Multilevel SEM part 2

Random effects models

Intro

Today's goal:

Teach how to do multi-level SEM with random effects in Mplus (this stuff doesn't work in R)

Outline:

- Theory of random effects
- Multilevel SEM example in Mplus

$x \to y$

Theory

of random effects models

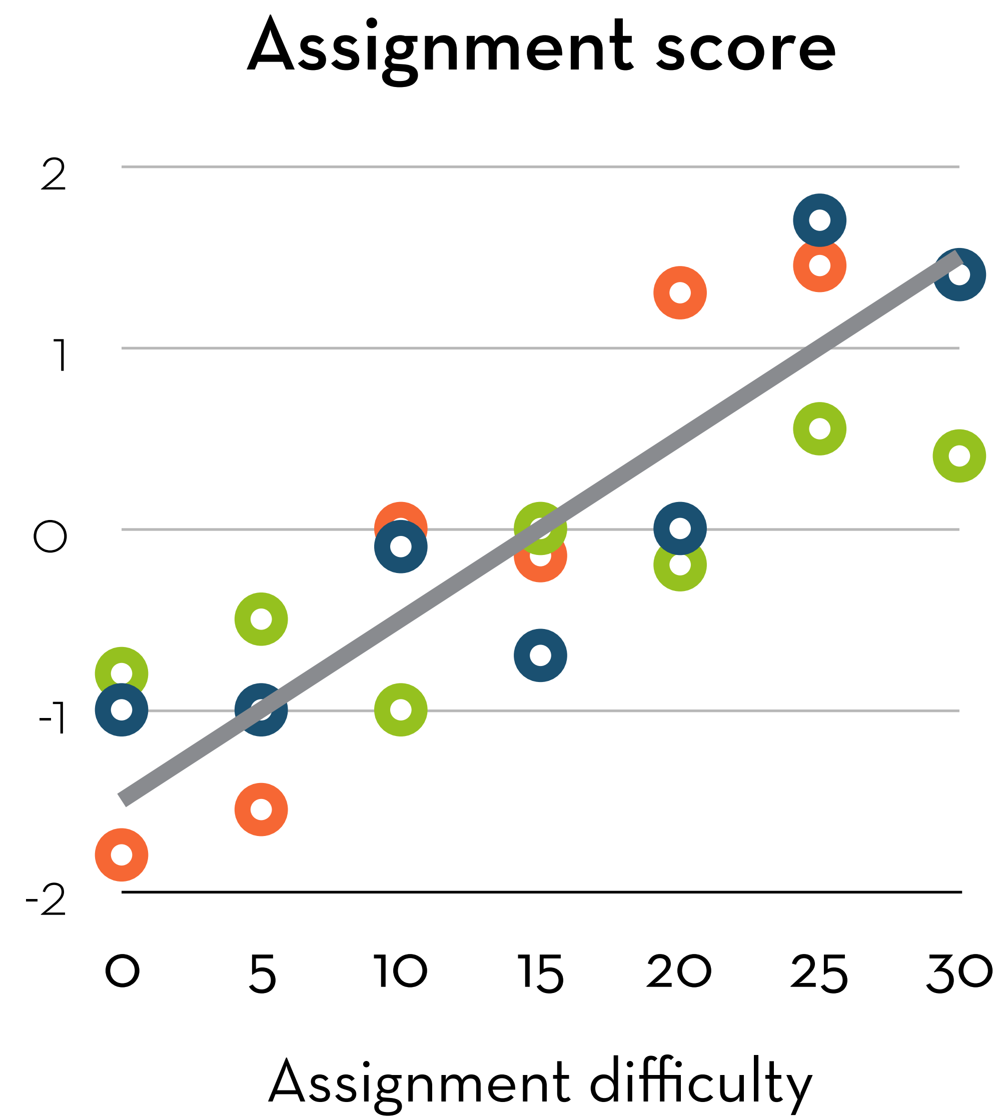
Random effects

Data from three participants:

Adam, Brian, Chen

Fixed intercept + slope

$Y_i = a + b_1 X_{diff} + e_i$



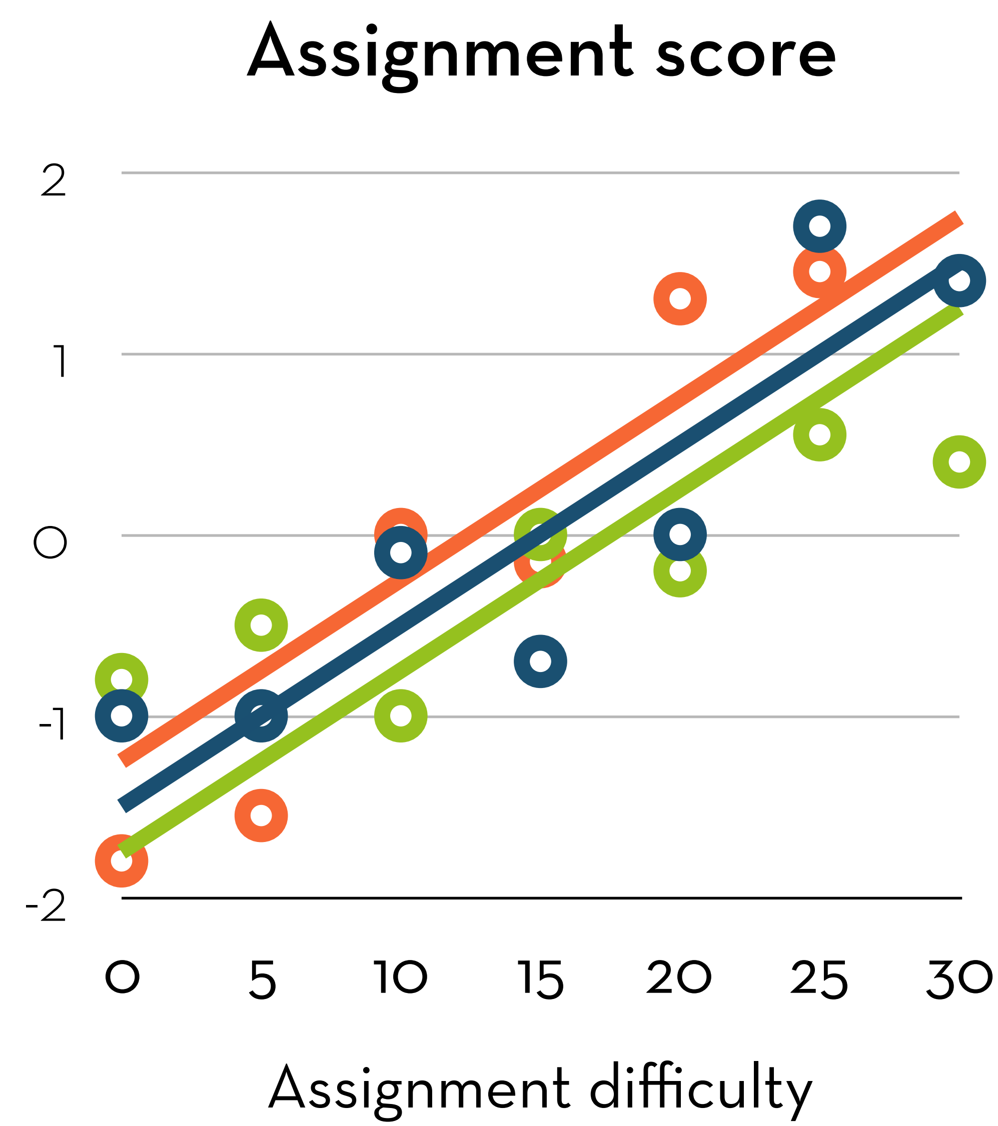
Random effects

Data from three participants:

Adam, Brian, Chen

Different intercept + fixed slope

$$Y_i = a + b_1X_{diff} + b_2X_{brian} + b_3X_{chen} + e_i$$



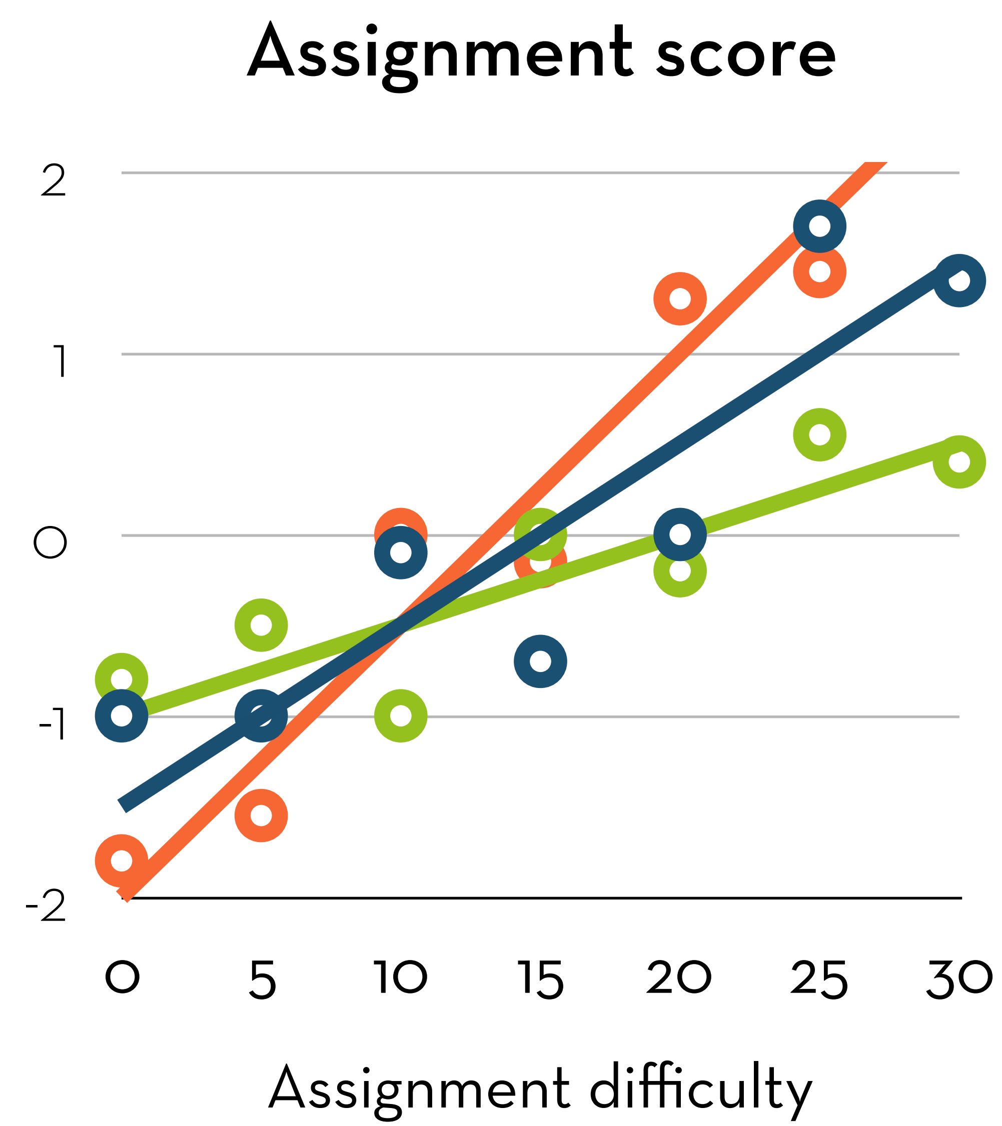
Random effects

Data from three participants:

Adam, Brian, Chen

Different intercept + different slope

$$Y_i = a + b_1X_{diff} + b_2X_{brian} + b_3X_{chen} + b_4X_{diff}X_{brian} + b_5X_{diff}X_{chen} + e_i$$



Random effects

Data from **many** participants

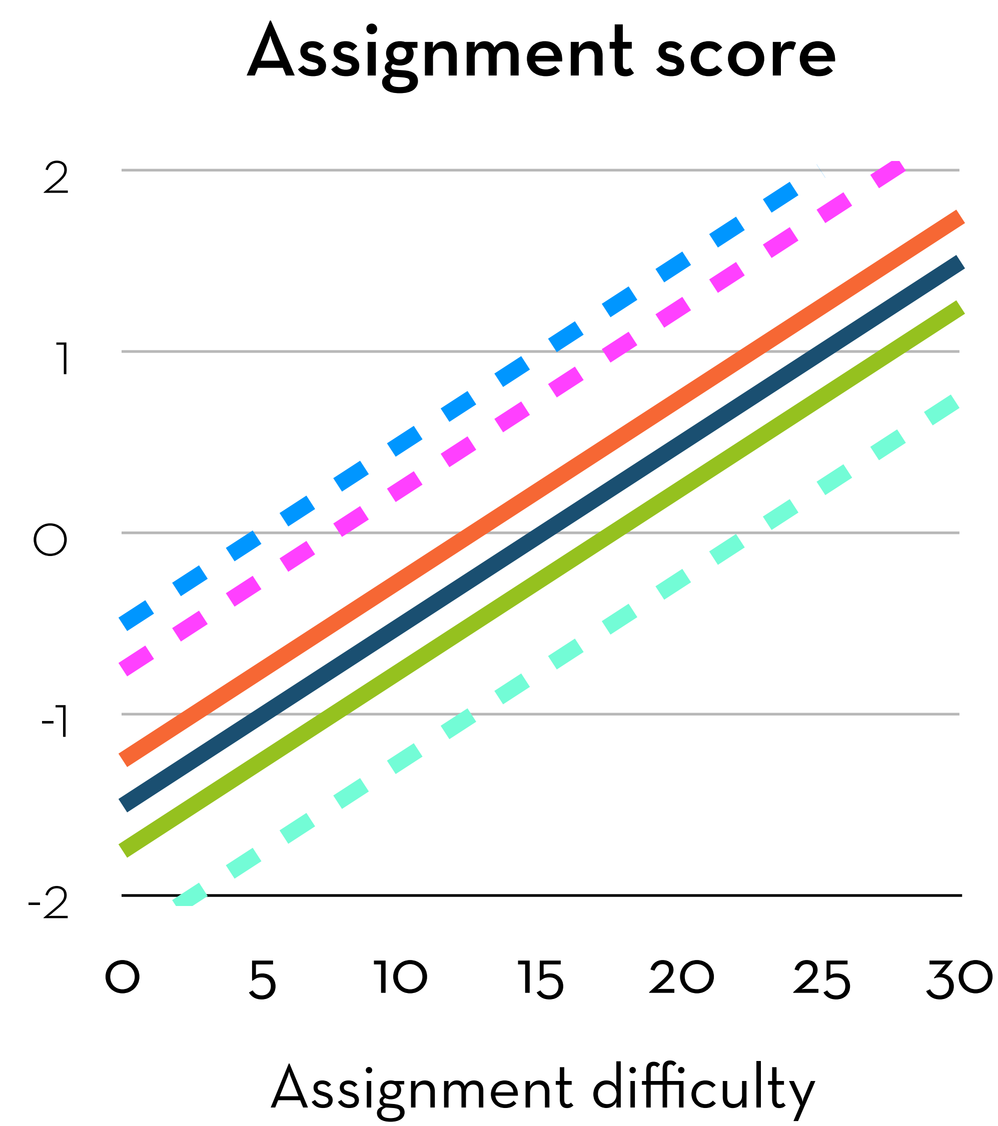
Random intercept + fixed slope

$Y_{ip} = a_p + b_1 X_{diff} + e_{ip}$

where $a_p = a + u_p$

u_p differs per participant!

we fit a single parameter for it (variance)



Random effects

Data from **many** participants

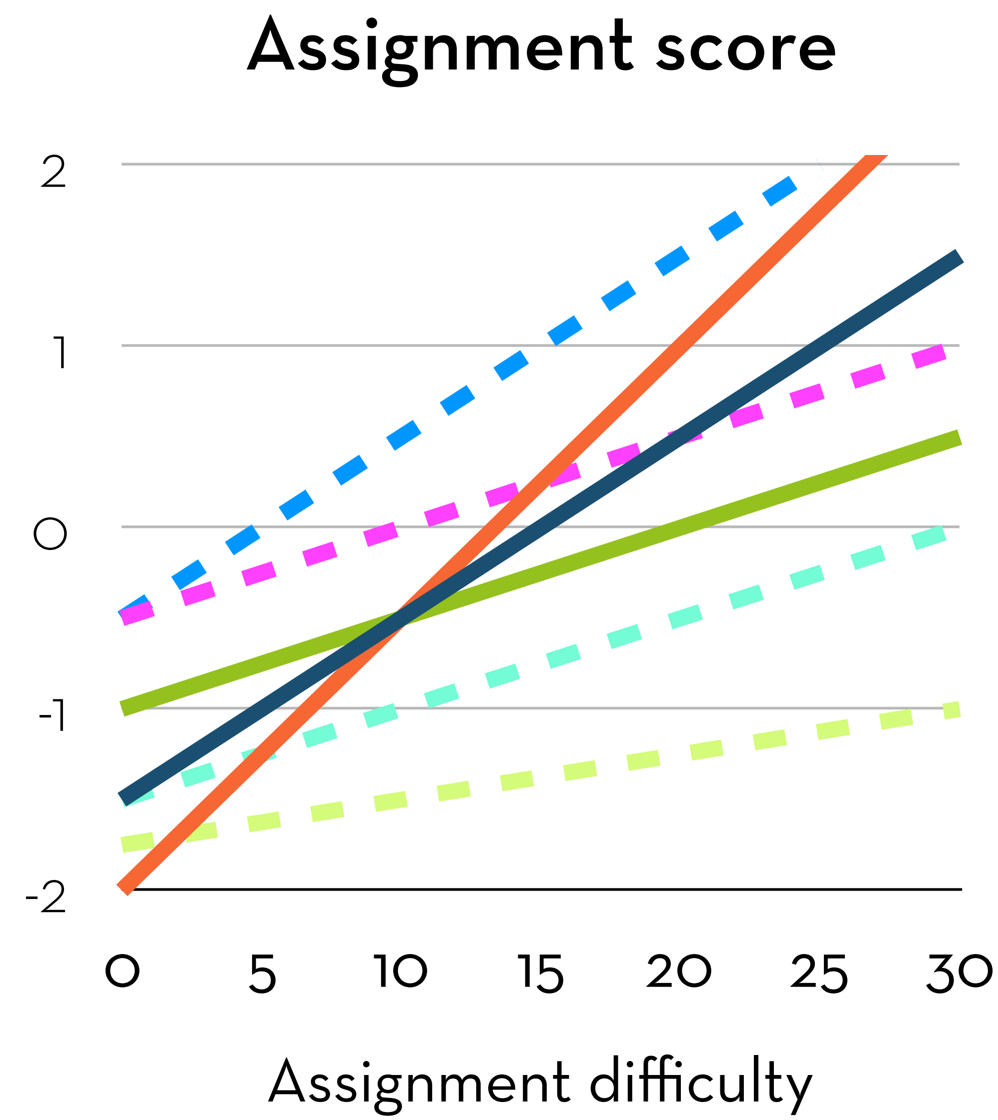
Random intercept +
random slope

$$Y_{ip} = a_p + b_{1p}X_{diff} + e_{ip}$$

where $a_p = a + u_p$

and $b_{1p} = b_1 + v_p$

Both u_p and v_p differ per participant!



Random effects in Mplus

Too complicated for lavaan

Dataset

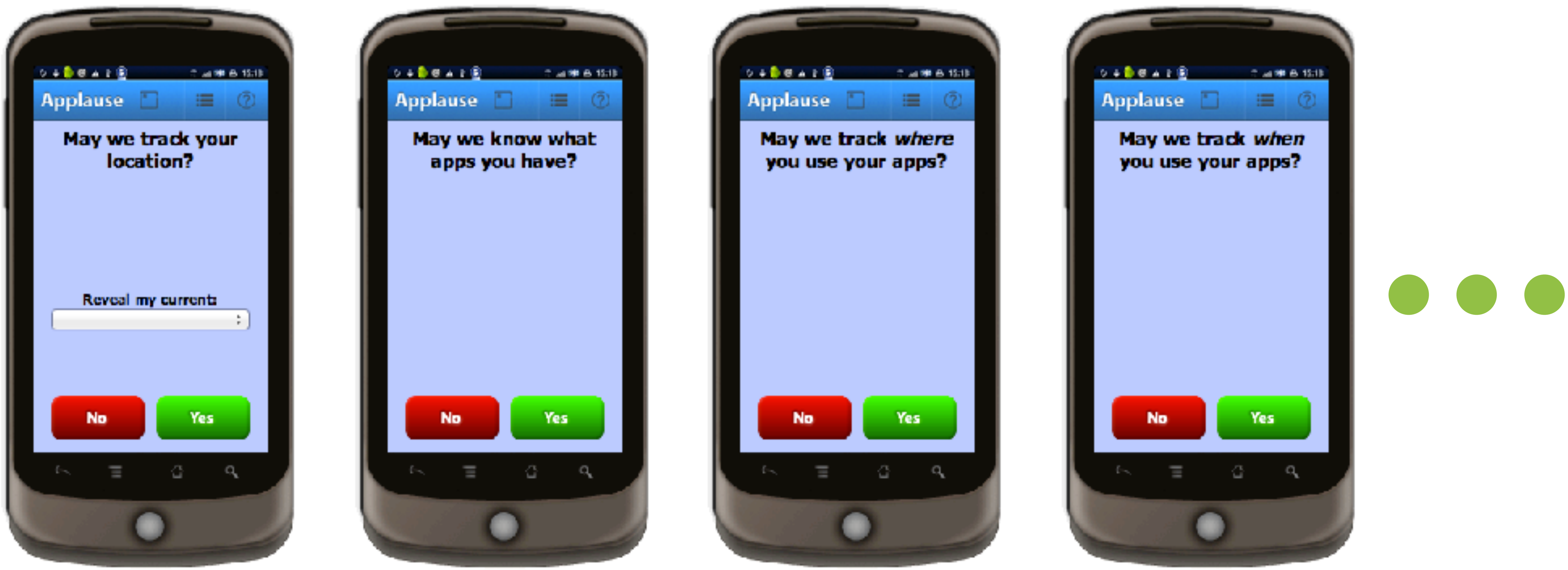
Dataset: f.dat

- 396 participants (level 2) each make disclosure decisions (binary) about 31 items (level 1)

Justifications (between subjects):

- None
- Useful-for-you
- % of others
- Useful for others
- Explanation

Dataset



Applause
May we track your location?
Reveal my currents
No
Yes
Applause
May we know what apps you have?
No
Yes
Applause
May we track *where* you use your apps?
No
Yes
Applause
May we track *when* you use your apps?
No
Yes

Dataset

Context data first

Demographical data first

Dataset

5 justification types

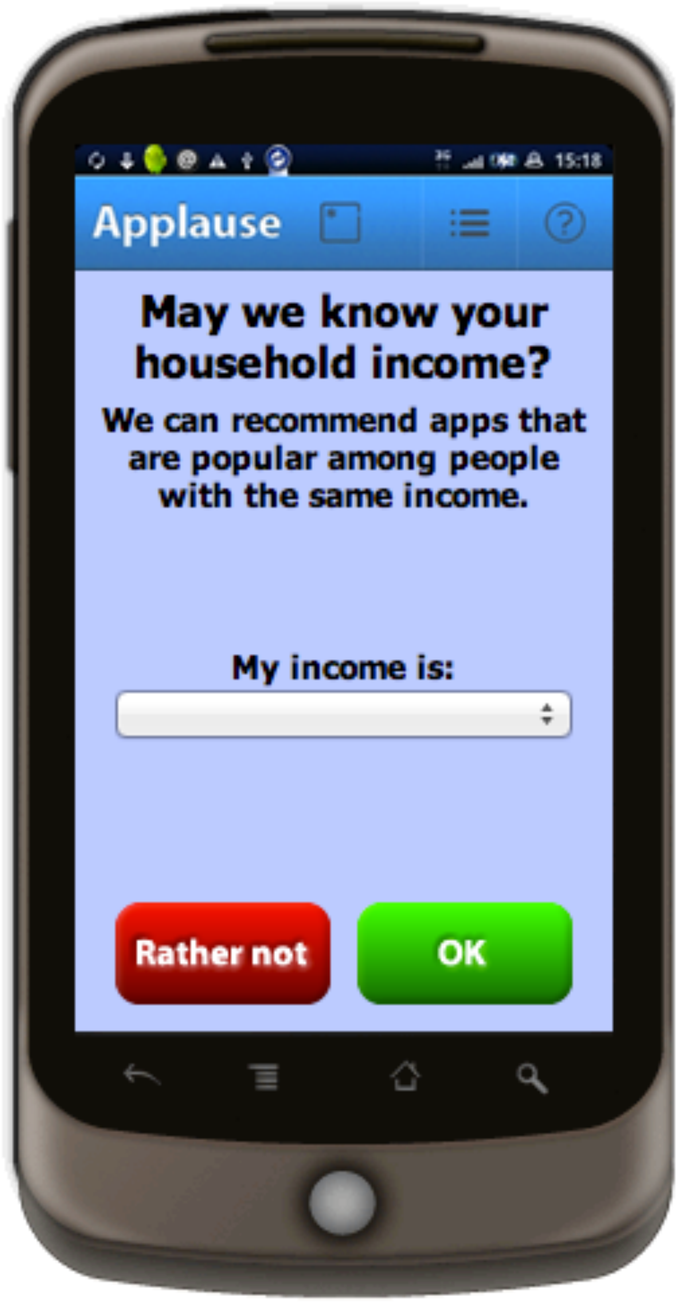
None

Useful for you

Number of others

Useful for others

Explanation



Dataset

Variables at level 1:

- decision: whether the participant disclosed the item (1) or not (1)
- qid: question ID
- qcat: type of question (context or demographic)
- pos: position of the question (semi-randomized)
- perc: percentage used in the justification, centered around 50% (manipulated, only for types 2, 3 and 4)

Dataset

Relevant variables at level 2:

id: participant id

message: the justification (manipulated)

gord: order in in which questions are asked (manipulated)

sat1–intent11: expected satisfaction with the system

clear12–15: perceived decision support

gipc16–21: privacy concerns

Dataset

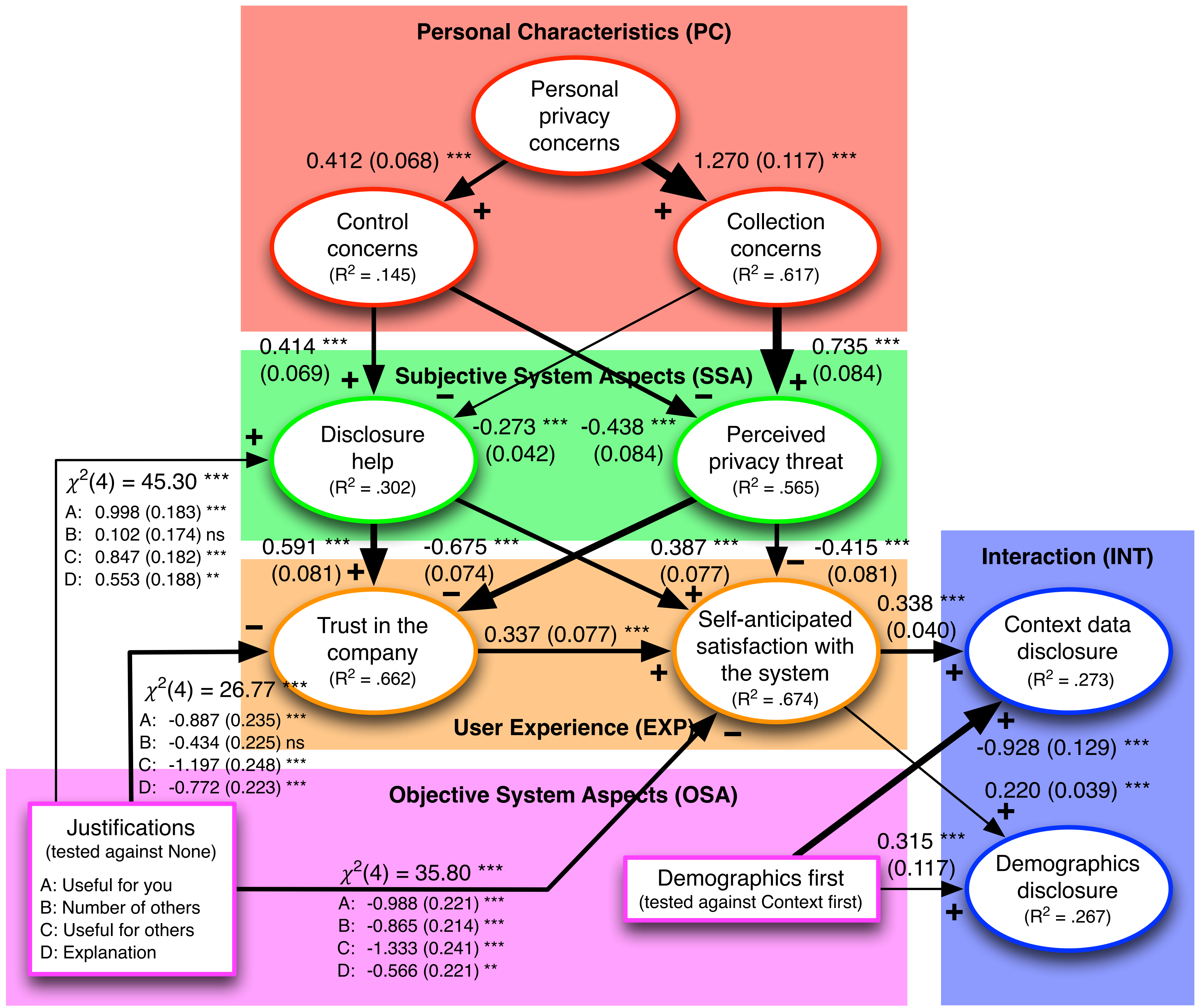
Relevant variables at level 2 (continued):

- collct22–27: collection concerns
- ctrl28–32: control concerns
- compny33–40: trust in the company providing the system
- threat41–46: perceived privacy threat
- age
- gender

$x \rightarrow y$ Research question

What is the effect of the justification types, and does the percentage displayed in the justification play any role?

1. Initial model



Research question

What is the effect of the justification types, and does the percentage displayed in the justification play any role?

2. Percentage

Add **decision on p cup csp ccp cwp**

Notes:

- Percentage is centered around 50 (to prevent multicollinearity), and divided by 45 (to reduce variance)
- Interaction effects with justification types
- Expectation: p and cap have no effect, cup csp and ccp will have a significant positive effect

3. Twolevel

Change **type = twolevel**

Add a **%between%** and **%within%** section in the model

Notes:

- Cannot use wlsmv! Items will have to be treated as ratio…
- No real improvement here; the actual benefit comes from being able to run the next couple of models…

4. Random slope

Remove the interaction effects (for now)

Add a random slope: **s | decision on p**

Notes:

- This takes a pretty long time to estimate
- Shows us whether there is variations between participants in the effect of percentage (There should be! Why?)

5. Predicted slope

Add: **s on useful csocial ccombi cwhy**

Notes:

- This reintroduces the interaction effect!
- Slope is now predicted between subjects by condition
- Expectation: s on csocial is going to be significant
- Residual variance of s may no longer be significant

6. More predictors

Add: **s on sat company threat clear control collect privacy**

Notes:

- Test whether the effect of percentage is also dependent on users' subjective perceptions (e.g. satisfaction, perceived threat, etc.)

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

T H A N K S !

George Bernard Shaw