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A unifying account of spurious multidimensionality in psychological questionnaires

Karel Rečka, David Elek

Department of Psychology, Faculty of Social Studies, Masaryk University, Brno, Czech Republic

Content

- Previous explanations of multidimensionality
- Our explanation of the phenomenon
- Empirical study:
  - Design and hypotheses
  - Results
  - Model vs. Item fit in detail
- Conclusions

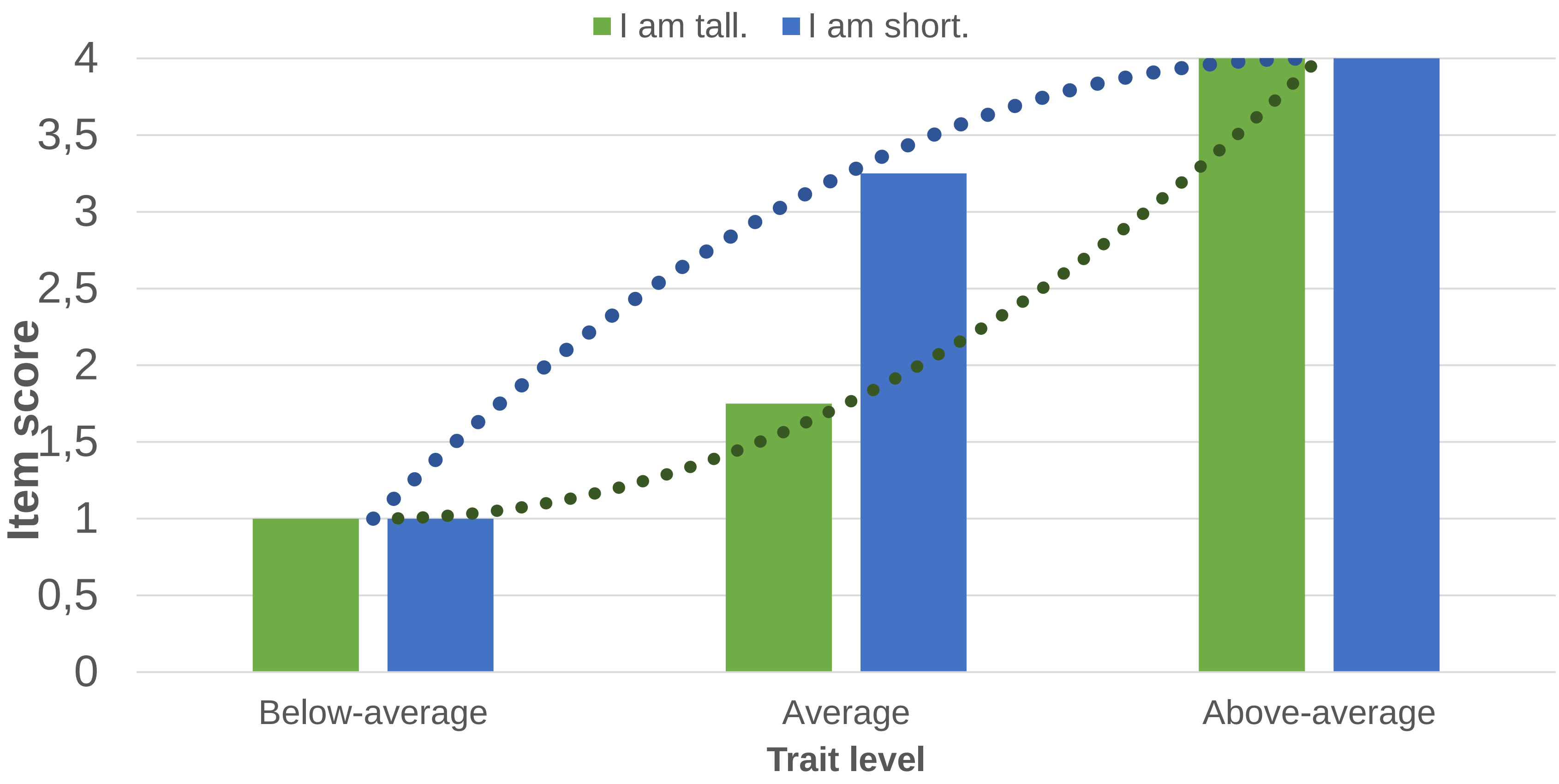
Motivation

- **Psychological questionnaires are rarely unidimensional**, especially when they contain both regular and reverse items.
- **Some authors dismiss reverse items** (multidimensionality contradicts theory, more complex models are necessary, lower reliability, confused respondents).
- Potential **benefits of reverse items**: implicit correction of response bias, reduction of monotony (higher engagement), better construct coverage (higher content validity).

Previous explanations

- Responses to reversed items are influenced by **construct-irrelevant factors to a greater extent or in a different direction than regular items**, such as acquiescence bias (Cronbach, 1942; 1950); social desirability (Krumpal, 2013; Paulhus, 1991; Rauch et al. , 2007); carelessness (Schmitt & Stults, 1985; Woods, 2006); or insufficient verbal ability (Marsh, 1996; Gnambs & Schroeders, 2020).
- More recently, Kam et al. (Kam et al., 2021; Kam & Meyer 2022) found that the relationship between the scores derived from regular and reverse items are **related in a nonlinear fashion**.
- Kam et al. argue that **the pattern of responses of "average" respondents to regular vs. reverse items is inconsistent** because they disagree with both regular and reverse items.

Item	Below-average	Average	Above-average
I am tall. (regular)	**Disagree** – – score **below** the midpoint	**Disagree** – score **below** the midpoint	**Agree** ++ score **above** the midpoint
I am short. (reversed)	**Agree** – – score **below** the midpoint	**Disagree** + score **above** the midpoint	**Disagree** ++ score **above** the midpoint



Older literature

- The notions of ***spurious multidimensionality*** appear in much older sources (Bernstein & Teng, 1989; Carroll, 1945; Ferguson, 1941).
- However, these authors framed the problem differently: **item difficulty**, together with their **ordinal** and **bounded** nature, affect the distribution of item responses (more difficult items are right skewed, easier items are left skewed).
- This affects the **strength of the correlations** between items, because the more the item distributions differ, the smaller the maximum correlation value can be.
- Regular items are usually more difficult than reverse items.

Our account

- What the previous authors describe is only a symptom.
- The true cause of spurious multidimensionality is a **misspecified relationship between a latent variable and its indicator (item response)**.
- In other words, the model implied relationships between a latent variable and its indicator(s) does match the empirical one.
- If the item response function is misspecified, items can **share a similar pattern of misfit/residuals**.
- If there are **multiple such shared patterns**, the unidimensional model will, by definition, show a poor fit to the data.
- Since **items share certain characteristics** (e.g., common response scale, difficulty), it is likely that the shared patterns of misfit/residuals emerge.

An empirical study

Instruments and design

- Three self-report inventories: Height Inventory, Weight Inventory, Age Inventory.
- Sample items: *I am taller than men of my age. I often need a stool to reach something other people would reach normally.*
- Two response scales: Likert (agree–disagree), item-specific (expanded item format).
- Two types of factor analysis: continuous (MLR) vs. ordinal (WLSMV).
- The participants also reported their height, weight, and age.
- For simplicity, we will focus on the **Height Inventory** with the traditional **Likert response scale** and **linear factor analysis** (that treats items as continuous, interval variables).

Research sample

- ***N* = 12,158 (49 % male)**.
- **Height ranged from 143 to 215 cm (*M* = 174.8, *SD* = 10.1).**
- Age ranged from 18 to 85 years (*M* = 36.5, *SD* = 13.8).
- Weight ranged from 40 to 172 kg (*M* = 81.0, *SD* = 19.6).
- BMI ranged from 14.2 to 59.1 kg/m^2 (*M* = 26.4, *SD* = 5.67).

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Aims and hypotheses

- Demonstrate that a **misspecified response function is a sufficient cause of spurious multidimensionality**.
- We expected:

1. More misfitting items to have stronger loadings on the specific factor.
2. The specific factor to still contain construct-relevant variance, that is, to be related to the general factor, but in a non-linear fashion.
3. The shape of their relationship to mirror the shared pattern of item misfit.

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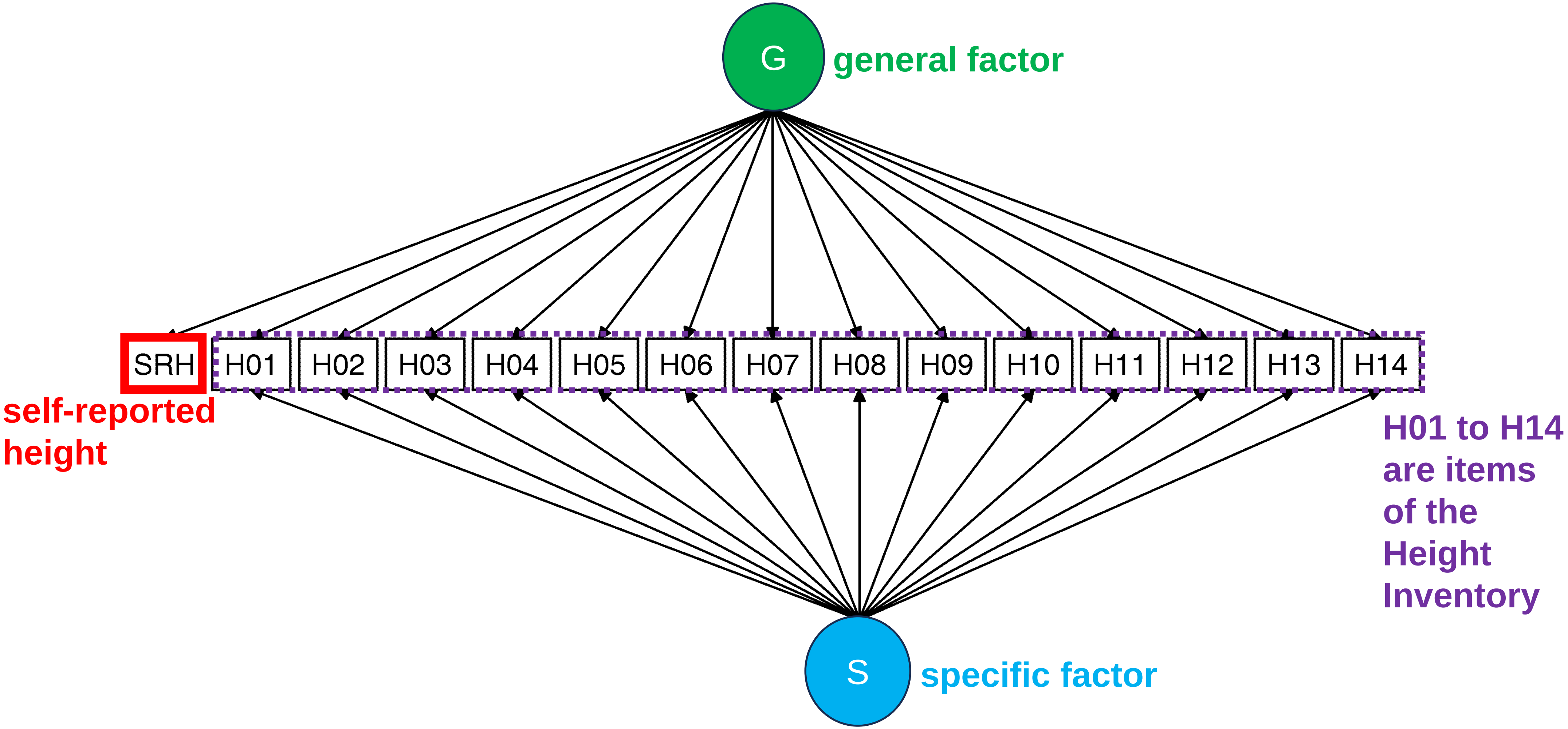
G
general factor
SRH
H01
H02
H03
H04
H05
H06
H07
H08
H09
H10
H11
H12
H13
H14
self-reported height
H01 to H14 are items of the Height Inventory
S
specific factor

Model fit

- **The unidimensional model showed a mediocre fit to the data**: $\chi^2(180) = 5280.9$ (unscaled 6623.1), $p < 0.001$, CFI = 0.917, TLI = 0.903, RMSEA = 0.077 (90% CI [0.075, 0.079]), SRMR = 0.049.
- **The bifactor i-1 model showed an excellent fit to the data**: $\chi^2(180) = 672.5$, (unscaled = 736,4) $p < 0.001$, CFI = 0.992, TLI = 0.989, RMSEA = 0.025 (90% CI [0.024, 0.027]), SRMR = 0.012.
- **The difference in fit was statistically significant**: $\chi^2(180) = 5085{,}6$, $p < 0.001$.

Item fit

- First, we have computed **factor scores estimates** for reach respondent**.**
- Second, we computed **model-predicted item scores** for each respondent and item.
- Then we computed "**empirical" item scores** using spline regression.
- The correlation between the model-predicted item scores and empirical item scores was used as a **measure of item fit**.
- As expected, the items with poor fit tended to have stronger loadings on the secondary factor.
- **The correlation between item fit and the loadings on the specific factor was strong**: Spearman's $\rho = -.70$,
  95% CI [–.86, –.41], $p < .001$.

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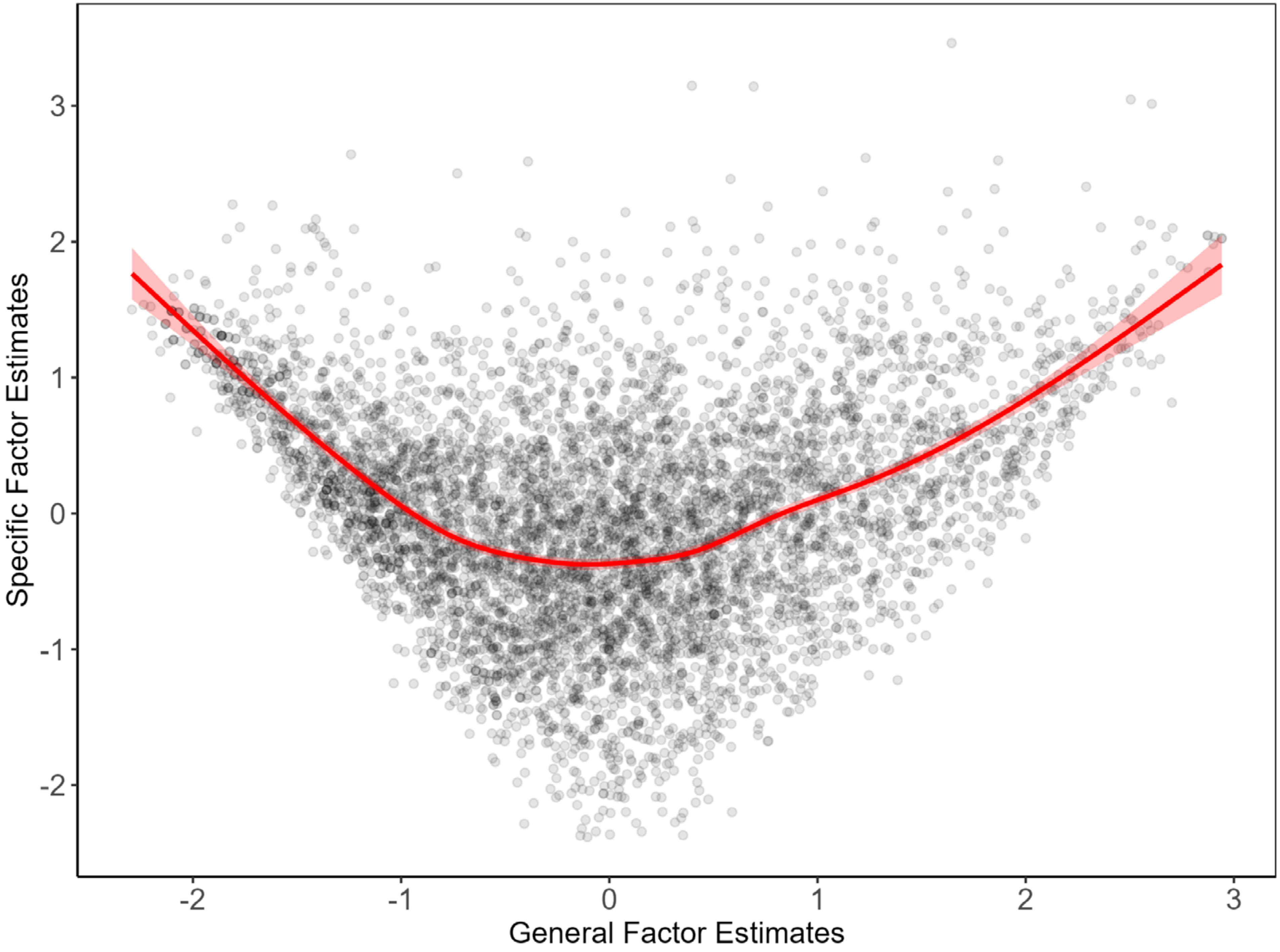
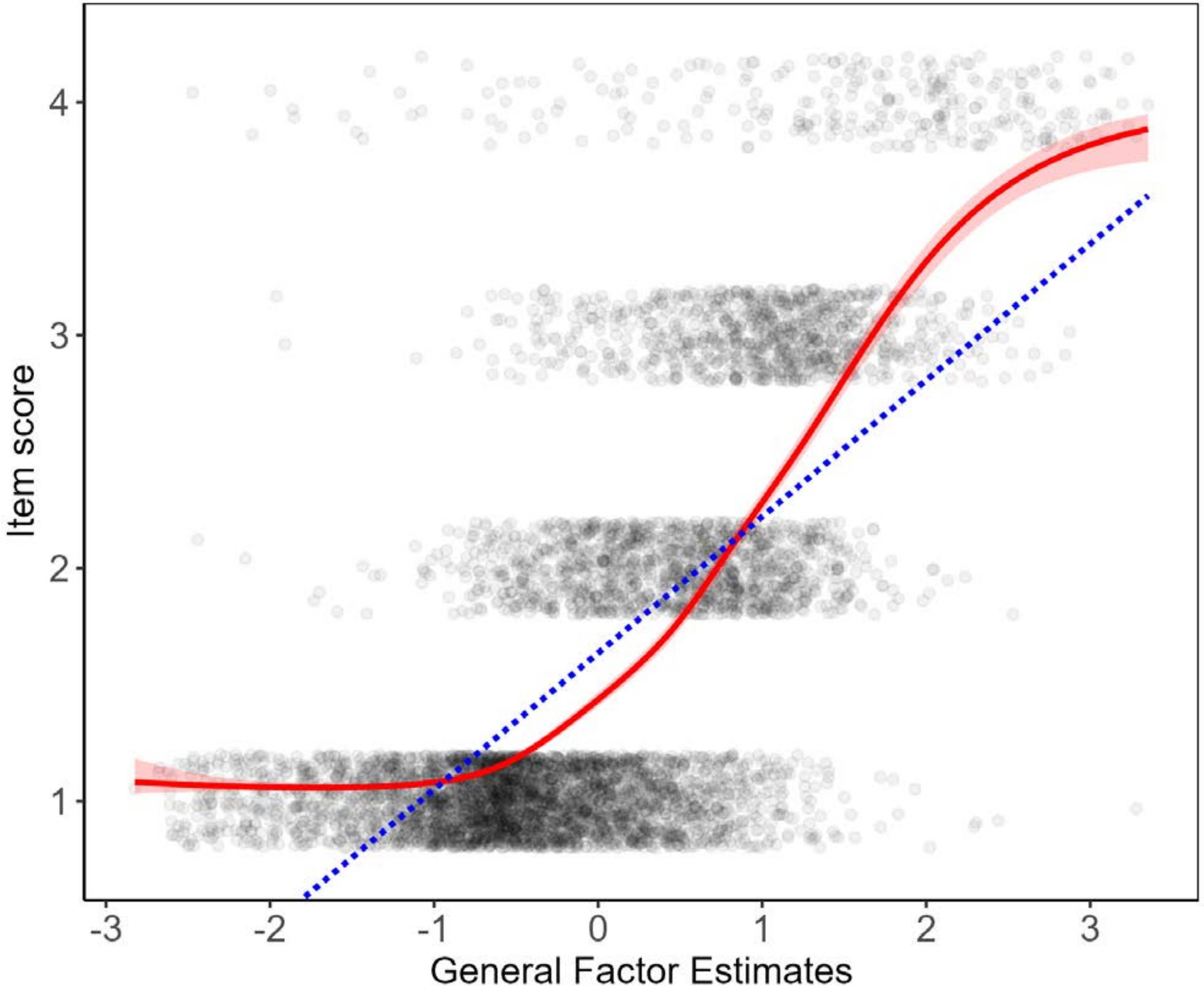


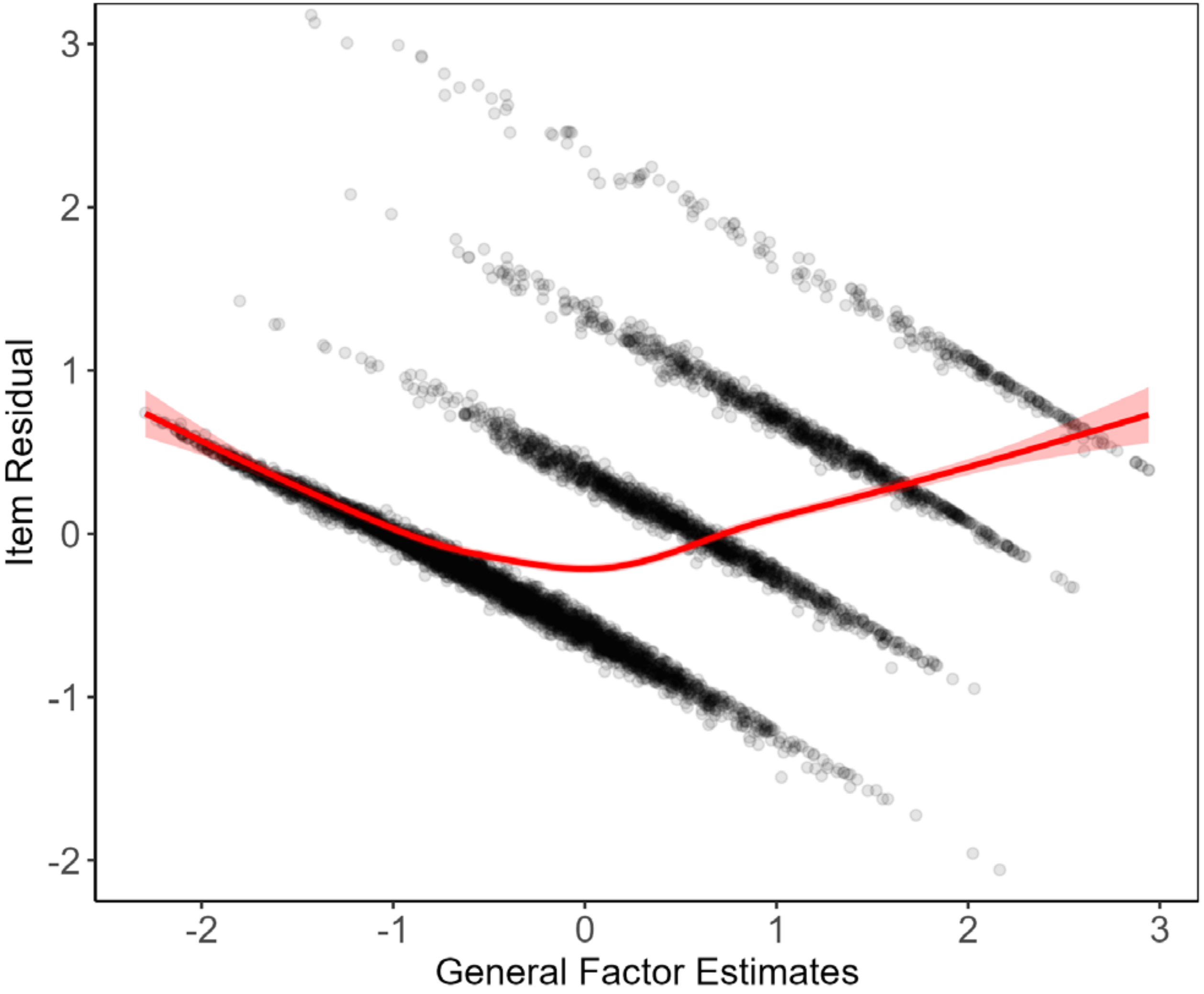
Cubic splines regression:
$R^2 = 0.28$

Linear regression with a quadratic term:
$R^2 = 0.27$

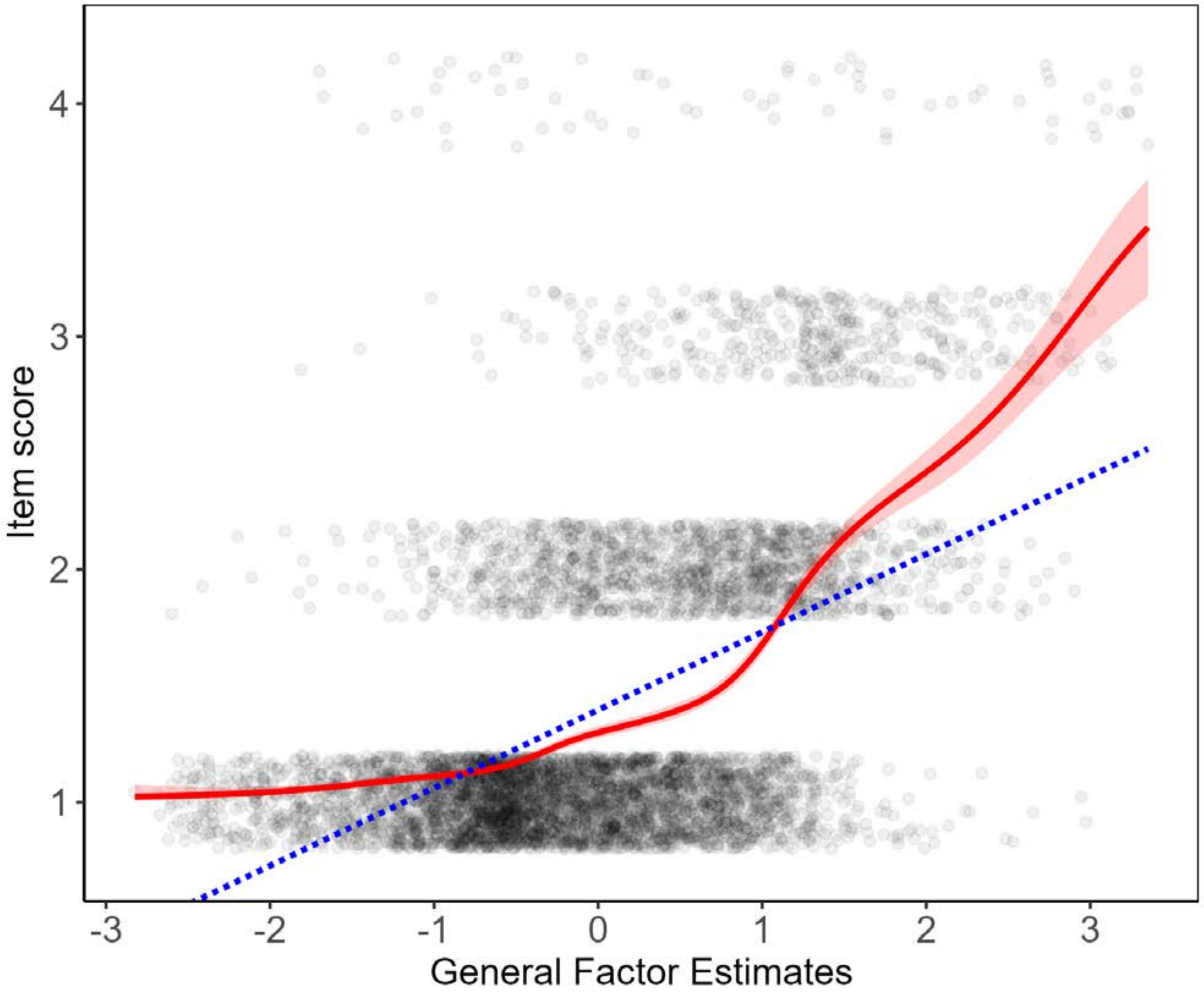
Squared Pearson correlation:
$r^2 < 0.01$

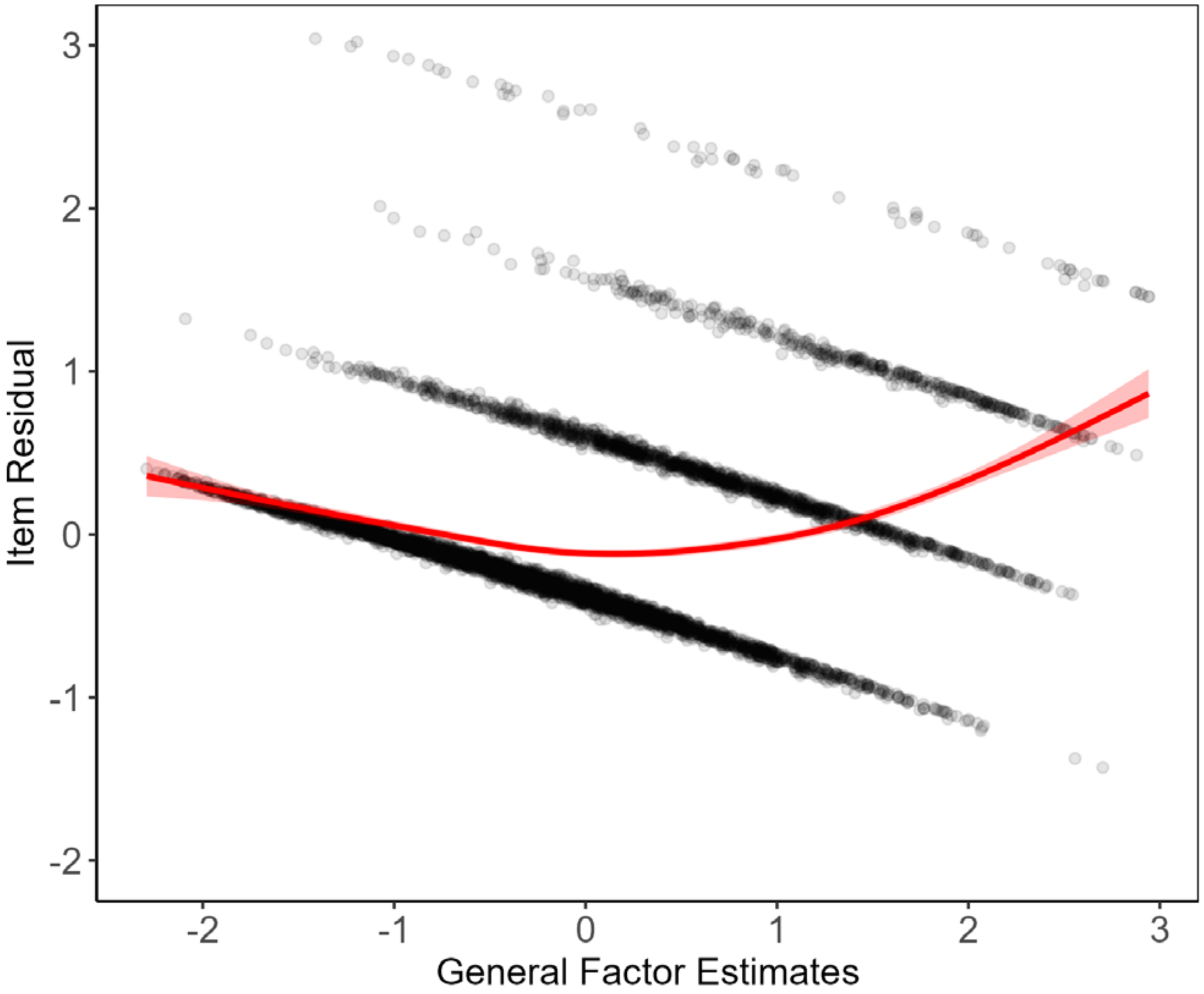
I am used to hearing comments about how tall I am.



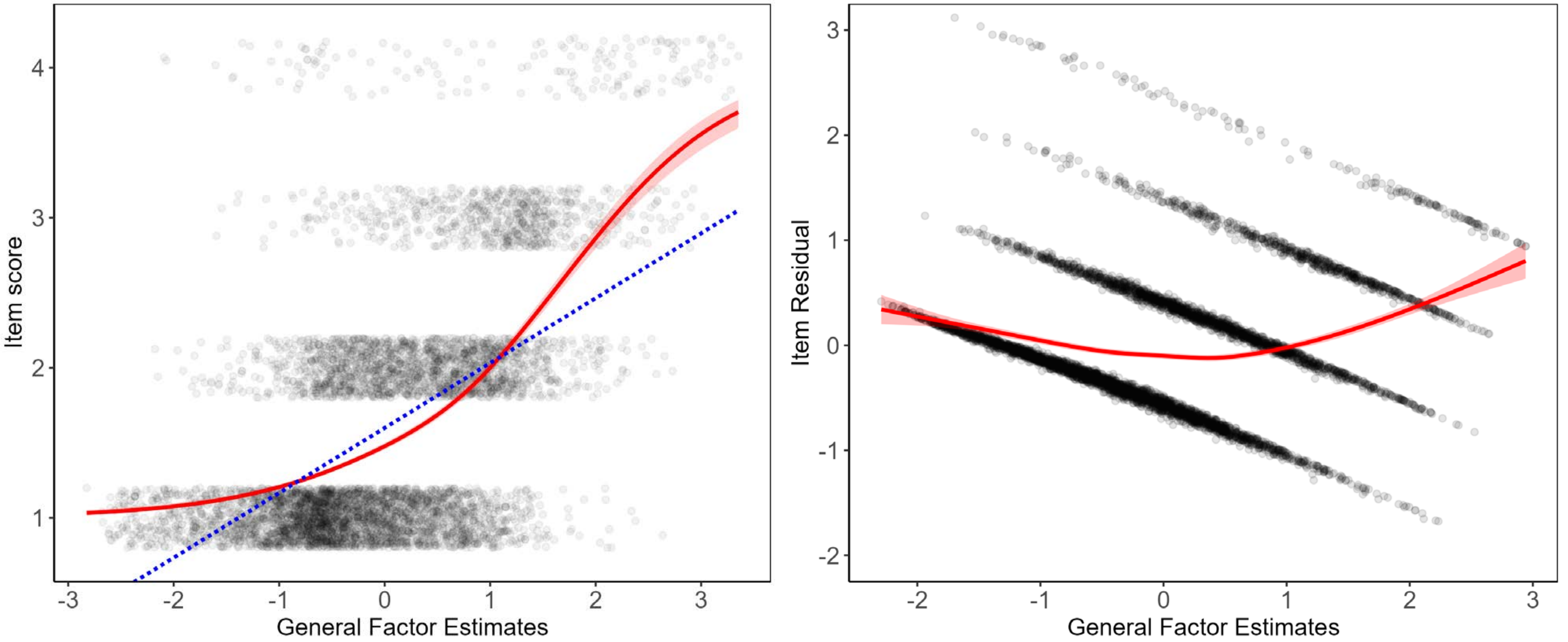


Ordinary beds are too short for me.

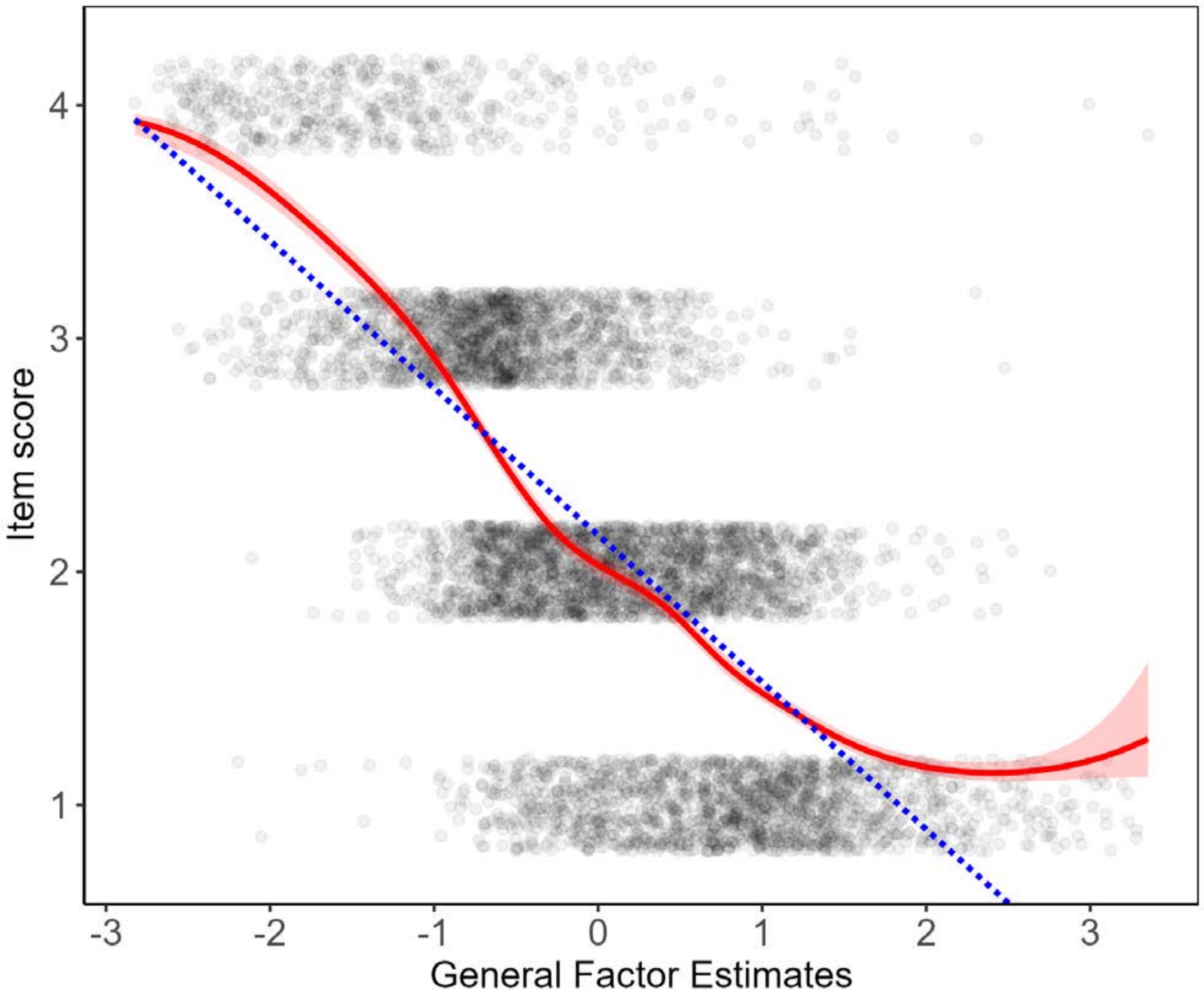


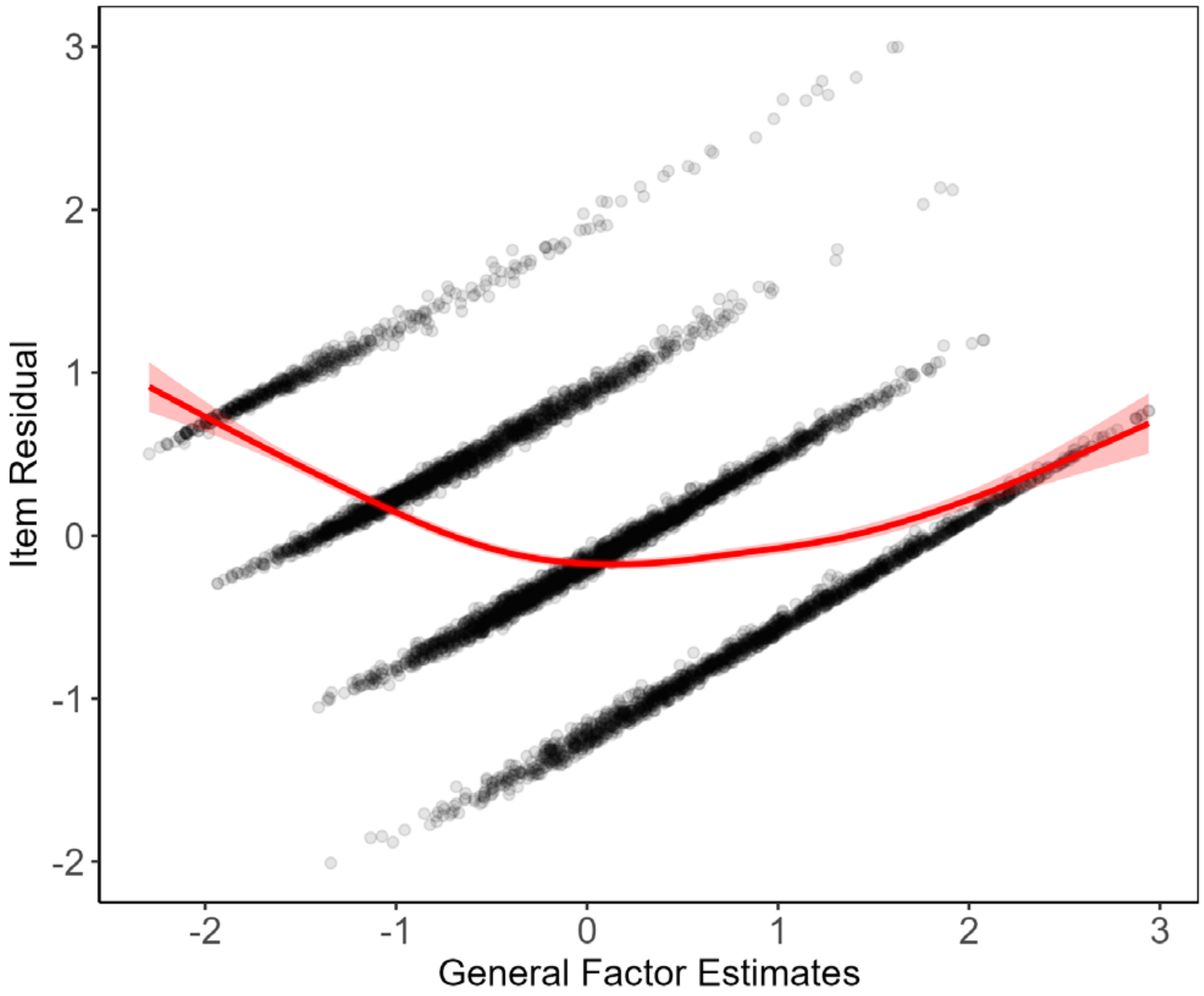


I often need to be careful to avoid bumping my head against a doorjamb or a low ceiling.

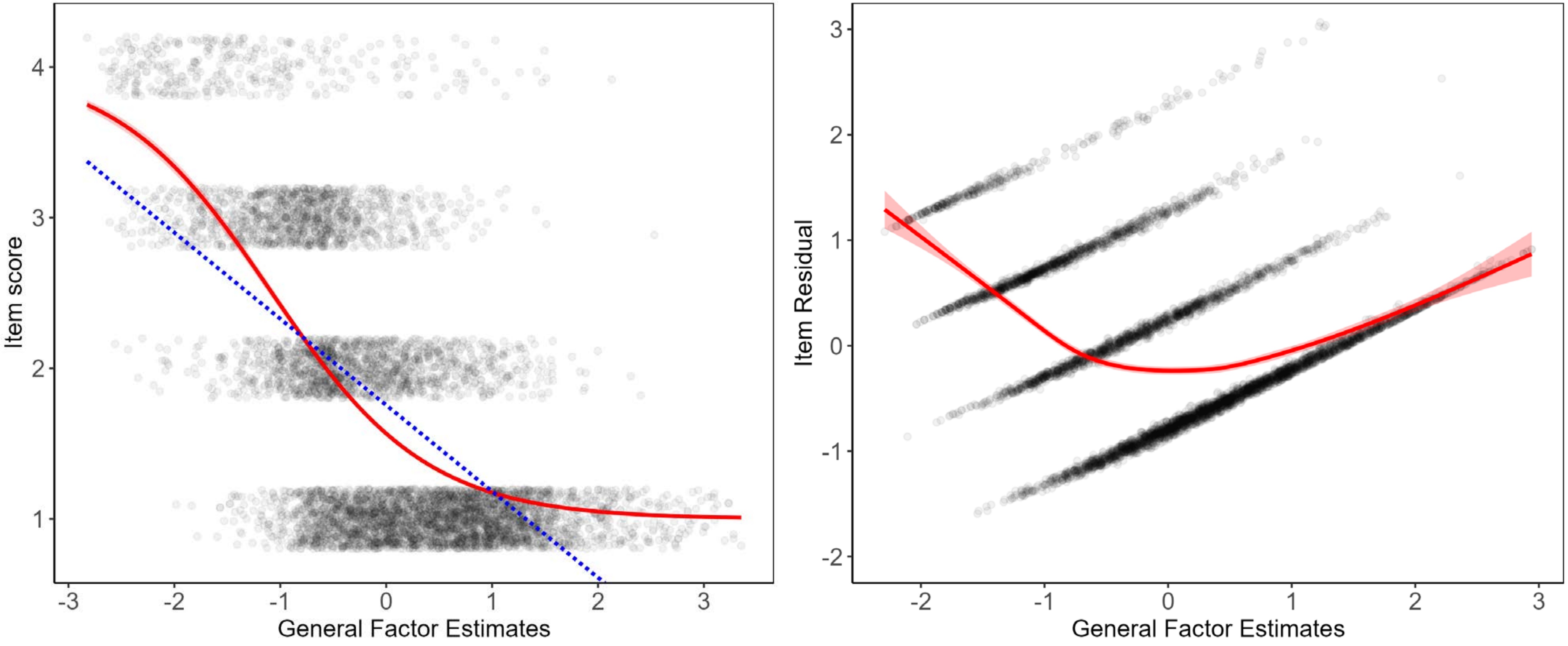


I often need a stool to reach something other people would reach without it. (reversed)





I could play a dwarf. (reversed)



Conclusions

- The results supported the hypothesis that a misspecified relationship between a latent variable and its indicator (item response) results in a shared pattern of misfit/residuals between items,
- In turn, this shared pattern results in a worse fit of a unidimensional model and the "emergence" of secondary factor(s).
- We know that these factors are "spurious" because they are nonlinearly related to the general factor and thus still contain construct-relevant variance.

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Main takeaway

- In order to interpret the secondary factors as substantive, or content factors, it is first necessary to verify that the relationship between the latent variable and the items is not misspecified.
- Otherwise. there is a risk that the secondary factors are merely a statistical artifact.

What to do about it

- Thus, in the practical application of factor analysis, we recommend checking the following things to avoid interpreting spurious factors as substantive factors:

1. Is the relationship between the latent variable and the item specified correctly?
2. Do the items with the largest loadings on the secondary factor(s) share the same (or mirror-reversed) pattern of misfit/residuals (when plotted against the general factor)?
3. Is the primary factor strongly, but non-linearly related to the secondary factor(s). And if so, does the shape of the relationship mirror the pattern of residuals (from the previous step).

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