



Examining the Factor Structure of Personality with Bayesian SEM

2024 Midwestern Psychological Association, Chicago, IL

April 18, 2024

Alfonso J. Martinez

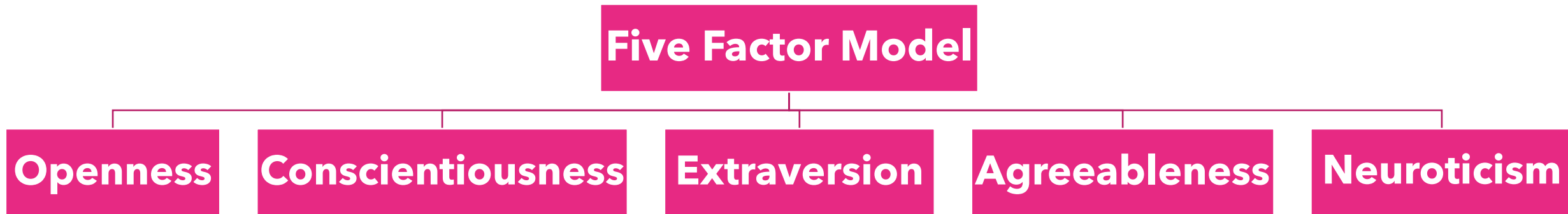
University of Iowa

Hyeri Hong

California State University, Fresno

Personality Inventories

- ❑ Personality inventories that measure personality traits under the (Big) **Five Factor Model** are widely used in psychological research
 - ❑ Predicting well-being from personality (Anglim et al., 2020)
 - ❑ Changes in personality traits during the pandemic (Sutin et al., 2020)
 - ❑ Association between personality and student achievement (Meyer et al., 2023)
 - ❑ Influence of personality traits on attitudes towards AI (Kaya et al., 2024)



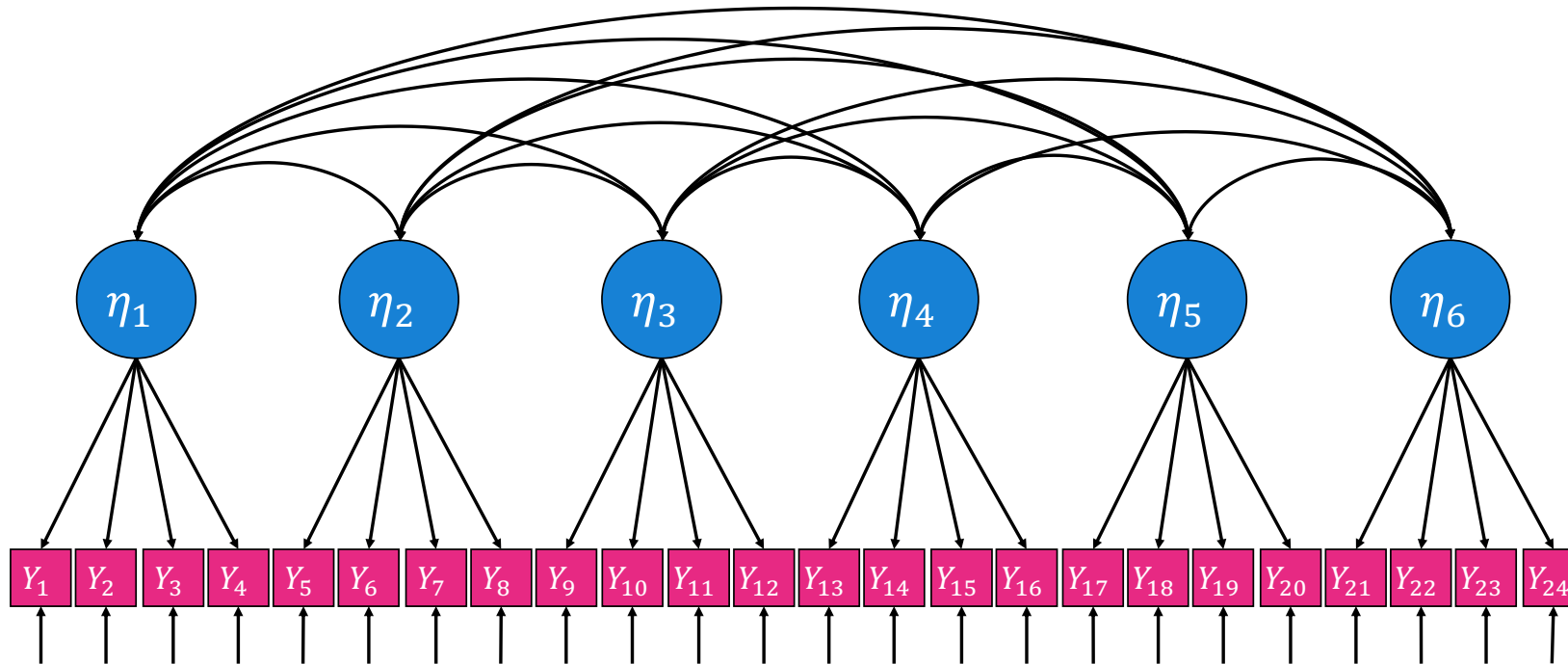
- ❑ Popular personality inventories include **NEO PI-R** (Costa & McCrae, 2000), **BFI-2** (Soto & John, 2017), **IPIP-NEO-120** (Johnson, 2014), and variants of these

Independent Cluster Structures in Personality Research

- It is common to analyze responses from personality inventories with **confirmatory factor analysis** under an **independent cluster** structure (McDonald, 2013)

- IC-CFA models assume that **indicators load onto a single factor**

Visual representation of IC-CFA for conscientiousness domain of the IPIP-NEO-120



Conscientiousness facets

η_1 : Self-efficacy
 η_2 : Orderliness
 η_3 : Dutifulness
 η_4 : Achievement-striving
 η_5 : Self-discipline
 η_6 : Cautiousness

Are Independent Cluster Structures Too Restrictive?

- ❑ Quantitative methodologists have argued that IC-CFA is **overly restrictive**
 - ❑ It is **unlikely** that indicators are **"pure"** measures of a factor (Asparouhov et al., 2015)
 - ❑ Item **residuals** likely **covary** (Zyphur & Oswald, 2015)
 - ❑ IC-CFA models in applied research **fail to meet acceptable fit criteria** (Marsh et al., 2014)

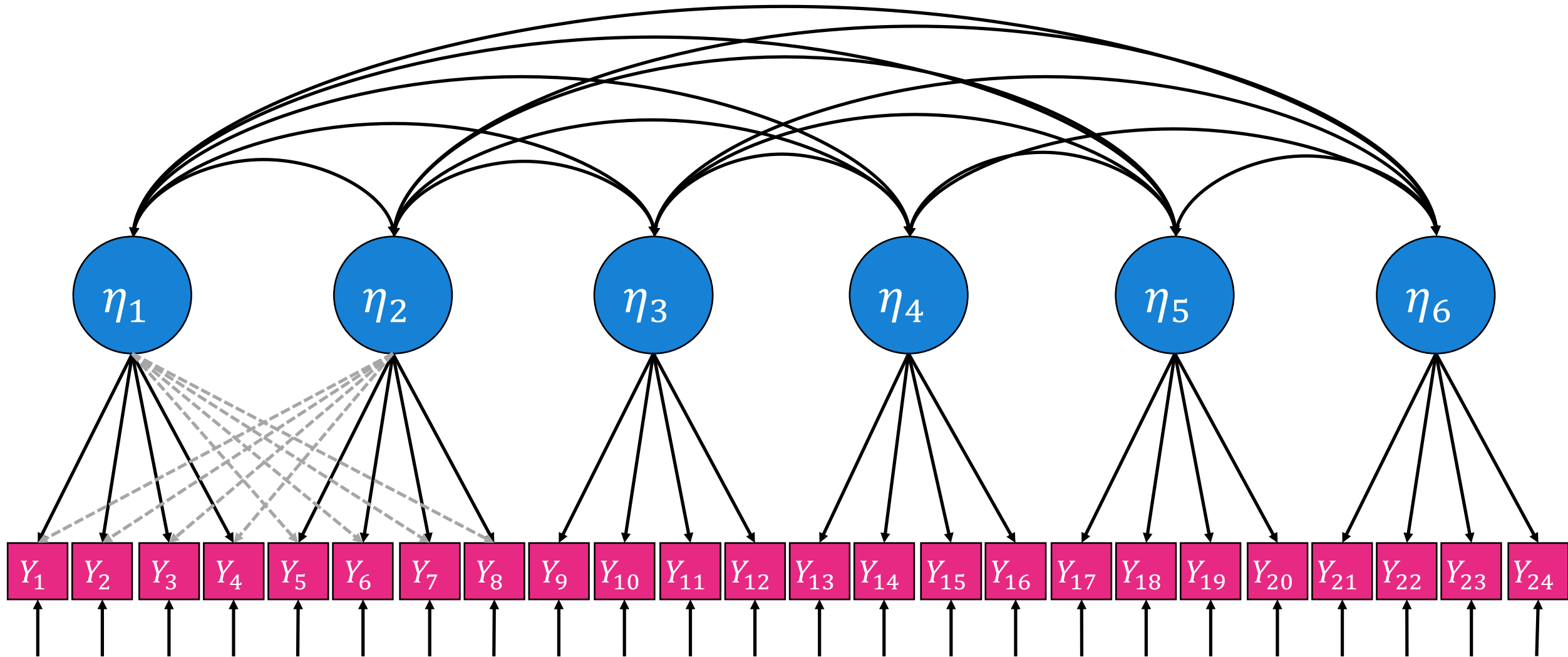
What Happens if we impose IC Structures when we Shouldn't?

- ❑ Factor correlations are **overestimated**
- ❑ **Biased structural coefficients** when predicting external variables
- ❑ **Error propagation** (other parts of the model "absorb" the error)

What are Some Solutions/Alternatives?

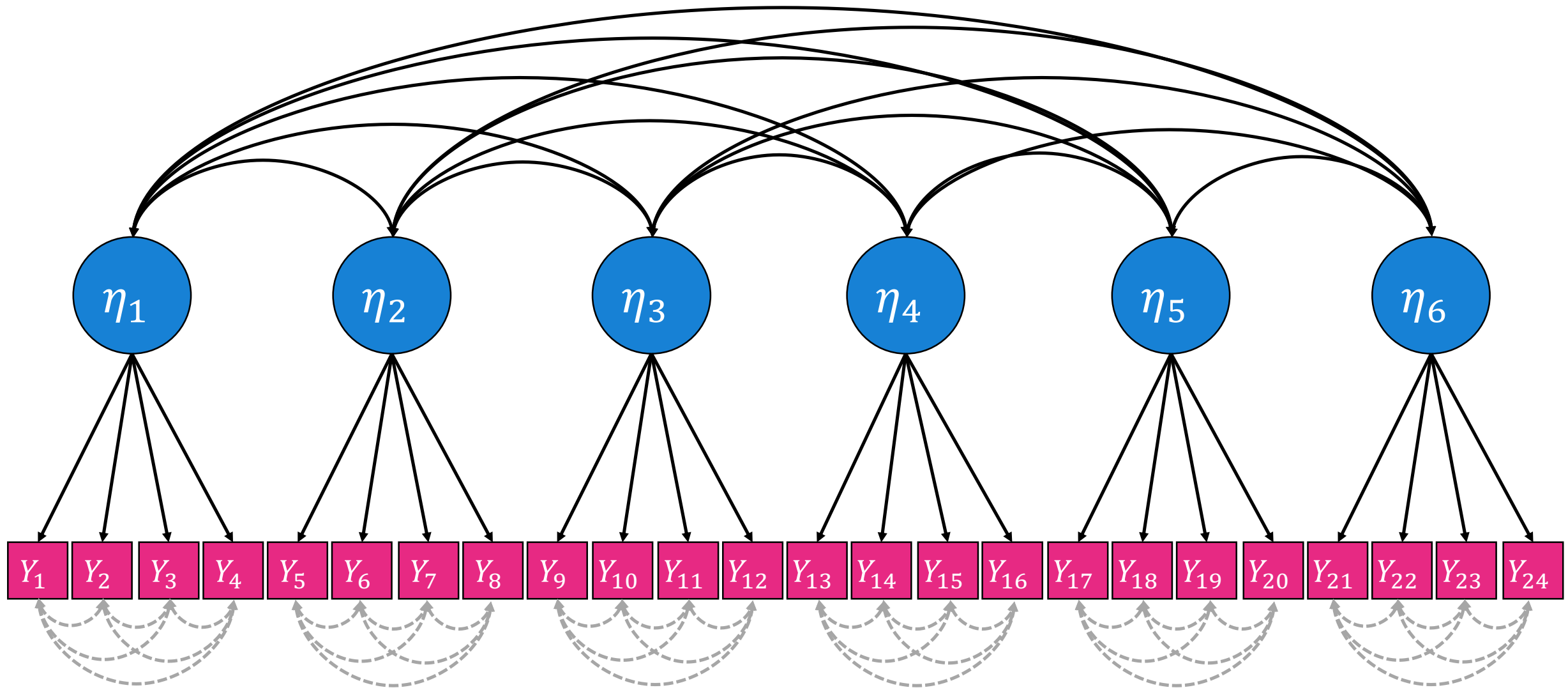
- ❑ Allowing cross-loadings
- ❑ Estimating within-factor residual covariances

Cross-loadings (CLs)



- ❑ Cross-loadings reflect the hypothesis that **indicators are never "pure" reflections** of a factor and load onto more than one factor

Residual Covariances (RCs)



□ Residual covariances capture any otherwise **unmodeled sources of variation** not attributable to the factor (e.g., similarities in wording)

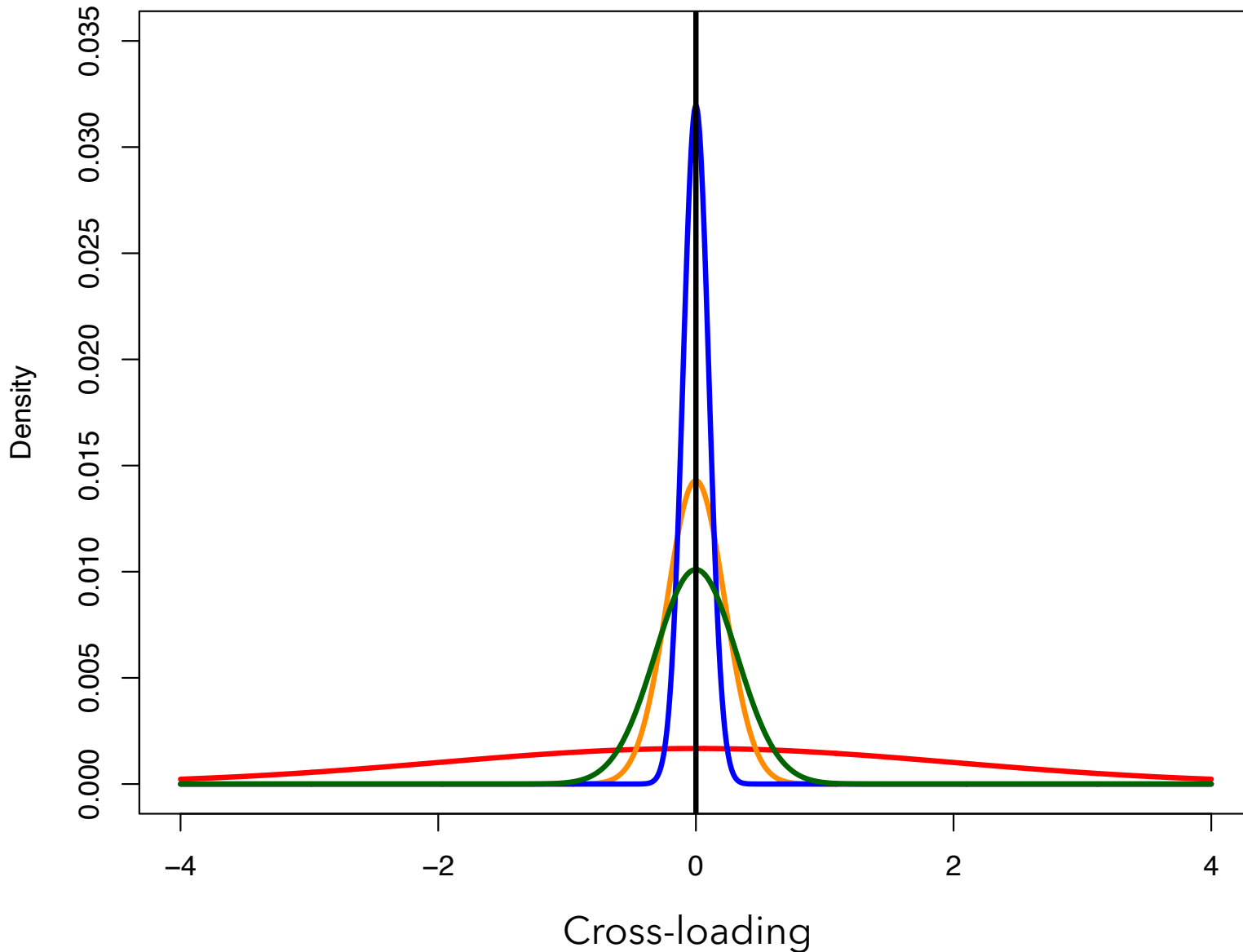
Challenges with Estimating Models with CL or RCs

- ❑ **Estimating CL or RCs** is difficult when models are estimated with **maximum likelihood**
 - ❑ Identification issues (models can become **unidentified**)
 - ❑ No way to **"control"** the amount of influence the CL or RCs have on estimates
 - ❑ Number of parameters can **increase** substantially

Bayesian Structural Equation Models (BSEM)

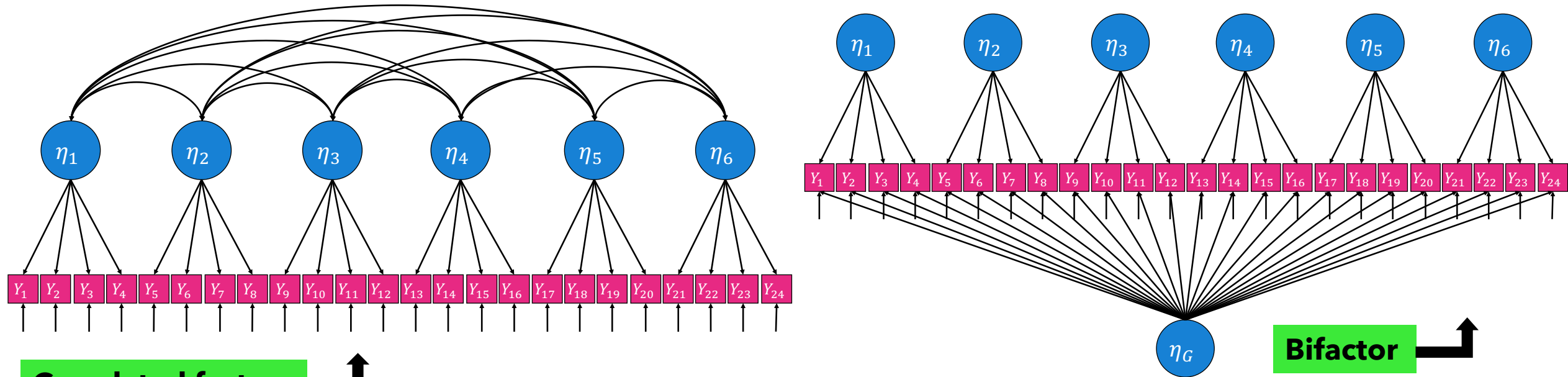
- ❑ **BSEM** leverages the **Bayesian** framework to estimate CLs and/or RCs
- ❑ **Small-variance priors (aka informative priors)** to reflect hypotheses that CLs/RCs are **near** zero but not **exactly** zero
 - ❑ Researcher can choose what **near** zero means by specifying a value for the prior variance

Examples of Different Small-Variance Priors



Prior	Informativeness	95%
$N(0, 0)$	Extremely informative	0
$N(0, 0.01)$	Informative	± 0.196
$N(0, 0.05)$	Informative	± 0.438
$N(0, 0.10)$	Informative	± 0.619
$N(0, 4)$	Uninformative	± 3.919

What's the Best Way to Represent the Structure of Personality Domains?



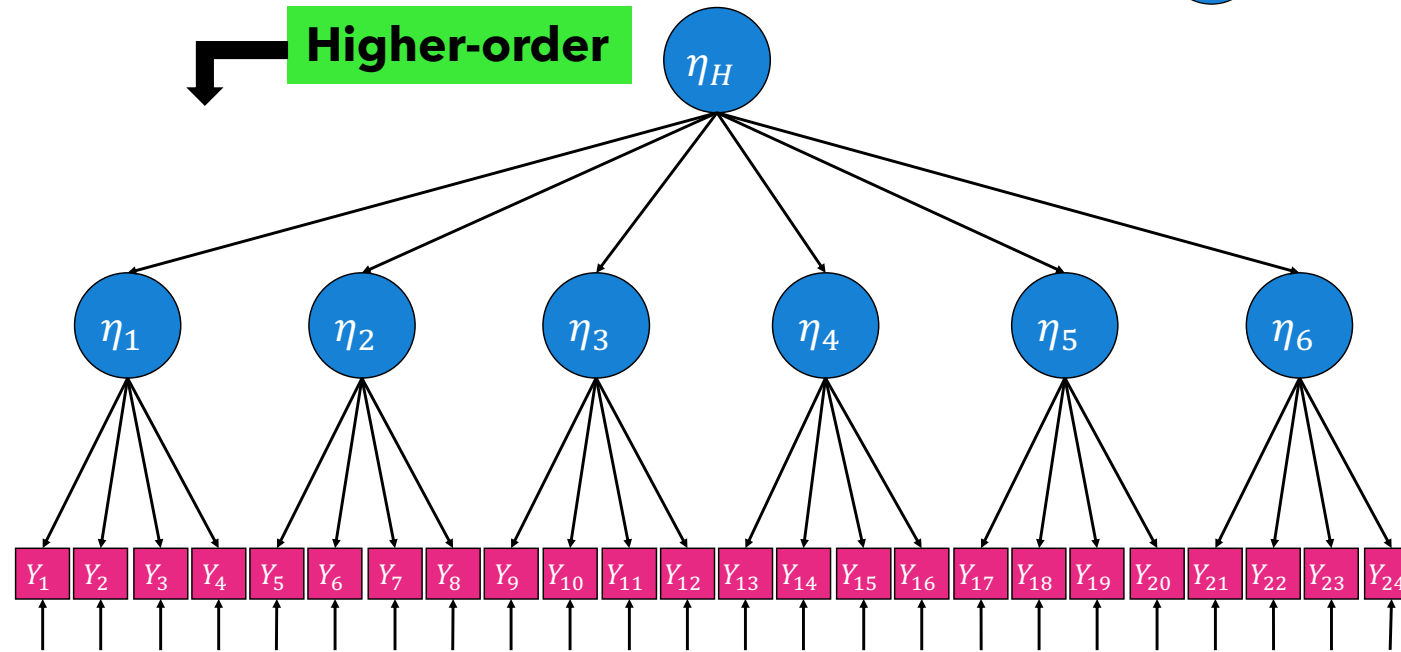
Correlated factors

Higher-order

Bifactor

Conscientiousness facets

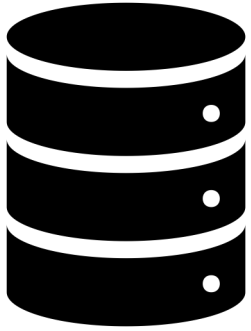
- η_1 : Self-efficacy
- η_2 : Orderliness
- η_3 : Dutifulness
- η_4 : Achievement-striving
- η_5 : Self-discipline
- η_6 : Cautiousness



Research Questions

- **Research question 1:** Does BSEM with **small-variance priors** offer an improvement over IC-CFA in personality inventories **with respect to model fit indices?**
- **Research question 2:** According to BSEM model fit indices, which factor structure (correlated factors, bifactor, higher-order) fits the data the best?

Methods

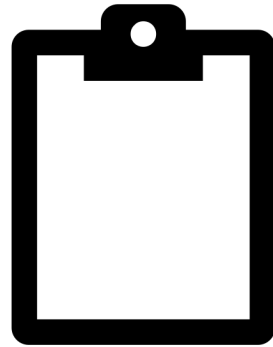


❑ **Data Source:**
International Personality
item Pool (IPIP)

❑ **IPIP-120-NEO** is a
public version of the
NEO PI-R

❑ Open-access dataset
❑ 440,000+ responses

❑ Random sample of
 $N = 500$ individuals
from US analyzed in
this study



❑ **Conscientiousness**
factor
❑ Six 4-item facets

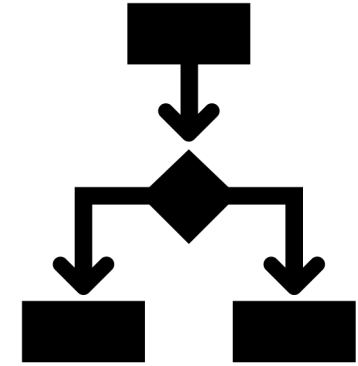
Conscientiousness Facet
Self-efficacy
Orderliness
Dutifulness
Achievement-striving
Self-discipline
Cautiousness



❑ 18 Bayesian models
fit in **Mplus** v8.8

Factor Structure	Model Type
Correlated factor	IC-CFA
Bifactor	CLs only
Higher- order	RCs only

❑ For CLs models, prior
was $N(0, \nu)$ where $\nu =$
0.005, 0.01, 0.02,
0,03; for RCs models,
prior was **IW(1, 30)**



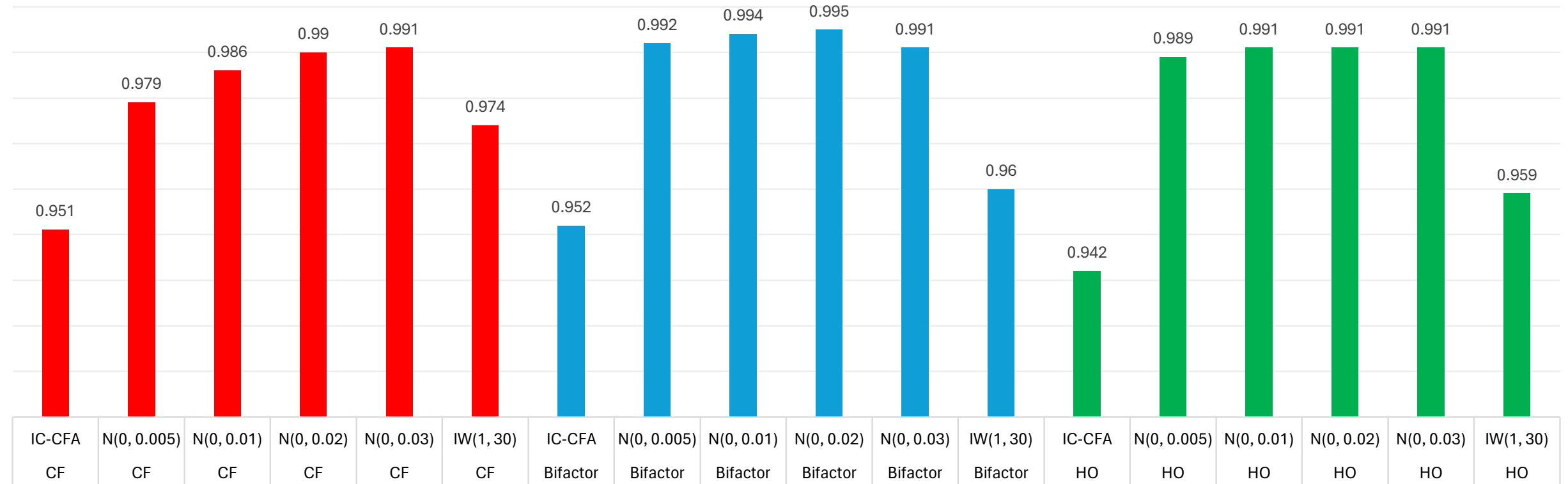
❑ **Outcomes** (model fit):

- ❑ Bayesian information criterion (**BIC**)
- ❑ Deviance information criterion (**DIC**)
- ❑ Comparative fit index (**BCFI**)
- ❑ Tucker-Lewis index (**BTLI**)
- ❑ Root mean square error of approximation (**BRMSEA**)

Results

BCFI is a measure of goodness of fit; larger values = better fit

BCFI



❑ IC-CFA < BSEM-RC < BSEM-CL

❑ **Bifactor models fit better** (marginally) than CF and HO models

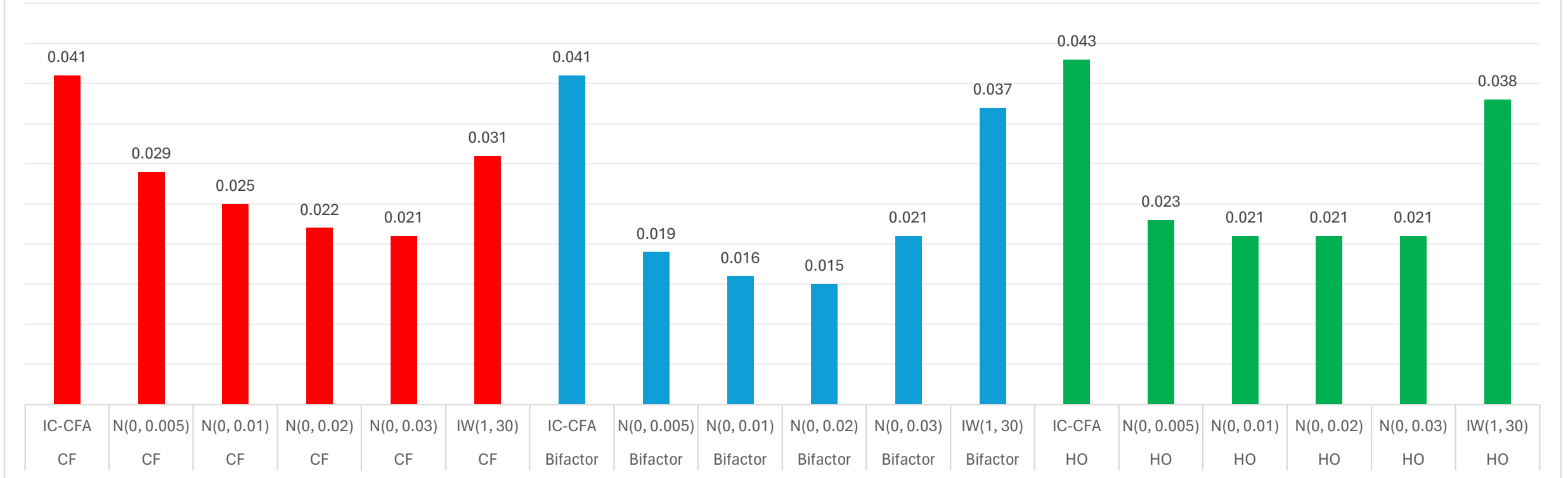
❑ **Increasing variance prior** in BSEM-CL models had almost **no impact** in bifactor and HO models; slight improvement in CF models

❑ Results from TLI were nearly identical to CFI

Results

BRMSEA is a measure of badness of fit; larger values = worse fit

BRMSEA



❑ IC-CFA > BSEM-RC > BSEM-CL

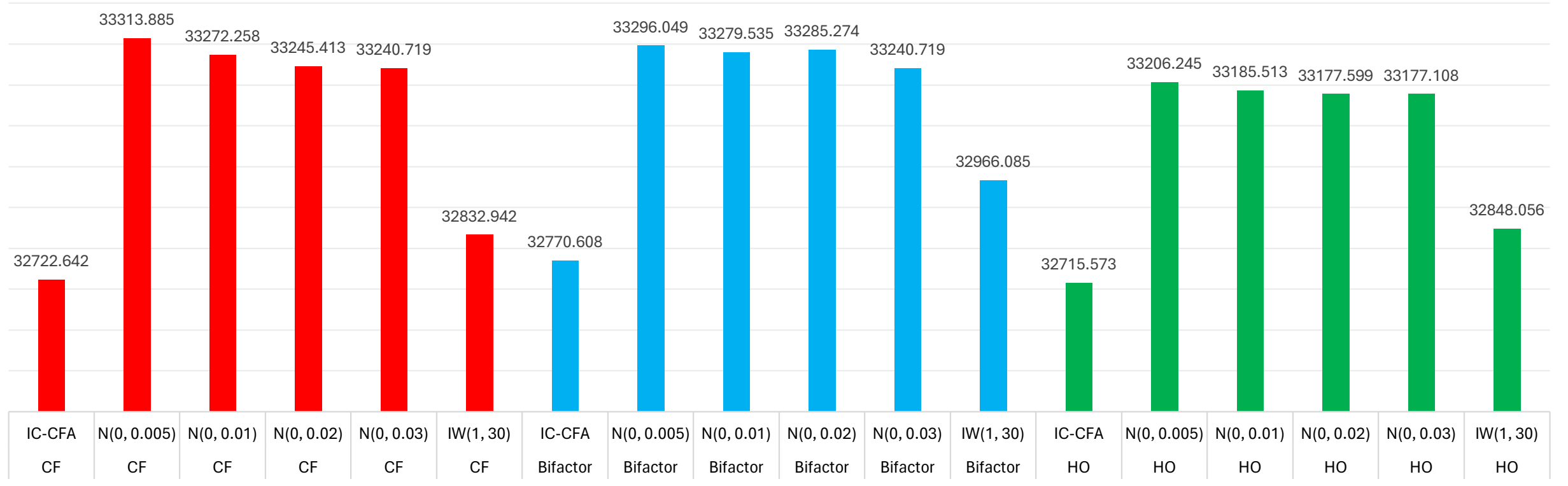
❑ **Bifactor models fit better** than CF and HO models

❑ **Increasing variance prior** in BSEM-CL models had **differential impact** depending on factor structure

Results

BIC penalizes models based on complexity; smaller values = better fit

BIC



❑ **BIC preferred IC-CFA** over BSEM-RC and BSEM-CL models

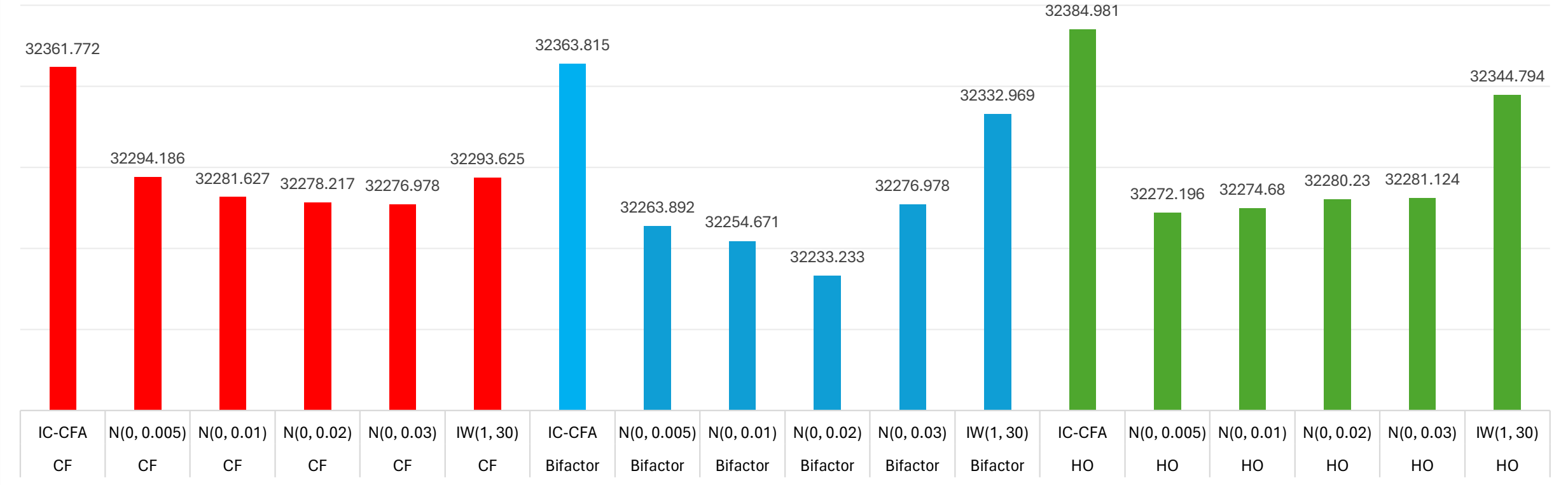
❑ **BIC preferred HO IC-CFA** over CF IC-CFA and bifactor IC-CFA

❑ Within factor structure, BIC values for BSEM models were mostly consistent

Results

DIC penalizes models based on complexity; smaller values = better fit

DIC



- ❑ According to DIC, IC-CFA **fit worse** than BSEM
- ❑ Out of all 18 models, **bifactor BSEM-CL** with N(0, 0.02) prior fit best
- ❑ All **BSEM-CL models fit better** than BSEM-RC models

Discussion & Implications

- ❑ We found the **BSEM-CLs** provided the best fit across factor structures
- ❑ We found evidence that **bifactor** structures fit conscientiousness data better than CT and HO factor structures when **SEM-based fit measures** were considered; **BIC** preferred **IC-CFA**; **DIC** preferred **bifactor**

Limitations

- ❑ We focused on one personality domain (conscientiousness), not all five
- ❑ **Possible** that we are **overfitting** data in BSEM-CL and BSEM-RC models
- ❑ Only considered measures of model fit (**theory should take precedence**)

Future Research

- ❑ Do we really need all those CLs and/or RCs?
- ❑ Do we see the same trend in other personality domains?
- ❑ Are slight increases in model fit practically important and meaningful to substantive researchers?

Thank You!



Alfonso J. Martinez

PhD Candidate, University of Iowa

Email: alfonso-martinez@uiowa.edu

Website: ajmquant.com

Twitter/X: alfonsoMpsych



Hyeri Hong, PhD

Asst. Prof., California State University, Fresno

Email: hyerihong@mail.fresnostate.edu

Website:

<https://kremen.fresnostate.edu/about/directory/hong-hyeri.html>

References (I/II)

- ❑ Anglim, J., Horwood, S., Smillie, L. D., Marrero, R. J., & Wood, J. K. (2020). Predicting psychological and subjective well-being from personality: A meta-analysis. *Psychological bulletin*, 146(4), 279.
- ❑ Asparouhov, T., Muthén, B., & Morin, A. J. (2015). Bayesian structural equation modeling with cross-loadings and residual covariances: Comments on Stromeier et al. *Journal of Management*, 41(6), 1561-1577.
- ❑ Costa Jr, P. T., & McCrae, R. R. (2000). *Neo Personality Inventory*. American Psychological Association.
- ❑ Johnson, J. A. (2014). Measuring thirty facets of the Five Factor Model with a 120-item public domain inventory: Development of the IPIP-NEO-120. *Journal of Research in Personality*, 51, 78-89.
<https://doi.org/10.1016/j.jrp.2014.05.003>
- ❑ Kajonius, P. J., & Johnson, J. A. (2019). Assessing the structure of the Five Factor Model of Personality (IPIP-NEO-120) in the public domain. *Europe's Journal of Psychology*, 15(2), 260-275.
<https://doi.org/10.5964/ejop.v15i2.1671>
- ❑ Kaya, F., Aydin, F., Schepman, A., Rodway, P., Yetişensoy, O., & Demir Kaya, M. (2024). The roles of personality traits, AI anxiety, and demographic factors in attitudes toward artificial intelligence. *International Journal of Human-Computer Interaction*, 40(2), 497-514.

References (II/II)

- ❑ Marsh, H. W., Morin, A. J., Parker, P. D., & Kaur, G. (2014). Exploratory structural equation modeling: An integration of the best features of exploratory and confirmatory factor analysis. *Annual review of clinical psychology, 10*, 85-110.
- ❑ McDonald, R. P. (2013). *Test theory: A unified treatment*. Psychology press.
- ❑ Meyer, J., Jansen, T., Hübner, N., & Lüdtke, O. (2023). Disentangling the association between the Big Five personality traits and student achievement: Meta-analytic evidence on the role of domain specificity and achievement measures. *Educational Psychology Review, 35*(1), 12.
- ❑ Soto, C. J., & John, O. P. (2017). The next Big Five Inventory (BFI-2): Developing and assessing a hierarchical model with 15 facets to enhance bandwidth, fidelity, and predictive power. *Journal of Personality and Social Psychology, 113*(1), 117-143. <https://doi.org/10.1037/pspp0000096>
- ❑ Sutin, A. R., Luchetti, M., Aschwanden, D., Lee, J. H., Sesker, A. A., Strickhouser, J. E., ... & Terracciano, A. (2020). Change in five-factor model personality traits during the acute phase of the coronavirus pandemic. *PloS one, 15*(8), e0237056.
- ❑ Zyphur, M. J., & Oswald, F. L. (2015). Bayesian estimation and inference: A user's guide. *Journal of Management, 41*(2), 390-420.

Extra Slides

Number of Parameters in Each Model

Factor Structure	Model Type	# Parameters
Correlated Factor	Independent Clusters	87
	BSEM CLs	207
	BSEM RCs	123
Bifactor	Independent Clusters	96
	BSEM CLs	216
	BSEM RCs	133
Higher-order	Independent Clusters	78
	BSEM CLs	198
	BSEM RCs	198

Descriptive Statistics

Facet	Mean (SD)	Reliability Alpha
Self-efficacy	4.02 (0.12)	0.767
Orderliness	3.09 (0.28)	0.837
Dutifulness	3.97 (0.44)	0.669
Achievement-striving	3.85 (0.22)	0.738
Self-discipline	3.44 (0.29)	0.669
Cautiousness	3.23 (0.10)	0.874
Total	3.60 (0.44)	0.898