



# Researching response-scale format effects in questionnaires: Using the Height Inventory

IMPS 2024 | July 16-19

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# Measurement

What we have: observations.

• We decide about their nature and how we code them to obtain data.

### What we assume: an existence of quantitative attribute.

Theory decides about its quality and properties.

Measurement is then **linking** of the observations to the attribute through data.

Two cardinal principles:

- 1. Coordination (linking) function.
- 2. Calibration of the measure.

# Measurement approaches in psychology

Problem: Psychological phenomena cannot be observed directly.

• Are they quantitative? What is their nature? How to establish the linking function?

Early attempts: Linking **sensory events** to external physical stimuli using a "law".

- Deriving the scale from well established physical scale (e.g., pain as a function of a pressure).
- Psychophysics failed to provide an exact link "Ferguson committee" (Ferguson et al., 1940).

### Realism: Latent trait models (FA, IRT).

- An independently existing trait causes behavior (responses) to a questionnaire.
- Ontological claim: An existence of an attribute can only be assumed (e.g., Borsboom et al., 2003).
- Usually also distributional assumption, etc.

### Operationalism: Classical test theory

- Attribute is operationalized using the measurement tool.
- Multiplication of entities: each questionnaire measures a different attribute (e.g., Fried, 2017).

# Likert scale item format (LS)

The most common approach to measure personality and attitudes

LS as the scaling procedure vs. LS as an item format.

Many forms of Likert-like items.

- Number of response options (usually 4–7).
- Presence of the middle point.
- Extremity and actual labeling of verbal anchors.
- Presence of the reversed items.

These response format moderates the performance of the questionnaire.

- **Reliability** (internal consistency, test-retest).
- **Convergent validity** (may be biased by method factors if all the attributes are measured by LS).
- **Criterion validity** usually only indirect criteria, as attributes cannot be measured independently.

We don't have an objective criterion to study measurement performance in psychology.

# Really?

# Don't we have any objective criterion to study measurement performance in psychology?



# Using human height as the attribute

Well, we have an objective criterion: Introducing the **Height Inventory** (HI)!

Example of the items:

- + A lot of trousers are too short for me.
- + I have an appropriate height for playing basketball or volleyball.
- + I must often be careful to avoid bumping my head against a doorjamb or a low ceiling.
- + At concerts, my stature usually obstructs other people's views.
- - I have enough room for my legs when traveling by bus.
- - I could play a dwarf.

•

- - When I buy clothes, children's sizes often fit me well.
- - When talking to other adults, I have to look upwards if I want to meet their eyes.

# Using human height as the attribute

Measuring the physical rather than a psychological phenomenon using the same procedure.

- The idea is not entirely new and has repeatedly appeared (e.g., van der Linden, 2017).
- However, we propose to use the human height for researching measurement in psychology.

#### Advantages:

- Human height (length) exists, is quantitative, and people differ in it.
- We can measure it independently with high precision.
- It also solves the "duality problem" (distribution assumption of a trait vs. response link function shape).
- People even know their height with sufficient precision (*ICC* > .999; Rečka, 2018).

### **Disadvantages:**

- HI items are "save" compared to common questionnaires small non-response rate.
- Does it measure the "true height" or "psychological height"?

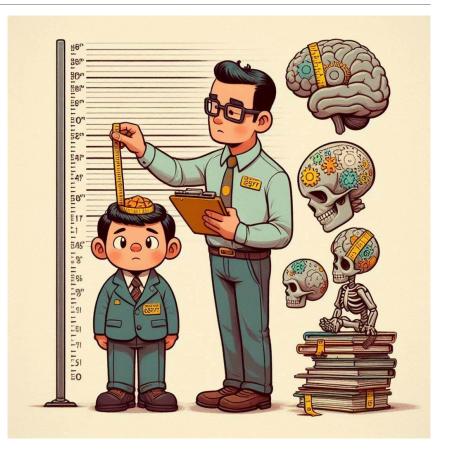
# Isn't it just a ... "psychological height"?

No. We use questionnaires to measure extraversion, self-efficacy, aggression...

... not a "self perception" of extraversion, selfefficacy, or aggression.

Until psychological phenomena measured using questionnaires are not explicitly defined as "subjective self-efficacy", we may measure height in the exactly same way.

 Actually, measuring height using a questionnaire needs weaker assumptions compared to measure of psychological phenomena.



# Height Inventory

Original version (Rečka, 2018): 26 items (13 reverse scored).

- Open data with gender and self-reported height (<a href="mailto:ShinyItemAnalysis::HeightInventory">ShinyItemAnalysis::HeightInventory</a>).
- High internal consistency ( $\omega_{tot} \approx .96$ ) and criterion validity (r  $\approx .87$ ).

Shortened version (Hubatka et al., 2024): 11 items (6 reverse scored).

- Used in most of our studies.
- Still high internal consistency ( $\omega_{tot} \approx .90$ ), test-retest reliability (r  $\approx .94$ ), and criterion validity (r  $\approx .85$ ).

More datasets are available so far.

• Different data collection designs, response formats, etc.

Additional attempts: Weight Inventory, Age Inventory.

• Performed slightly worse then height.

# Height Inventory (26 items)

Almost **linear relationship** of sum scores with actual height.

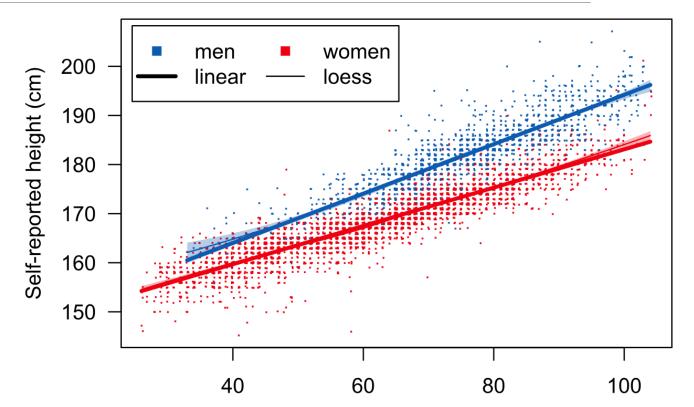
Different criterion validity across gender.

• Predictive bias.

Slightly non-invariant across gender.

- Especially the short version.
- Establishing invariance do not resolve predictive bias.

All the further analyses performed separately for men and women.



Height Inventory (total sum score)

(all points were slightly jittered)

# Identification of the latent trait

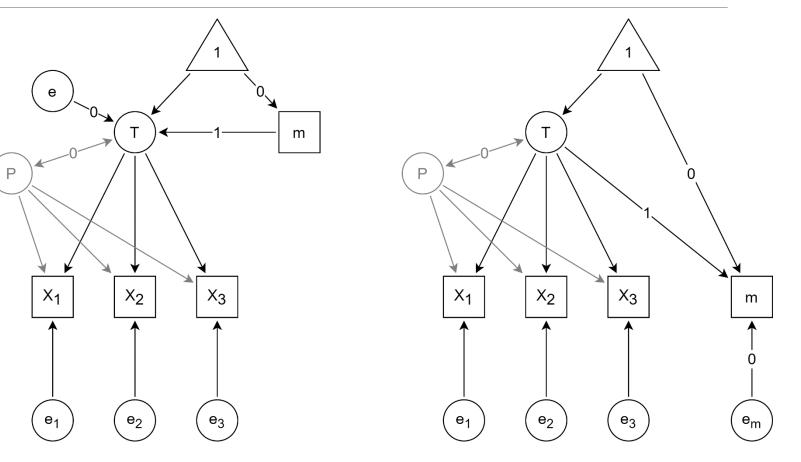
Left: height as the perfect cause of factor.

Right: height as the perfect indicator of factor.

Trait scale is in meters.

- T latent variable identified as height.
- P orthogonalized personal trait causing responses, but not related to the actual height.

Additional constraints on items are available.



### Existing applications (examples)

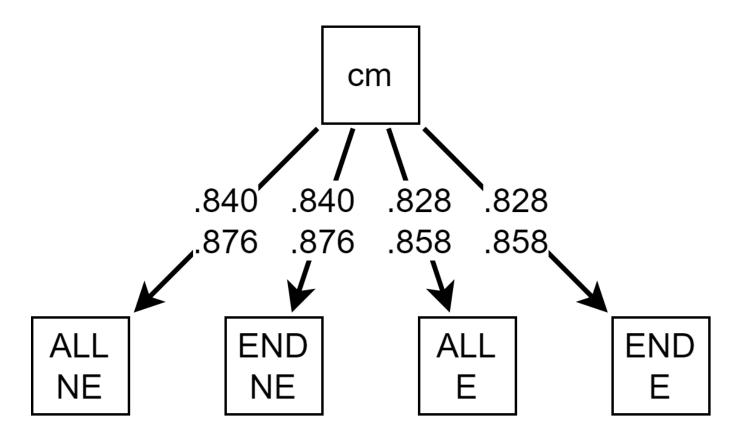
Number of response options

Extremity and presence of verbal labels

Comparison of Visual Analogue Scale with Likert scale

Intuitive vs. careful responding

**Reverse-scored items** 



....

# Verbal labels (five options)

Presence manipulation:

- All options labeled (ALL)
- Only outer options labeled (END).

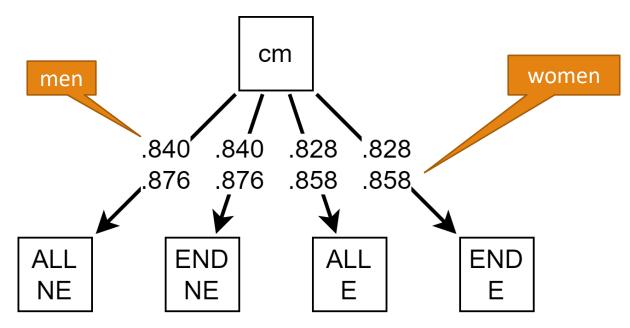
Extremity manipulation:

- Extreme condition (E): strongly agree/agree...
- Non-extreme condition (NE): agree/slightly agree...

Strict measurement invariance.

**Negligible differences in reliability** in favor for all, non-extreme labeled options.

Negligible differences in criterion validity.



Reliability: .904–.908 (men) / .935–.947 (women)

Model fit:  $\chi^2(10) = 5.72$ , p = .838.

# Number of response options

Manipulation: 2, 6, or 10 options.

Strict measurement invariance

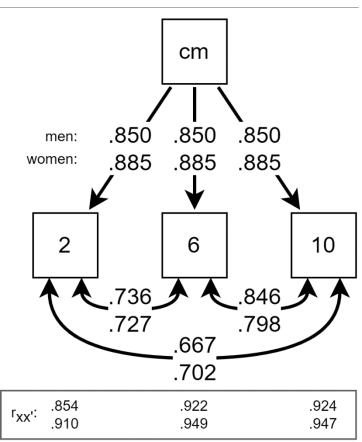
**Strong differences in reliability**  $(2 < 6 \approx 10)$ .

No differences in criterion validity,  $\chi^2(12) = 11.21$ , p = .511.

 However, higher residual correlation between 6 and 10 options than between 2 and 6 or 2 and 10.

### Conclusion: The increase of internal consistency is caused by systematic, but construct irrelevant variance.

- Method factor (response style).
- Acquiescence bias? Extreme response style?
- Method factor thus might bias scale correlations.



## Presentated at the IMPS 2024

Posters at IMPS (presented on Wednesday, 16:45):

- Šragová, Cígler, & Kalistová: Do visual analogue scales perform better than Likert-type scales?
- **Strojil** & Cígler: Video-administered questionnaire: Psychometric properties and comparison with a textbased format.

All the results are available at OSF repository:

 Cígler, H., Ježek, S., Rečka, K., Elek, D., Hubatka, P., Tancoš, M., & Šragová, E. (2024). SCALING project. https://doi.org/10.17605/OSF.IO/GQTA5

### Using HI to identify latent trait

Example using reversed scored items

Using data available in

ShinyItemAnalasis::HeightInventory

• *N* = 4885; about 68 % of women.

#### Ordinal confirmatory factor analysis.

- Estimated in lavaan.
- Scaled test and statistics (WLSMV).
- Theta parameterization.
- Pairwise missing data.
- Slight model improvement (items with residual covariances removed).
- Exploratory models estimated using ESEM syntax.
- Skewed geomin rotation if desirable.

Multiple-group analysis for men and women separately.

# Factor analysis of HI

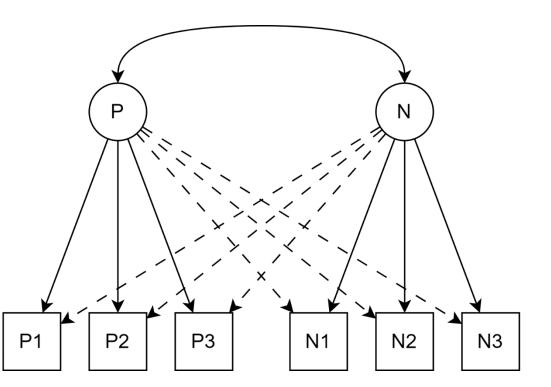
	x2	df	TLI	RMSEA [90% CI]	SRMR
1-factor	15836.5	378	.934	.129 [.128–.131]	.076
2-factors CFA	5200.9	372	.979	.073 [.071–.075]	.038
S-1 bifactor (specific factor for reversed items)	4317.8	354	.982	.068 [.066–.070]	.031
symmetric bifactor	3033.2	336	.987	.057 [.055–.059]	.024
2-factors EFA	1641.0	338	.994	.040 [.038–.042]	.016

### M0: EFA without manifest height.

Baseline model.

Strong latent correlation (geomin rotation):

- men: r = .630
- women: r = .739
- But not strong enough to be considered as the same construct.



#### M1: True height loads indicators directly. Factors are unrelated to the "height construct".

Factors are (almost) uncorrelated (geomin):

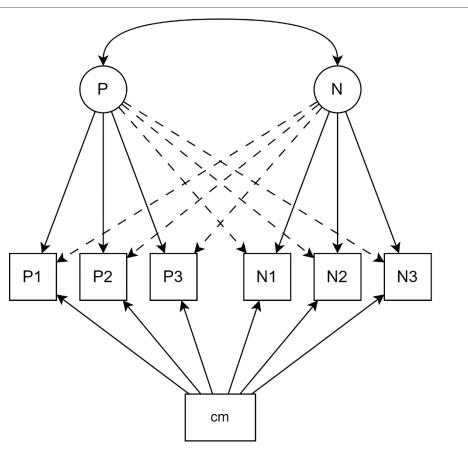
- men: r = .151, p = .151
- women: r = -.203, p < .001
- Factors mostly independent conditionally on height  $(r_{PN|cm} \ll r_{PN})$ .

Low factor scores (and reliability):

- men: M = .10 (SD = .22, min = -.34, max = .51)
- women: M = .12 (SD = .20, min = -.27, max = .38)
- There is no longer any positive and negative factor!

Standardized regression coefficients:

- men: M = .71 (SD = .12, min = .34, max = .84)
- women: M = .77 (SD = .08, min = .56, max = .87)



M2: The true height is loaded by both factors. Both factors are together the "height construct".

Geomin rotation of factors:

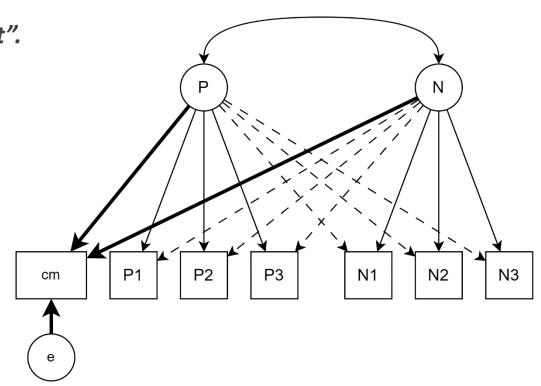
- men: r = .676
- women: r = .743

Standardized factor loadings of the true height:

- men:  $\lambda_P = .663$ ,  $\lambda_N = .317$
- women:  $\lambda_P = .485$ ,  $\lambda_N = .502$

Explained variance of height:

- men:  $R^2 = .807$
- women:  $R^2 = .848$



M3: The true height is loaded by one factor. Only the first factor represents the "height construct".

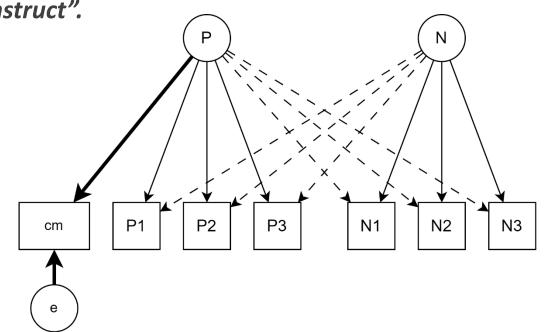
The factors are identified, so we don't use a rotation (r = 0).

Standardized factor loadings of the true height:

- men:  $\lambda_P = .899$ ,  $\lambda_N = 0$
- women:  $\lambda_P = .921$ ,  $\lambda_N = 0$

Explained variance of height:

- men: R<sup>2</sup> = .807
- women: R<sup>2</sup> = .848



M4: The true height is perfectly loaded by both factors. Both factors are just identified as the "height construct".

Geomin rotation of factors:

- men: r = .638
- women: r = .743

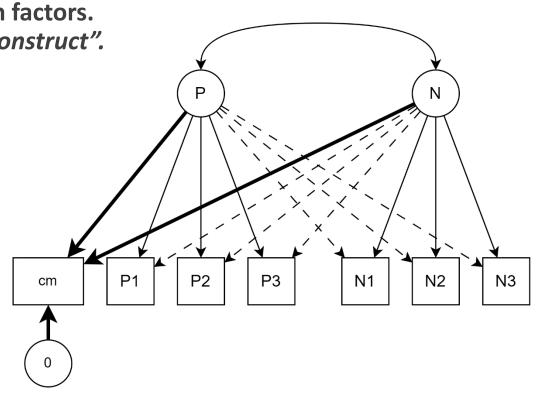
Standardized factor loadings of the true height:

- men:  $\lambda_P = .339$ ,  $\lambda_N = .749$
- women:  $\lambda_P = .547$ ,  $\lambda_N = .524$

Explained variance of height:

• men: R<sup>2</sup> = 1

• women: R<sup>2</sup> = 1



M5: The true height is perfectly loaded by one factor. *The first factor only is just identified as the "height construct".* 

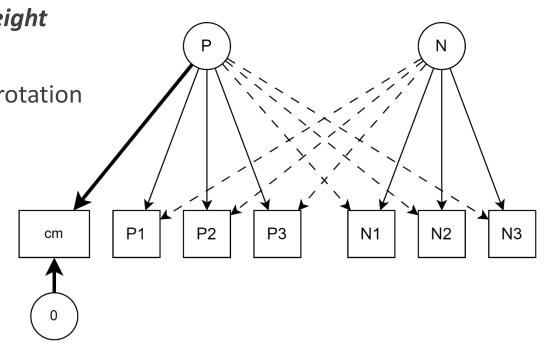
The factors are identified, so we don't use any rotation (r = 0).

Standardized factor loadings of the true height:

- men:  $\lambda_P = 1$ ,  $\lambda_N = 0$
- women:  $\lambda_P = 1$ ,  $\lambda_N = 0$

Explained variance of height:

- men: R<sup>2</sup> = .807
- women: R<sup>2</sup> = .848



M6: Additional three-factors model. The true height is perfectly loaded by one factor.

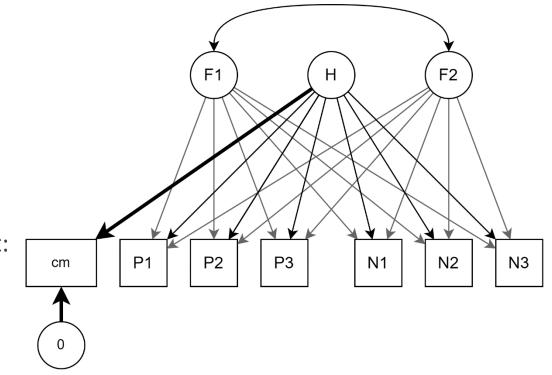
First factors are identified. Method factors correlation:

- men: r = .151, p = .234
- women: r = -.203, p < .001

Standardized factor loadings of the true height:

• men:  $\lambda_P = 1$ ,  $\lambda_N = 0$ 

• women: 
$$\lambda_P = 1$$
,  $\lambda_N = 0$ 



	x2	df	TLI	RMSEA [90% CI]	SRMR
M1	1371.5	338	.994	.035 [.033–.037]	.013
M2, M3	1884.1	376	.993	.041 [.039–.042]	.016
M4, M5	2077.1	378	.992	.043 [.041–.045]	.016
M6	1371.5	338	.994	.035 [.033–.037]	.013

- M1 indicators loaded by the height
- M2 height loaded by both factor; M3 height loaded by one factor
- M4 height perfectly loaded by both factor; M5 height perfectly loaded by one factor
- M6 height perfectly loaded by one factor; two additional factors (3 in total).

If the latent trait is identified as the true height (model M5), then reliability should equal to  $R^2$  of sum score and true height. This is not true:

- Men:  $\omega_h$  = .929; but observed  $R^2$  = .767.
- Women:  $\omega_h$  = .959; but observed  $R^2$  = .816.

However, it is true in the M3, estimating validity as  $\hat{r}^2 = \omega_h \lambda_{cm}^2$ : •  $\hat{r}^2 = \omega_h \lambda_{cm}^2 = .931 \cdot .899^2 = .752$ ; observed  $R^2 = .767$ . •  $\hat{r}^2 = \omega_h \lambda_{cm}^2 = .959 \cdot .921^2 = .813$ ; observed  $R^2 = .816$ .

Models M4, M5 introduce local misfit, despite the overall fit statistics are perfect.

- M3:  $\chi^2(376) = 1884.1$ , *TLI* = 0.993, *RMSEA* = 0.041 with <sub>90%</sub>*CI* = [0.039, 0.042], SRMR = 0.016
- M5:  $\chi^2(378) = 2077.1$ , *TLI* = 0.992, *RMSEA* = 0.043 with <sub>90%</sub>*CI* = [0.041, 0.045], *SRMR* = 0.016.
- Modification indices related to the height residual variance don't help to identify the problem. ( $\chi_m^2(df = 1) = 24.1, \chi_f^2(df = 1) = 36.5$ ). Visual inspection of residual covariances does.

# Latent trait identification: Conclusion

Factor score indetermination is not a problem.

Using rotation (or CFA with specific factors for positively and negatively scored items) biased the construct identification.

Using external criterion may identify a latent trait.

Common estimator failed to identify latent trait precisely as a height in restricted model, which was not obvious from the total fit statistics.

General, systematic, but height-irrelevant variance can be studied and used.

• It almost disappears in binary items!

# Using the Height Inventory

References and more information:

- Cígler, H., Ježek, S., Rečka, K., Elek, D., Hubatka, P., Tancoš, M., & Šragová, E. SCALING project. <u>https://doi.org/10.17605/OSF.IO/GQTA5</u>
- The project is supported by the Czech Science Foundation (<u>GA23-06924S</u>).

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- GitHub: <u>https://github.com/hynekcigler</u>

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Many thanks to several colleagues and our students, mainly:

 Standa Ježek, Karel Rečka, David Elek, Petra Hubatka, Martin Tancoš, Eva Šragová, Adam Strojil, Gabriela Kalistová, Petr Palíšek

