



Practical Statistics

for UX & Customer Research

Jeff Sauro, PhD & Jim Lewis, PhD



Measuring
University™

Instructors



Jeff Sauro, PhD

Founding Principal

Jeff Sauro PhD, is the founding principal of MeasuringU. For over twenty years he's been conducting UX research, including benchmarking studies for clients.

Jeff has published over twenty-five peer-reviewed research articles and five other books, including *Benchmarking the User Experience*, *Customer Analytics for Dummies* and *Quantifying the User Experience*.

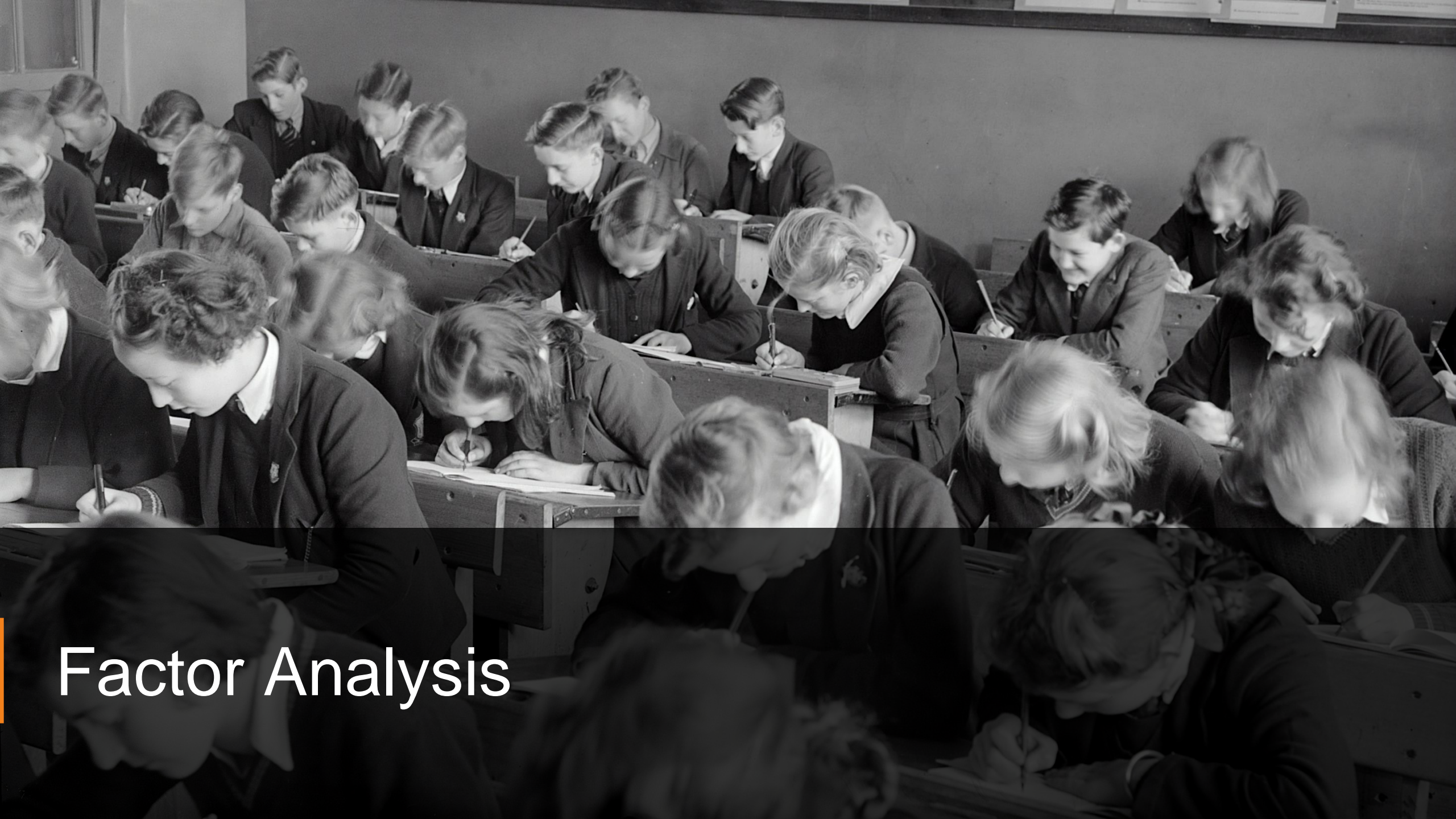


Jim Lewis, PhD, CHFP

Distinguished User Experience Researcher

Jim is a Certified Human Factors Professional with a Ph.D. in Experimental Psychology (and M.A. in Engineering Psychology, minor in applied statistics).

Before joining MeasuringU Jim worked at IBM for nearly 40 years. He is an IBM Master Inventor (> 90 US patents) and has published over 100 articles and papers.



Factor Analysis

Topics Covered

1. History of Factor Analysis
2. Exploratory (EFA) vs. Principal Components (PCA) vs. Confirmatory Factor Analysis (CFA)
3. Conducting an Exploratory Factor Analysis
4. Worked Exploratory FA Example

Overview of advanced UX analytical methods

Analysis of Differences

- t-Test
- A/B Two-Proportion Test

- Basic ANOVA

- Advanced ANOVA

- Basic Linear Regression

- Advanced Regression

- Top Task Analysis

- Discriminant Analysis
- Kano Model

- Logistic Regression
- Conjoint/MaxDiff

Analysis of Structure

- Correlation

- Cluster Analysis
- Factor Analysis

- Latent Class Analysis

Lower Complexity

Higher Complexity

Applications of advanced analytical methods

Question	Methods	Sample Application
<i>Are there significant differences?</i>	Two Proportion Test	A/B testing
	t-Test	Test two designs
	ANOVA	Test multiple designs and interactions
<i>Are there significant similarities?</i>	Correlation	Assess relationships (e.g., CSAT and age)
<i>Are there significant predictors?</i>	Linear Regression	Key driver analysis
<i>Is there latent (hidden) structure?</i>	Cluster Analysis	Persona development
	Factor Analysis	Develop standardized UX questionnaire
	Latent Class Analysis	Advanced persona development
<i>Can we determine membership in classes?</i>	Discriminant Analysis	Customer segment classification tool
	Logistic Regression	Statistical basis for feature prioritization
<i>What are the most important features/tasks?</i>	Conjoint Analysis	Exhaustive feature prioritization
	MaxDiff Analysis	Streamlined feature prioritization
	Kano Model	Alternative feature prioritization method
	Top Task Analysis	Identify most important tasks

A History of Factor Analysis



Charles Spearman 1863-1945



Spearman noticed children's scores on seemingly unrelated subjects were positively correlated.

Is there a single general mental ability “*g*” underlying human cognitive performance?

Factor Analysis Reduces Correlated Variables

	Classics	French	English	Math	Pitch	Music
Classics	–					
French	0.83	–				
English	0.78	0.67	–			
Math	0.70	0.67	0.64	–		
Pitch discrimination	0.66	0.65	0.54	0.45	–	
Music	0.63	0.57	0.51	0.51	0.40	–
g	0.958	0.882	0.803	0.75	0.673	0.646

Correlation Matrix from Spearman (1904)

g summary variable characterizing the correlations between all the different tests in a test battery.

Latent Variables



Latent Means Hidden

You can't see:

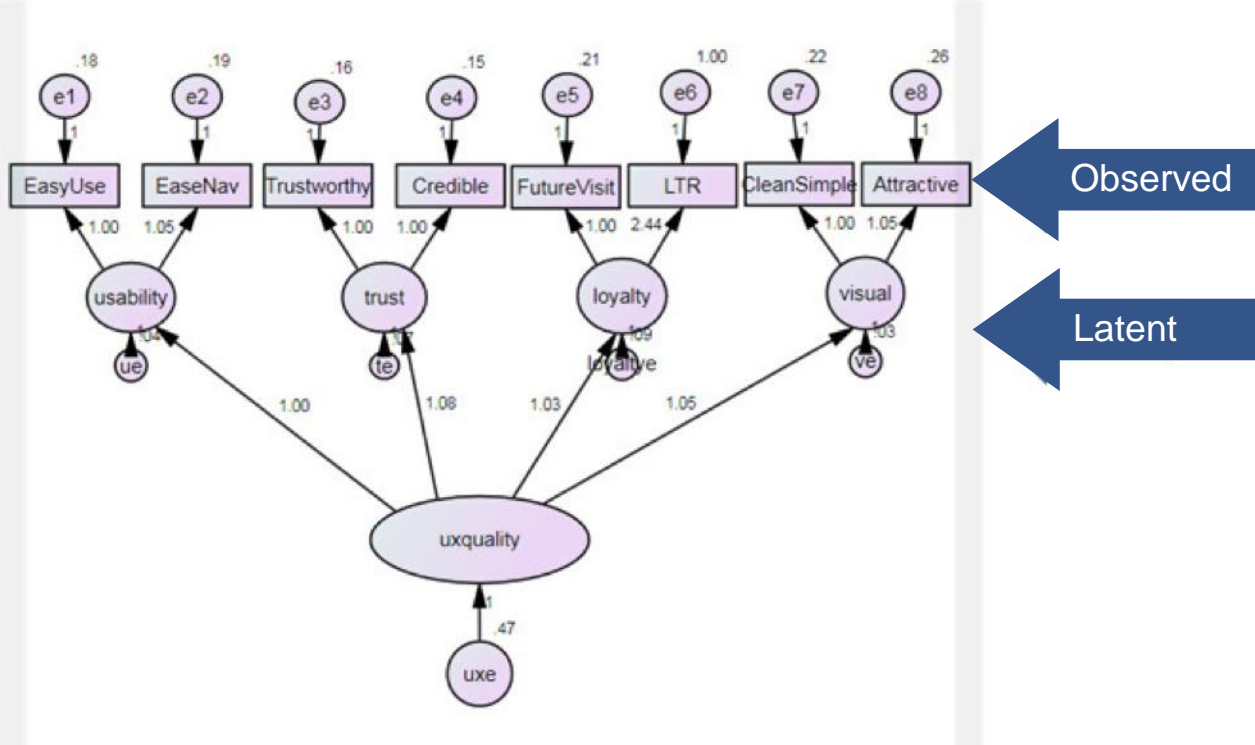
- Intelligence
- Satisfaction
- Usability
- Loyalty

We can't measure these experiences directly.

Instead, we used observed variables:

- Test questions
- Ability assessments
- Questionnaires

Latent and Observed Factors in the SUPR-Q



Observed

Latent

Used to identify the latent variables based on hypothesis around the data.

We used an EFA to identify four latent factors around UX quality:

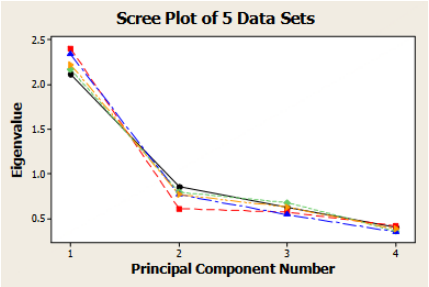
- Usability
- Trust
- Loyalty
- Appearance

Exploratory vs. Confirmatory vs. PCA

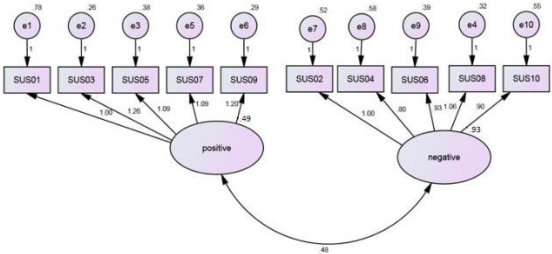
Item	1	2
Q1	0.71	0.21
Q2	0.62	0.46
Q3	0.69	0.43
Q4	0.28	0.58
Q5	0.60	0.26
Q6	0.58	0.39
Q7	0.62	0.46
Q8	0.77	0.38
Q9	0.64	0.47
Q10	0.32	0.79

Exploratory Factor Analysis (EFA) is the most commonly used approach for uncovering the latent factors in data.

- Used when no strong underlying assumptions about underlying factors
- Need to decide on rotation type and number of factors
- Many types of EFA (e.g., unweighted least squares, principal axis factoring)



Principal Components Analysis (PCA) is an analytical method similar to factor analysis that aims to reduce the number of variables (EFA aims to uncover latent structure).



Confirmatory FA uses structural equation modeling (SEM) to assess how well data match a specified model using fit statistics.

Steps For Running a Factor Analysis

Decide the Type of Factor Analysis

1. Exploratory Factor Analysis (EFA)
 - a. Unweighted least squares
 - b. Principal axis factoring
2. Principal Components Analysis (PCA)
3. Confirmatory Factor Analysis (CFA)

Exploratory Factor Analysis Steps

1. Inspect correlations between observed variables
2. Use software to conduct the analysis
3. Identify the number of factors to retain
4. Determine factor rotation
5. Name the factors based on variable loadings

Step 1: Inspect Item Correlations for SUPR-Q

	EasyUse	EaseNav	Promises	ConfBiz	FutureVisit	Attractive	CleanSimple	Trustworthy	Credible
EaseNav	0.741								
Promises	0.614	0.619							
ConfBiz	0.672	0.656	0.717						
FutureVisit	0.670	0.625	0.616	0.706					
Attractive	0.649	0.672	0.662	0.666	0.637				
CleanSimple	0.701	0.727	0.631	0.645	0.615	0.703			
Trustworthy	0.666	0.692	0.739	0.751	0.668	0.680	0.674		
Credible	0.687	0.669	0.724	0.754	0.684	0.683	0.663	0.793	
LTR	0.665	0.644	0.665	0.731	0.755	0.672	0.633	0.687	0.711

Inspect correlation matrix as sanity check

– multicollinearity? Expected high/low correlations?

Step 2: Decide on the Number of Factors to Retain

Kaiser Rule

- Run the factor analysis to get the unrotated eigenvalues
- Retain the number of factors for which the eigenvalues are greater than one
- Simplest procedure, but discredited due to tendency for retention of too few factors

Scree Plot Discontinuity Analysis

- Run the factor analysis to get the unrotated eigenvalues
- Create a line graph of the eigenvalues to get a scree plot
- Discontinuity locations (large change in slope of line) indicate number of factors to retain

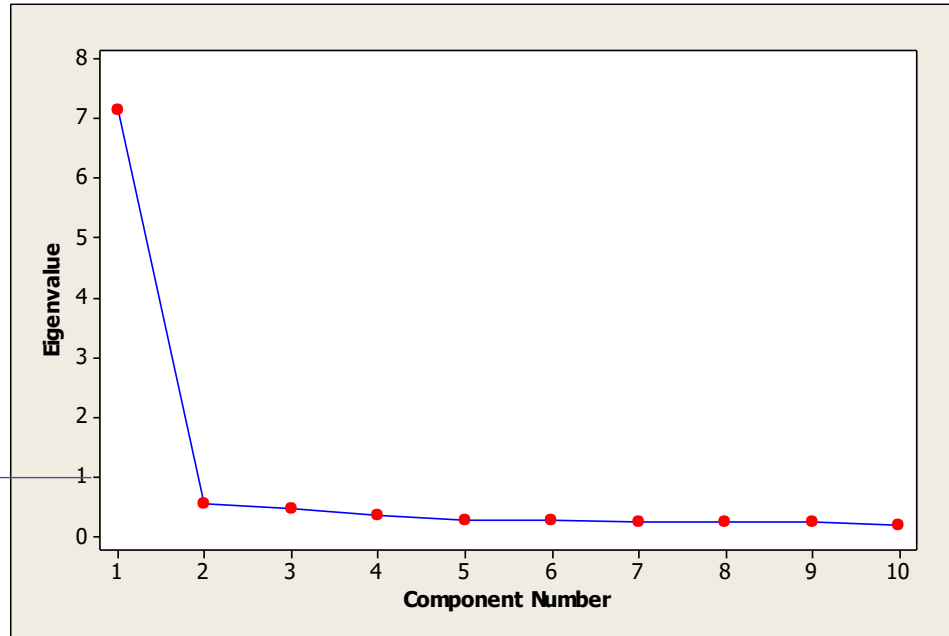
Parallel Analysis

- Run the data through a parallel analysis routine
- Compare observed eigenvalues with randomly generated values
- Retain number of factors where observed exceeds randomly generated values

Theoretical Expectation

- Applicable when there is theoretical justification from previous research for a number of factors

Scree Plot & Kaiser Rule



Parallel Analysis: Compares eigenvalues to randomly ones

Raw Data Eigenvalues, & Mean & Percentile Random Data Eigenvalues

Root	Raw Data	Means	Prcntyle
1.000000	6.203402	.483150	.575471
2.000000	.851915	.392265	.459848
3.000000	.737591	.323285	.382787
4.000000	.475217	.265255	.320384
5.000000	.234515	.210107	.257889
6.000000	.071682	.161181	.203758
7.000000	.020645	.115684	.153970
8.000000	.012999	.071206	.108569
9.000000	-.010601	.028937	.063202
10.000000	-.030683	-.010293	.024266
11.000000	-.063244	-.050005	-.018089
12.000000	-.099227	-.088742	-.057080
13.000000	-.108952	-.126636	-.096597
14.000000	-.146275	-.165375	-.136201
15.000000	-.178106	-.204434	-.173747
16.000000	-.237536	-.247253	-.213653
17.000000	-.247763	-.298180	-.258370

Root: Raw Eigenvalue
Mean: Mean of thousands of randomly generated eigenvalues
Percentile: 95th Percentile of the random eigenvalues

Retain when the observed "Raw" Eigenvalue > Percentile

Step 3: Decide on the Rotation

No Rotation

Limited investigation of latent structure
When only interested in properties of first factor (e.g., g or u)

Measures	1	2	3	4	5
Comp	0.82	-0.20	0.38	0.26	0.27
Time	-0.70	0.45	0.53	0.06	-0.16
Errors	-0.80	0.41	-0.17	0.11	0.40
Task-Sat	0.71	0.56	0.09	-0.41	0.13
Test-Sat	0.63	0.65	-0.22	0.32	-0.17
Eigenvalue	2.70	1.14	0.51	0.35	0.30
% Variance	53.97	22.78	10.14	7.05	6.06

Table 16. Unrotated PCA loadings.

Varimax

Orthogonal factors
When treating factors as uncorrelated

Measures	1	2
Comp	0.70	0.33
Time	-0.65	-0.14
Errors	-0.88	-0.15
Task-Sat	0.24	0.79
Test-Sat	0.15	0.76

Table 17. Rotated factor loadings.

Oblimin

Nonorthogonal factors
When expecting factors to be correlated

Pattern Matrix^a

Measures	Factor	
	1	2
Comp	.676	.172
Time	-.671	.024
Errors	-.927	.073
Task-Sat	.053	.803
Test-Sat	-.032	.784

Extraction Method: Principal Axis Factoring.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 4 iterations.

Step 3: SUPR-Q Factor Loadings with Oblimin Rotation

	Factor 1	Factor 2	Factor 3	Factor 4
The website is easy to use.	0.88	0.02	0.02	-0.02
It is easy to navigate within the website.	0.80	0.02	0.03	0.06
I feel comfortable purchasing from the website.	-0.01	0.87	-0.05	0.02
I feel confident conducting business on the website.	0.03	0.83	0.08	-0.02
How likely are you to recommend the website to a friend or colleague?	-0.01	-0.01	0.80	0.05
I will likely return to the website in the future.	0.03	0.01	0.79	-0.03
I find the website to be attractive.	-0.05	0.03	0.05	0.76
The website has a clean and simple presentation.	0.25	0.00	-0.02	0.64
Eigenvalues (Based on 4 Factors)	4.26	0.80	0.42	0.18
% of Variance	53.24	10.05	5.30	2.26
Cumulative %	53.24	63.30	68.60	70.85

Used an Oblimin Rotation (Correlated Factors) and Retained 4 Factors

Step 4: Naming the Factors

	Usability	Trust	Loyalty	Appearance
The website is easy to use.	0.88	0.02	0.02	-0.02
It is easy to navigate within the website.	0.80	0.02	0.03	0.06
I feel comfortable purchasing from the website.	-0.01	0.87	-0.05	0.02
I feel confident conducting business on the website.	0.03	0.83	0.08	-0.02
How likely are you to recommend the website to a friend or colleague?	-0.01	-0.01	0.80	0.05
I will likely return to the website in the future.	0.03	0.01	0.79	-0.03
I find the website to be attractive.	-0.05	0.03	0.05	0.76
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Used an Oblimin Rotation (Correlated Factors) and Retained 4 Factors

EFA Example: Does SUS only measure usability (1 Factor)?

Item	Usability		Learnability	
	1	2	1	2
Q1	0.70	0.22		
Q2	0.59	0.38		
Q3	0.71	0.45		
Q4	0.27	0.69		
Q5	0.71	0.23		
Q6	0.58	0.39		
Q7	0.64	0.36		
Q8	0.60	0.41		
Q9	0.60	0.52		
Q10	0.31	0.69		

Bangor et al. Dataset

Item	Usability		Learnability	
	1	2	1	2
Q1	0.71	0.21		
Q2	0.62	0.46		
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Q7	0.62	0.46		
Q8	0.77	0.38		
Q9	0.64	0.47		
Q10	0.32	0.79		

Sauro & Lewis Dataset



Q4: I think that I would need the support of a technical person to be able to use this system



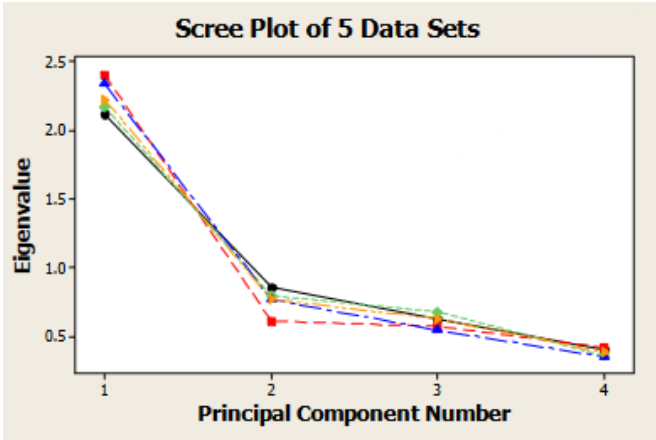
Q10: I needed to learn a lot of things before I could get going with this system

Used Varimax Rotation and Retained Two Factors
Named them Usability & Learnability based on the content of 2 items

PCA Example: Single Usability Metric (SUM)

	Time	Errors	Satisfaction
Errors			
A	.490		
B	.594		
C'03	.578		
C'04	.523		
Combined	.517		
Satisfaction			
A	-.379	-.396	
B	-.454	-.449	
C'03	-.512	-.403	
C'04	-.464	-.286	
Combined	-.478	-.348	
Completion			
A	-.145	-.428	.369
B	-.403	-.492	.410
C'03	-.302	-.380	.503
C'04	-.251	-.380	.433
Combined	-.268	-.384	.454

Correlation Between Variables



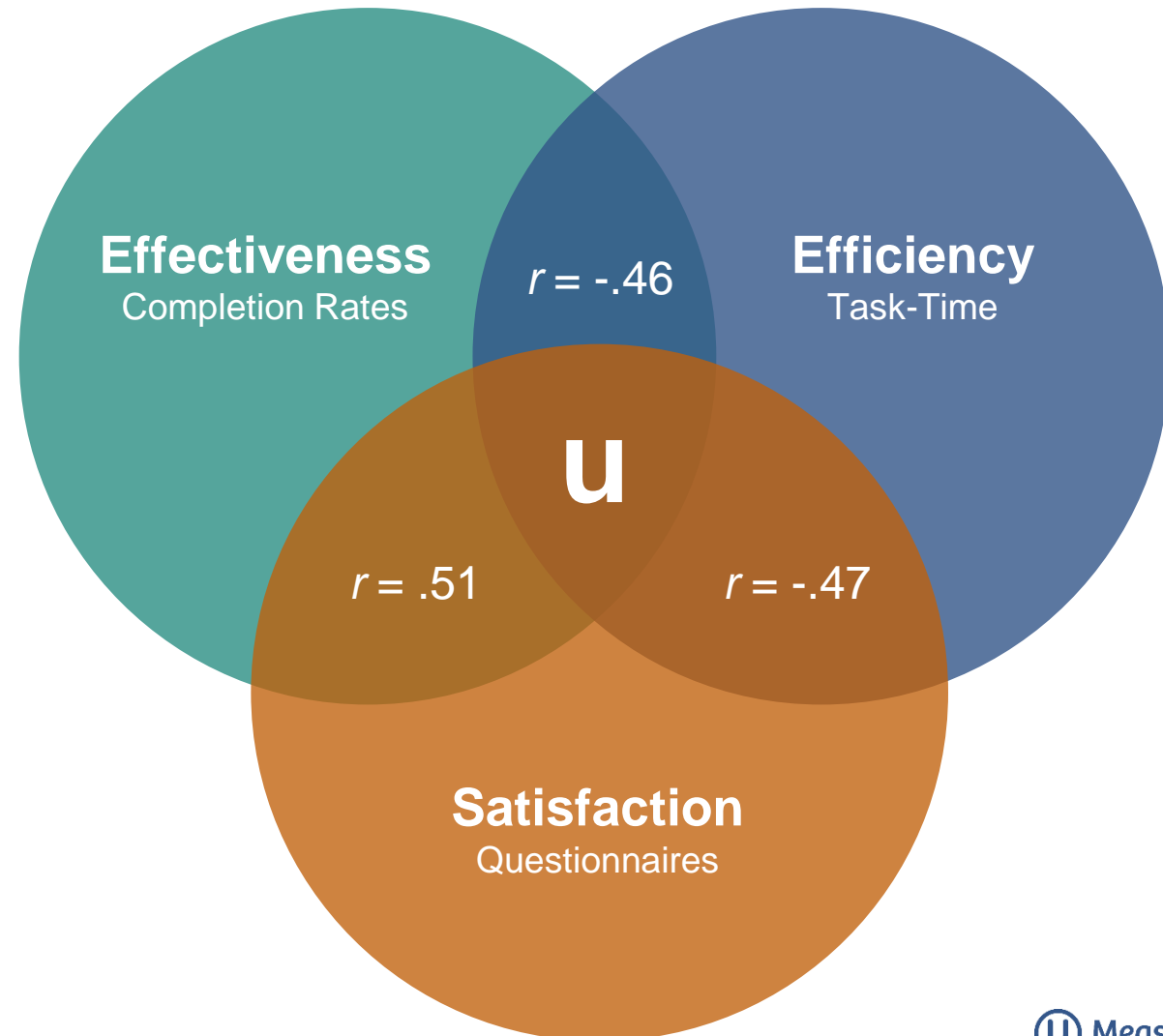
One Factor Solution

	Data Sets				
	A	B	C'04	C'03	Combined
Variance	52.9%	60.1%	54.3%	58.5%	55.6%
Errors	-.561	-.526	-.507	-.508	-.508
Time	-.479	-.524	-.525	-.517	-.515
Completion	.445	.478	.463	.453	.461
Satisfaction	.508	.470	.503	.519	.515

One Average Score Accounts for 55% of Variance

One Component Explained the Majority of Variance in 4 Task-Level Usability Metrics Showing Roughly Equal Weighting Between Metrics

Principal Components Analysis (PCA)



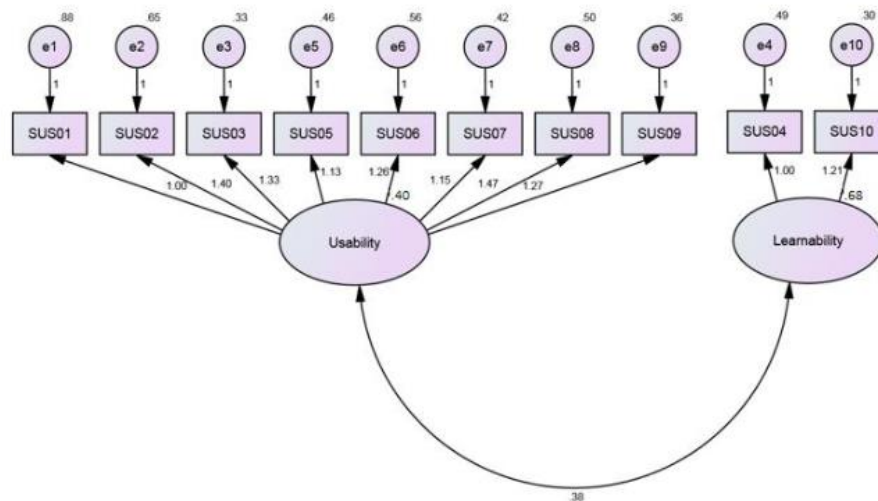
PCA revealed evidence for a general construct of usability.

[Correlations among Prototypical Usability Metrics](#)

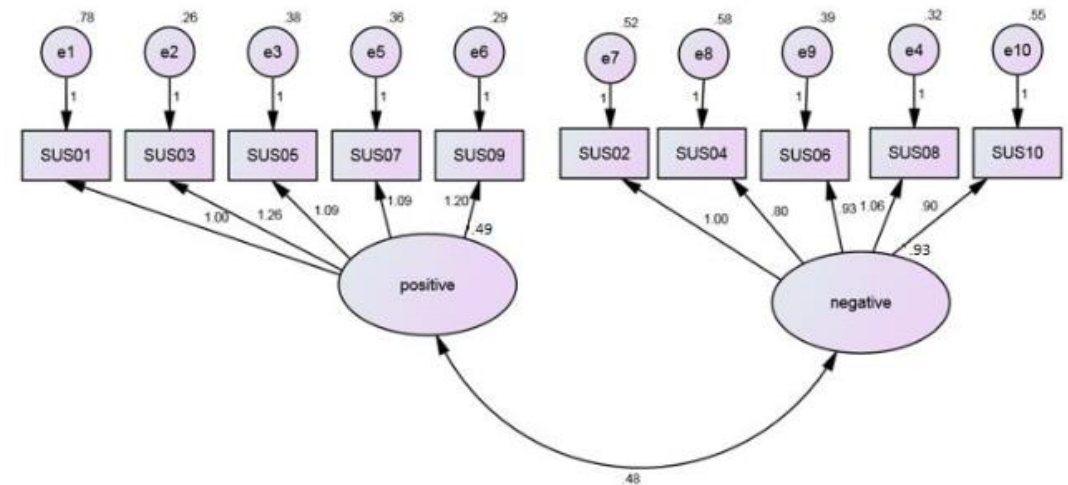
[Table 19] Sauro, J. & Lewis J.R. (2009)

CFA Example: Does the 2 Factor Structure Hold on New Data?

Usability & Learnability



Positive & Negative



We used a CFA to dis(confirm) the learnability and usability factors.
Positive and negative tone model fit better than usability and learnability model.

Summary

Types of Factor Analysis

- Exploratory Factor Analysis (used to explore potential structural models)
- Principal Components Analysis (used to summarize variables into a smaller uncorrelated set)
- Confirmatory Factor Analysis (used to assess fit of proposed measurement model)

Steps for Exploratory Factor Analysis (most common method)

1. Look for correlations between observed variables
2. Use software to conduct the analysis
 - typically using unweighted least squares or principal axis factoring
3. Identify the number of factors to retain
 - Multiple methods but we recommend parallel analysis
4. Determine factor rotation
 - Oblimin if need to account for correlation among factors
 - Otherwise Varimax
 - Different methods usually produce similar factor structures
5. Name the factors based on patterns of variable loadings



MeasuringU



Moderated UX Studies
(in our Denver labs or remotely)



Unmoderated Studies
(using our MUIQ platform)



Participant Recruiting
(US & International)



Eye Tracking &
Facial Expression Analysis



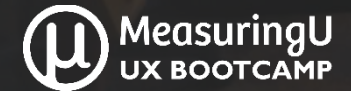
Navigation Testing
(Card-Sorting/Tree-Testing)



Survey Design & Analysis
(including MaxDiff & Kano)



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