* with a certain pattern of parameters. It does not tell us what those parameters mean. And experience has shown that our belief that we do know what they mean is often ill-founded.

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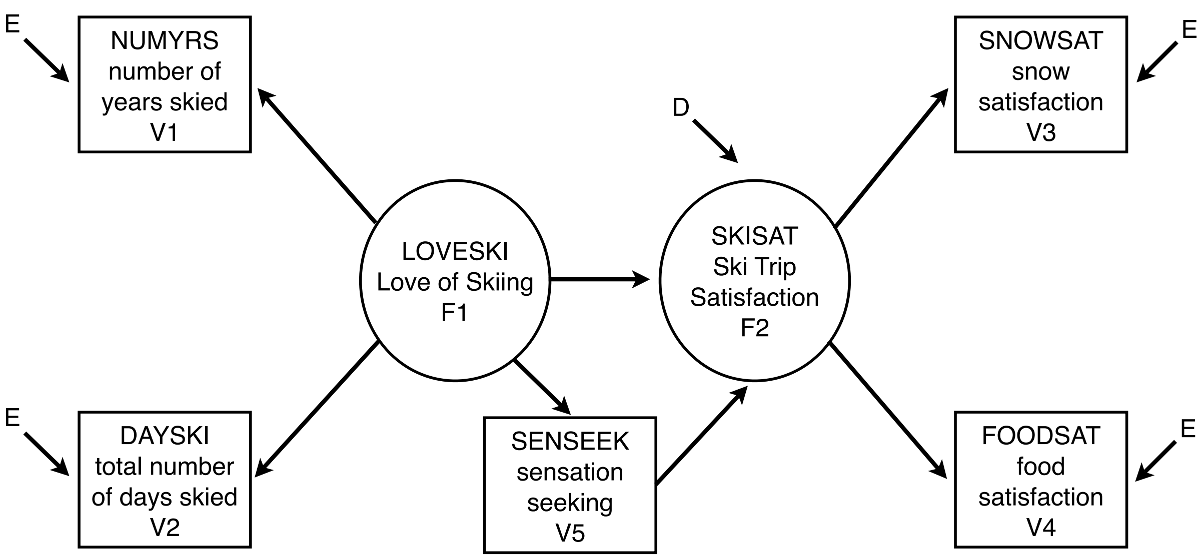
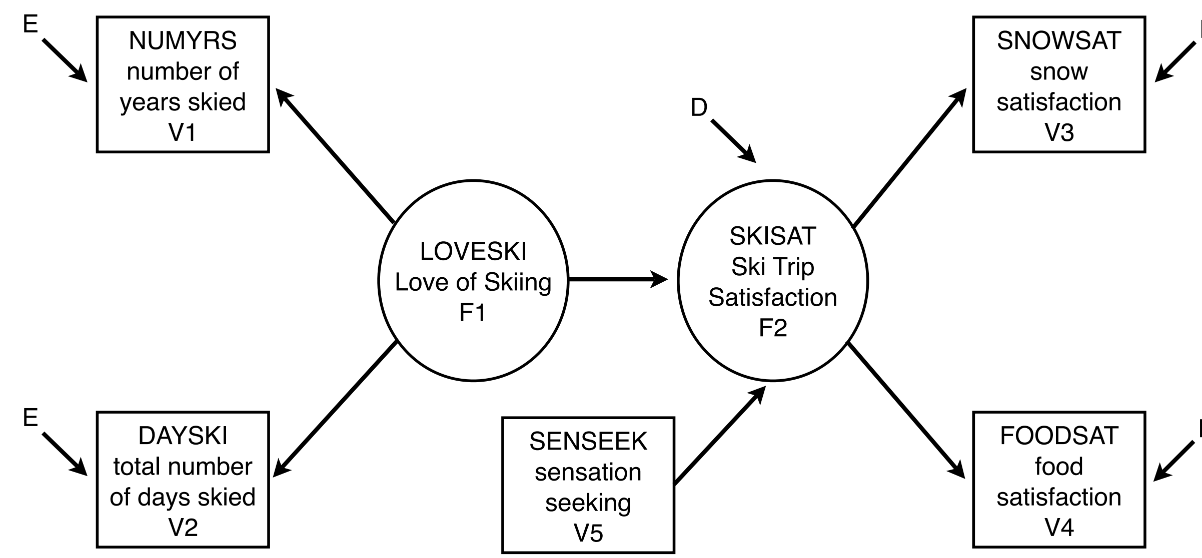
Four Basic Principles of Scientific Inference

4. The unreliability of hindsight





$\chi^2 = 9.492$, $p = .047$

$\chi^2 = 9.337$, $p = .053$

If you look around and try to find out what made the model fail, and, say, omit the LOVESKI → SENSEEK link which results in a new model that "fits", according to the statistical criterion. Now what?

BEWARE OF HINDSIGHT!

Cliff, N. (1983). Some cautions concerning the application of causal modeling methods. *Multivariate Behavioral Research*, *18*, 115–126. [download from the course webpage]

Four Basic Principles of Scientific Inference
4. The unreliability of hindsight

Learning about an outcome causes a person to search for the cause. Instead of looking at all the evidence however, s/he focuses only on outcome-confirmatory evidence because it is seen as more relevant to the question at hand. This process forms a coherent whole (theory, schema) which cues the memory to all evidence that confirms the outcome, and any information subsequently processed tends to be seen as being congruent.

Given a sufficiently complex model, consider how many possible adjustments could be made that would result in a similar outcome.

In ANOVA or regression, there are ways of treating *ex post facto* tests of paramters (e.g., Tukey or Sheffé corrections).

There are no equivalent procedures for confirmatory analyses.

The way in which data is collected and described is very much subject to the expectations and understandings of the scientist. That is, we see what we expect to see...

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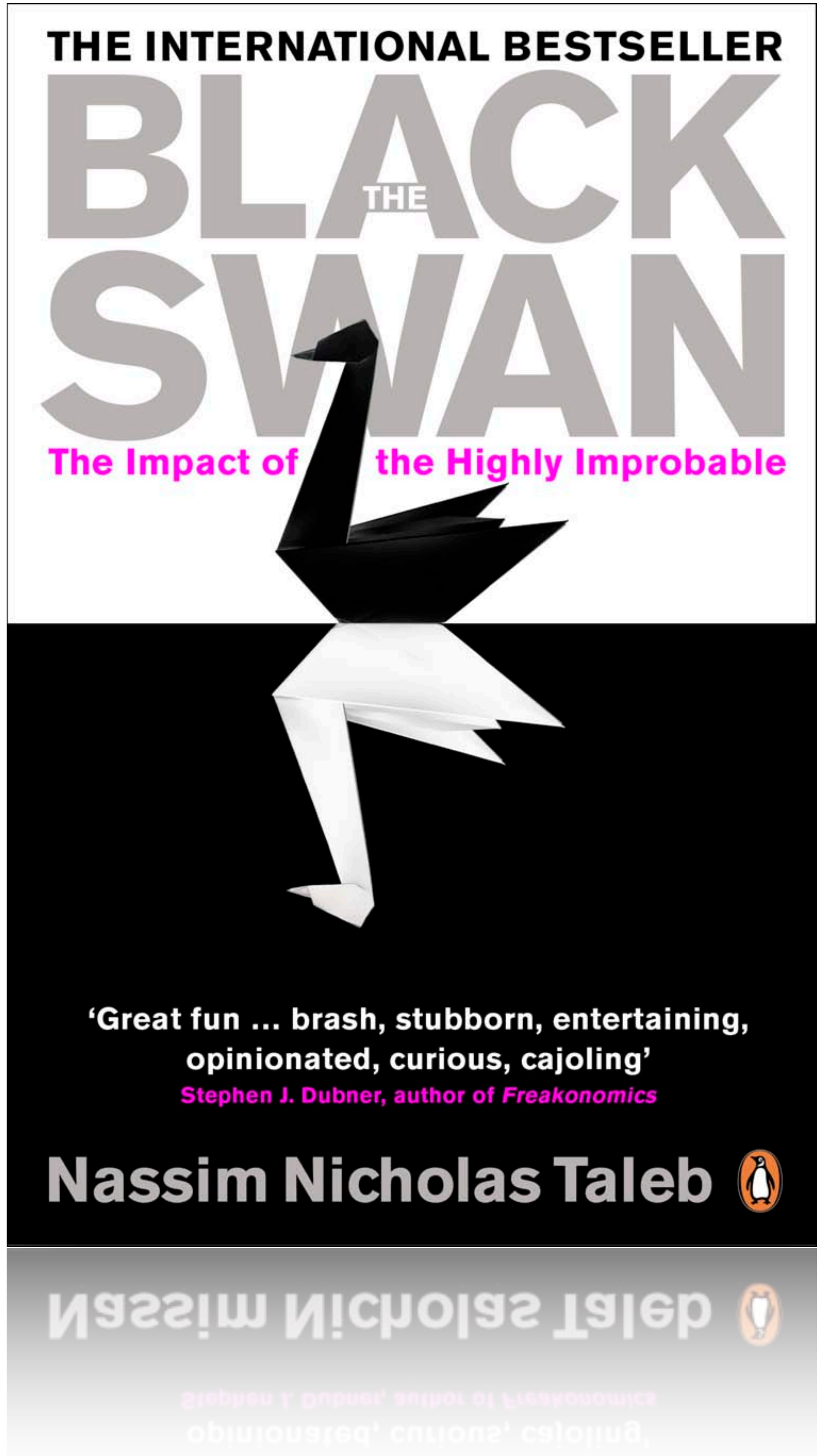
THE INTERNATIONAL BESTSELLER
THE BLACK SWAN
The Impact of the Highly Improbable
'Great fun ... brash, stubborn, entertaining, opinionated, curious, cajoling'
Stephen J. Dubner, author of Freakonomics
Nassim Nicholas Taleb

Eigenspaces

I will upload these slides after the lecture