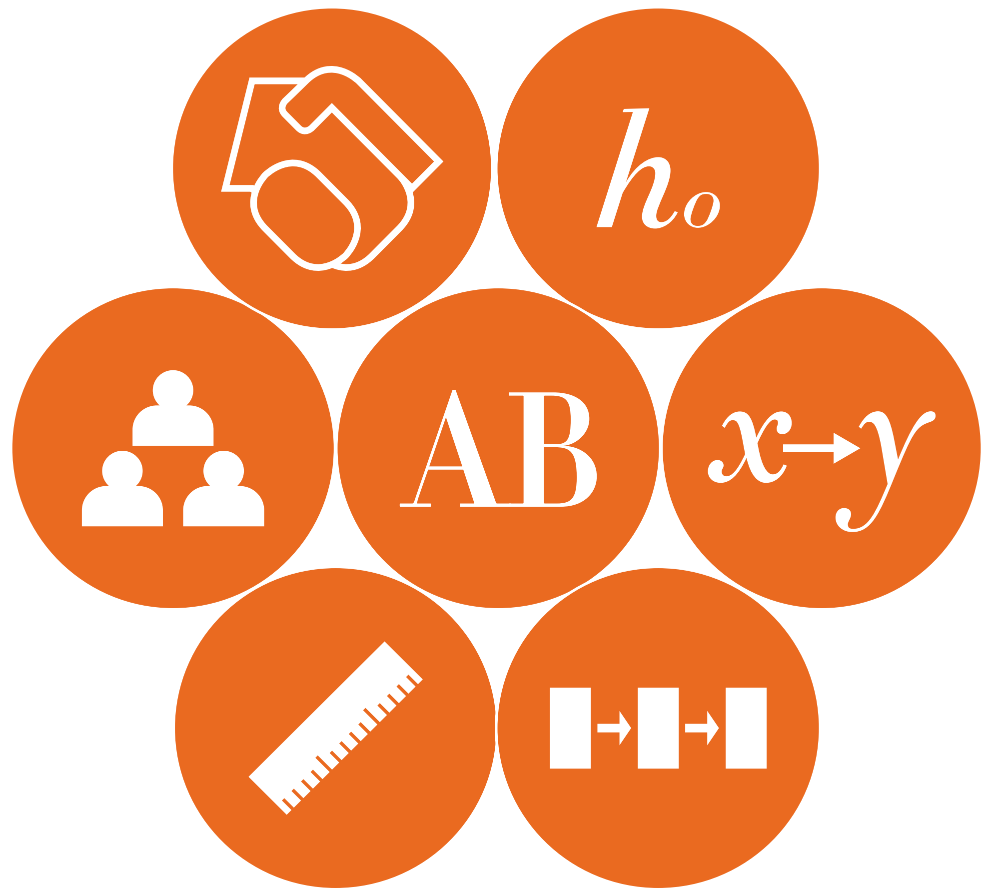

Structural Equation Modeling

for Human-Subject Experiments in Virtual and Augmented Reality

h_o
AB
$x \to y$

Introduction

Welcome everyone!

Introduction

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Asst. Prof. in Human-Centered Computing

University of California, Irvine

PhD in Informatics

Carnegie Mellon University

Master in Human-Computer Interaction

Eindhoven University of Technology

Researcher & teacher
MS in Human-Technology interaction
BS in Innovation Sciences

Introduction

Research areas

Recommender systems

Research on preference elicitation methods

Privacy decision-making

Research on adaptive privacy decision support

Human-like interface agents

Research on user expectations and usability

Introduction

User-centric evaluation work

Framework for user-centric evaluation of recommender systems (bit.ly/umuai)

Chapter in Recommender Systems Handbook (bit.ly/userexperiments)

Tutorials at Recommender Systems (RecSys) and Intelligent User Interfaces (IUI) conferences

11 years of experience as a statistics teacher and consultant

Introduction

"A user experiment is a scientific method to investigate factors that influence how people interact with systems"

"A user experiment systematically tests how different system aspects (manipulations) influence the users' experience and behavior (observations)."

Introduction

My goal:

Teach how to scientifically evaluate intelligent user interfaces using a user-centric approach

My approach:

- I will talk about how to develop a research model
- I will cover every step in conducting a user experiment
- I will teach the "statistics of the 21st century"

Introduction

Slides and data:

www.usabart.nl/QRMS

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Introduction
Welcome everyone!

Hypotheses
Developing a research model

Participants
Population an

Testing
Experimental

Analysis
Statistical evaluation of the results

www.usabart.nl/eval

Measurement
Measuring subjective valuations

Evaluating Models
An introduction to Structural Equation Modeling

Hypotheses

Developing a research model

Hypotheses

"Can you test if my system is good?"

Problem...

What does **good** mean?

- Learnability? (e.g. number of errors?)
- Efficiency? (e.g. time to task completion?)
- Usage satisfaction? (e.g. usability scale?)
- Outcome quality? (e.g. survey?)

We need to define **measures**

Measurement

Measurements: **observed** or **subjective**?

Behavior is an "observed" variable

- Relatively easy to quantify
- E.g. time, EDA, eye movements, clicks, yes/no decision

Perceptions, attitudes, and intentions (subjective valuations) are "unobserved" variables

- They happen in the user's mind
- Harder to quantify (more on this later)

Better…

“Can you test if the user interface of my system scores high on this satisfaction scale?”

However...

What does **high** mean?

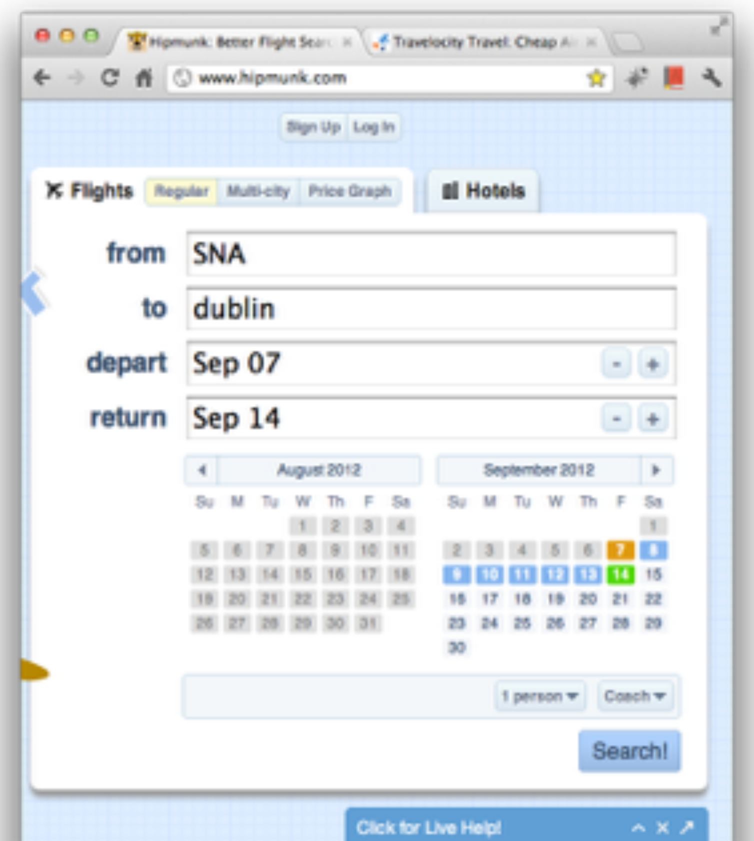
- Is 3.6 out of 5 on a 5-point scale "high"?
- What are 1 and 5?
- What is the difference between 3.6 and 3.7?

We need to **compare** the UI against something

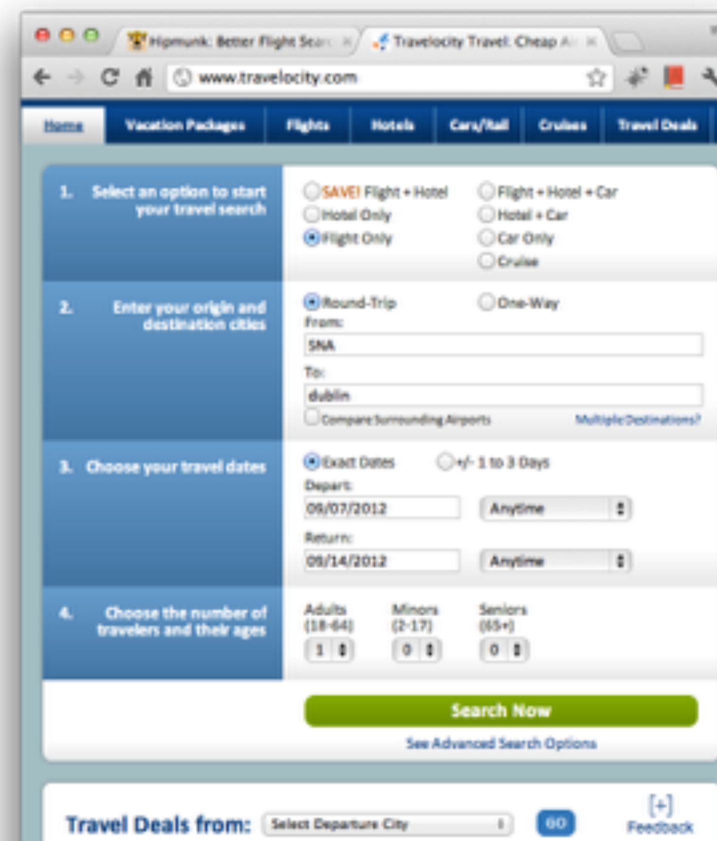
Even better...

"Can you test if the UI of my system scores high on this satisfaction scale compared to this other system?"

Testing A vs. B



My new travel system



Travelocity

However...

If we find that it scores higher on satisfaction... **why** does it?

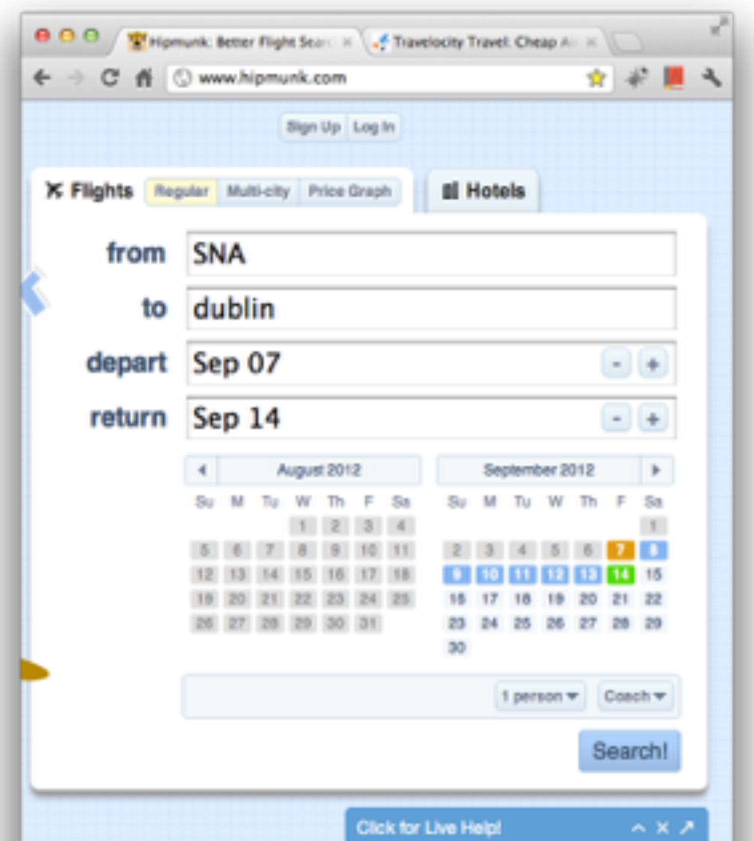
- different date-picker method
- different layout
- different number of options available

Apply the concept of **ceteris paribus** to get rid of confounding variables

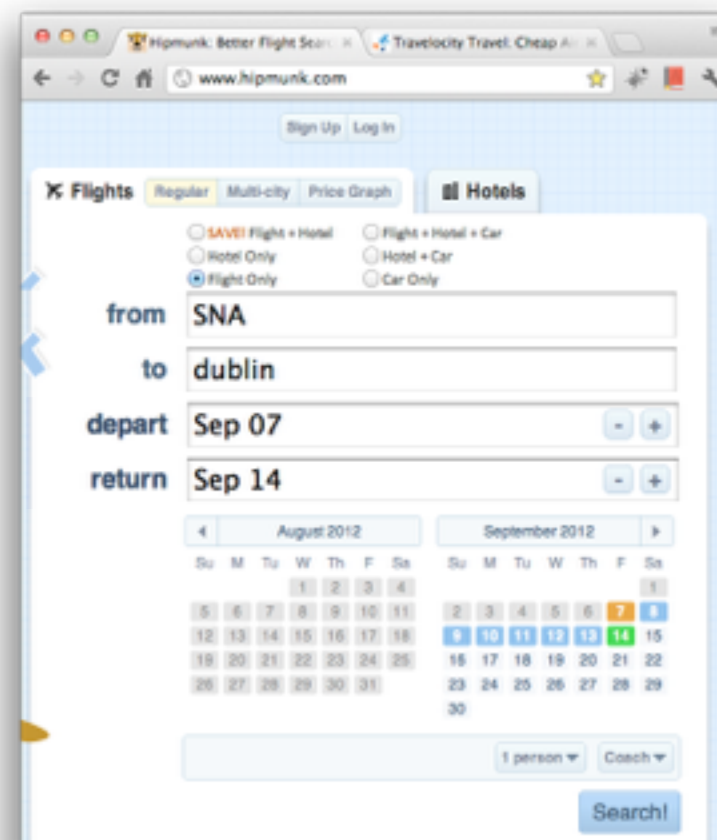
Keep everything the same, except for the thing you want to test (the manipulation)

Any difference can be attributed to the manipulation

Ceteris Paribus



My new travel system



Previous version

(too many options)

Theory behind x->y

To learn something from a study, we need a **theory** behind the effect

- This makes the work generalizable
- This may suggest future work

How to test a theory?

- A theory can be implicit in the manipulations
- But it can also be explicitly measured using **mediating variables**

Theory behind x->y

Measuring **mediating variables**

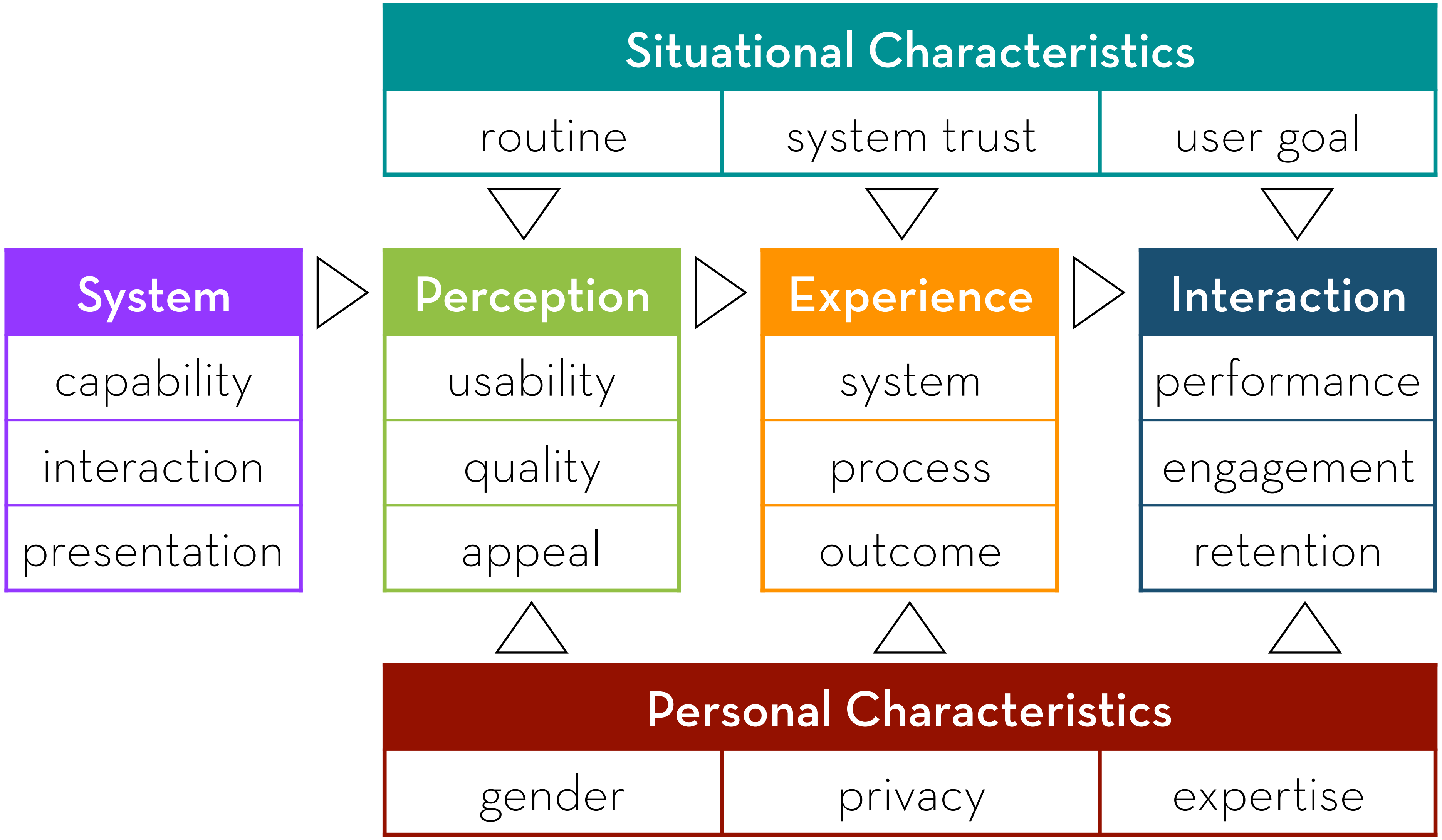
- Measure understandability (and a number of other concepts) as well
- Find out how they mediate the effect on satisfaction

Create a **research model**

- System aspect -> perception -> experience -> behavior

Theory behind x->y

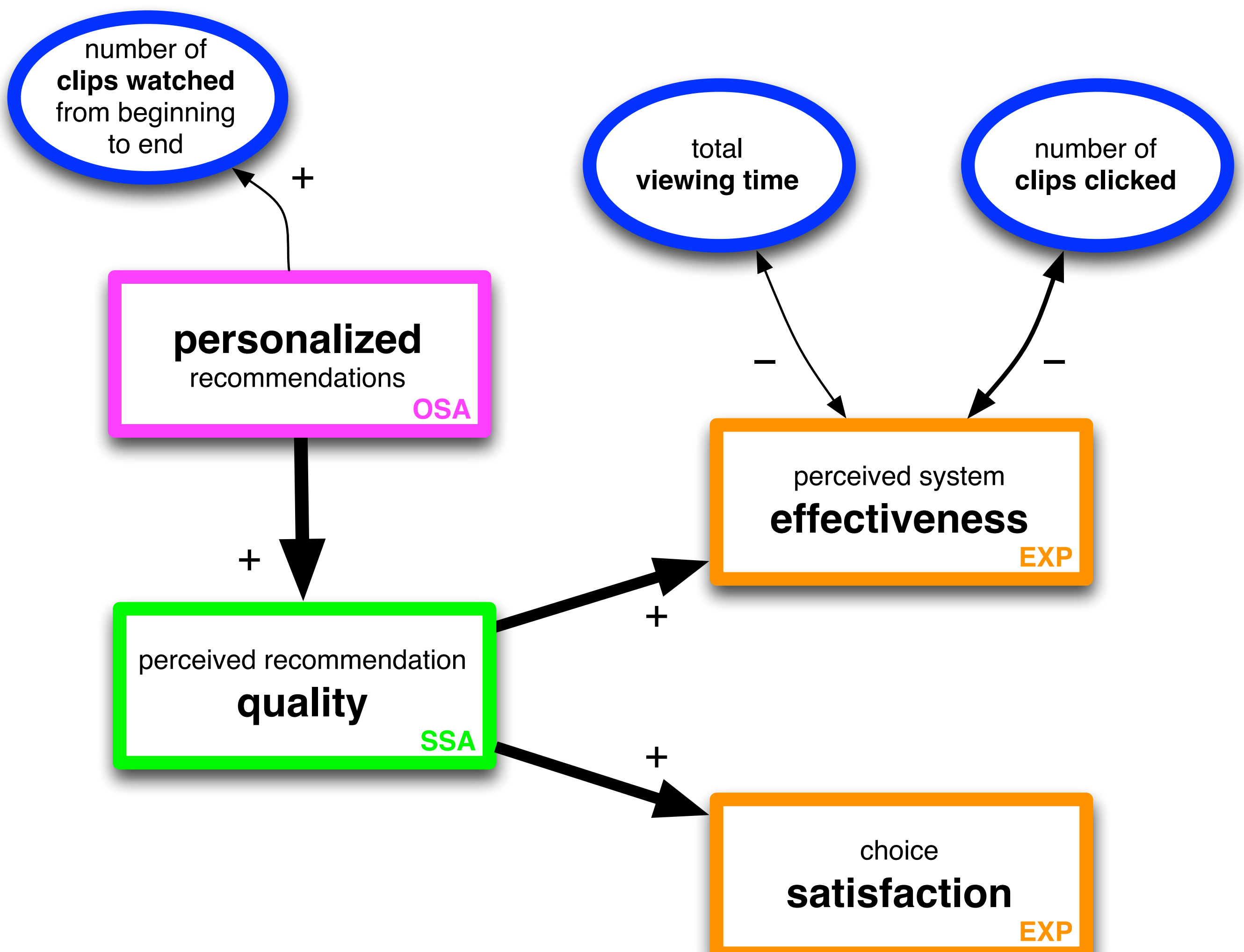
Knijnenburg et al., UMUAI 2012



Example

"Testing a recommender against a random videoclip system, the number of clicked clips and total viewing time went down!"

Example



Knijnenburg et al.: “Receiving Recommendations and Providing Feedback”, EC-Web 2010

Lessons learned

Behavior is **hard to interpret**

Relationship between behavior and satisfaction is not always trivial

User experience is a better predictor of long-term **retention**

With behavior only, you will need to run for a long time

Questionnaire data is more **robust**

Fewer participants needed

h_0 Hypotheses

Measure **subjective valuations** with questionnaires

- Perception, experience, intention

Triangulate these data with behavior

- Ground subjective valuations in observable actions
- Explain observable actions with subjective valuations

Create a **research model**

- System aspect -> perception -> experience -> behavior define **measures**

compare system aspects against each other

apply the concept of **ceteris paribus**

h_o

measure **subjective valuations**

look for a **theory** behind the found effects

Hypotheses

What do I want to find out?

measure **mediating variables** to explain the effects

Measurement

Measuring subjective valuations

Measurement

"To measure satisfaction, we asked users whether they liked the system (on a 5-point rating scale)."

Why is this bad?

Does the question mean the **same** to everyone?

- John likes the system because it is convenient
- Mary likes the system because it is easy to use
- Dave likes it because the outcomes are useful

A single question is not enough to establish **content validity**

We need a multi-item measurement scale

Why use a scale?

Objective traits can usually be measured with a single question

(e.g. age, income)

For subjective traits, single-item measurements lack **content validity**

Each participant may interpret the item differently

This reduces precision and conceptual clarity

Accurate measurement requires a **shared conceptual understanding** between all participants and researcher

Use existing scales

Why?

- Constructing your own scale is a lot of work
- "Famous" scales have undergone extensive validity tests
- Ascertains that two related papers measure exactly the same thing

Finding existing scales:

- In related work (especially if they tested them)
- The Inter-Nomological Network (INN) at inn.theorizeit.org

Popular scales

(Differential Emotion Survey) DES

- 30 adjectives, grouped into 10 emotional states

(Positive and Negative Affect Scale) PANAS

- 10 positive, 10 negative affective states

Uncanny Valley questionnaire

- 19 bipolar items

Social presence

- Under continuous development (Harms & Biocca)

Create new scales

When?

- Existing scales do not hold up
- Nobody has measured what you want to measure before
- Scale relates to the **specific context** of measurement

How:

- Adapt existing scales to your purpose
- Develop a brand new scale

Adapting scales

Information collection concerns:	System-specific concerns:
It usually bothers me when websites ask me for personal information.	It bothered me that [system] asked me for my personal information.
When websites ask me for personal information, I sometimes think twice before providing it.	I had to think twice before providing my personal information to [system].
It bothers me to give personal information to so many websites.	n/a
I am concerned that websites are collecting too much personal information about me.	I am concerned that [system] is collecting too much personal information about me.

Concept definition

Start by writing a good concept definition!

A concept definition is a careful explanation of what you want to measure

Examples: leadership

"Leadership is power, influence, and control" (objectivish)

"Leadership is status, respect, and authority" (subjectivish)

"Leadership is woolliness, foldability, and grayness" (nonsensical, but valid!)

Concept definition

Note: They need to be more detailed than this!

- A good definition makes it unambiguously clear what the concept is supposed to mean
- The foundation for a shared conceptual understanding

Note 2: A concept definition is an equality relation, not a causal relation

- Power, influence, control == leadership
- Not: power, influence, control —> leadership

Concept definition

If a concept becomes "too broad", split it up!

- e.g. you could create separate concept definitions for power, influence, and control

If two concepts are too similar, try to differentiate them, but otherwise integrate them!

- e.g. "attitude towards the system" and "satisfaction with the system" are often very similar

Good items...

Use both positively and negatively phrased items

- They make the questionnaire less “leading”
- They help filtering out bad participants
- They explore the “flip-side” of the scale

The word “not” is easily overlooked

Bad: “The results were not very novel.”

Good: “The results felt outdated.”

Good items...

Choose simple over specialized words

Bad: “Do you find the illumination of your work environment sufficient to work in?”

Avoid double-barreled questions

Bad: “The recommendations were relevant and fun.”

Avoid loaded or leading questions

Bad: “Is it important to treat people fairly?”

Good items...

"Undecided" and "neutral" are not the same thing

Bad: disagree - somewhat disagree - undecided - somewhat agree - agree

Good: disagree - somewhat disagree - neutral (or: neither agree nor disagree) - somewhat agree - agree

Soften the impact of objectionable questions

Bad: "I do not care about the environment."

Good: "There are more important things than caring about the environment."

Answer categories

Most common types of items: binary, 5- or 7-point scale

Why? We want to measure the **extent** of the concept:

- Agreement (completely disagree - - - completely agree) or (no - yes)
- Frequency (never - - - very frequently)
- Importance (unimportant - - - very important)
- Quality (very poor - - - very good)
- Likelihood (almost never true - - - almost always true) or (false - true)

Answer categories

Sometimes, the answer categories represent the item

Based on what I have seen, FormFiller makes it _______ to fill out online forms.

- easy - - neutral - - difficult
- simple - - neutral - - complicated
- convenient - - neutral - - inconvenient
- effortless - - neutral - - daunting
- straightforward - - neutral - - burdensome

How many items?

One scale for each concept

At least 3 (but preferably 5 or more) items per scale

Developing items involves multiple iterations of testing and revising

- First develop 10–15 items
- Then reduce it to 5–7 through discussions with domain experts and comprehension pre-tests with test subjects
- You may remove 1-2 more items in the final analysis

Testing items

Experts discussion:

- Card-sorting into concepts (with or without definition)
- Let experts write the definition based on your items, then show them your definition and discuss difference

Comprehension pre-tests:

- Also card-sorting
- Think-aloud testing: ask users to 1) give an answer, 2) explain the question in their own words, and 3) explain their answer

Examples

Satisfaction:

- In most ways FormFiller is close to ideal.
- I would not change anything about FormFiller.
- I got the important things I wanted from FormFiller.
- FormFiller provides the precise functionality I need.
- FormFiller meets my exact needs.

(completely disagree - disagree - somewhat disagree - neutral - somewhat agree - agree - completely agree)

Examples

Satisfaction (alternative):

- Check-it-Out is useful.
- Using Check-it-Out makes me happy.
- Using Check-it-Out is annoying.
- Overall, I am satisfied with Check-it-Out.
- I would recommend Check-it-Out to others.

(completely disagree - disagree - somewhat disagree - neutral - somewhat agree - agree - completely agree)

Examples

Satisfaction (another alternative):

I am ________ with FormFiller.

- very dissatisfied - - neutral - - very satisfied
- very displeased - - neutral - - very pleased
- very frustrated - - neutral - - very contended

Attention checks

Always begin with clear directions

- Ask comprehension questions about the directions

Make sure your participants are paying attention!

- "To make sure you are paying attention, please answer somewhat agree to this question."
- "To make sure you are paying attention, please do not answer agree to this question."
- Repeat certain questions
- Test for non-reversals of reverse-coded questions

OK solution...

"We asked users ten 5-point scale questions and summed the answers."

What is missing?

Is the scale really measuring a **single** thing?

- 5 items measure satisfaction, the other 5 convenience
- The items are not related enough to make a reliable scale

Are two scales really measuring **different** things?

- They are so closely related that they actually measure the same thing

We need to establish **construct validity**

This makes sure the scales are unidimensional

Construct validity

Discriminant validity

Are two scales really measuring different things? (e.g. attitude and satisfaction may be too highly correlated)

Convergent validity

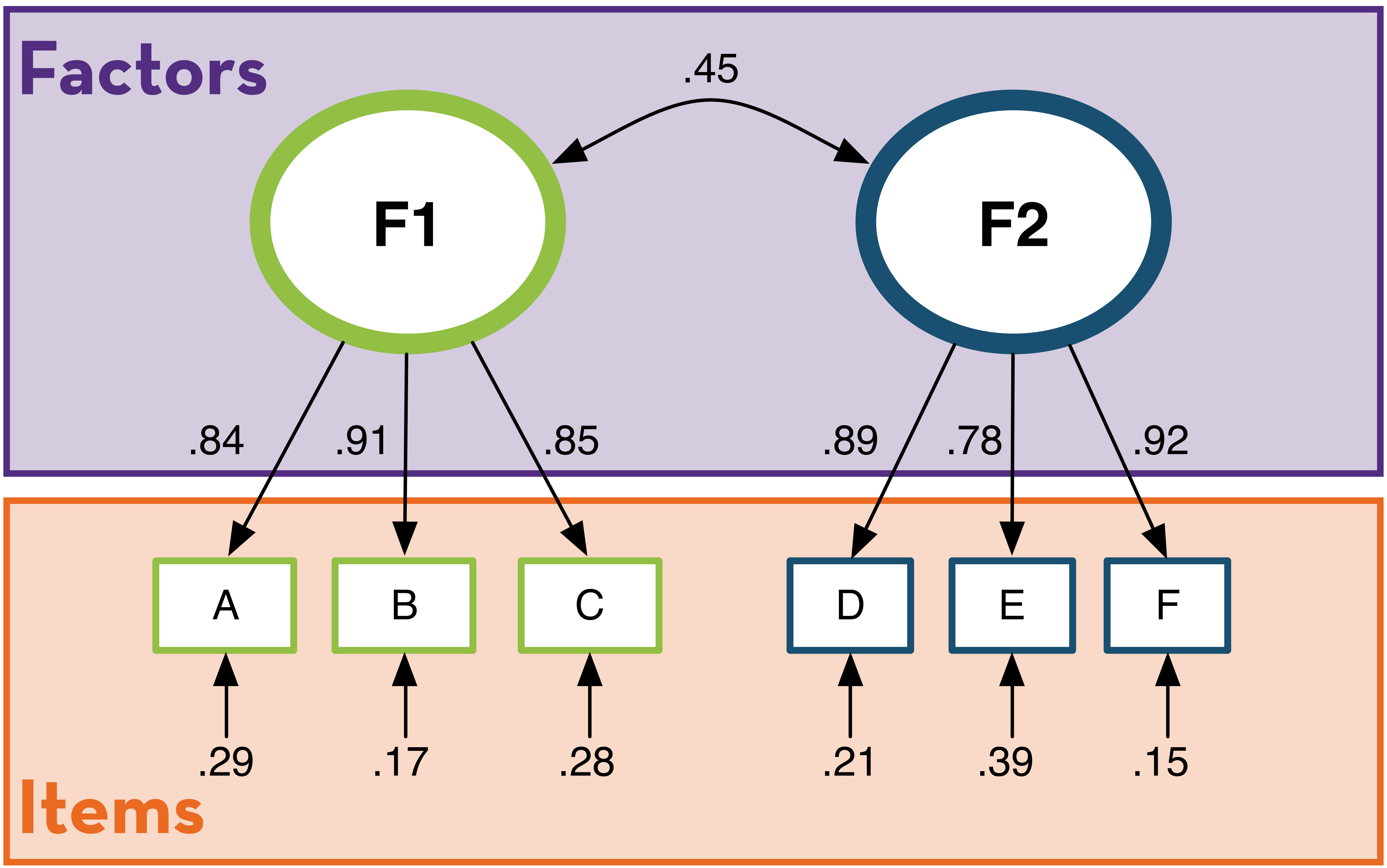
Is the scale really measuring a single thing? (e.g. a usability scale may actually consist of several sub-scales: learnability, effectiveness, efficiency, satisfaction, etc.)

Factor analysis (CFA) helps you with construct validity

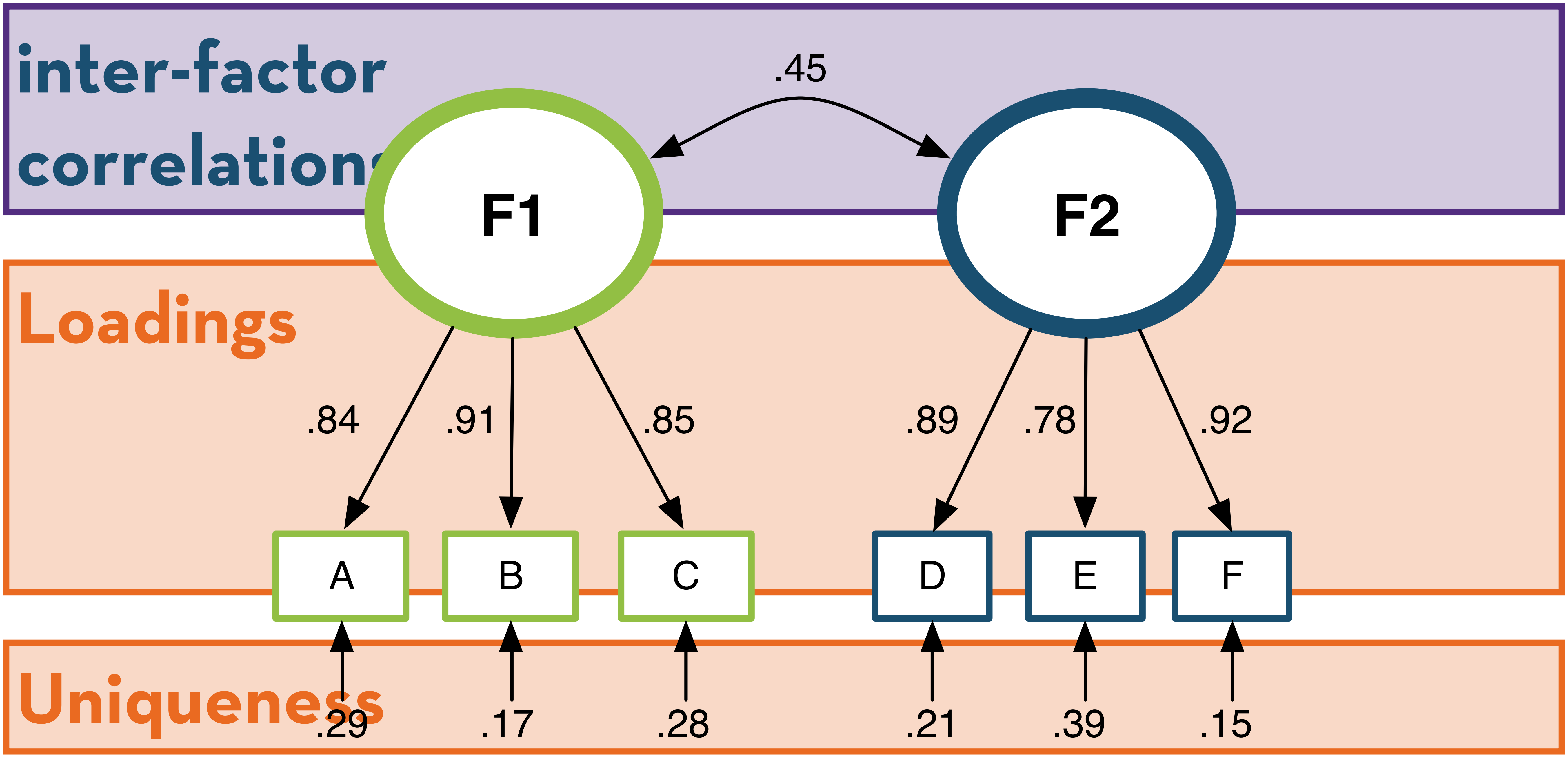
Why CFA?

- Establish convergent and discriminant validity
  - CFA can suggest ways to remedy problems with the scale
- Outcome is a normally distributed measurement scale
  - Even when the items are yes/no, 5- or 7-point scales!
- The scale captures the “shared essence” of the items
  - You can remove the influence of measurement error in your statistical tests!

CFA: the concept



CFA: the concept



CFA: the concept

Factors are **latent constructs** that represent the trait or concept to be measured

- The latent construct cannot be measured directly

The latent construct "**causes**" users' answers to items

- Items are therefore also called **indicators**

Like any measurement, indicators are not perfect measurements

- They depend on the true score (loading) as well as some measurement error (uniqueness)

How it works

By looking at the **overlap** (covariance) between items, we can separate the measurement error from the true score!

- The scale captures the "shared essence" of the items

The basis for Factor Analysis is thus the item correlation matrix

How do we determine the loadings etc?

- By **modeling** the correlation matrix as closely as possible!

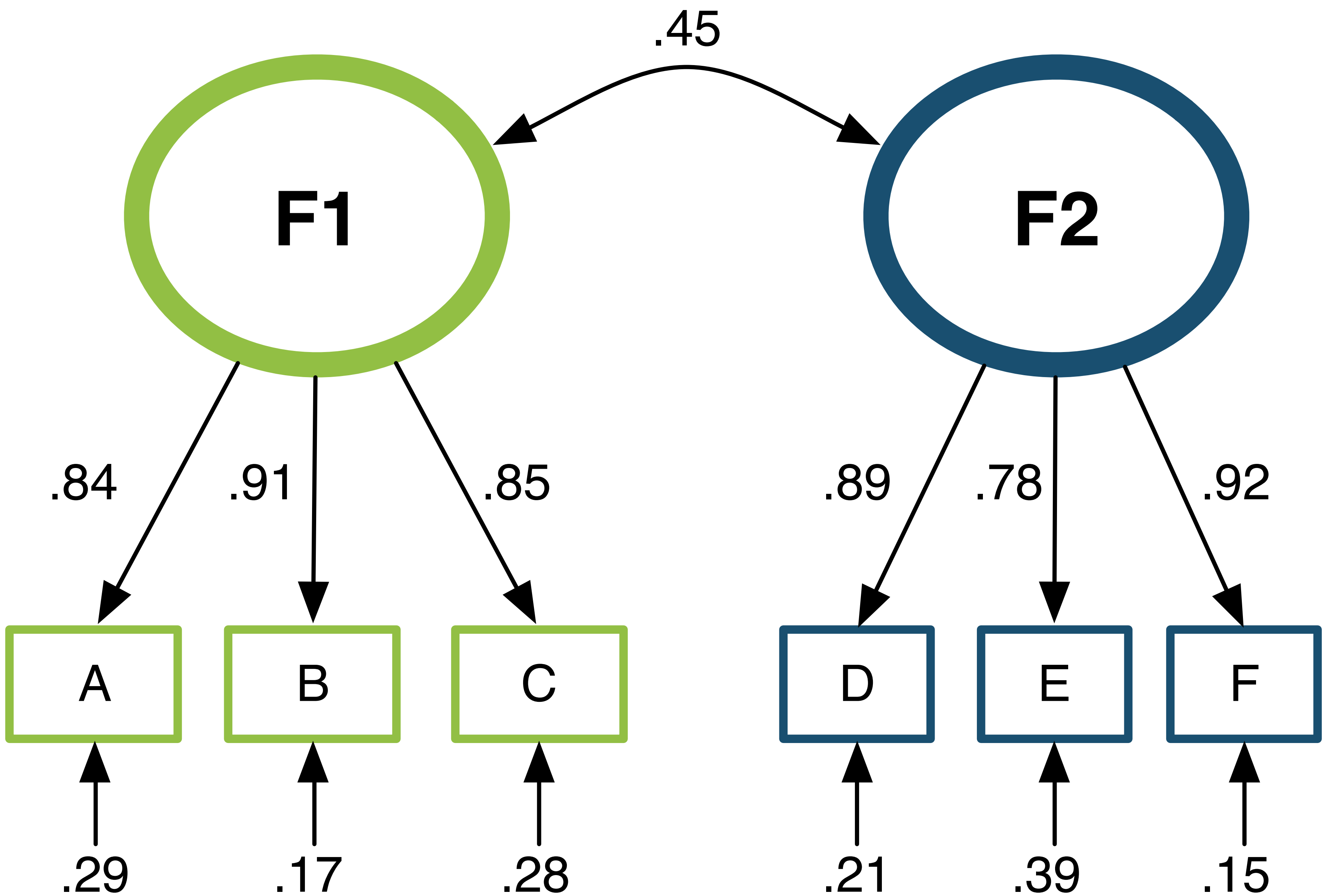
Observed

	A	B	C	D	E	F
A	1.00	0.73	0.71	0.34	0.49	0.34
B	0.73	1.00	0.79	0.35	0.32	0.32
C	0.71	0.79	1.00	0.29	0.33	0.35
D	0.34	0.35	0.29	1.00	0.74	0.81
E	0.49	0.32	0.33	0.74	1.00	0.75
F	0.34	0.32	0.35	0.81	0.75	1.00

Observed

	A	B	C	D	E	F
A	1.00	0.73	0.71	0.34	0.49	0.34
B	0.73	1.00	0.79	0.35	0.32	0.32
C	0.71	0.79	1.00	0.29	0.33	0.35
D	0.34	0.35	0.29	1.00	0.74	0.81
E	0.49	0.32	0.33	0.74	1.00	0.75
F	0.34	0.32	0.35	0.81	0.75	1.00

Model



Estimated

	A	B	C	D	E	F
A	0.71	0.76	0.71	0.34	0.29	0.35
B	0.76	0.83	0.77	0.36	0.32	0.38
C	0.71	0.77	0.72	0.34	0.30	0.35
D	0.34	0.36	0.34	0.79	0.69	0.82
E	0.29	0.32	0.30	0.69	0.61	0.72
F	0.35	0.38	0.35	0.82	0.72	0.85

Residual

	A	B	C	D	E	F
A	0.29	–0.03	0.00	0.00	0.20	–0.01
B	–0.03	0.17	0.02	–0.01	0.00	–0.06
C	0.00	0.02	0.28	–0.05	0.03	0.00
D	0.00	–0.01	–0.05	0.21	0.05	–0.01
E	0.20	0.00	0.03	0.05	0.39	0.03
F	–0.01	–0.06	0.00	–0.01	0.03	0.15

Example

Knijnenburg et al. (2012): “Inspectability and Control in Social Recommenders”, *RecSys'12*

The TasteWeights system uses the overlap between you and your friends' Facebook “likes” to give you music recommendations.

- Friends “weights” based on the overlap in likes w/ user
- Friends' other music likes—the ones that are not among the user's likes—are tallied by weight
- Top 10 is displayed to the user

Example

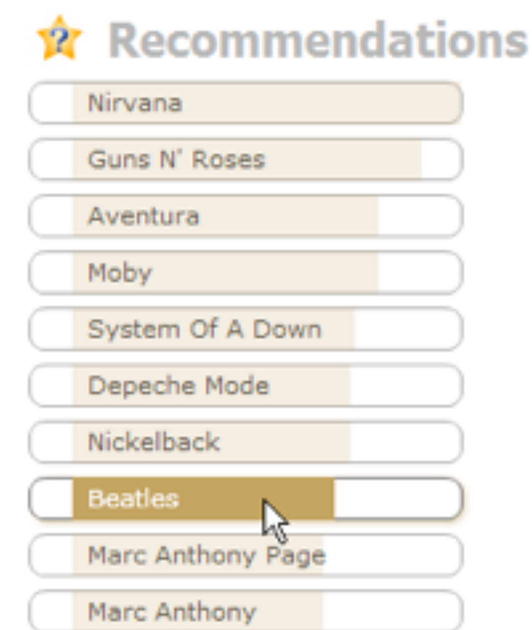
3 control conditions:

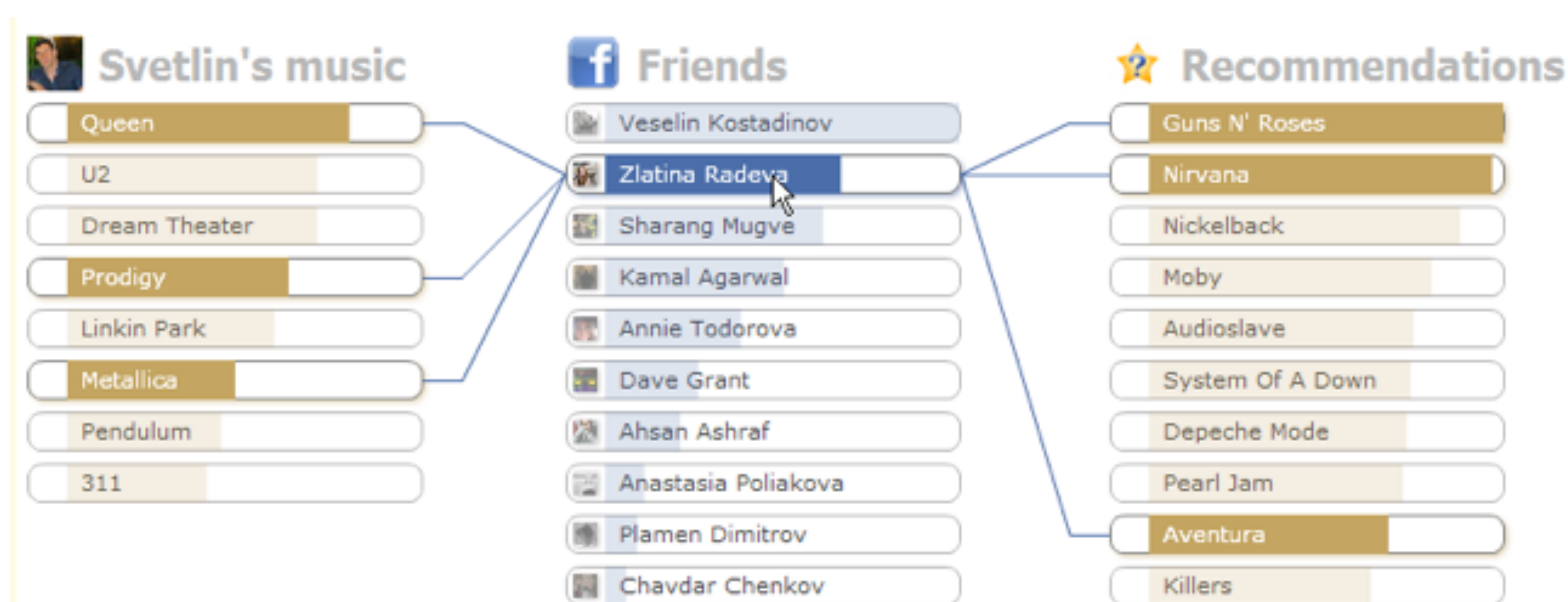
- No control (just use likes)
- Item control (weigh likes)
- Friend control (weigh friends)

Example

2 inspectability conditions:

– List of recommendations vs. recommendation graph





Example

twq.dat, variables:

- **cgraph**: inspectability manipulation (0: list, 1: graph)
- **citem-cfriend**: two dummies for the control manipulation (baseline: no control)
- **s1-s7**: satisfaction with the system (5-point scale items)
- **q1-q6**: perceived quality of the recommendations
- **c1-c5**: perceived control over the system
- **u1-u5**: understandability of the system

Example

twq.dat, variables:

- **e1-e4**: user music expertise
- **t1-t6**: propensity to trust
- **f1-f6**: familiarity with recommenders
- average **rating** of, and number of **known** items in, the top 10
- **time** taken to inspect the recommendations

Download the data at **www.usabart.nl/QRMS**

Run the CFA

Write model definition:

```
model <- ‘satisf =~ s1+s2+s3+s4+s5+s6+s7
quality =~ q1+q2+q3+q4+q5+q6
control =~ c1+c2+c3+c4+c5
underst =~ u1+u2+u3+u4+u5’
```

Run cfa (load package lavaan):

```
fit <- cfa(model, data=twq, ordered=names(twq), std.lv=TRUE)
```

Inspect model output:

```
summary(fit, rsquare=TRUE, fit.measures=TRUE)
```

Run the CFA

Output (model fit):

```
lavaan (0.5-17) converged normally after  39 iterations

  Number of observations                           267

  Estimator                                       DWLS      Robust
  Minimum Function Test Statistic              251.716     365.719
  Degrees of freedom                               224         224
  P-value (Chi-square)                           0.098       0.000
  Scaling correction factor                                  1.012
  Shift parameter                                          117.109
    for simple second-order correction (Mplus variant)

Model test baseline model:

  Minimum Function Test Statistic            48940.029   14801.250
  Degrees of freedom                               253         253
  P-value                                        0.000       0.000
```

Run the CFA

Output (model fit, continued):

```
User model versus baseline model:

  Comparative Fit Index (CFI)                    0.999       0.990
  Tucker-Lewis Index (TLI)                       0.999       0.989

Root Mean Square Error of Approximation:

  RMSEA                                          0.022       0.049
  90 Percent Confidence Interval          0.000  0.034       0.040  0.058
  P-value RMSEA <= 0.05                          1.000       0.579

Weighted Root Mean Square Residual:

  WRMR                                           0.855       0.855

Parameter estimates:

  Information                                 Expected
  Standard Errors                           Robust.sem
```

Run the CFA

Output (loadings):

```
                   Estimate  Std.err  Z-value  P(>|z|)
  Latent variables:
    satisf =~
      s1              0.888    0.018   49.590    0.000
      s2             -0.885    0.018  -48.737    0.000
      s3              0.771    0.029   26.954    0.000
      s4              0.821    0.025   32.363    0.000
      s5              0.889    0.018   50.566    0.000
      s6              0.788    0.031   25.358    0.000
      s7             -0.845    0.022  -38.245    0.000
    quality =~
      q1              0.950    0.013   72.421    0.000
      q2              0.949    0.013   72.948    0.000
      q3              0.942    0.012   77.547    0.000
      q4              0.805    0.033   24.257    0.000
      q5             -0.699    0.042  -16.684    0.000
      q6             -0.774    0.040  -19.373    0.000
```

Run the CFA

Output (loadings, continued):

```
  control =~
    c1                0.712    0.038   18.684    0.000
    c2                0.855    0.024   35.624    0.000
    c3                0.905    0.022   41.698    0.000
    c4                0.723    0.037   19.314    0.000
    c5               -0.424    0.056   -7.571    0.000
  underst =~
    u1               -0.557    0.047  -11.785    0.000
    u2                0.899    0.016   57.857    0.000
    u3                0.737    0.030   24.753    0.000
    u4               -0.918    0.016  -58.229    0.000
    u5                0.984    0.010   97.787    0.000
```

Run the CFA

Output (factor correlations):

```
Covariances:
  satisf ~~
    quality             0.686    0.033   20.503    0.000
    control            -0.760    0.028  -26.913    0.000
    underst             0.353    0.048    7.320    0.000
  quality ~~
    control            -0.648    0.040  -16.041    0.000
    underst             0.278    0.058    4.752    0.000
  control ~~
    underst            -0.382    0.051   -7.486    0.000
```

Run the CFA

Output (variance extracted):

```
R-Square:

    s1              0.788
    s2              0.782
    s3              0.594
    s4              0.674
    s5              0.790
    s6              0.621
    s7              0.714
    q1              0.903
    q2              0.901
    q3              0.888
    q4              0.648
    q5              0.489
    q6              0.599
    c1              0.506
    c2              0.731
    c3              0.820
    c4              0.522
    c5              0.179
    u1              0.310
    u2              0.808
    u3              0.544
    u4              0.843
    u5              0.968
```

Things to inspect

Item-fit: Loadings, communality, residuals

- Remove items that do not fit

Factor-fit: Average Variance Extracted

- Respecify or remove factors that do not fit

Model-fit: Chi-square test, CFI, TLI, RMSEA

- Make sure the model meets criteria

Item-fit metrics

Variance extracted (squared loading):

- The amount of variance explained by the factor (1-uniqueness)
- Should be > 0.50 (although some argue 0.40 is okay)

In lavaan output: r-squared

Based on r-squared, iteratively remove items:

c5 (r-squared = 0.180)

u1 (r-squared = 0.324)

Item-fit metrics

Residual correlations:

- The observed correlation between two items is significantly higher (or lower) than predicted
- Might mean that factors should be split up

Cross-loadings:

- When the model suggest that the model fits significantly better if an item also loads on an additional factor
- Could mean that an item actually measures two things

Item-fit metrics

In R: modification indices

We only look the ones that are significant and large enough to be interesting (decision == "epc")

```
mods <- modindices(fit,power=TRUE)
mods[mods$decision == "epc",]
```

Based on modification indices, remove item:

u3 loads on control (modification index = 24.667)

Some residual correlations within Satisfaction (might mean two factors?), but we ignore those because AVE is good (see next couple of slides)

Item-fit metrics

For all these metrics:

- Remove items that do not meet the criteria, but be careful to keep at least 3 items per factor
- One may remove an item that has values much lower than other items, even if it meets the criteria

Factor-fit

Average Variance Extracted (AVE) in lavaan output:

- average of R-squared per factor

Convergent validity:

- AVE > 0.5

Discriminant validity

- $\sqrt{(AVE)}$ > largest correlation with other factors

Factor-fit

Satisfaction:

AVE = 0.709, $\sqrt{(AVE)}$ = 0.842, largest correlation = 0.762

Quality:

AVE = 0.737, $\sqrt{(AVE)}$ = 0.859, largest correlation = 0.687

Control:

AVE = 0.643, $\sqrt{(AVE)}$ = 0.802, largest correlation = 0.762

Understandability:

AVE = 0.874, $\sqrt{(AVE)}$ = 0.935, largest correlation = 0.341

Model-fit metrics

Chi-square test of model fit:

- Tests whether there any significant misfit between estimated and observed correlation matrix
- Often this is true ($p < .05$)... models are rarely perfect!
- Alternative metric: chi-squared / df < 3 (good fit) or < 2 (great fit)

Model-fit metrics

CFI and TLI:

- Relative improvement over baseline model; ranging from 0.00 to 1.00
- CFI should be > 0.96 and TLI should be > 0.95

RMSEA:

- Root mean square error of approximation
- Overall measure of misfit
- Should be < 0.05, and its confidence intervall should not exceed 0.10.

Model-fit

Use the “robust” column in R:

- Chi-Square value: 288.517, df: 164 (value/df = 1.76, good)
- CFI: 0.990, TLI: 0.989 (both good)
- RMSEA: 0.053 (slightly high), 90% CI: [0.043, 0.063] (ok)

Summary

Specify and run your CFA

Alter the model until all remaining items fit

Make sure you have at least 3 items per factor!

Report final loadings, factor fit, and model fit

Summary

We conducted a CFA and examined the validity and reliability scores of the constructs measured in our study.

Upon inspection of the CFA model, we removed items c5 (communality: 0.180) and u1 (communality: 0.324), as well as item u3 (high cross-loadings with several other factors). The remaining items shared at least 48% of their variance with their designated construct.

Summary

To ensure the convergent validity of constructs, we examined the average variance extracted (AVE) of each construct. The AVEs were all higher than the recommended value of 0.50, indicating adequate convergent validity.

To ensure discriminant validity, we ascertained that the square root of the AVE for each construct was higher than the correlations of the construct with other constructs.

Summary

Construct	Item	Loading
System satisfaction Alpha: 0.92 AVE: 0.709	I would recommend TasteWeights to others.	0.888
	TasteWeights is useless.	-0.885
	TasteWeights makes me more aware of my choice options.	0.768
	I can make better music choices with TasteWeights.	0.822
	I can find better music using TasteWeights.	0.889
	Using TasteWeights is a pleasant experience.	0.786
	TasteWeights has no real benefit for me.	-0.845
Perceived Recommendation Quality Alpha: 0.90 AVE: 0.737	I liked the artists/bands recommended by the TasteWeights system.	0.950
	The recommended artists/bands fitted my preference.	0.950
	The recommended artists/bands were well chosen.	0.942
	The recommended artists/bands were relevant.	0.804
	TasteWeights recommended too many bad artists/bands.	-0.697
	I didn't like any of the recommended artists/bands.	-0.775
Perceived Control Alpha: 0.84 AVE: 0.643	I had limited control over the way TasteWeights made recommendations.	0.700
	TasteWeights restricted me in my choice of music.	0.859
	Compared to how I normally get recommendations, TasteWeights was very limited.	0.911
	I would like to have more control over the recommendations.	0.716
	I decided which information was used for recommendations.	
Understandability Alpha: 0.92 AVE: 0.874	The recommendation process is not transparent.	
	I understand how TasteWeights came up with the recommendations.	0.893
	TasteWeights explained the reasoning behind the recommendations.	
	I am unsure how the recommendations were generated.	-0.923
	The recommendation process is clear to me.	0.987

Summary

	Alpha	AVE	Satisfaction	Quality	Control	Underst.
Satisfaction	0.92	0.709	**0.842**	0.687	–0.762	0.336
Quality	0.90	0.737	0.687	**0.859**	–0.646	0.282
Control	0.84	0.643	–0.762	–0.646	**0.802**	–0.341
Underst.	0.92	0.874	0.336	0.282	–0.341	**0.935**

diagonal: $\sqrt{(\text{AVE})}$

off-diagonal: correlations

establish content validity with **multi-item scales**

follow the general principles for **good questionnaire items**

establish **convergent** and **discriminant** validity

Measurement

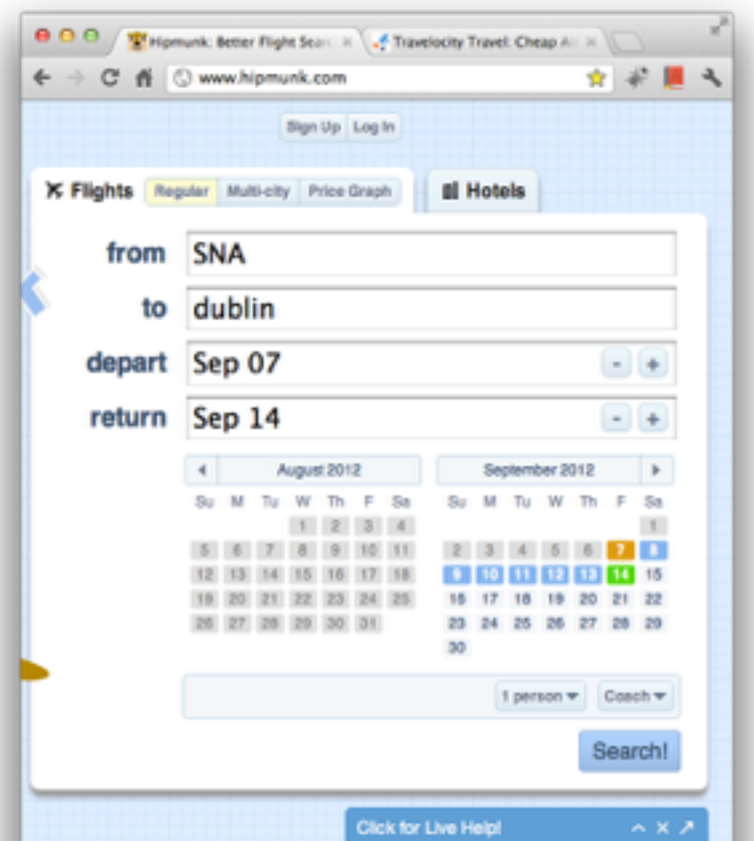
Measuring subjective valuations

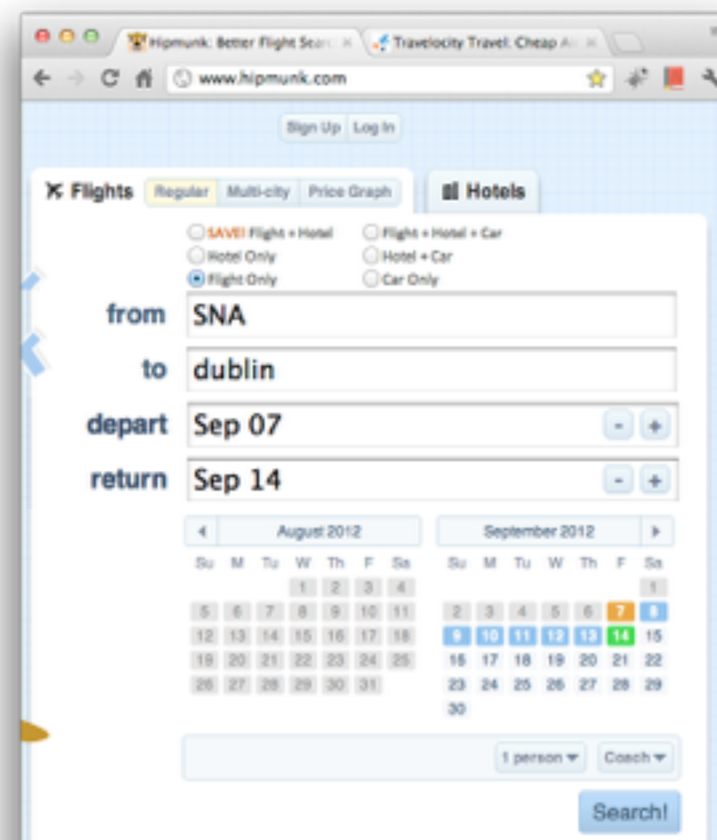
use **factor analysis**

Evaluating Models

An introduction to Structural Equation Modeling

Evaluating Models





Test whether fewer options leads to lower/higher usability

Theory behind x->y

To learn something from a study, we need a **theory** behind the effect

- This makes the work generalizable
- This may suggest future work

Measure **mediating variables**

- Measure understandability (and a number of other concepts) as well
- Find out how they mediate the effect on usability

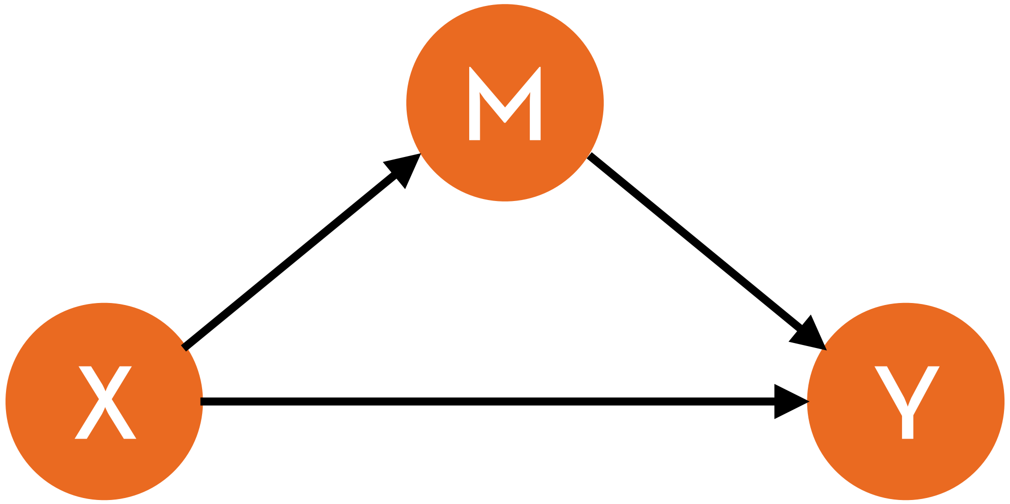
Mediation Analysis

X -> M -> Y

Does the system (X) influence usability (Y) via understandability (M)?

Types of mediation

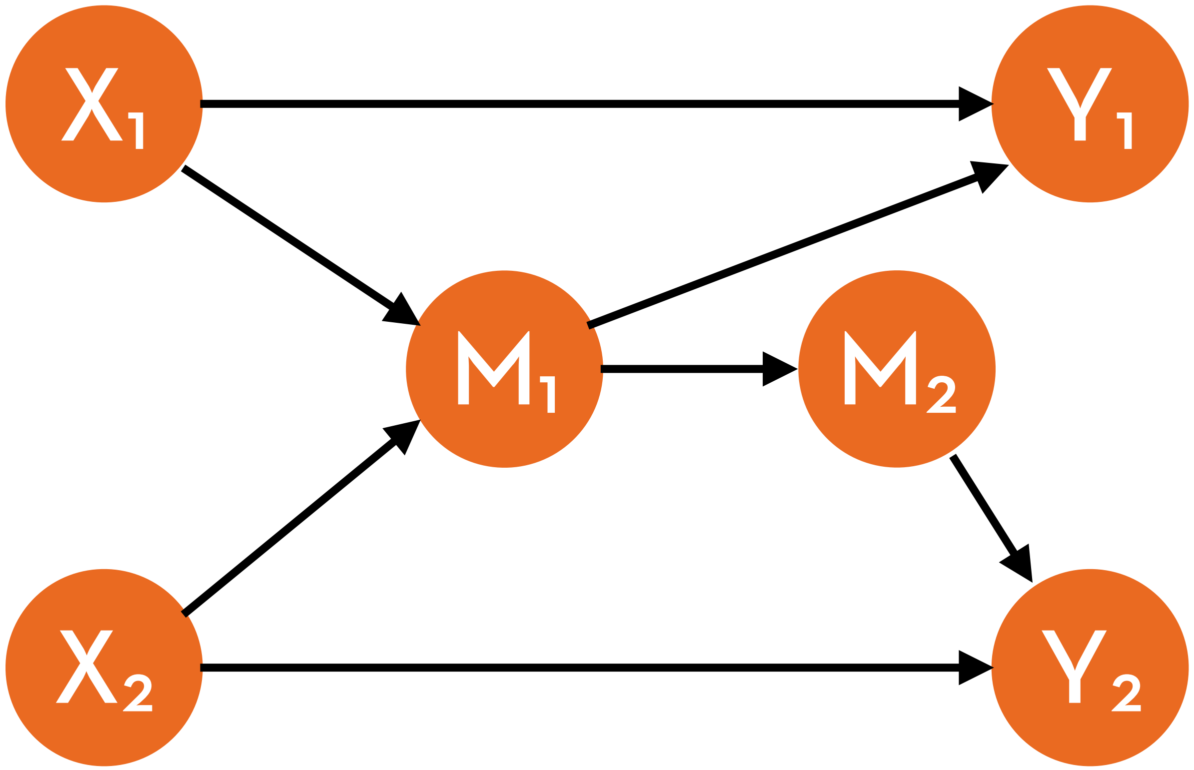
- Partial mediation
- Full mediation
- Negative mediation



Mediation Analysis

More complex models:

- What is the total effect of X1 on Y2?
- Is this effect significant?
- Is this effect fully or partially mediated by M1 and M2?



What is SEM?

A Structural Equation Model (SEM) is a CFA where the factors are regressed on each other and on the experimental manipulations

(observed behaviors can also be incorporated)

The regressions are not estimated one-by-one, but **all at the same time**

(and so is the CFA part of the model, actually)

Why SEM?

Easy way to test for **mediation**

...without doing many separate tests

You can **keep factors** as factors

This ascertains normality, and leads to more statistical power in the regressions

The model has several **overall fit indices**

You can judge the fit of an entire model, rather than just its parts

Keep the factors!

Let's say we have a factor F measuring trait Y, with AVE = 0.64

- On average, 64% of the item variance is communality, 36% is uniqueness

If we **sum the items** of the factor as S, this results in 36% error

- This is random noise that does not measure Y

Result: no regression with S as dependent can have an R-squared > 0.64!

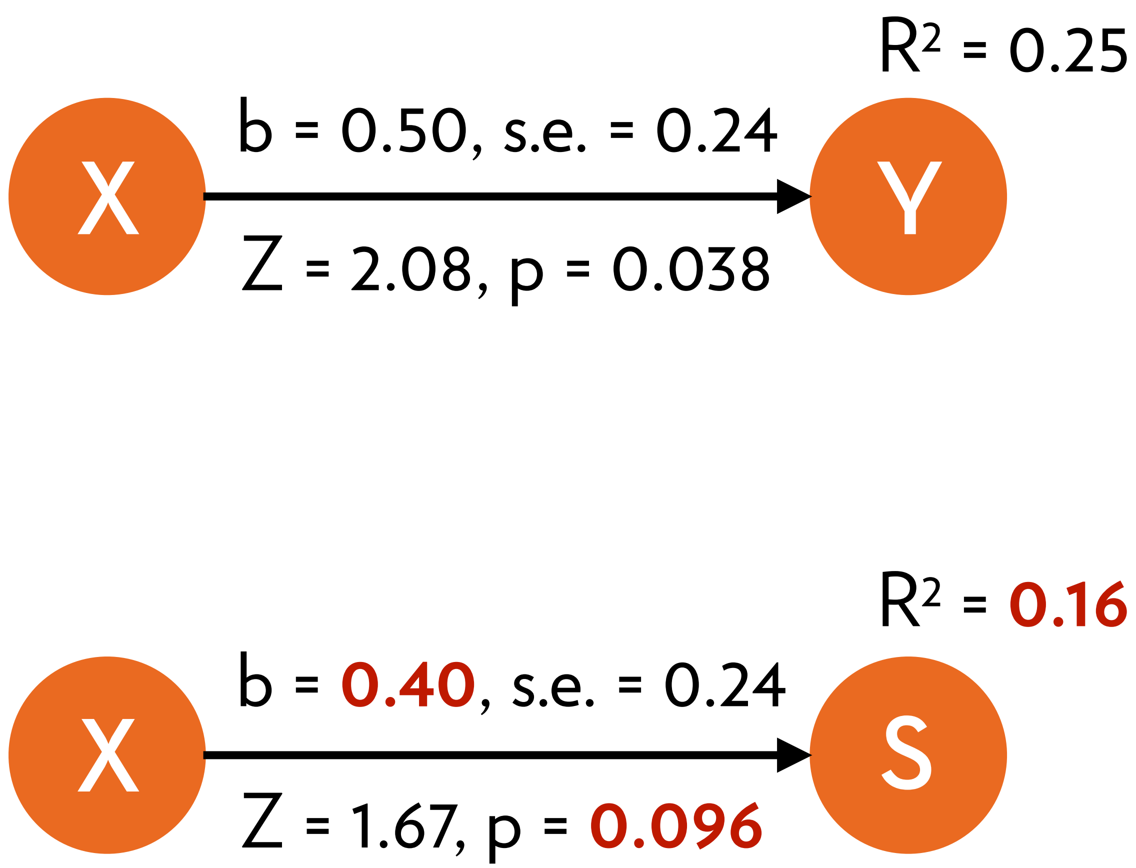
Keep the factors!

Any regression coefficient will be **attenuated** by the AVE of S!

Take for instance this X, which potentially explains 25% of the variance of Y…

…it only explains 16% of the variance of S!

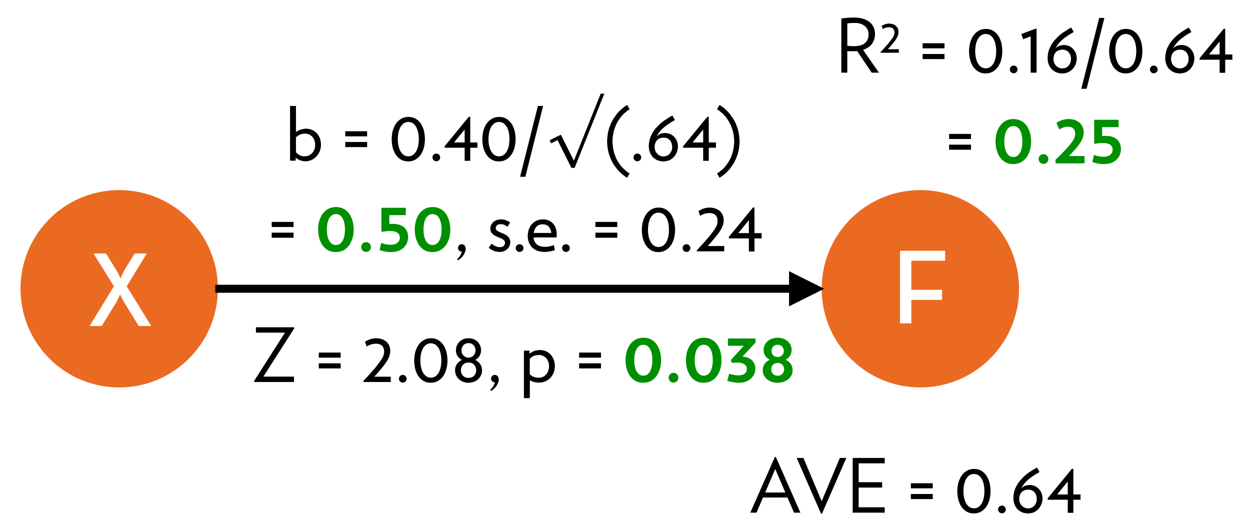
…and the effect is non-significant!



Keep the factors!

If we use F instead of S, we **know** that the AVE is 0.64

...so we can **compensate** for the incurred measurement error!



Estimates

In a SEM you can get the following estimates (all at once):

- Item loadings
- R^2 for every dependent variable
- Regression coefficients for all regressions (B, s.e., p-values)

Plus, you can get omnibus tests for testing manipulations with > 2 conditions

Steps

Steps involved in constructing a SEM:

(a method that is confirmatory, but leaves room for data-driven changes in the model)

Step 1: Build your CFA ✓

Step 2: Analyze the marginal effects of the manipulations

Step 3: Set up a model based on theory

Step 4: Test and trim a saturated version of this model

2. Marginal effects

First analysis: manipulations —> factors

MIMIC model (Multiple Indicators, Multiple Causes)

The SEM equivalent of a t-test / (factorial) ANOVA

Steps involved:

- Create dummies for your experimental conditions
- Run regressions factor-by-factor

Create dummies

Already built for our dataset:

- Control conditions ("no control" is the baseline):

  `citem cfriend`

- Inspectability conditions ("list view" is the baseline):

  `cgraph`

What about the interaction effect?

- Use citem*cgraph and cfriend*cgraph!

  `cig cfg`

Add regression

Add a regression to your final CFA model:

```
model <- ‘satisf =~ s1+s2+s3+s4+s5+s6+s7
quality =~ q1+q2+q3+q4+q5+q6
control =~ c1+c2+c3+c4
underst =~ u2+u4+u5
satisf ~ citem+cfriend+cgraph+cig+cfg’;

fit <-
sem(model,data=twq,ordered=names(twq[9:31]),std.lv=TRUE);

summary(fit);
```

Results

Note: effects are not significant (but that's okay for now)

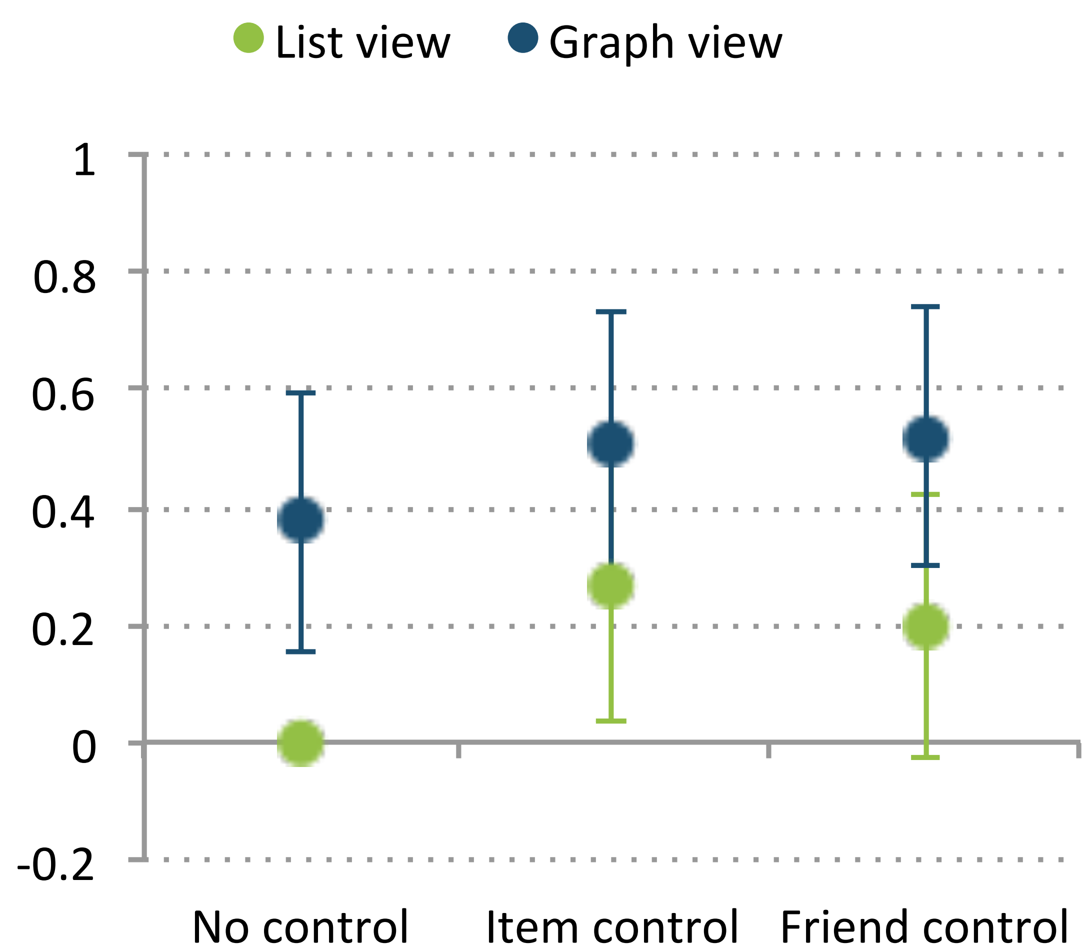
```
                   Estimate  Std.err  Z-value  P(>|z|)
...(factors)...         ...      ...      ...      ...
Regressions:
  satisf ~
    citem              0.269    0.234    1.153    0.249
    cfriend            0.197    0.223    0.882    0.378
    cgraph             0.375    0.221    1.694    0.090
    cig               -0.131    0.320   -0.408    0.683
    cfg               -0.048    0.309   -0.156    0.876
```

Code for a graph

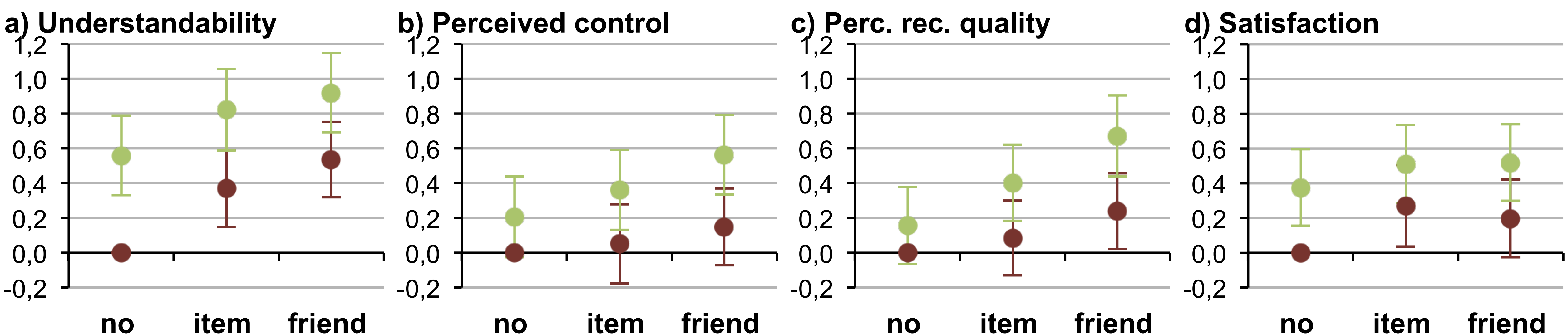
Use dummies for each condition (except "list view, no control" condition):

```
model <- 'satisf =~ s1+s2+s3+s4+s5+s6+s7
quality =~ q1+q2+q3+q4+q5+q6
control =~ c1+c2+c3+c4
underst =~ u2+u4+u5
satisf ~ cil+cfl+cng+cig+cfg';

fit <-
sem(model,data=twq,ordered=names(twq[1:23]),std.lv=TRUE);

summary(fit);
```

Create a graph



Repeat



From: Knijnenburg et al. (2012): "Inspectability and Control in Social Recommenders", *RecSys'12*

Main finding

Main effects of inspectability and control conditions on understandability (no interaction effect)

Similar to regression!

```
                       Estimate  Std.err  Z-value  P(>|z|)
...(factors)...             ...      ...      ...      ...
Regressions:
  underst ~
    citem                 0.367    0.220    1.666    0.096
    cfriend               0.534    0.216    2.466    0.014
    cgraph                0.556    0.227    2.450    0.014
    cig                  -0.105    0.326   -0.323    0.746
    cfg                  -0.178    0.320   -0.555    0.579
```

3. Modeling: theory

Do this **before** you do your study!

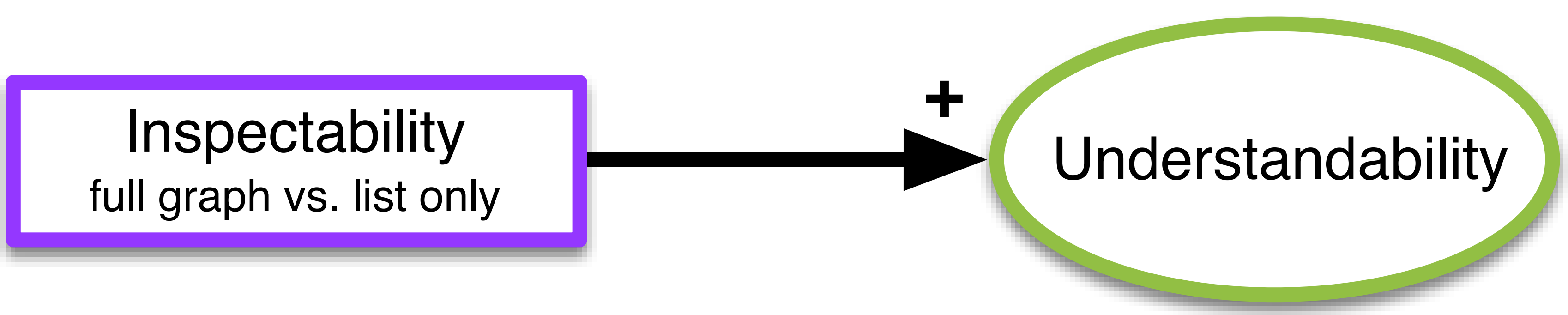
Motivate expected effects, based on:

- previous work
- theory
- common sense

If in doubt, create alternate specifications!

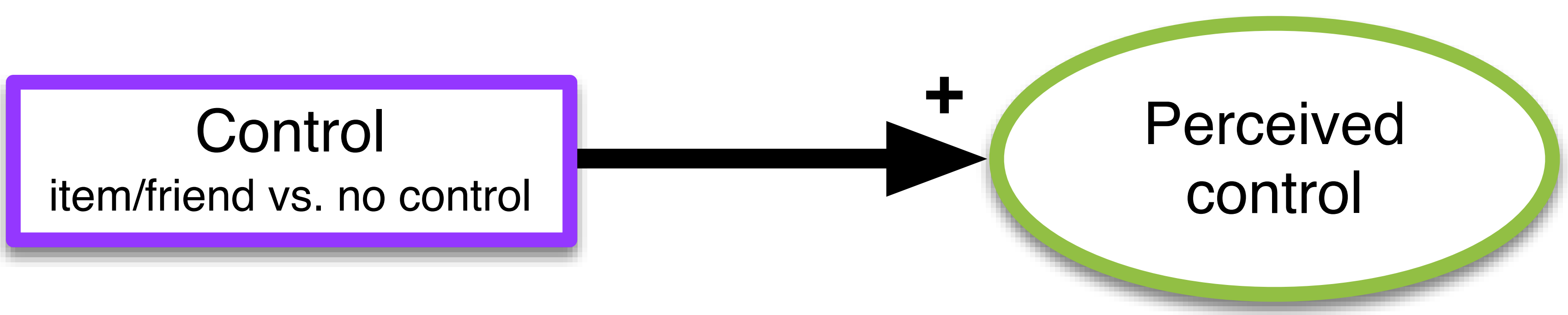
Inspectability

Herlocker argues that explanation provides transparency, "exposing the reasoning behind a recommendation".



Control

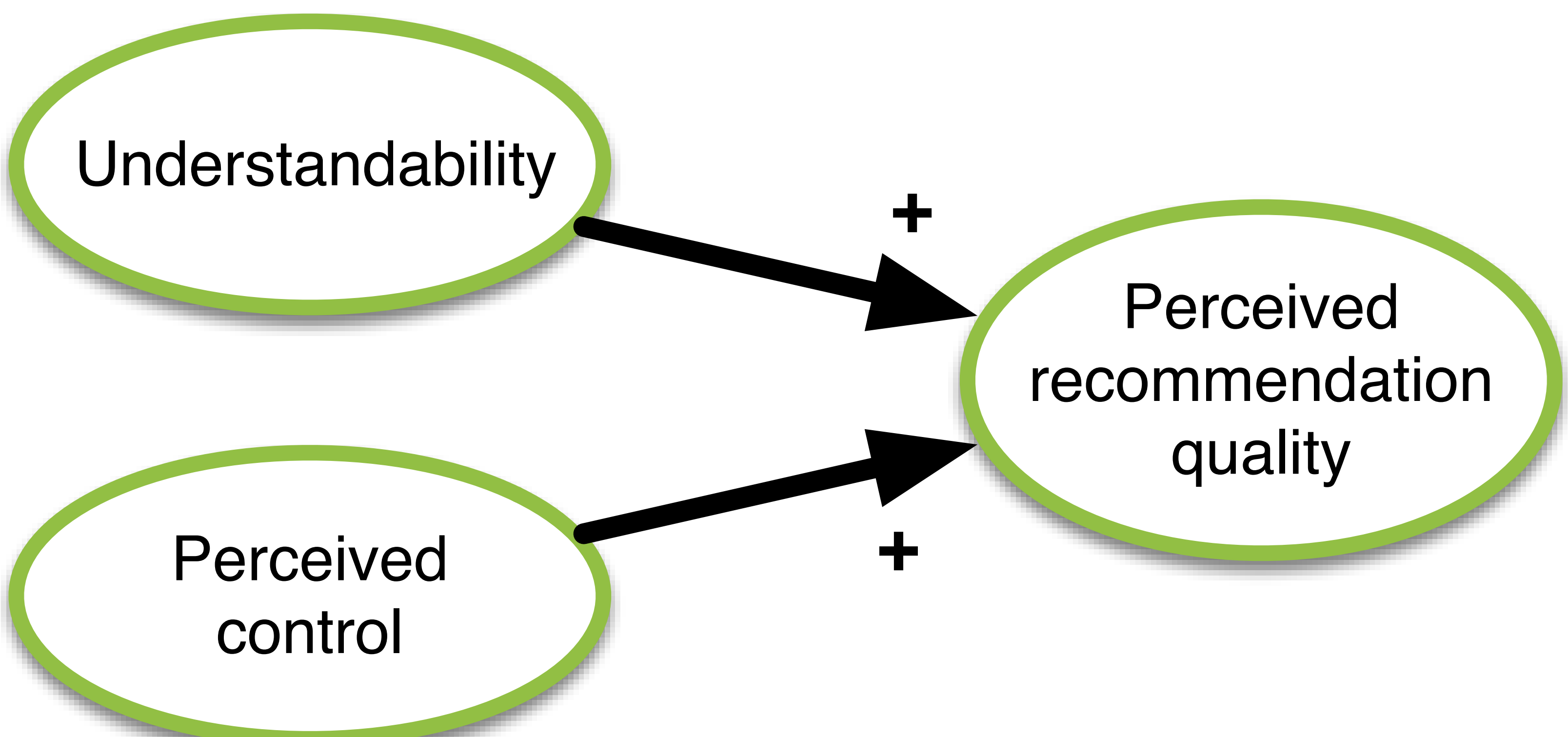
Multiple studies highlight the benefits of interactive interfaces that support control over the recommendation process.



Perceived quality

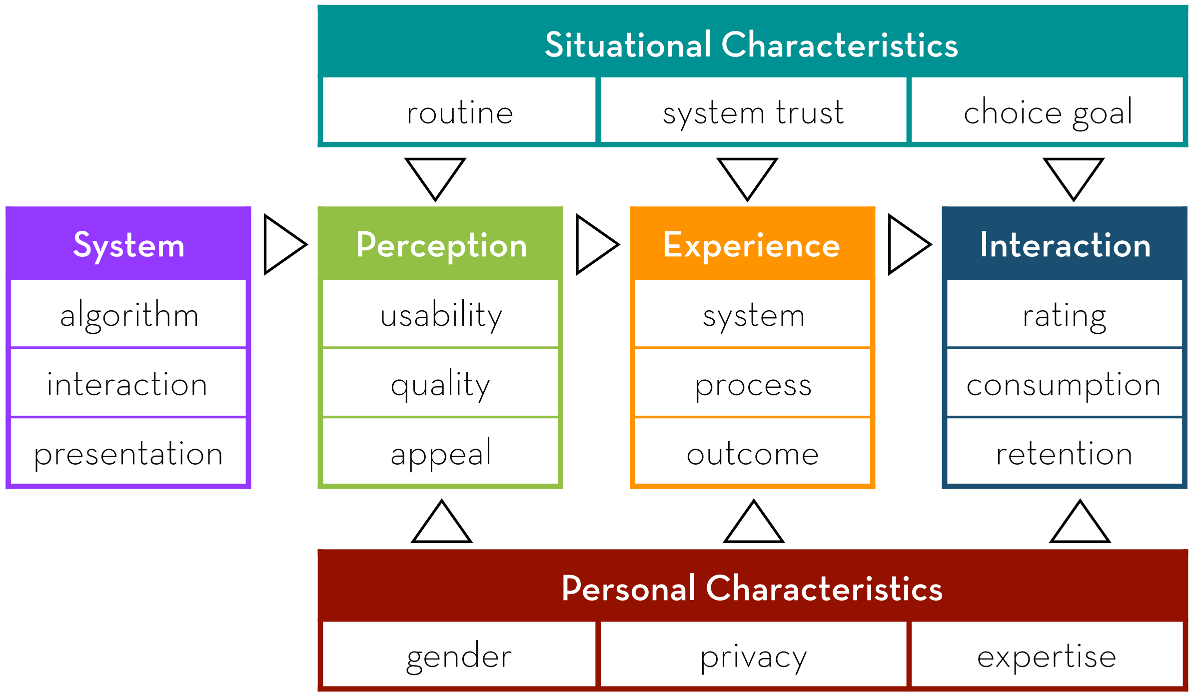
Tintarev and Masthoff show that explanations make it easier to judge the quality of recommendations.

McNee et al. found that study participants preferred user-controlled interfaces because these systems "best understood their tastes".



Satisfaction

Knijnenburg et al. developed a framework that describes how certain manipulations influence subjective system aspects (i.e. understandability, perceived control and recommendation quality), which in turn influence user experience (i.e. system satisfaction).



Satisfaction

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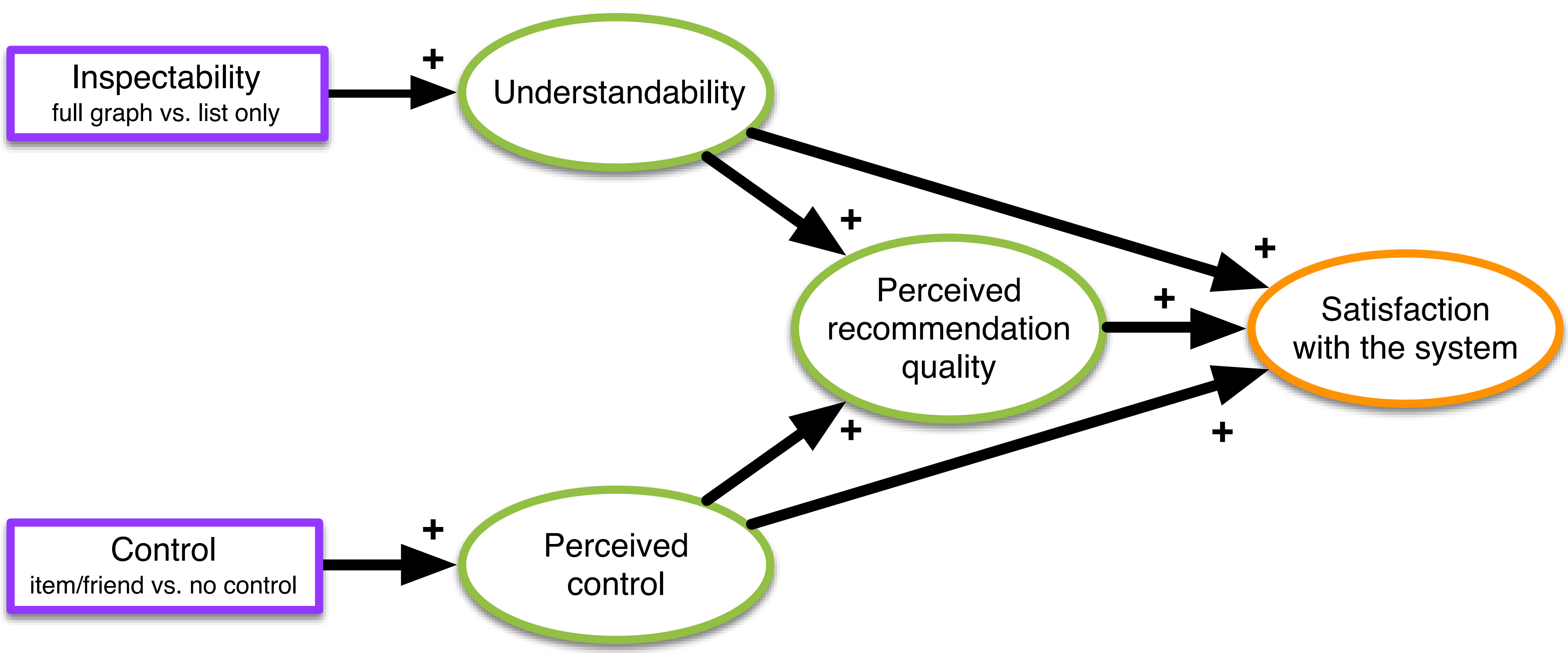


4. Test the model

Steps:

- Build a saturated model
- Trim the model
- Get model fit statistics
- Optional: expand the model
- Reporting

Saturated model

Be flexible with your model!

Ideal world:

> theory (hypothesis) -> testing -> accepted theory (evidence)

Real world:

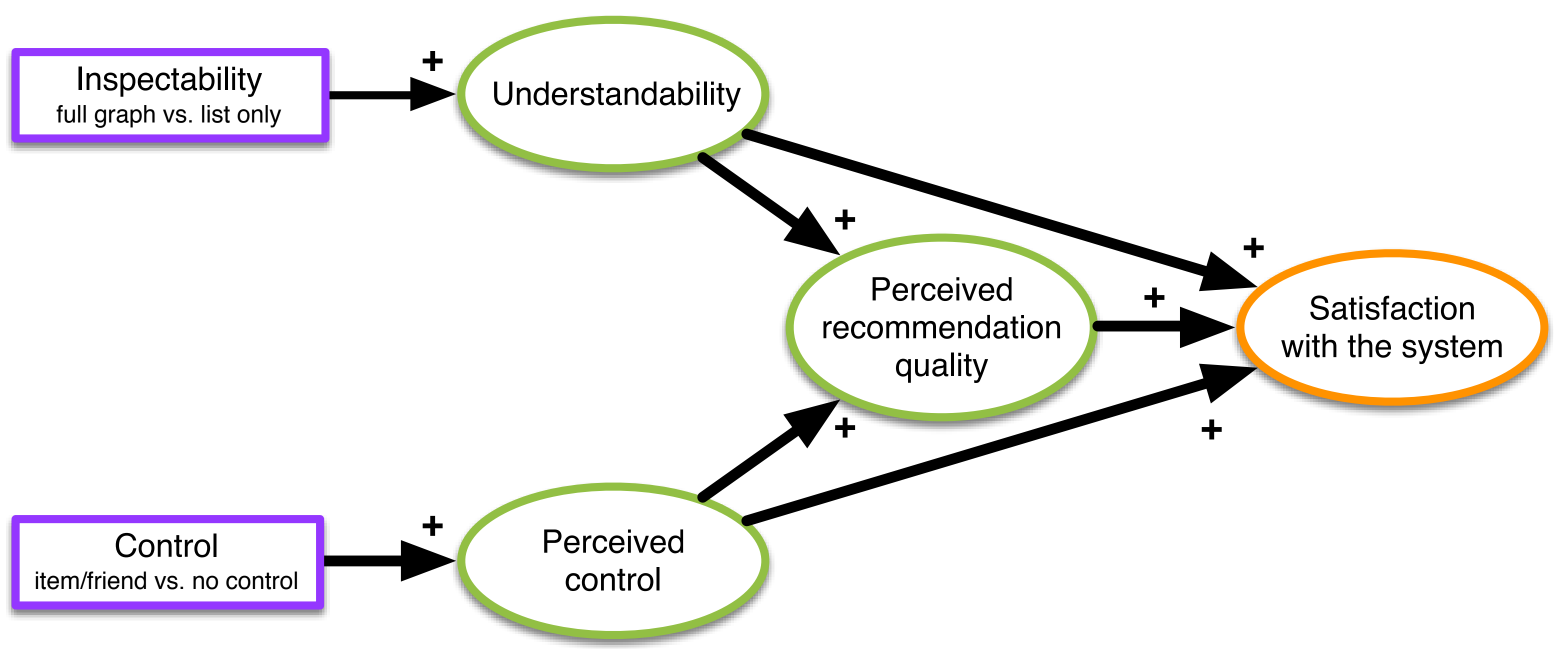
> theory (hypothesis) -> testing -> completely unexpected results -> interpretation -> revision -> new theory -> ...

Start with a **saturated model** and trim down

Causal order

Find the causal order of your model

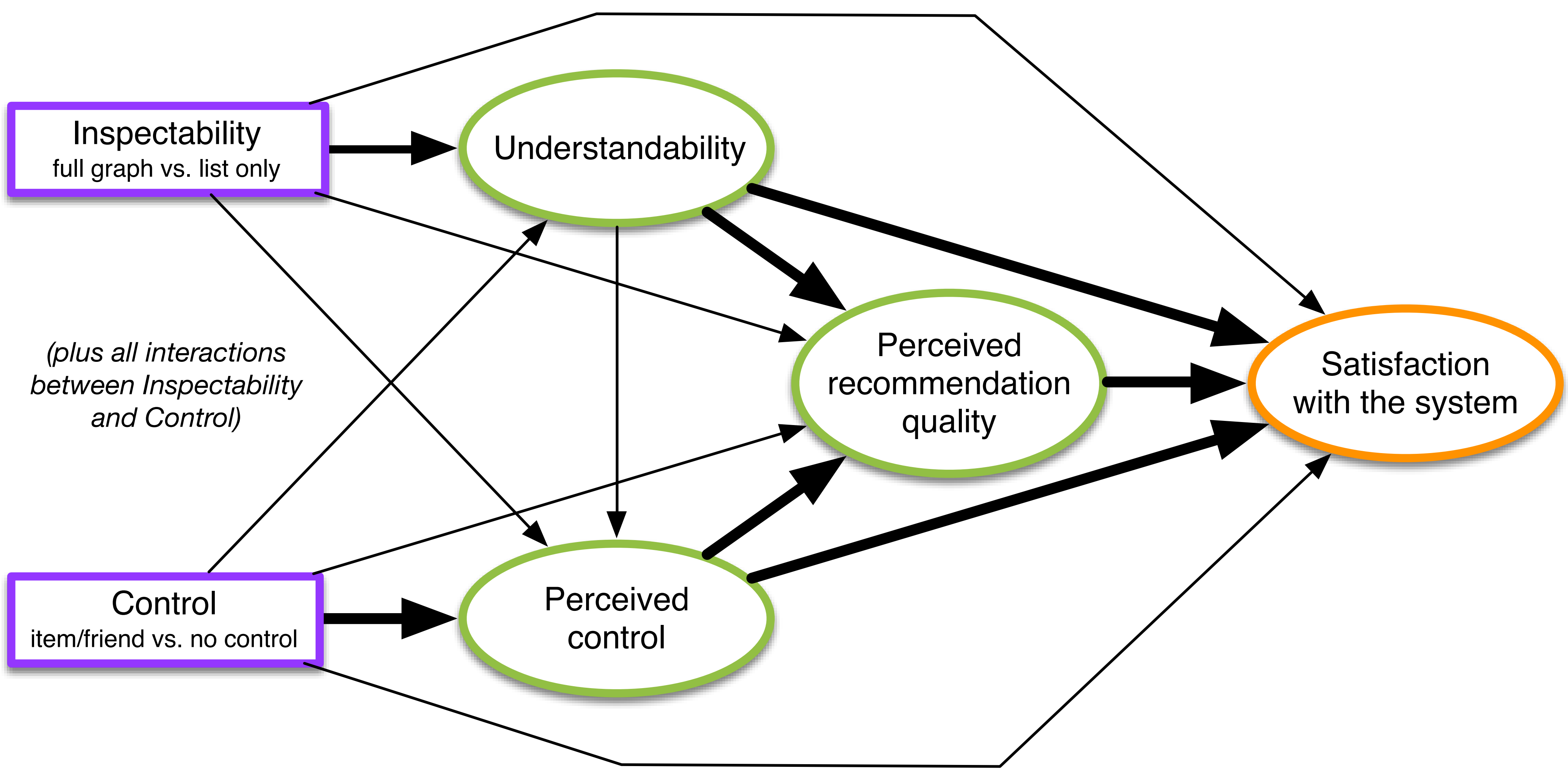
(fill the gaps where necessary)



conditions -> understandability -> perceived control -> perceived recommendation quality -> satisfaction

Saturated model

Fill in all forward-going arrows



Run model

In R:

```
model <- 'satisf =~ s1+s2+s3+s4+s5+s6+s7
  quality =~ q1+q2+q3+q4+q5+q6
  control =~ c1+c2+c3+c4
  underst =~ u2+u4+u5
  satisf ~ quality+control+underst+citem+cfriend+cgraph+cig+cfg
  quality ~ control+underst+citem+cfriend+cgraph+cig+cfg
  control ~ underst+citem+cfriend+cgraph+cig+cfg
  underst ~ citem+cfriend+cgraph+cig+cfg';

fit <- sem(model,data=twq,ordered=names(twq[9:31]),std.lv=TRUE);

summary(fit);
```

Trim model

Rules:

- Start with the least significant and least interesting effects (those that were added for saturation)
- Work iteratively
- Manipulations with >2 conditions: remove all dummies at once (if one is significant, keep the others as well)
- Interaction+main effects: never remove main effect before the interaction effect (if the interaction is significant, keep the main effect regardless)

Results

```
                    Estimate  Std.err  Z-value  P(>|z|)
...(factors)...          ...      ...      ...      ...
Regressions:
  satisf ~
    quality            0.439    0.076    5.753    0.000
    control           -0.838    0.107   -7.804    0.000
    underst            0.090    0.073    1.229    0.219
    citem              0.318    0.265    1.198    0.231
    cfriend            0.014    0.257    0.054    0.957
    cgraph             0.308    0.229    1.346    0.178
    cig               -0.386    0.356   -1.082    0.279
    cfg               -0.394    0.357   -1.103    0.270
  quality ~
    control           -0.764    0.086   -8.899    0.000
    underst            0.044    0.073    0.595    0.552
    citem              0.046    0.204    0.226    0.821
    cfriend            0.165    0.251    0.659    0.510
    cgraph             0.009    0.236    0.038    0.970
    cig                0.106    0.317    0.334    0.738
    cfg                0.179    0.374    0.478    0.632
```

Results

control ~				
underst	-0.308	0.066	-4.695	0.000
citem	0.053	0.240	0.220	0.826
cfriend	0.009	0.221	0.038	0.969
cgraph	-0.043	0.239	-0.181	0.857
cig	-0.148	0.341	-0.434	0.664
cfg	-0.273	0.331	-0.824	0.410
underst ~				
citem	0.367	0.220	1.666	0.096
cfriend	0.534	0.217	2.465	0.014
cgraph	0.556	0.227	2.451	0.014
cig	-0.106	0.326	-0.324	0.746
cfg	-0.178	0.320	-0.555	0.579

Trimming steps

Remove interactions -> (1) understandability, (2) quality, (3) control, and (4) satisfaction

Remove cgraph -> (1) satisfaction, and (2) quality

Trimming steps

Remove citem and cfriend -> control

But wait… did we not hypothesize that effect?

Yes, but we still have citem+cfriend -> underst -> control!

In other words: the effect of item and friend control on perceived control is mediated by understandability!

Argument: "Controlling items/friends gives me a better understanding of how the system works, so in turn I feel more in control"

Trimming steps

Remove citem and cfriend -> satisfaction

Remove understandability -> recommendation quality

- We hypothesized this effect, but it is still mediated by control.
- Argument: “Understanding the recommendations gives me a feeling of control, which in turn makes me like the recommendations better.”

Remove understandability -> satisfaction

- Same thing

Trimming steps

Remove citem and cfriend -> recommendation quality

Remove cgraph -> control

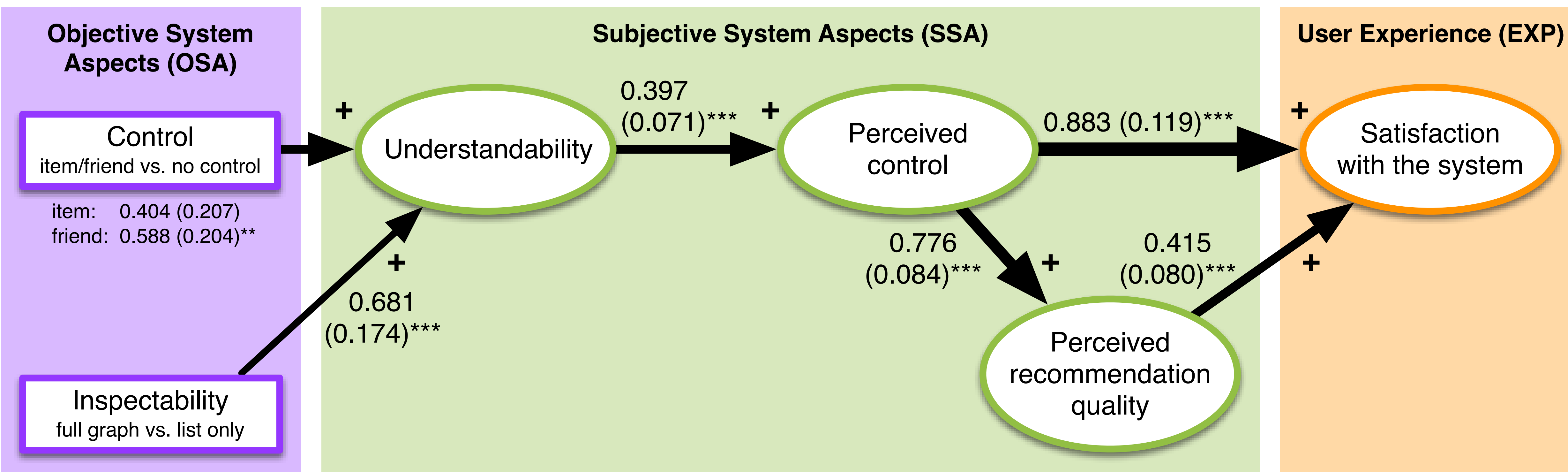
- Again: still mediated by understandability

Stop! All remaining effects are significant!

Trimmed model

```
                    Estimate  Std.err  Z-value  P(>|z|)
...(factors)...          ...      ...      ...      ...
Regressions:
  satisf ~
    quality            0.418    0.080    5.228    0.000
    control           -0.887    0.120   -7.395    0.000
  quality ~
    control           -0.779    0.084   -9.232    0.000
  control ~
    underst           -0.371    0.067   -5.522    0.000
  underst ~
    citem              0.382    0.200    1.915    0.056
    cfriend            0.559    0.195    2.861    0.004
    cgraph             0.628    0.166    3.786    0.000
```

Trimmed model



Modindices

	lhs	op	rhs	mi	mi.scaled	epc	sepc.lv	sepc.all	sepc.nox	delta	ncp	power	decision
1	satisf	=~	q2	7.008	5.838	-0.078	-0.132	-0.132	-0.132	0.1	11.522	0.924	epc
2	satisf	=~	q6	6.200	5.164	-0.084	-0.142	-0.141	-0.141	0.1	8.883	0.846	epc
3	s2	~~	s7	10.021	8.347	0.101	0.101	0.100	0.100	0.1	9.815	0.880	epc
4	s3	~~	s4	20.785	17.313	0.157	0.157	0.156	0.156	0.1	8.381	0.825	epc
5	s4	~~	s5	5.211	4.341	0.067	0.067	0.066	0.066	0.1	11.625	0.926	epc
6	q1	~~	q2	5.249	4.372	0.067	0.067	0.066	0.066	0.1	11.800	0.930	epc

No substantial and significant modification indices in the regression part of the model (only stuff we had left from the CFA)

Assess model fit

Item and factor fit should not have changed much

(please double-check!)

Great model fit!

- Chi-Square value: 306.685, df: 223 (value/df = 1.38)
- CFI: 0.994, TLI: 0.993
- RMSEA: 0.037 (great), 90% CI: [0.026, 0.047]

Regression R^2

Satisfaction: 0.654

Perceived Recommendation Quality: 0.416

Perceived Control: 0.156

Understandability: 0.151

These are all quite okay

Omnibus test

In model definition:

```
underst ~ cgraph+p1*citem+p2*cfriend
```

Then run:

```
lavTestWald(fit,'p1==0;p2==0');
```

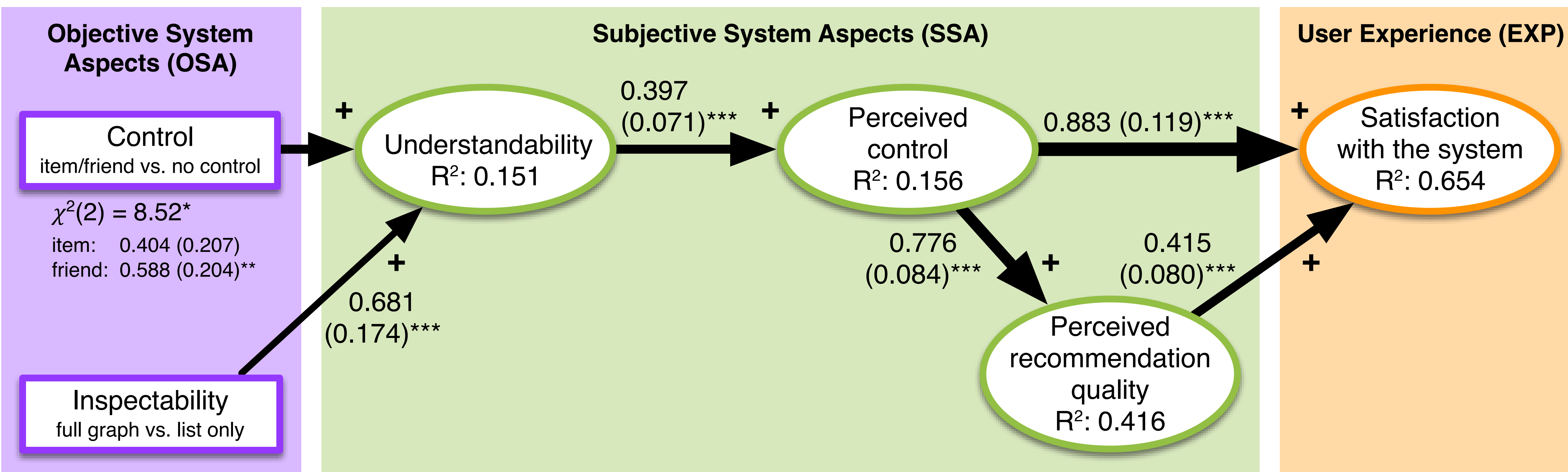
Result: Omnibus effect of control is significant (this is a chi-square test)

```
$stat
[1] 8.386272

$df
[1] 2

$p.value
[1] 0.01509886
```

Final core model



Reporting

We subjected the 4 factors and the experimental conditions to structural equation modeling, which simultaneously fits the factor measurement model and the structural relations between factors and other variables. The model has a good* model fit: chi-square(223) = 306.685, $p = .0002$; RMSEA = 0.037, 90% CI: [0.026, 0.047], CFI = 0.994, TLI = 0.993.

* A model should not have a non-significant chi-square ($p > .05$), but this statistic is often regarded as too sensitive. Hu and Bentler propose cut-off values for other fit indices to be: CFI > .96, TLI > .95, and RMSEA < .05, with the upper bound of its 90% CI below 0.10.

Reporting

The model shows that the inspectability and control manipulations each have an independent positive effect on the understandability of the system: the full graph condition is more understandable than the list only condition, and the item control and friend control conditions are more understandable than the no control condition. Understandability is in turn related to users' perception of control, which is in turn related to the perceived quality of the recommendations. The perceived control and the perceived recommendation quality finally determine participants' satisfaction with the system.

Expand the model

Expanding the model by adding additional variables

- This is typically where behavior comes in

Redo model tests and additional stats

Expanded model

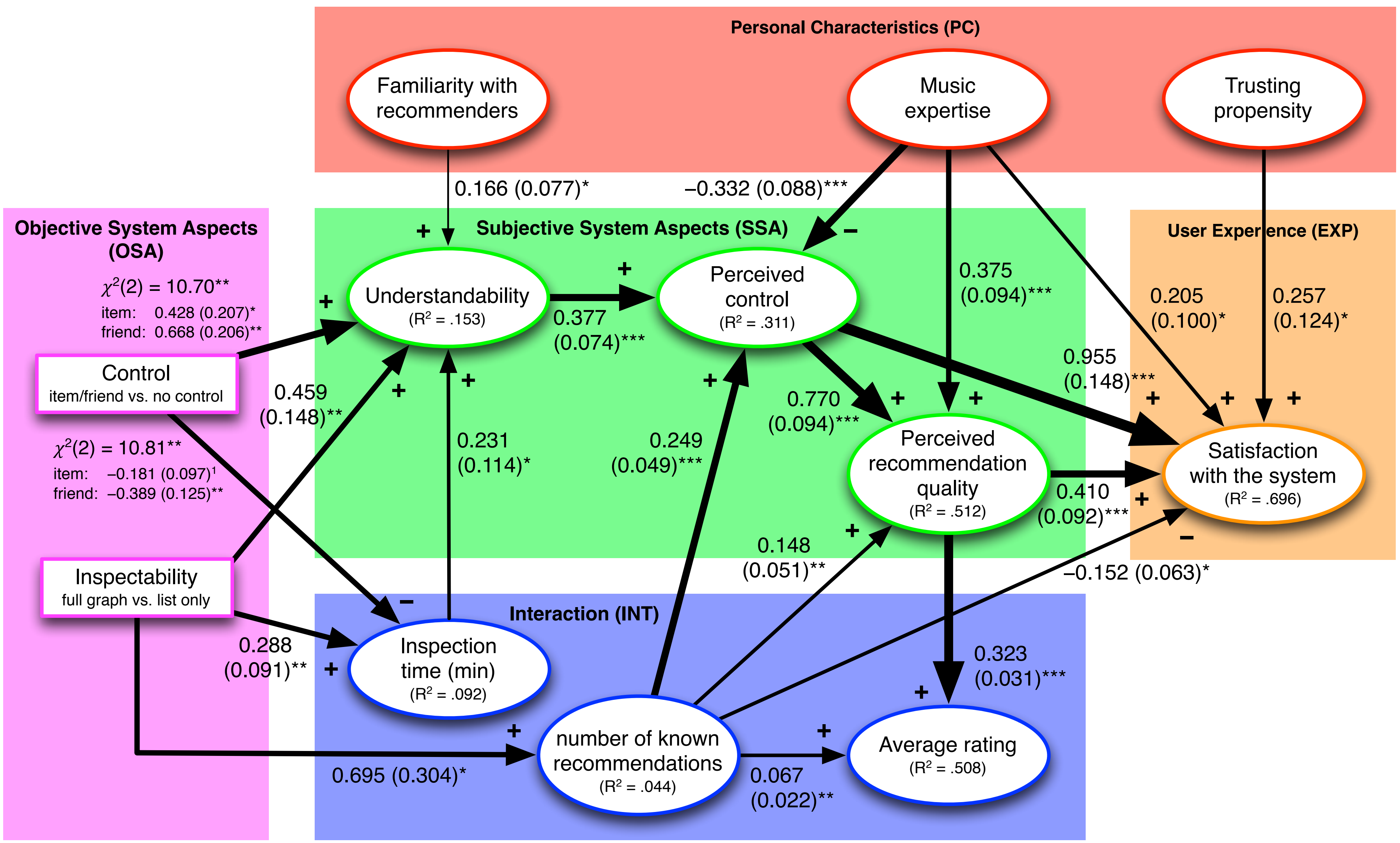
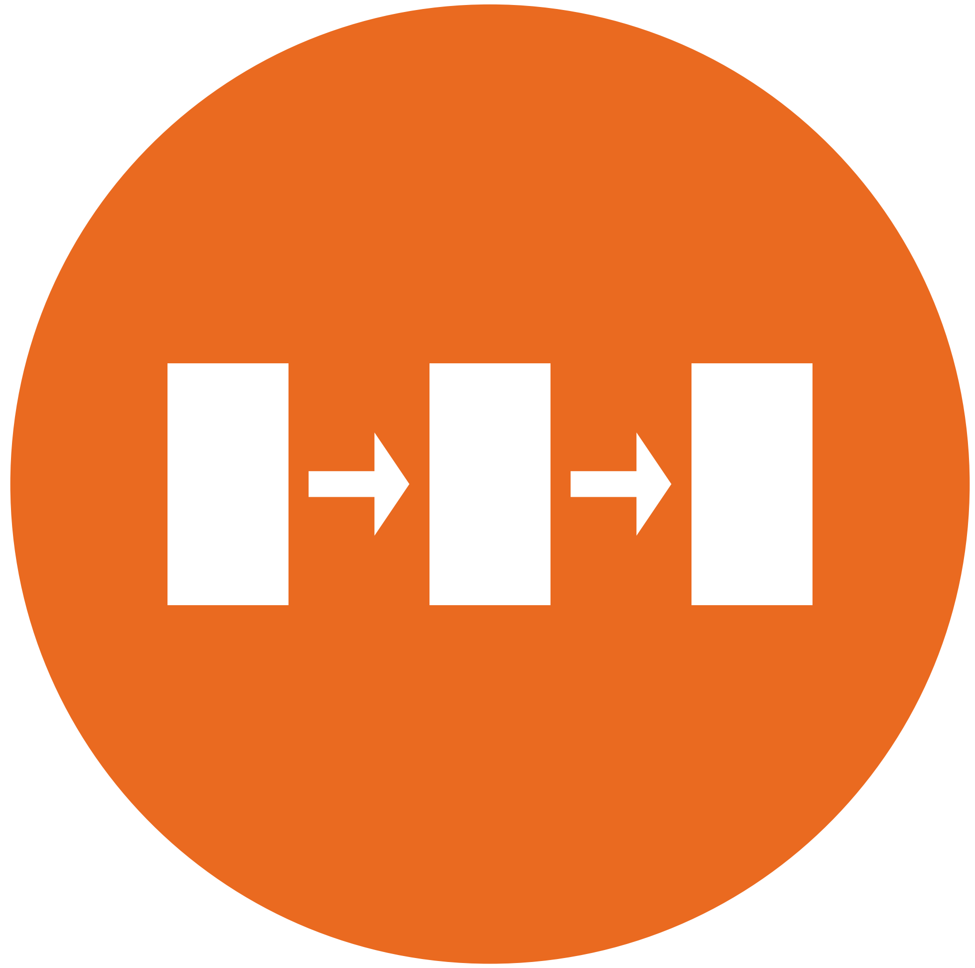


Figure 3. The structural equation model for the data of the experiment. Significance levels: *** $p < .001$, ** $p < .01$, 'ns' $p > .05$. R^2 is the proportion of variance explained by the model. Numbers on the arrows (and their thickness) represent the β coefficients (and standard error) of the effect. Factors are scaled to have an SD of 1.

use **structural equation modeling**

analyze the
marginal effects
of the manipulations



set up a **model**
based on theory
and related work

Evaluating Models

An introduction to Structural Equation Modeling

test and trim a **saturated** version of the model

Introduction
Welcome everyone!

Hypotheses
Developing a research model

Participants
Population and sampling

Testing A vs. B
Experimental manipulations

Analysis
Statistical evaluation of the results

Measurement
Measuring subjective valuations

Evaluating Models
An introduction to Structural Equation Modeling

"It is the mark of a truly intelligent person to be moved by statistics."

T H A N K S !

George Bernard Shaw

Resources

Slides and data:

www.usabart.nl/QRMS

Class slides (more detailed)

www.usabart.nl/eval

Handbook chapter:

bit.ly/userexperiments

Framework:

bit.ly/umuai

Resources

Questions? Suggestions? Collaboration proposals?

Contact me!

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