Using a Scale-Adjusted Latent Class Model to Establish Measurement Equivalence in Cross-Cultural Surveys:

An Application with the Myers-Briggs Personality Type Indicator (MBTI)

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Outline

- Introduction to Myers-Briggs Type Indicator (MBTI)

- New Factor Model for Continuous Indicators that Allows for Scale Heterogeneity

- Discuss Issue of Measurement Equivalence

*Acknowledgment: I wish to thank Consulting Psychologists Press for making the MBTI data available to me for this presentation.

Myers-Briggs Type Indicator (MBTI)

4 dichotomous personality factors:

- Extraversion (E) or Introversion (I)
- Sensing (S) or Intuition (N)
- Thinking (T) or Feeling (F)
- Judging (J) or Perceiving (P)

Based on Carl Jung's Theory of Psychological Types (1922) and Isabel Myers and Katherine Briggs theories of Psychological Preferences (1926, 1928, 1944)

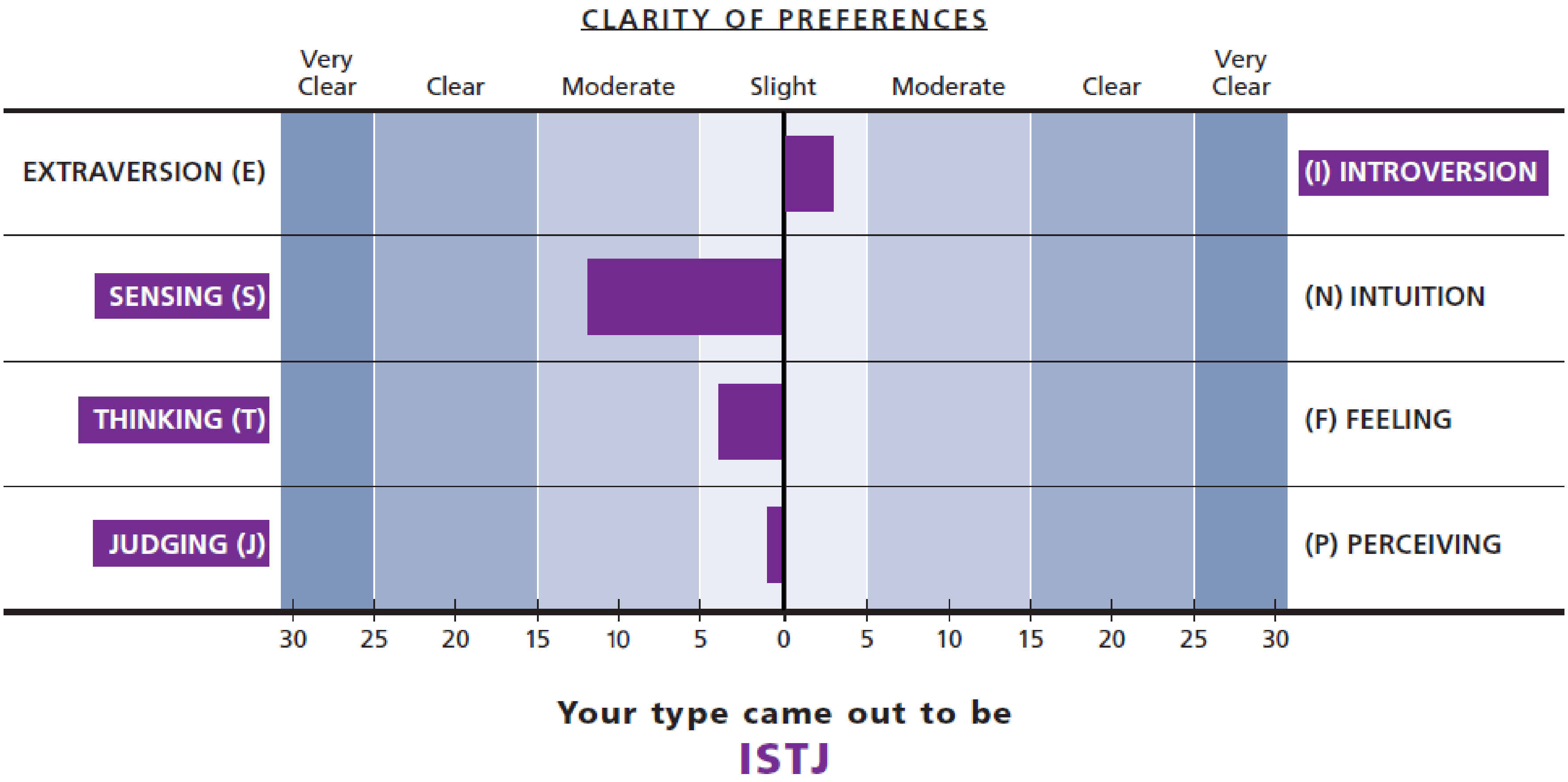
Preference Theory Analogy

Right vs. Left Handed

- Can use either hand but right-handed persons ‘prefer’ to use right hand

- Similarly, one might ‘prefer’ Extraversion to Introversion or vice versa, or prefer Thinking to Feeling, etc.

MBTI Theory also Allows for Differential Preference Clarity



Reproduced from MYERS-BRIGGS TYPE INDICATOR: MBTI® Step II Interpretive Report by Naomi L. Quenk and Jean M Kummerow (2002).

Measurement Equivalence

- For cross-cultural surveys it is unrealistic to believe that everyone responds with same level of clarity.

- Goal is to achieve measurement equivalence across different cultures in latent variables representing the 4 dichotomous personality dimensions, by allowing for latent clarity classes – similar to allowing heterogeneous error variances.

- New 2015 version of MBTI
  – administered in 20 countries, 17 languages
  – latent class models with latent scale (clarity) classes used to model latent dichotomies with ***dichotomous*** items

- Here, we introduce a new model appropriate for ***continuous*** variables

MBTI Facets

MBTI supplemented by 20 continuous *facets*
(5 for each *dichotomy*)

For example, Extraversion–Introversion (E–I):

- Initiating–Receiving
- Expressive–Contained
- Gregarious–Intimate
- Active–Reflective
- Enthusiastic–Quiet

New Bilinear Latent Profile Model

$$Y_1 = \alpha + c_s \lambda F^{EI} + \varepsilon$$

c_s = clarity parameter for clarity class s

$$F^{EI} = \begin{cases} 1 \; for \; \boldsymbol{E}xtrovert \\ -1 \; for \; \boldsymbol{I}ntravert \end{cases}$$

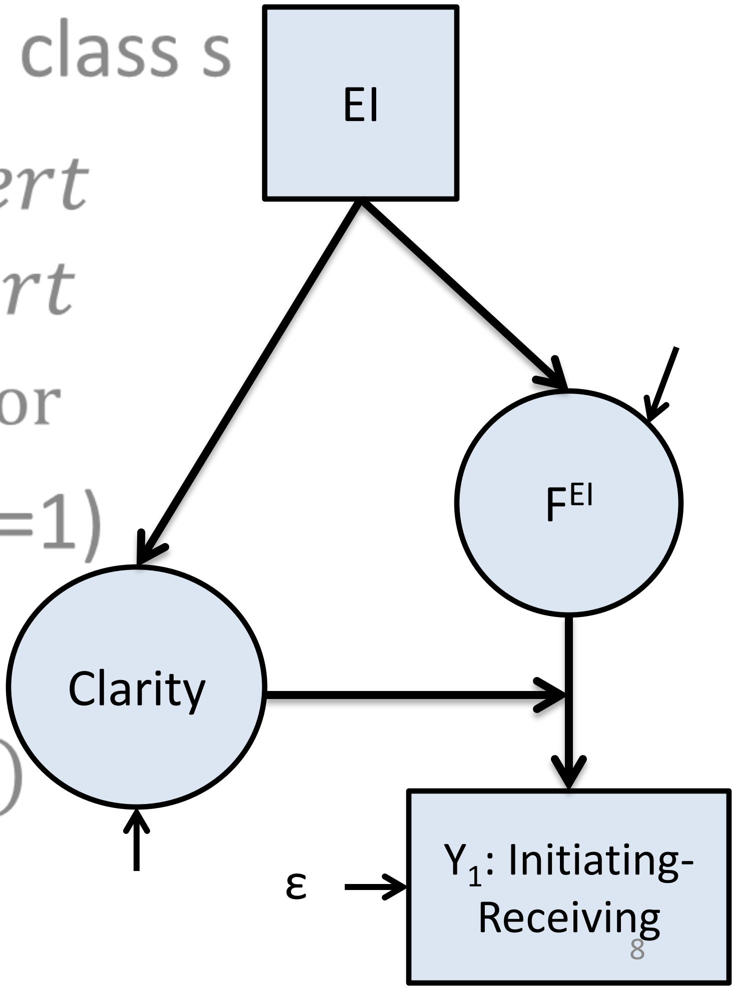
dichotomous latent factor

$\hat{\lambda}$ = -.21 (unstdized loading for s=1)

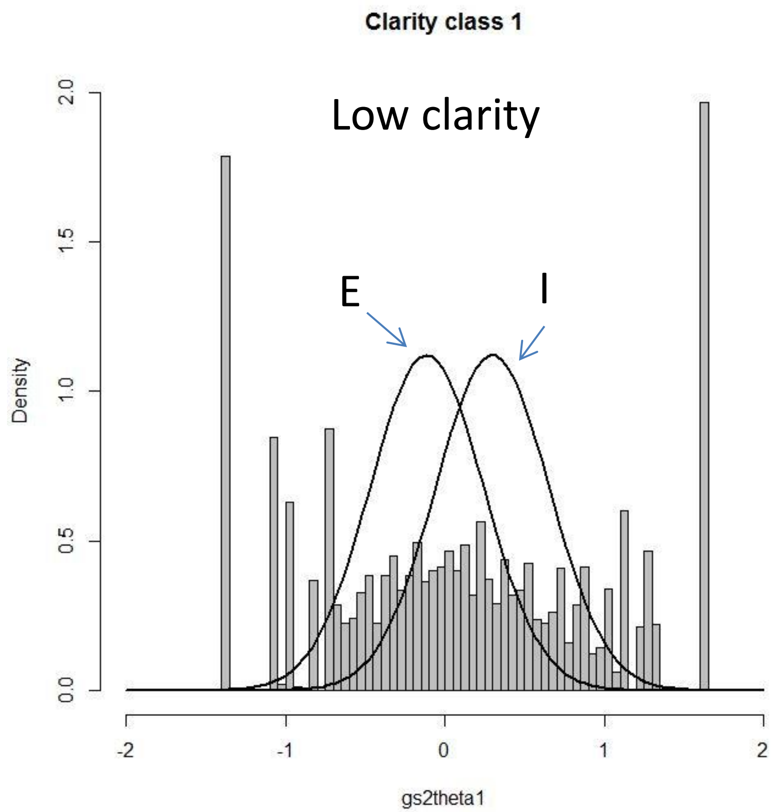
c_1 = 1 (for identification)

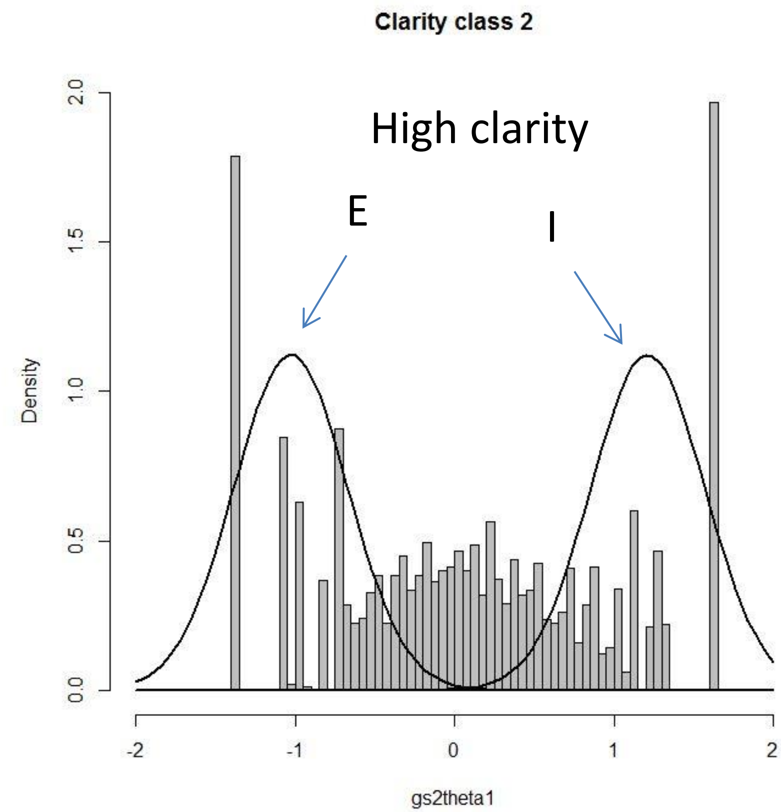
c_2= 5.44 (estimate: high clarity)

$\hat{\sigma}^2_{\varepsilon}$ = .13



Higher Clarity Yields More Extreme Bimodality





$\hat{\sigma}^2{}_{\varepsilon} = .13$

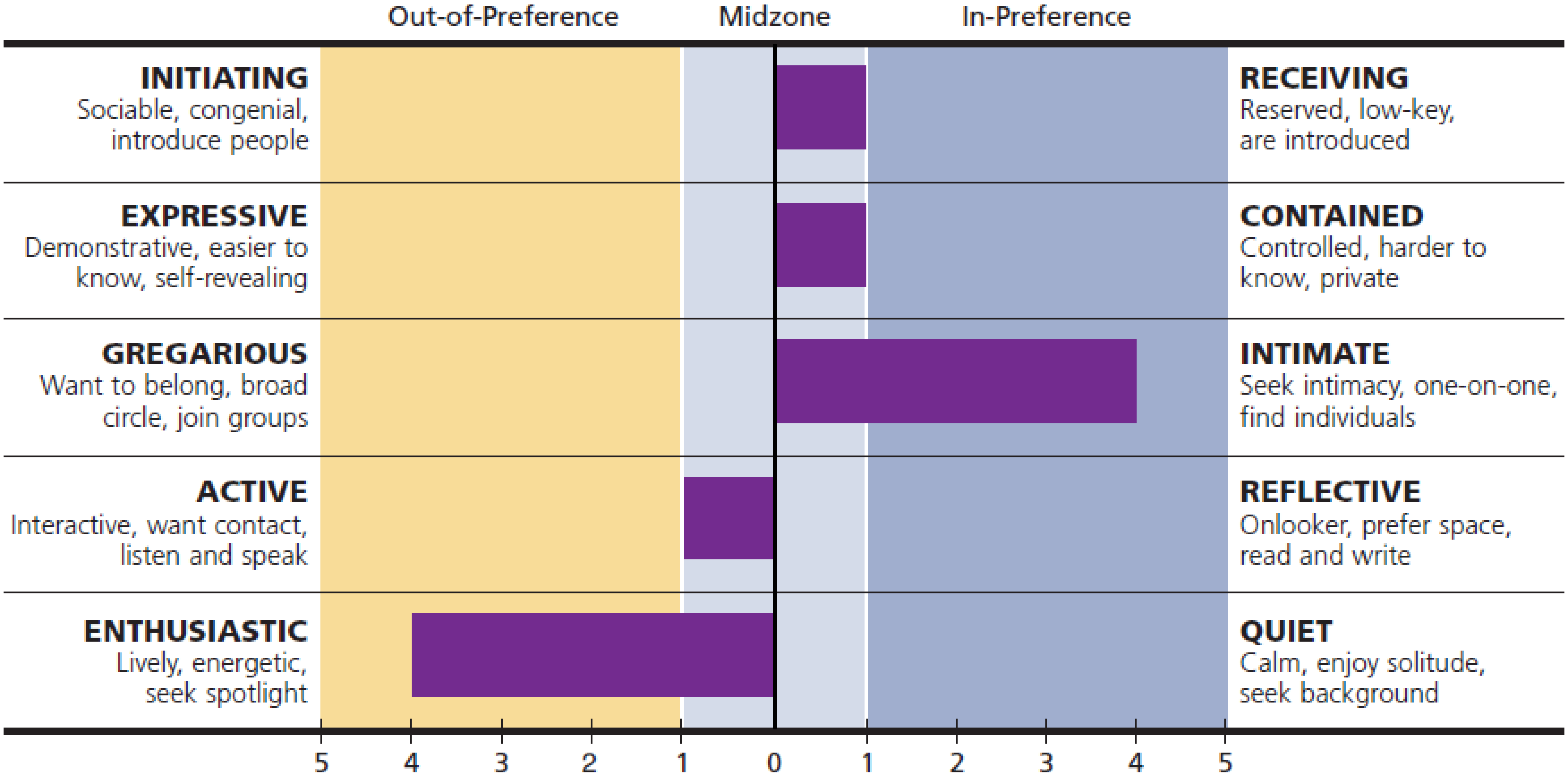
Results with 2 Clarity Classes

s	size	c	E(Y|F=E)	E(Y|F=I)
1	0.49	1	0.30	-0.11
2	0.51	5.44	1.21	-1.03

$\alpha =$ cutpoint for E vs. I: $\hat{\alpha} = .09$

Y1 > .09 classified as I on this facet, otherwise E
Can be used with EI classification to see whether in-preference or out-of-preference (OOPS) on this facet.

Example of an "OOPs": "Enthusiastic Introvert"



Analogy: Although I am right handed, I prefer to bat lefty when playing baseball.

Previous Step II Results (EI Facets Shown)

Table 26 Factor Analysis Rotated Component Matrix

Step II™ Facet Scale	Factor 1 (S–N)	Factor 2 (E–I)	Factor 3 (J–P)	Factor 4 (T–F)
E–I Facet Scales				
Initiating–Receiving	–.10	.85	.02	.00
Expressive–Contained	–.03	.78	–.03	–.14
Gregarious–Intimate	.00	.83	–.03	.01
Active–Reflective	.02	.86	–.04	–.01
Enthusiastic–Quiet	–.12	.86	–.05	–.01

Since the theoretical latent constructs are dichotomous, Latent Profile analysis is more appropriate than Factor analysis.

Schabut and Thompson (2011) MBTI Step II Manual Supplement

Bilinear Confirmatory 4-Factor Model

$Y_j = \alpha_j + c_s\lambda_j F^{EI} + \varepsilon$ j = 1 - 5

$Y_j = \alpha_j + c_s\lambda_j F^{SN} + \varepsilon$ j = 6-10

$Y_j = \alpha_j + c_s\lambda_j F^{TF} + \varepsilon$ j = 11-15

$Y_j = \alpha_j + c_s\lambda_j F^{JP} + \varepsilon$ j = 16-20

F^{SN} and F^{JP} allowed to correlate (theory)

Factors are dichotomous – Model estimated with discrete (ordinal) factors (DFactors) using syntax module of Latent GOLD version 5.0. Here, all 4 DFactors are dichotomous.

*Magidson and Vermunt (2001) "Latent class factor and cluster models, bi-plots and related graphical displays" *Sociological Methodology*, 31, 223-264

Inclusion of Clarity Classes in Model Results in Successful Confirmatory Model

Model	LL	BIC(LL)	Npar
4dfac_EFA	-345546	692298	124
4dfac_CFA	-355975	712582	65
4dfac + 2 clarity classes	-344946	690543	67
4dfac + 3 clarity classes	-343047	686765	69
4dfac_EFA_covars	-317980	637204	128
4dfac_CFA_covars	-324179	649029	69
+ 2 clarity classes	-313361	627452	75
+ 3 clarity classes	-311600	623989	81

Without allowing heterogeneity in clarity, the confirmatory models fails to fit better than the corresponding exploratory models.

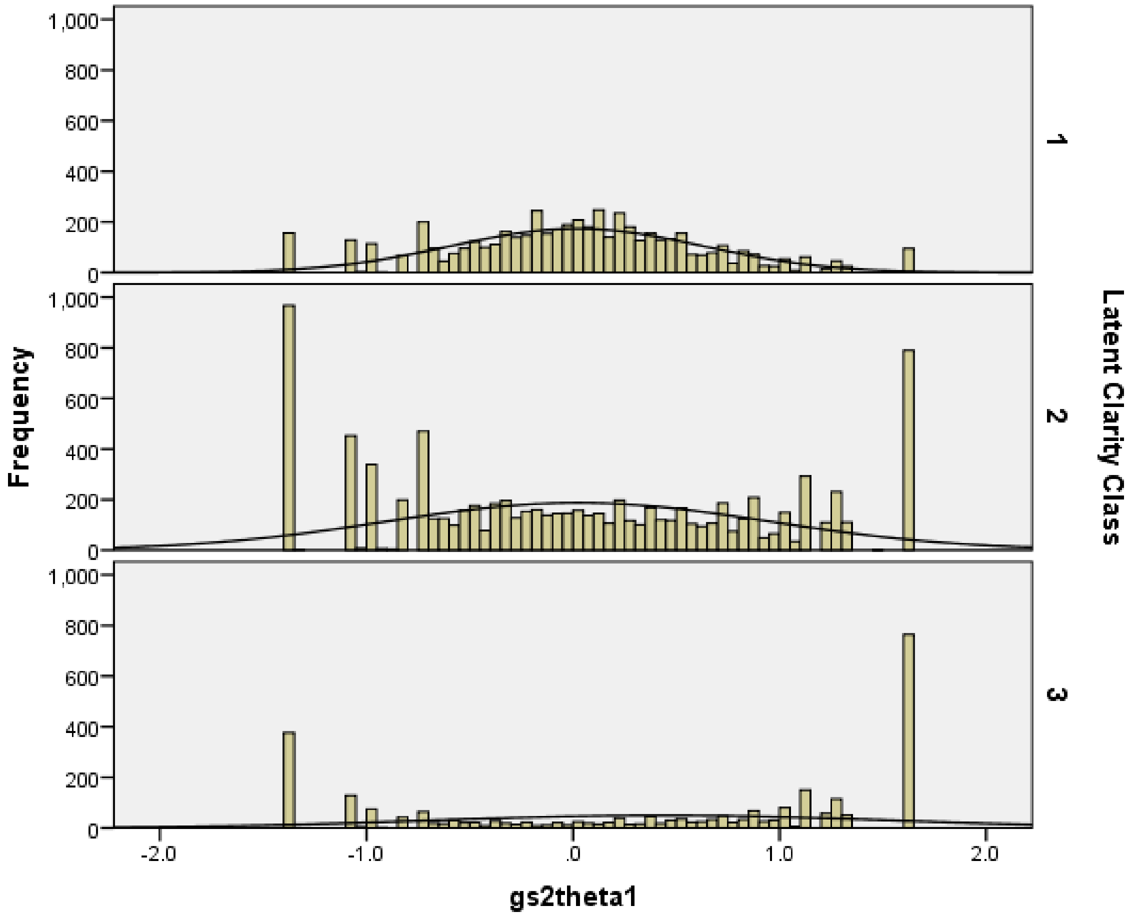
Standardized Loadings with 3-Clarity Classes

	Low Clarity Class				Middle Clarity Class				High Clarity Class			
	dfac1	dfac2	dfac3	dfac4	dfac1	dfac2	dfac3	dfac4	dfac1	dfac2	dfac3	dfac4
Y1	0.51	0.00	0.00	0.01	0.77	-0.01	0.00	0.01	0.88	-0.01	0.00	0.01
Y2	0.41	0.00	0.00	0.00	0.67	0.00	0.00	0.01	0.82	-0.01	0.00	0.01
Y3	0.39	0.00	0.00	0.00	0.65	0.00	0.00	0.01	0.80	-0.01	0.00	0.01
Y4	0.46	0.00	0.00	0.00	0.73	-0.01	0.00	0.01	0.86	-0.01	0.00	0.01
Y5	0.44	0.00	0.00	0.00	0.71	-0.01	0.00	0.01	0.85	-0.01	0.00	0.01
Y6	0.00	0.49	0.00	0.00	0.00	0.75	0.00	0.01	0.00	0.87	0.00	0.01
Y7	0.00	0.47	0.00	0.00	0.00	0.74	0.00	0.01	0.00	0.86	0.00	0.01
Y8	0.00	0.38	0.00	0.00	0.00	0.65	0.00	0.01	0.00	0.80	0.00	0.01
Y9	0.00	0.30	0.00	0.00	0.00	0.54	0.00	0.00	0.00	0.71	0.00	0.01
Y10	0.00	0.39	0.00	0.00	0.00	0.65	0.00	0.01	0.00	0.80	0.00	0.01
Y11	-0.01	-0.01	0.53	0.02	-0.01	-0.02	0.79	0.03	-0.01	-0.02	0.90	0.03
Y12	-0.01	-0.01	0.54	0.02	-0.01	-0.02	0.79	0.03	-0.01	-0.02	0.90	0.03
Y13	0.00	-0.01	0.33	0.01	-0.01	-0.02	0.59	0.02	-0.01	-0.02	0.75	0.03
Y14	0.00	-0.01	0.37	0.01	-0.01	-0.02	0.64	0.02	-0.01	-0.02	0.79	0.03
Y15	0.00	-0.01	0.45	0.02	-0.01	-0.02	0.72	0.03	-0.01	-0.02	0.85	0.03
Y16	-0.01	-0.04	0.00	0.53	-0.02	-0.06	0.00	0.83	-0.03	-0.07	0.00	0.97
Y17	-0.02	-0.04	0.00	0.56	-0.02	-0.06	0.00	0.86	-0.03	-0.07	0.00	0.99
Y18	-0.01	-0.03	0.00	0.34	-0.02	-0.05	0.00	0.62	-0.02	-0.06	0.00	0.81
Y19	-0.02	-0.05	0.00	0.65	-0.03	-0.07	0.00	0.93	-0.03	-0.08	0.00	1.00
Y20	-0.01	-0.03	0.00	0.35	-0.02	-0.05	0.00	0.63	-0.02	-0.06	0.00	0.82

32.4% lower clarity (s=1)
50.2% mid clarity (s=2)
17.4% higher clarity (s=3)

		E(Y1|F=E,I)	
s	c	E	I
1	1	-0.35	0.32
2	2.06	-0.71	0.67
3	3.25	-1.10	1.07

Facet Distributions Support Bimodality



Histograms show bimodality. On all 20 facets both tails are well above that predicted by the normal distribution for all 3 clarity classes. The higher the clarity, the more extreme the bimodal distribution.

These result supports Jung's theory of dichotomous personality factors.

Syntax Equations: Latent GOLD® 5.0

```
latent  // each dfactor is dichotomous with values -1 and +1, scale will have only 3 values
    dfactor1 ordinal 2 scores=(-1 1), dfactor2 ordinal 2 scores=(-1 1),
    dfactor3 ordinal 2 scores=(-1 1),  dfactor4 ordinal 2 scores=(-1 1),
    scale continuous,   sclass nominal 3 coding=first;  //sclass is dummy coded
equations
  DFactor1 <- 1 + EI.Conv.Cut ;
  DFactor2 <- 1 + SN.Conv.Adj.Cut;
  DFactor3 <- 1 + TF.Conv.Adj.Cut ;
  DFactor4 <- 1 + JP.Conv.Adj.Cut;
  sclass <- 1 + EI.Conv.Cut + TF.Conv.Adj.Cut + JP.Conv.Adj.Cut + SN.Conv.Adj.Cut ;

// next we set the variance of 'scale' to 0 and estimate it as '1 + a value for each sclass'
  (0) scale;
  scale <- (1) 1 + (+) sclass;   // since sclass is dummy coded, scale is set to '1' for sclass #1
  // '(+)' imposes order restriction so that 'scale' for sclasses 2 and 3 are not less than 1.
  gs2theta1 - gs2theta5     <- 1 + DFactor1 scale;
  gs2theta6 - gs2theta10   <- 1 + DFactor2 scale;
  gs2theta11 - gs2theta15 <- 1 + DFactor3 scale;
  gs2theta16 - gs2theta20 <- 1 + DFactor4 scale;
  gs2theta1 - gs2theta20;
  DFactor4 <-> DFactor2 ;
```

Summary

- A new model allows for proportional factor loadings in a confirmatory factor model to account for clarity differences among respondents.

- This model was illustrated with data used to develop the new 2015 version of the MBTI (which also allowed for differential clarity across respondents)

- Without accounting for heterogeneity in clarity the standard confirmatory model would be rejected and hence measurement equivalence would be suspect.

References

Magidson J. 2014 “Advantages of the latent class approach”, presented at the ATP Innovations in Testing Conference.

Vermunt, J.K. (2013). Categorical response data. In M.A. Scott, J.S. Simonoff, and B.D. Marx (Eds.), The SAGE handbook of multilevel modeling. Sage.

Vermunt, J.K., and Magidson, J. (2013). LG-Syntax User's Guide: Manual for Latent GOLD 5.0 Syntax Module. Belmont, MA: Statistical Innovations Inc.