

# EAM2025

## XI Conference

23RD - 25TH  
**JULY**  
2025

**Spain** Tenerife  
Canary Islands

European  
Association of  
Methodology



### Presentation 2

Andres Felipe Perez Alonso



Universidad  
de La Laguna



**cajasiete**



**Gobierno de Canarias**

Consejería de Universidades,  
Ciencia e Innovación y Cultura

Agencia Canaria de Investigación,  
Innovación y Sociedad  
de la Información



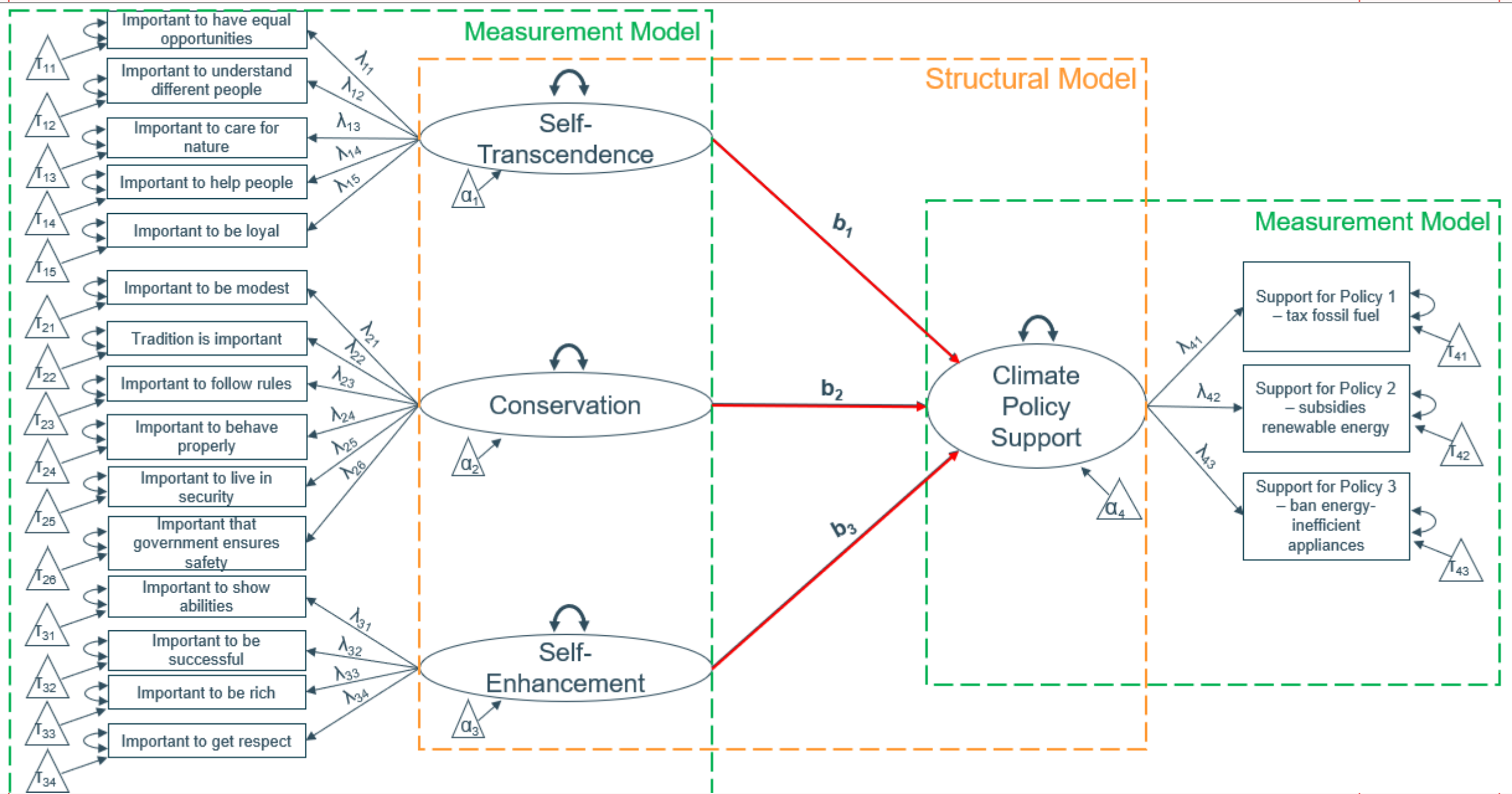
Instituto  
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de Igualdad



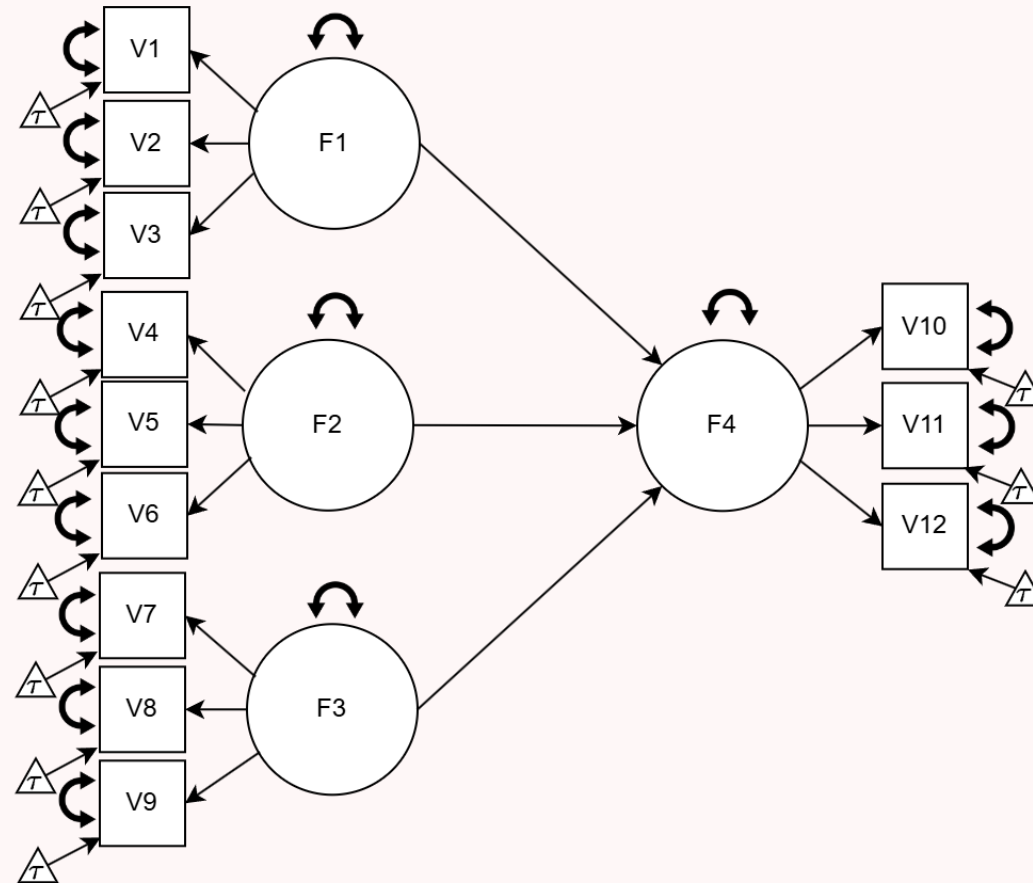
**hogrefe**

# Extending MMG-SEM for Ordinal Data

Andres Felipe Perez Alonso



# A bit simpler...

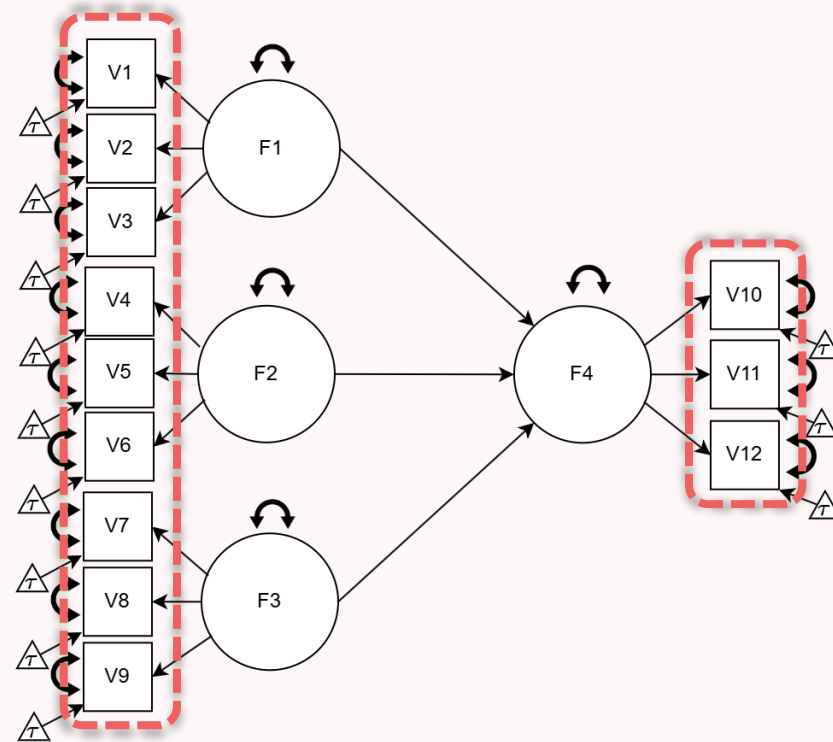


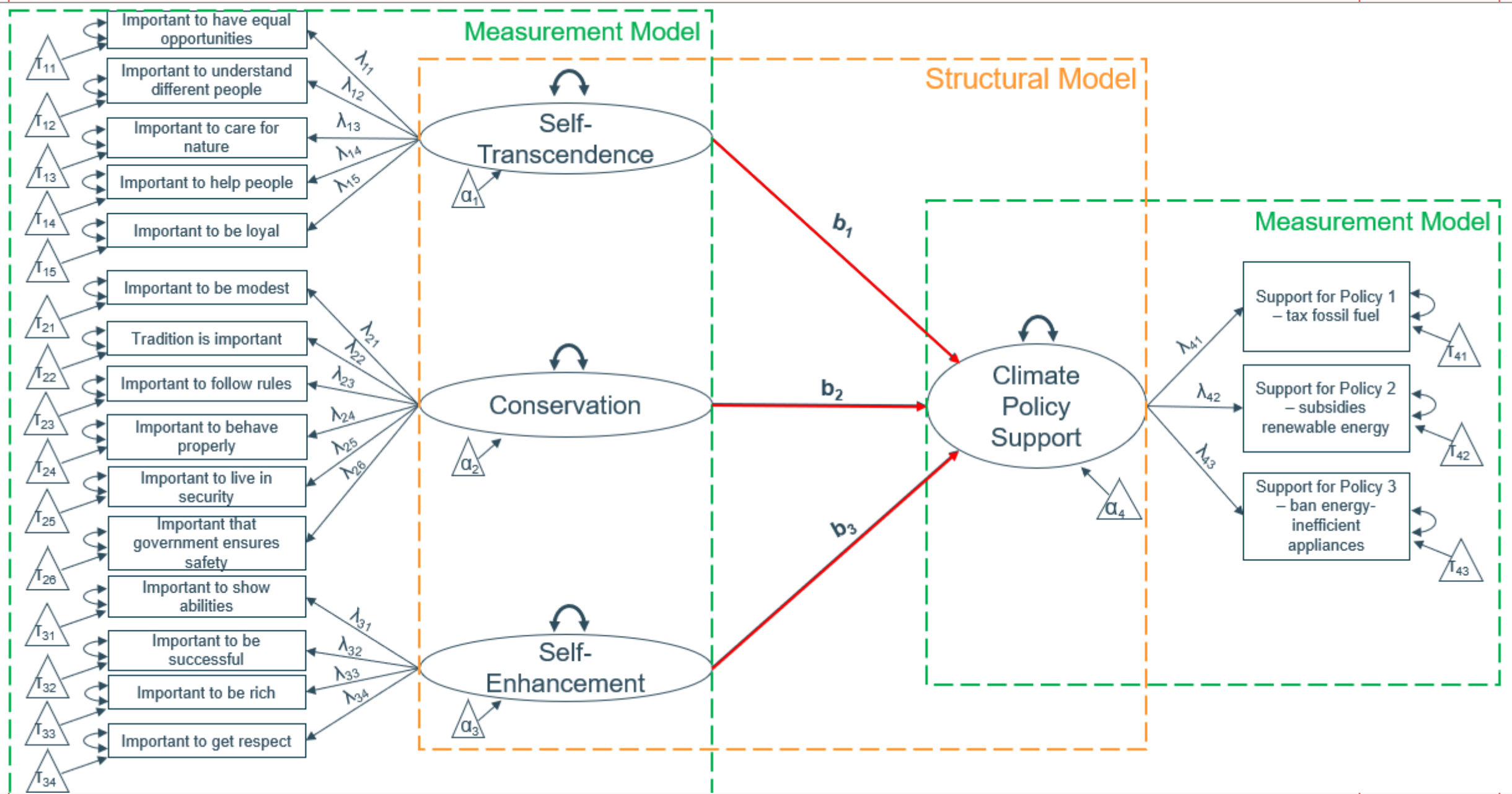
# The problem

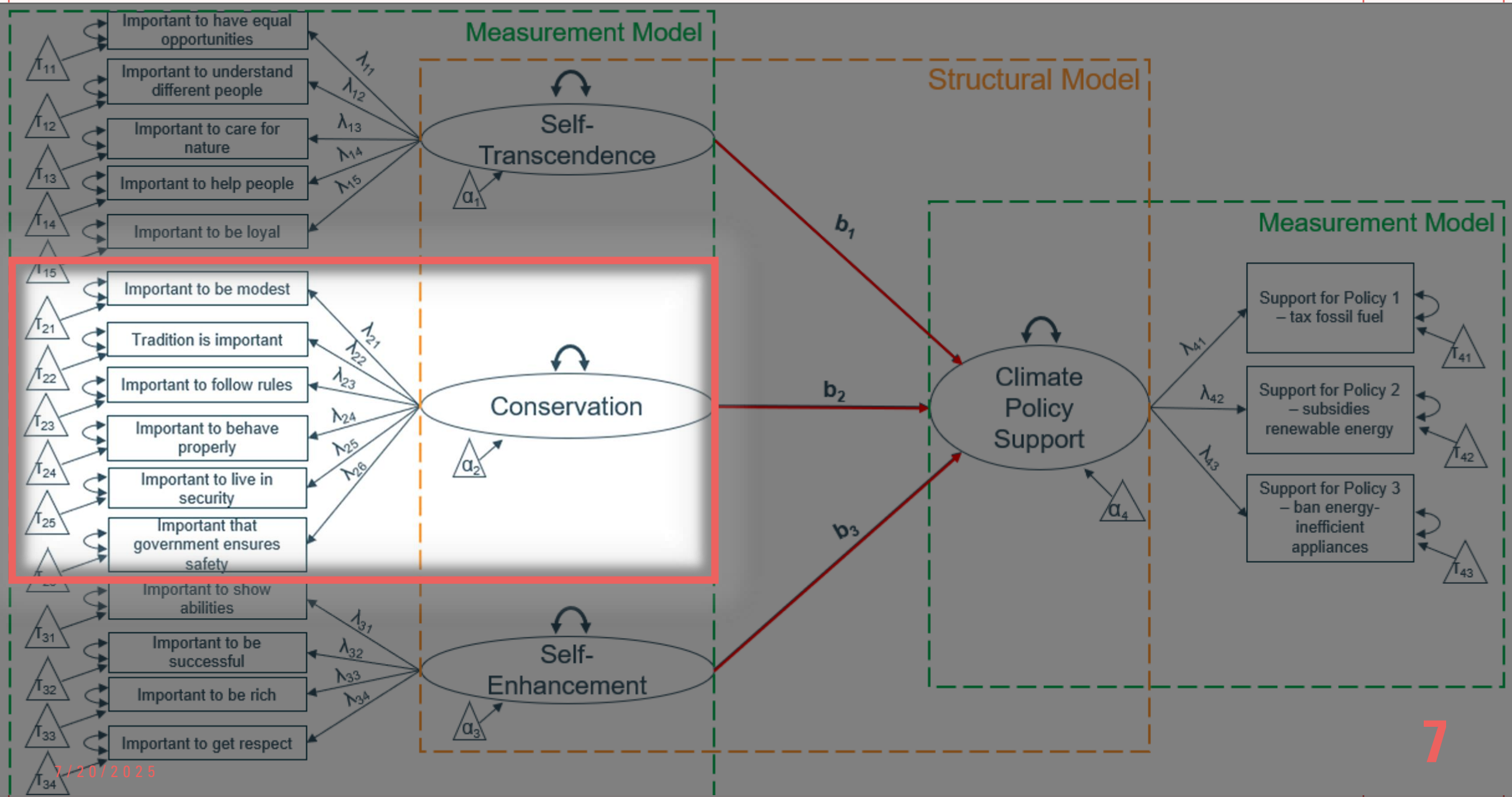
Dealing with real data...

# Real life

- Default MMG-SEM works for **continuous** indicators.



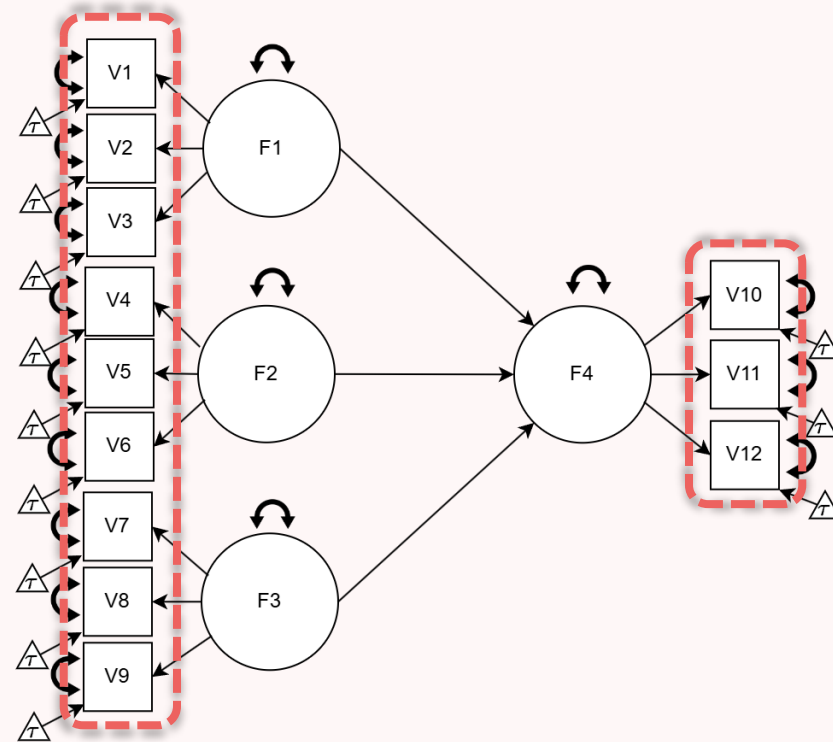






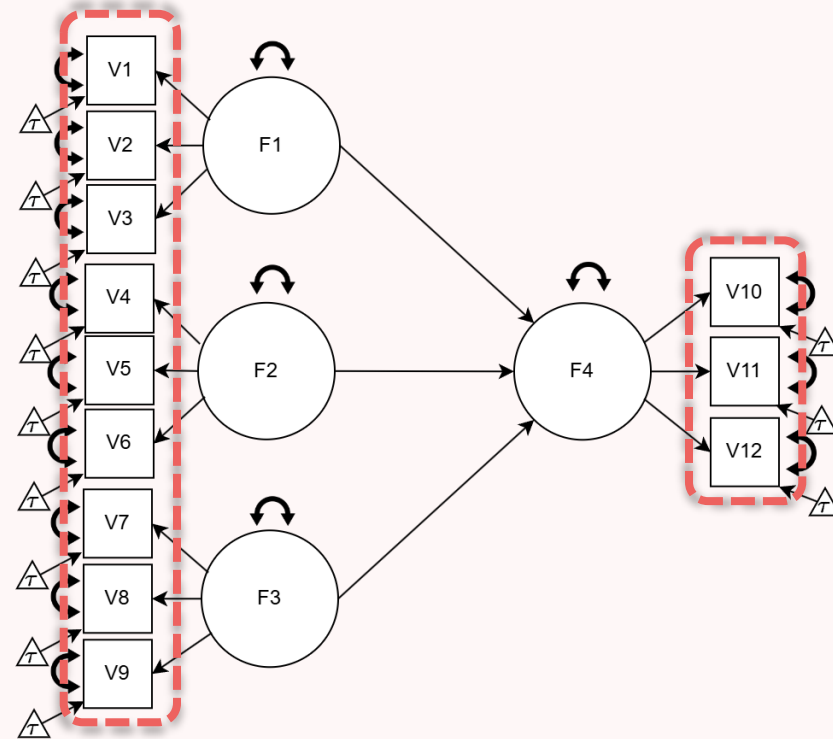
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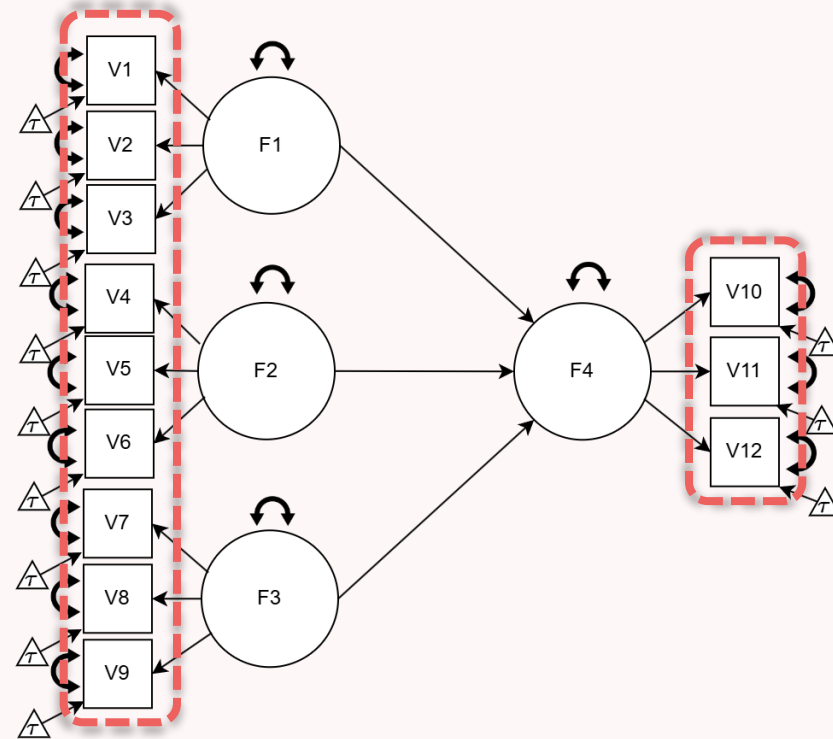
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- Default MMG-SEM works for **continuous** indicators.
- In real life, the items are (always) **ordinal**.



# Real life

- Default MMG-SEM works for **continuous** indicators.
- In real life, the items are (always) **ordinal**.
- Ignoring ordinality can cause **bias!**



## When Can Categorical Variables Be Treated as Continuous? A Comparison of Robust Continuous and Categorical SEM Estimation Methods Under Suboptimal Conditions

Mijke Rhemtulla  
University of Kansas

Patricia É. Brosseau-Liard and Victoria Savalei  
University of British Columbia

A simulation study compared the performance of robust normal theory maximum likelihood (ML) and robust categorical least squares (cat-LS) methodology for estimating confirmatory factor analysis models with ordinal variables. Data were generated from 2 models with 2–7 categories, 4 sample sizes, 2 latent distributions, and 5 patterns of category thresholds. Results revealed that factor loadings and robust standard errors were generally most accurately estimated using cat-LS, especially with fewer than 5 categories; however, factor correlations and model fit were assessed equally well with ML. Cat-LS was found to be more sensitive to sample size and to violations of the assumption of normality of the underlying continuous variables. Normal theory ML was found to be more sensitive to asymmetric category thresholds and was especially biased when estimating large factor loadings. Accordingly, we recommend cat-LS for data sets containing variables with fewer than 5 categories and ML when there are 5 or more categories, sample size is small, and category thresholds are approximately symmetric. With 6–7 categories, results were similar across methods for many conditions; in these cases, either method is acceptable.

**Keywords:** categorical indicators, confirmatory factor analysis, maximum likelihood, categorical least-squares, robust statistics

*Supplemental materials:* <http://dx.doi.org/10.1037/a0029315.supp>

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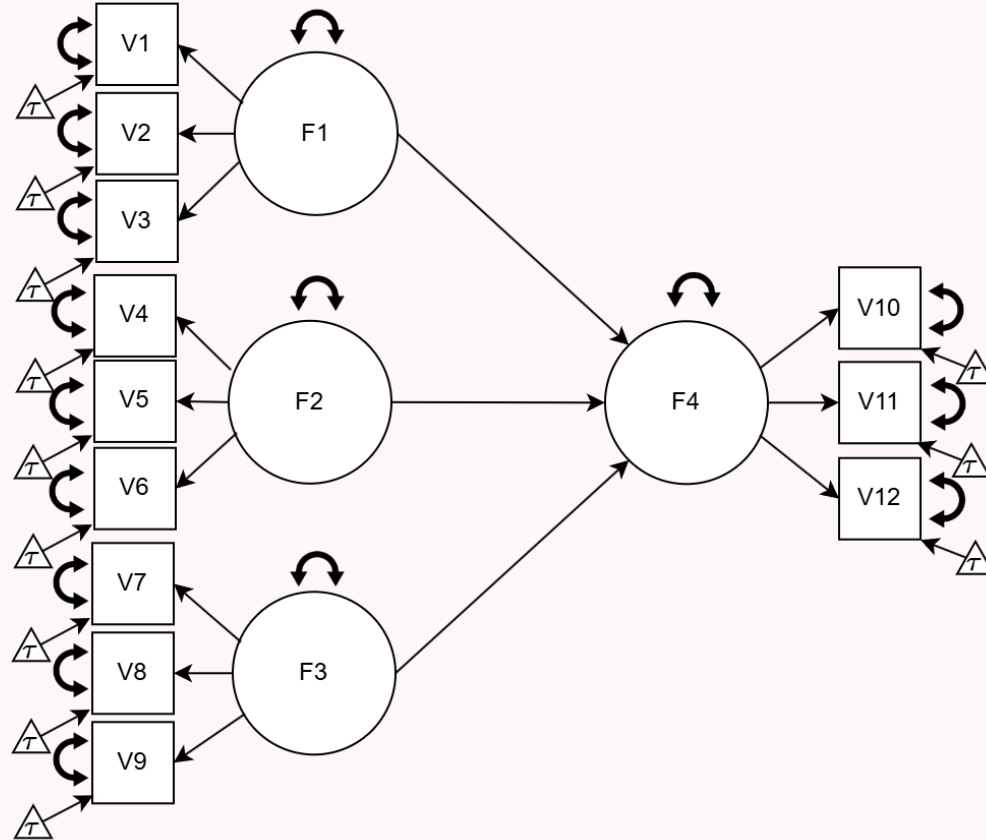
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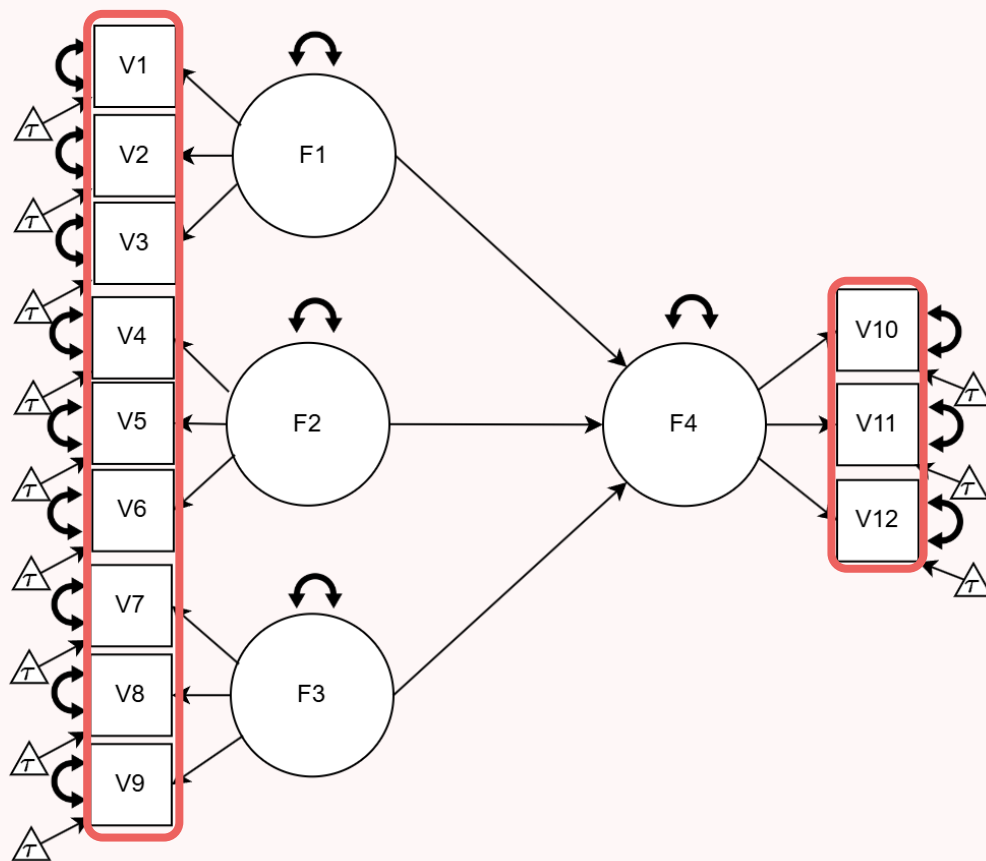
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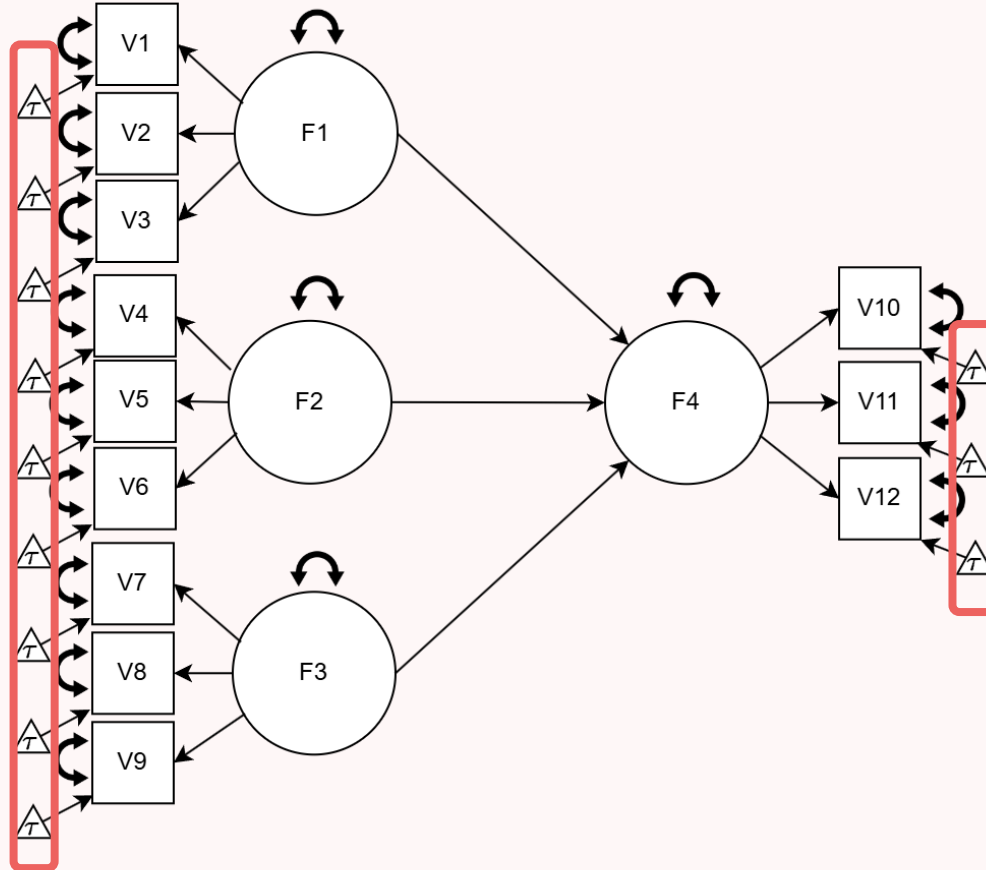
$$V_g = \tau_g + \Lambda_g \eta_g + \epsilon_g$$



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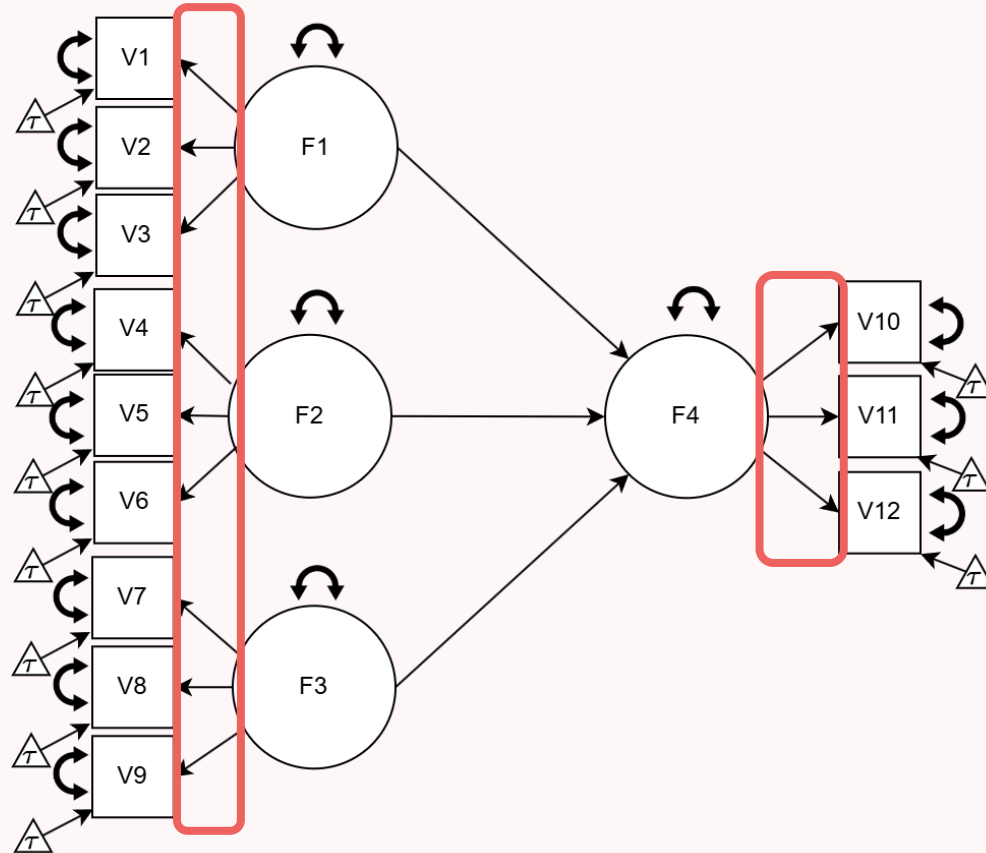


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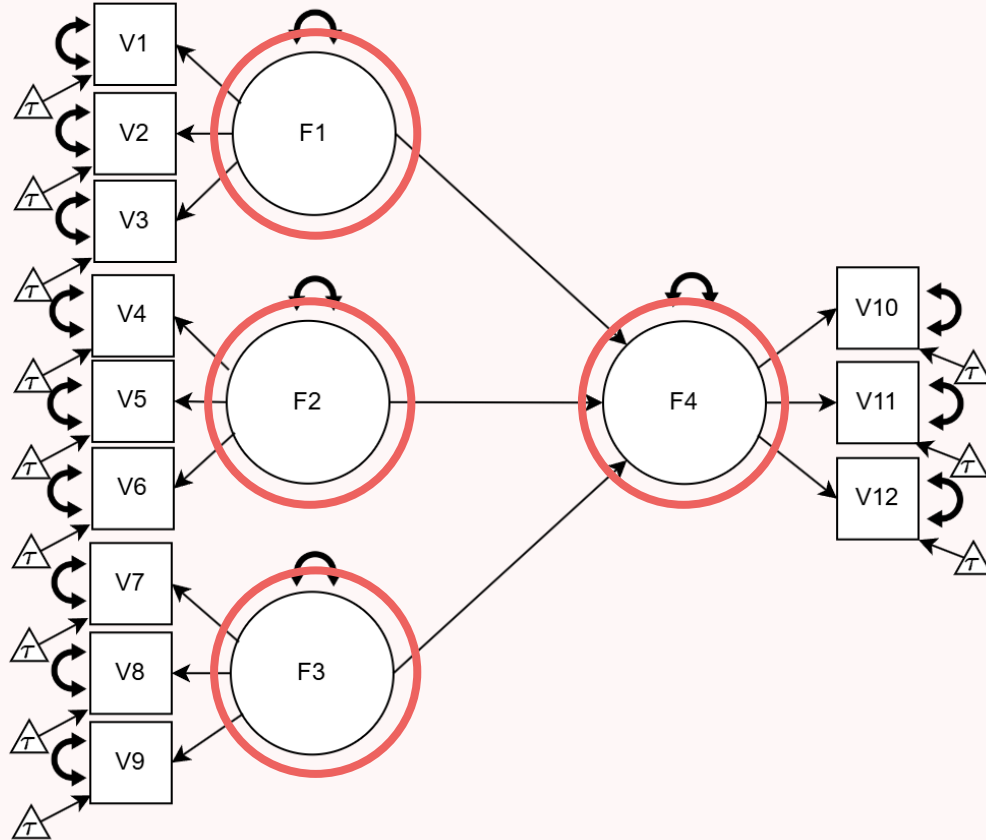




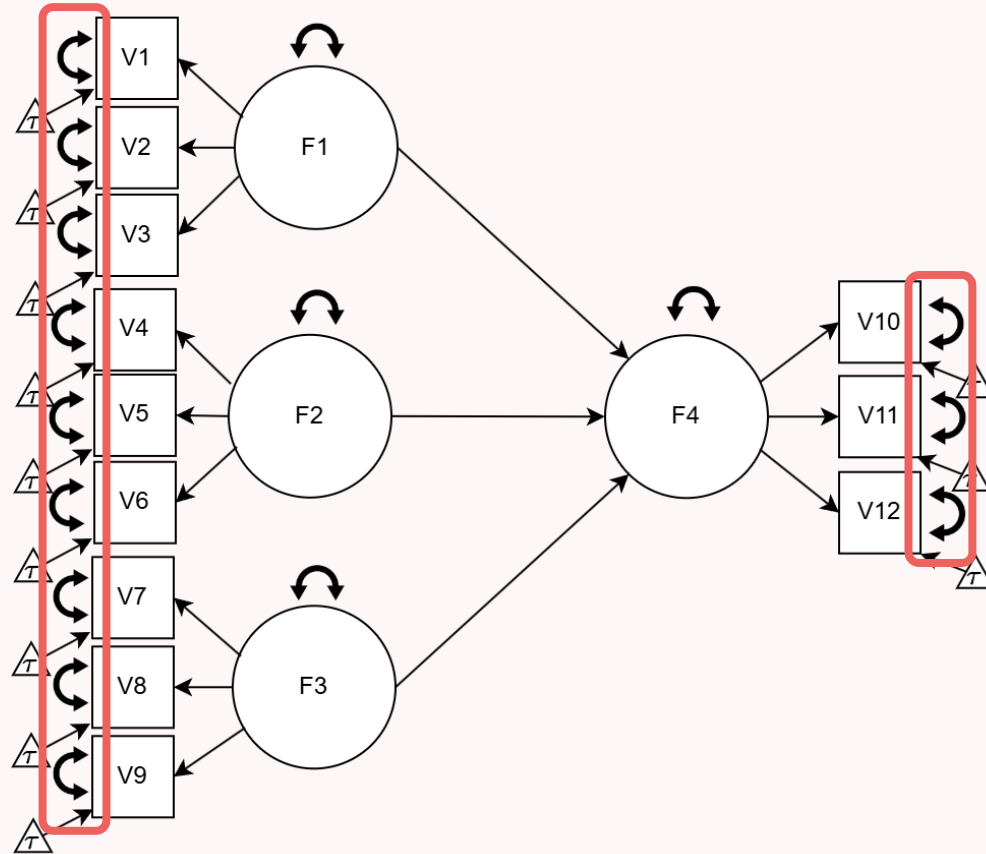
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$$V_{j,g}^* = c \quad \text{if} \quad \alpha_{j,c} < V_{j,g} < \alpha_{j,c+1} \quad c = 1, 2, \dots, C$$

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**Thresholds!**

# How do we compute thresholds?

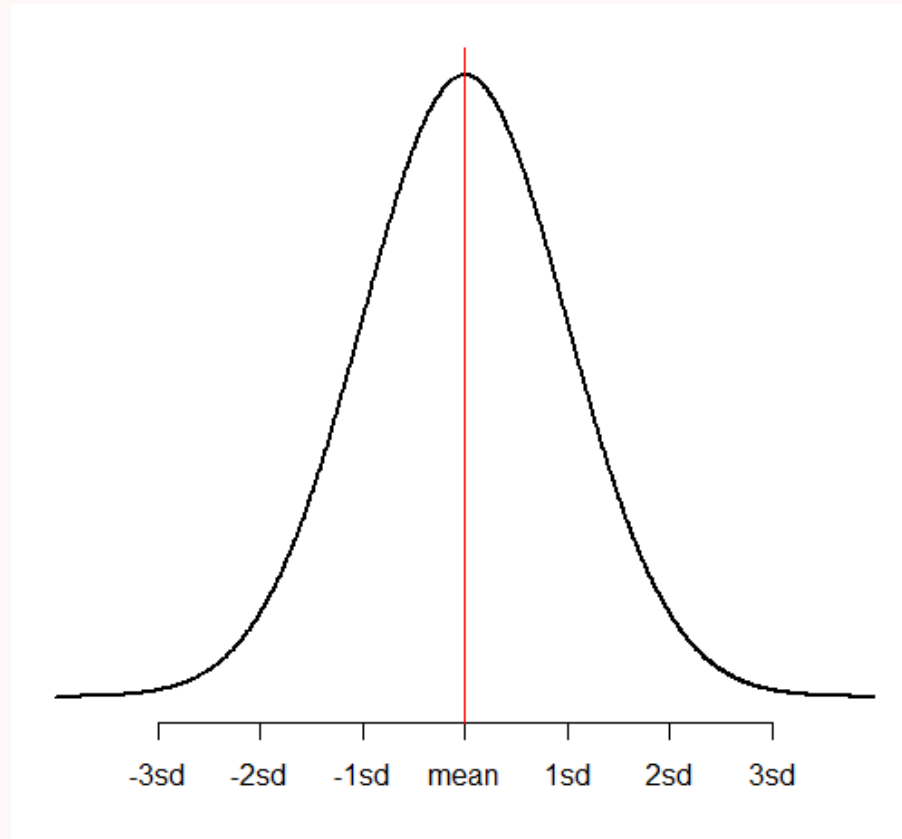
# How do we compute thresholds?

- The thresholds represent the proportion of people in each category.

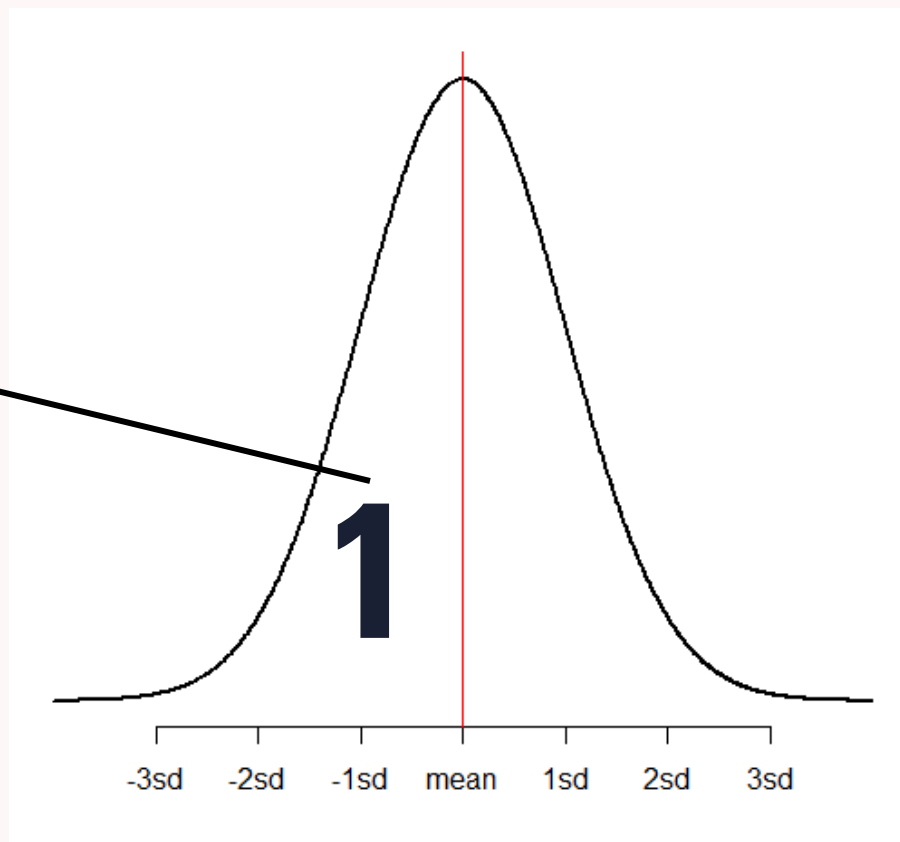


# How do we compute thresholds?

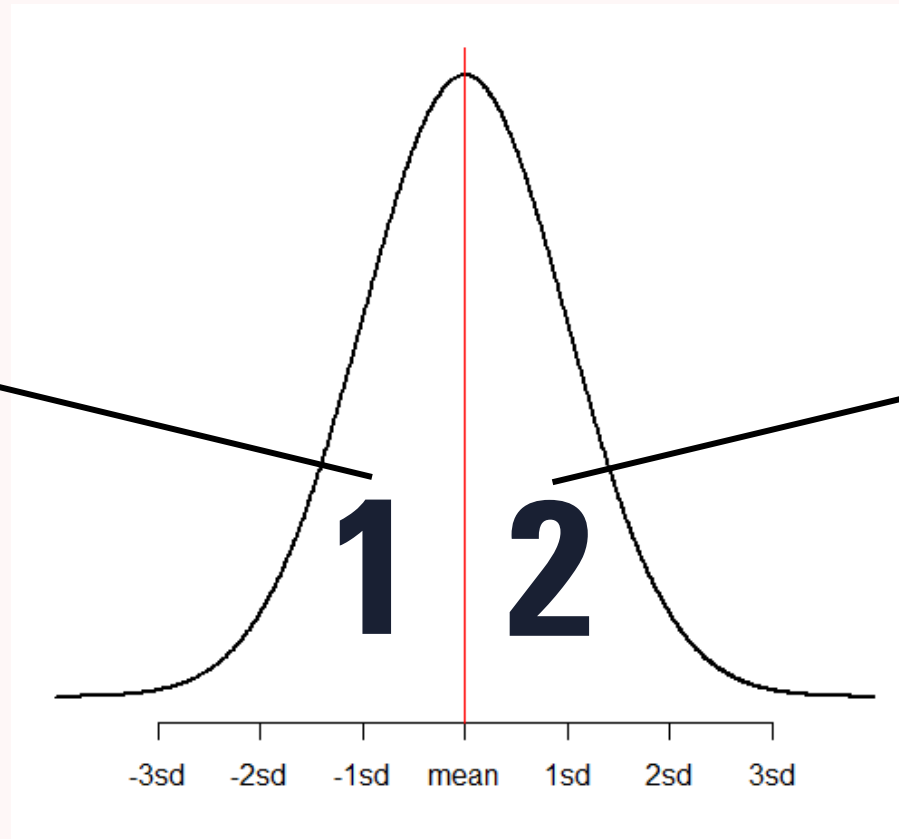
- The thresholds represent the proportion of people in each category.
- They are z-scores (we work with standardized latent scales).



50% answered 1

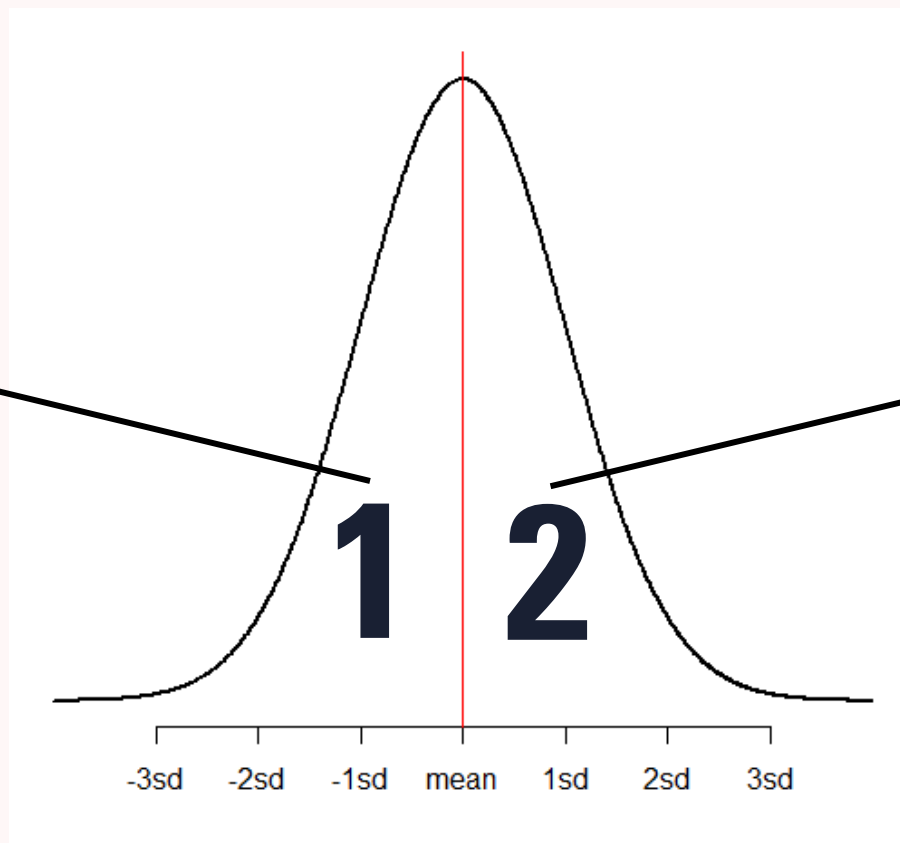


50% answered 1



50% answered 2

50% answered 1



50% answered 2

**Threshold is 0**

# Now, in MMG-SEM?

Challenges

# Ordinal estimation

# Ordinal estimation

- MMG-SEM also uses Maximum Likelihood for the clustering!



# Ordinal estimation

- MMG-SEM also uses Maximum Likelihood for the clustering!
- Multigroup **Categorical** Confirmatory Factor Analysis (MG-CCFA).
  - Instead of MG-CFA.

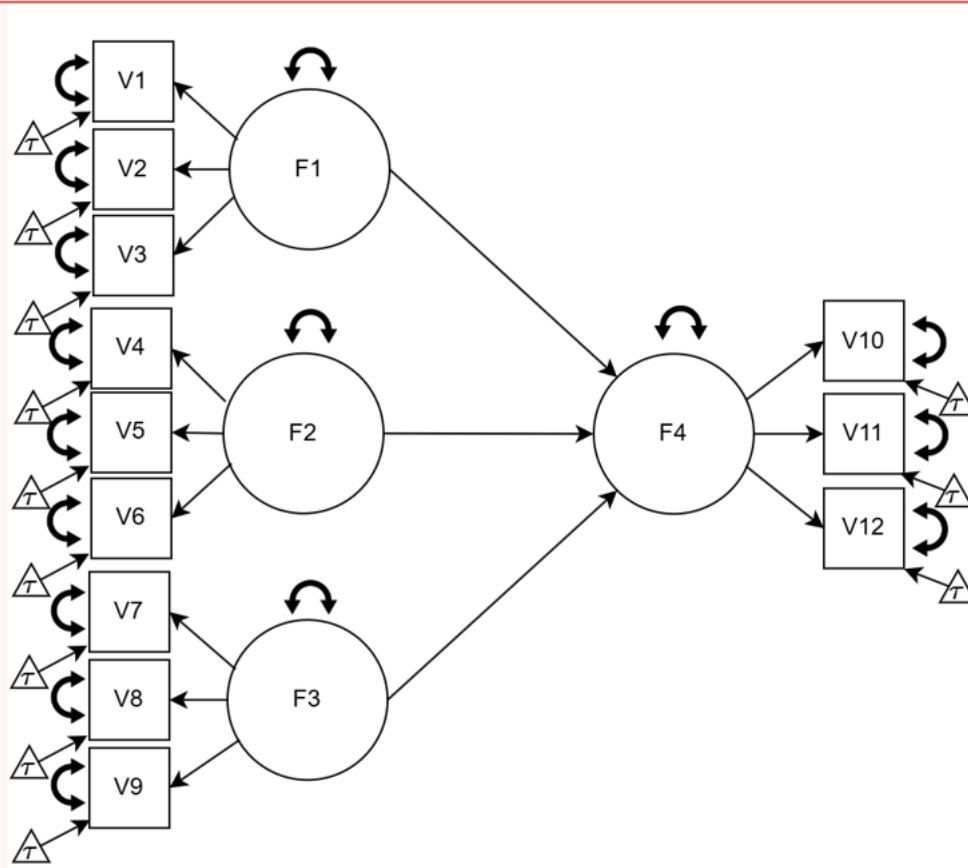
# Ordinal estimation

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  - Instead of MG-CFA.
- Least Squares (LS) estimation.
  - Instead of ML.

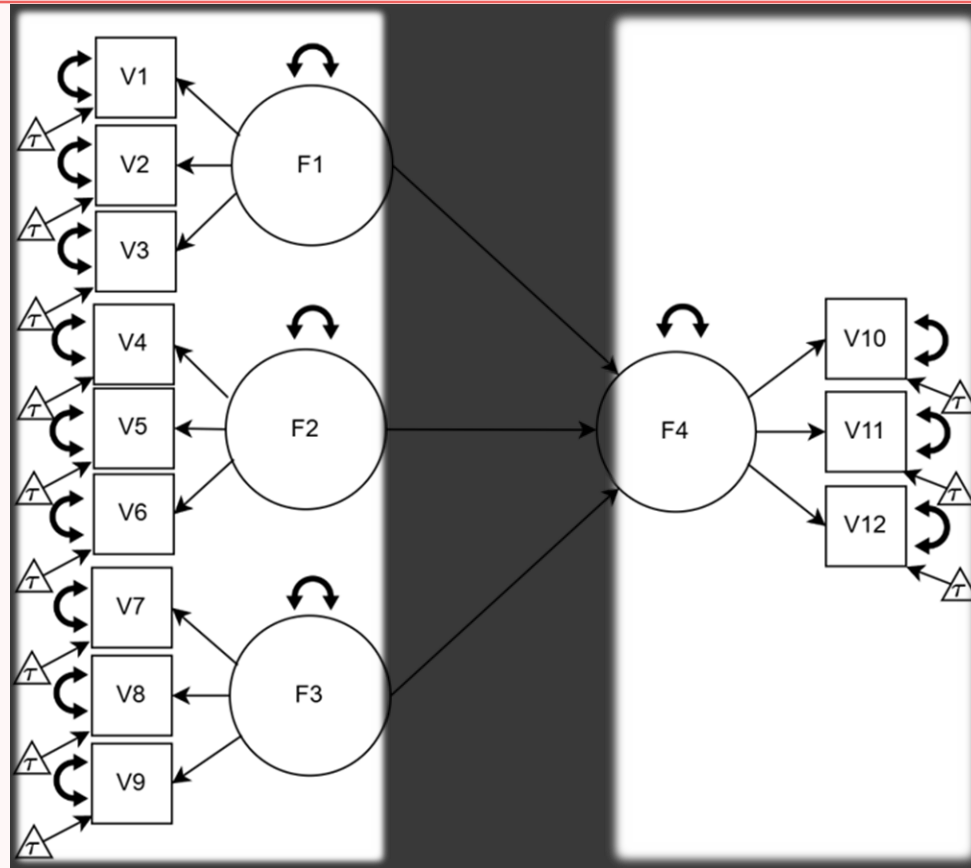
# Ordinal estimation

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- Multigroup **Categorical** Confirmatory Factor Analysis (MG-CCFA).
  - Instead of MG-CFA.
- Least Squares (LS) estimation.
  - Instead of ML.
- **How can we use LS (for MG-CCFA) and ML (for the clustering)?**

# The perks of stepwise estimation

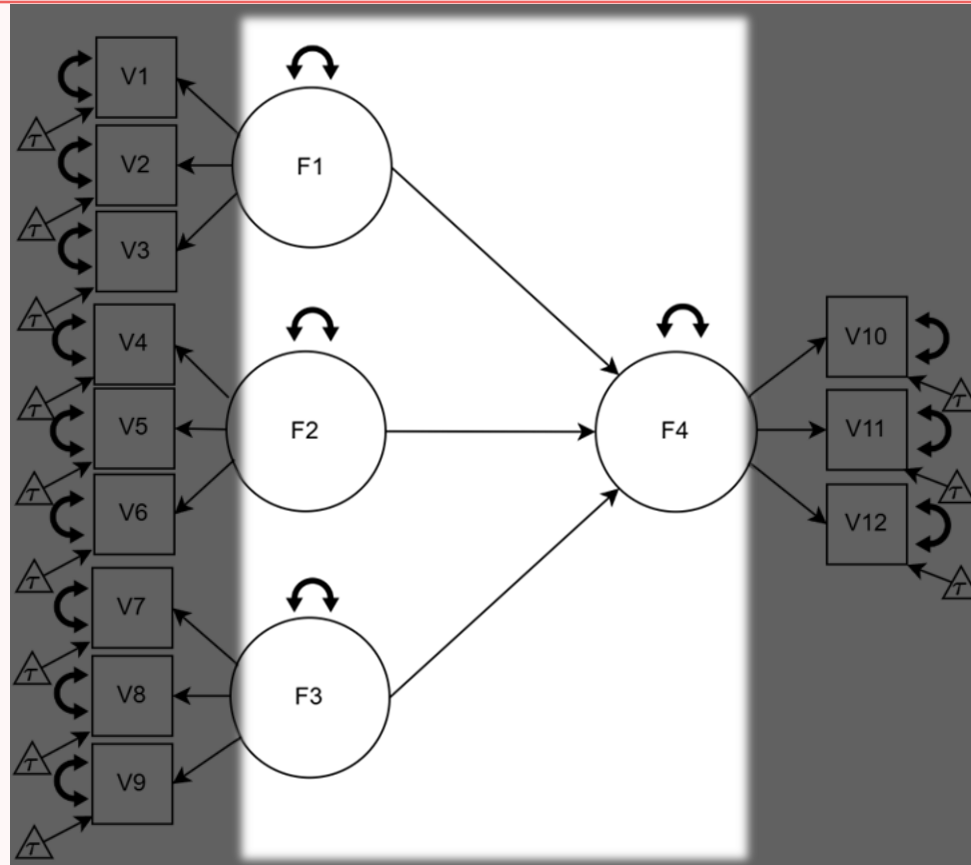


# The perks of stepwise estimation



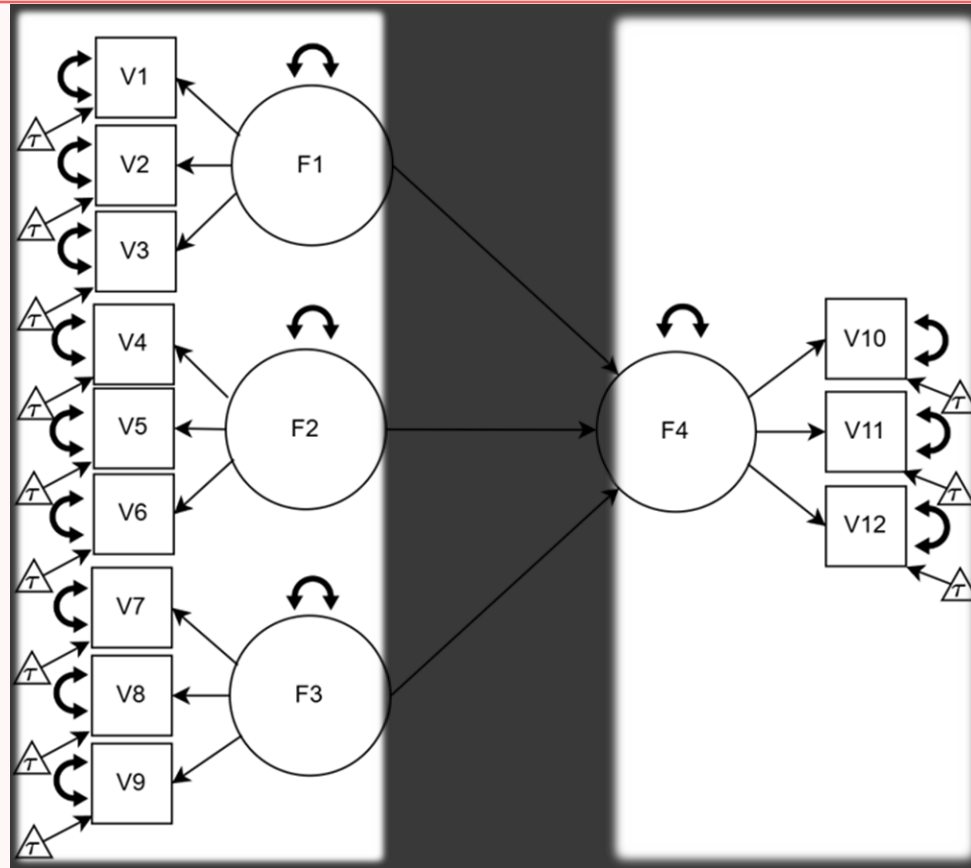
**Measurement model**

# The perks of stepwise estimation



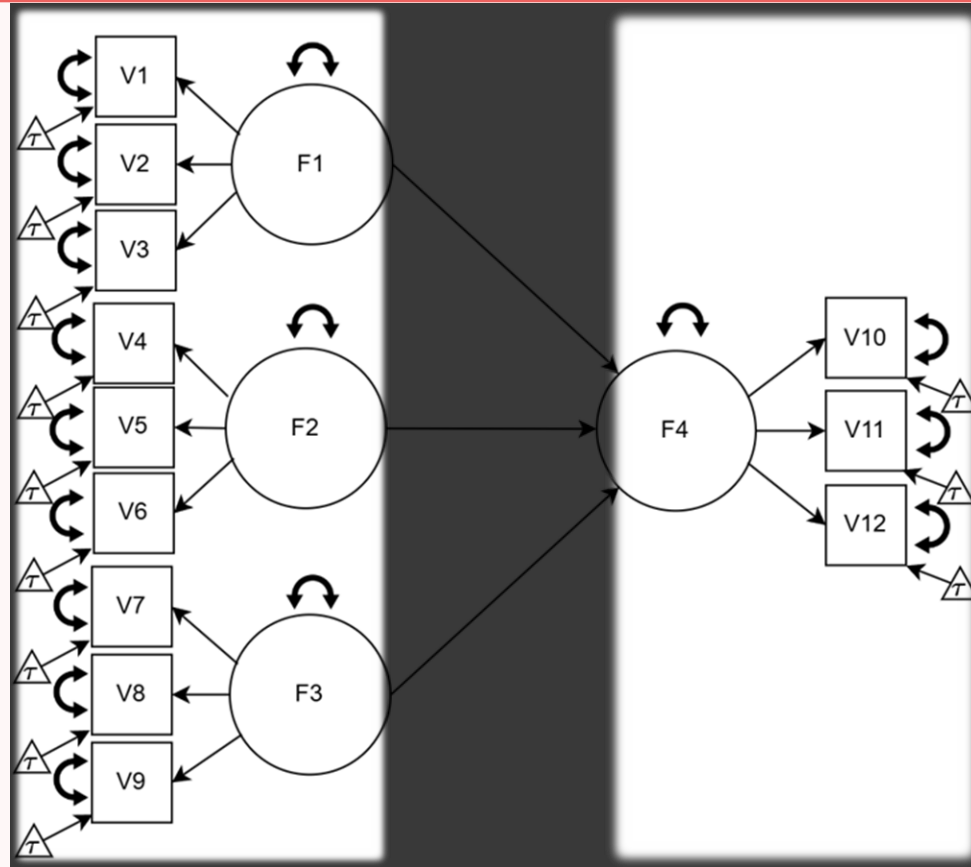
Structural model

# The perks of stepwise estimation



**Measurement model**

# The perks of stepwise estimation

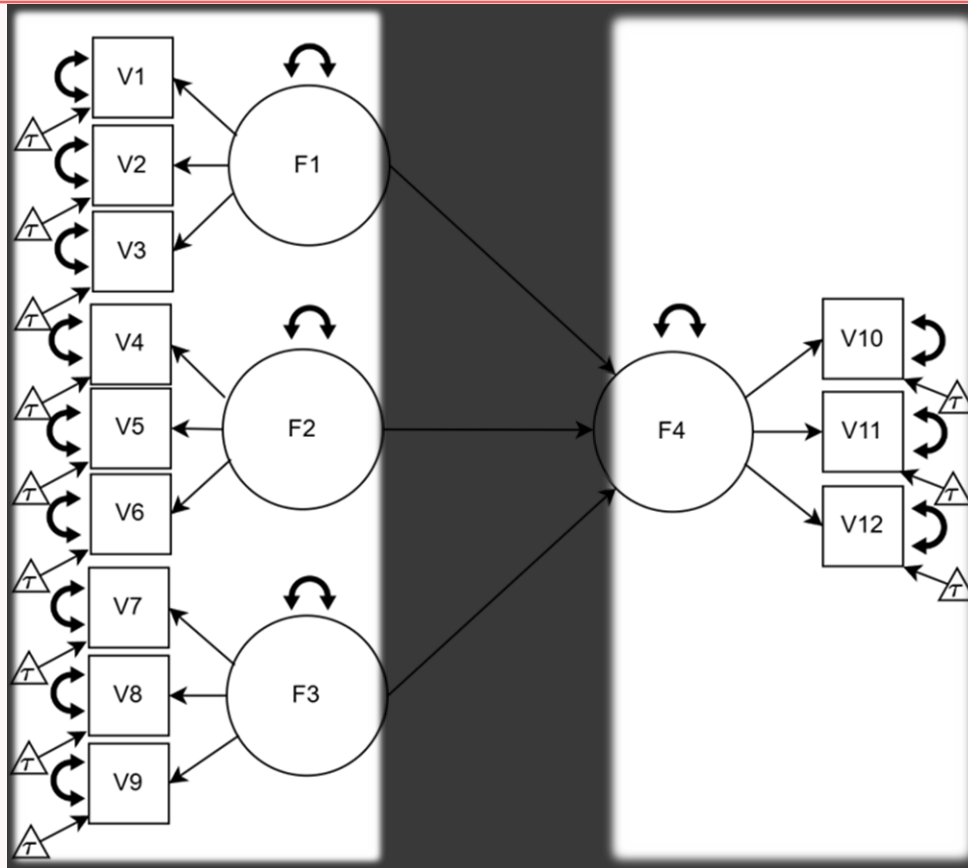


## Measurement model

Ordinal variables are important here!



# The perks of stepwise estimation

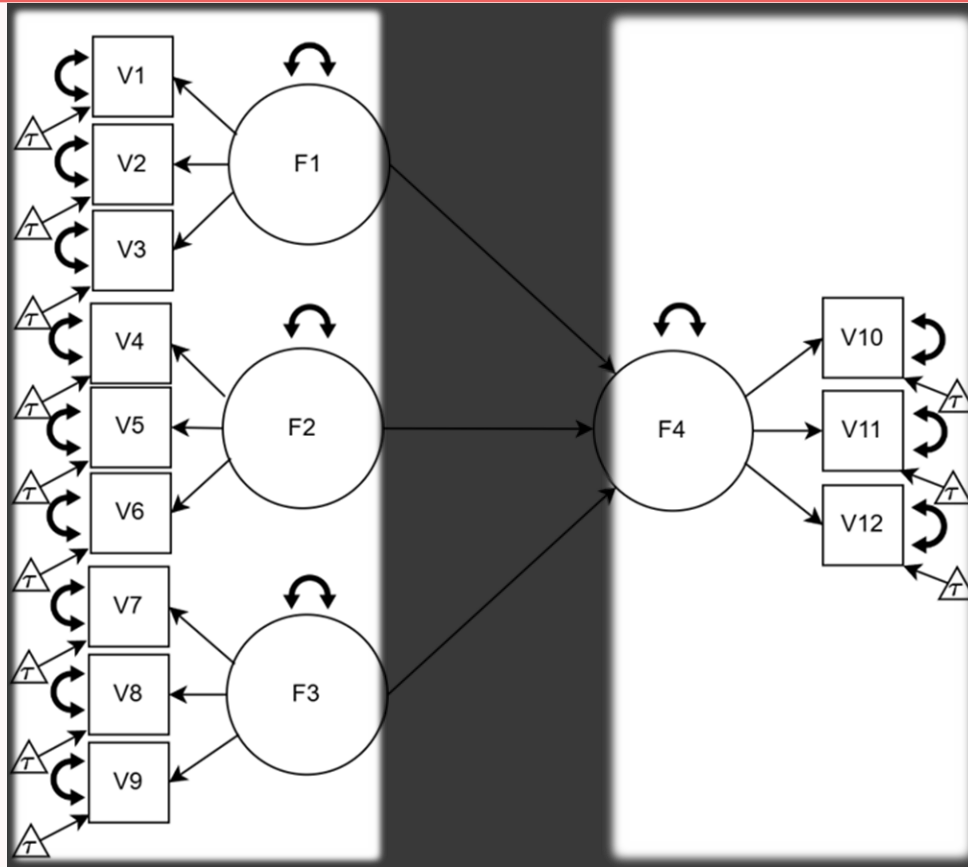


## Measurement model

Ordinal variables are important here!

MG-CFA → MG-CCFA

# The perks of stepwise estimation



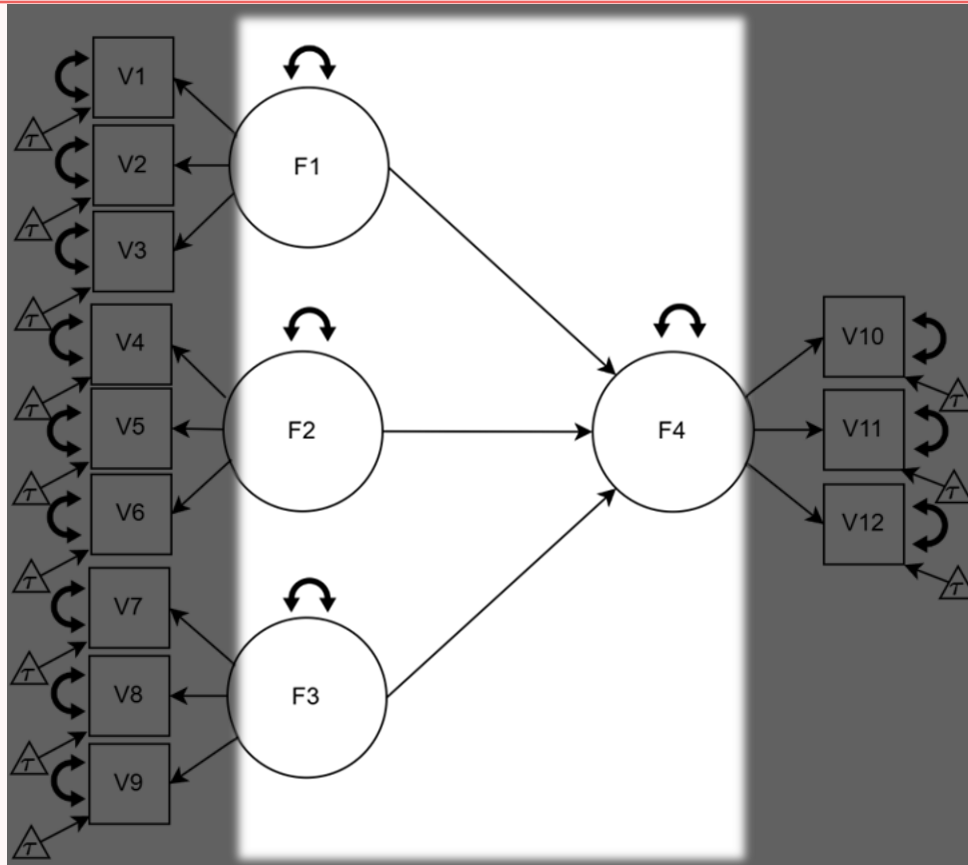
## Measurement model

Ordinal variables are important here!

MG-CFA → MG-CCFA

LS estimation here!

# The perks of stepwise estimation



**Structural model**

ML estimation here!

# Does this actually matter?

Some expectations and results

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## 2-4 categories

coverage for factor loadings. Consistent with previous studies, however, ML produced unbiased estimates of the factor correlation. These results suggest that it is the measurement model parameters that are most affected by wrongly assuming that a linear model describes the relations between categorical variables and latent factors. The structural model parameters (in this case, factor correlations) are not affected, and if the structural parameters are of greatest interest, robust ML can be an acceptable choice even with two- to four-category data and is in fact preferred when the sample size is small. While cat-LS was largely superior to ML with

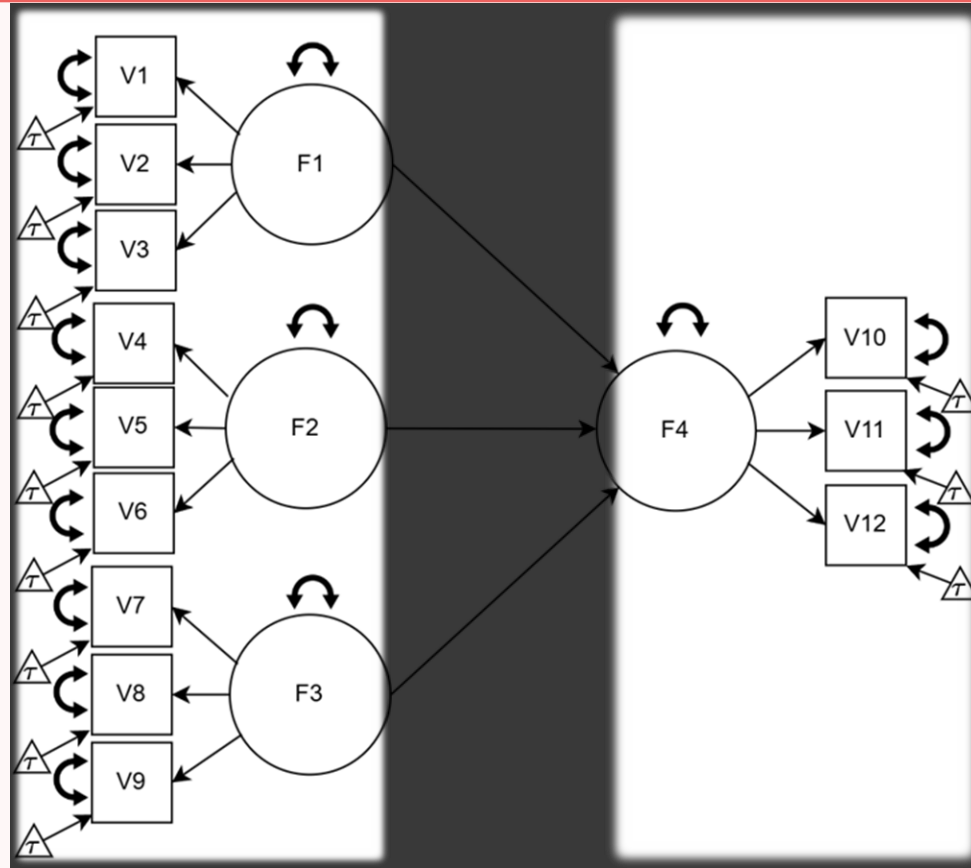
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## 5-7 categories

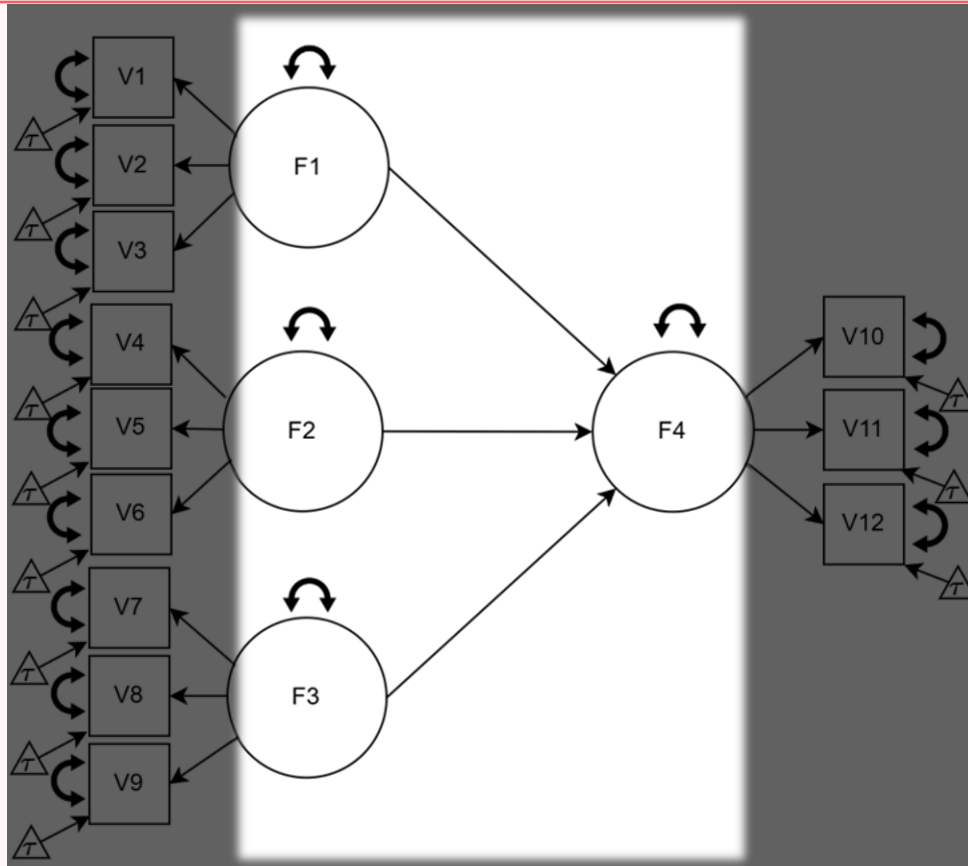
the greater the bias in ML estimates. As with two to four categories, ML estimates of the structural model parameters (in this case, the correlation between two factors) were extremely accurate, producing marginally better estimates than cat-LS.

# The perks of stepwise estimation



**Bias here!**

# The perks of stepwise estimation



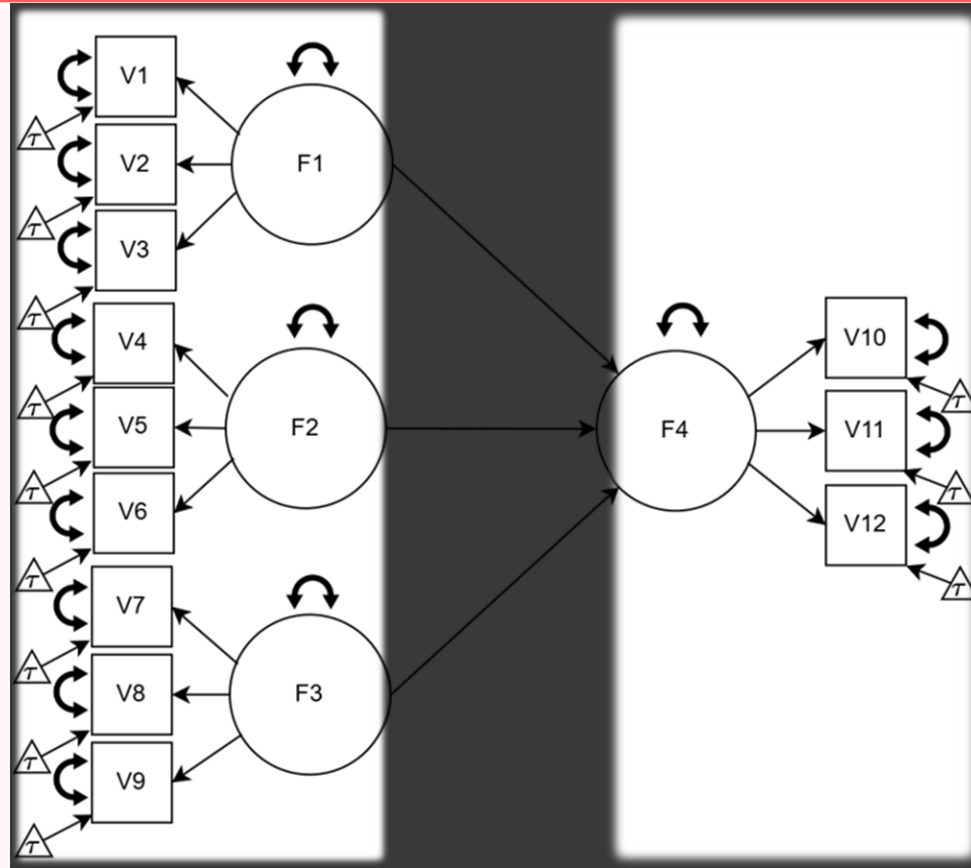
Often okay

# Simulation?

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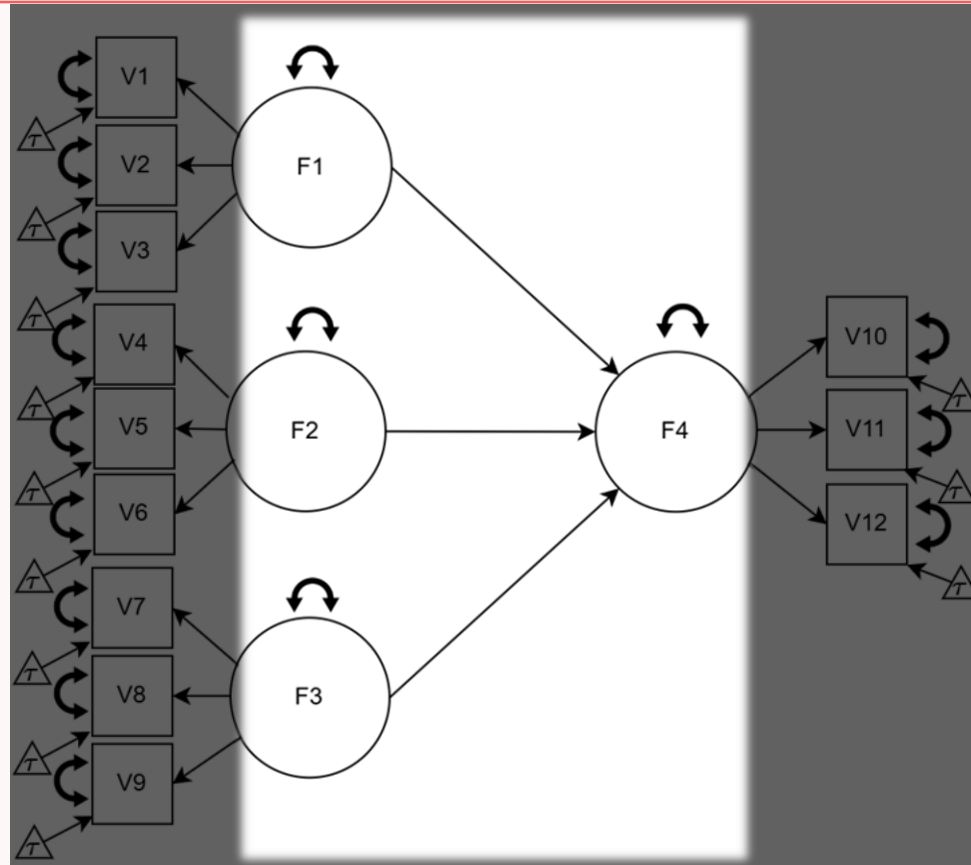
- We basically found the same 😊

# The perks of stepwise estimation



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# The perks of stepwise estimation



## Often okay



# Why do it?

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- If the measurement model is biased, measurement invariance (MI) is difficult to test.
- MI is necessary for valid comparisons of the regressions!

# Thanks!