Revisiting the factor structure of the French WISC-IV: Insights through Bayesian structural equation modeling (BSEM)*

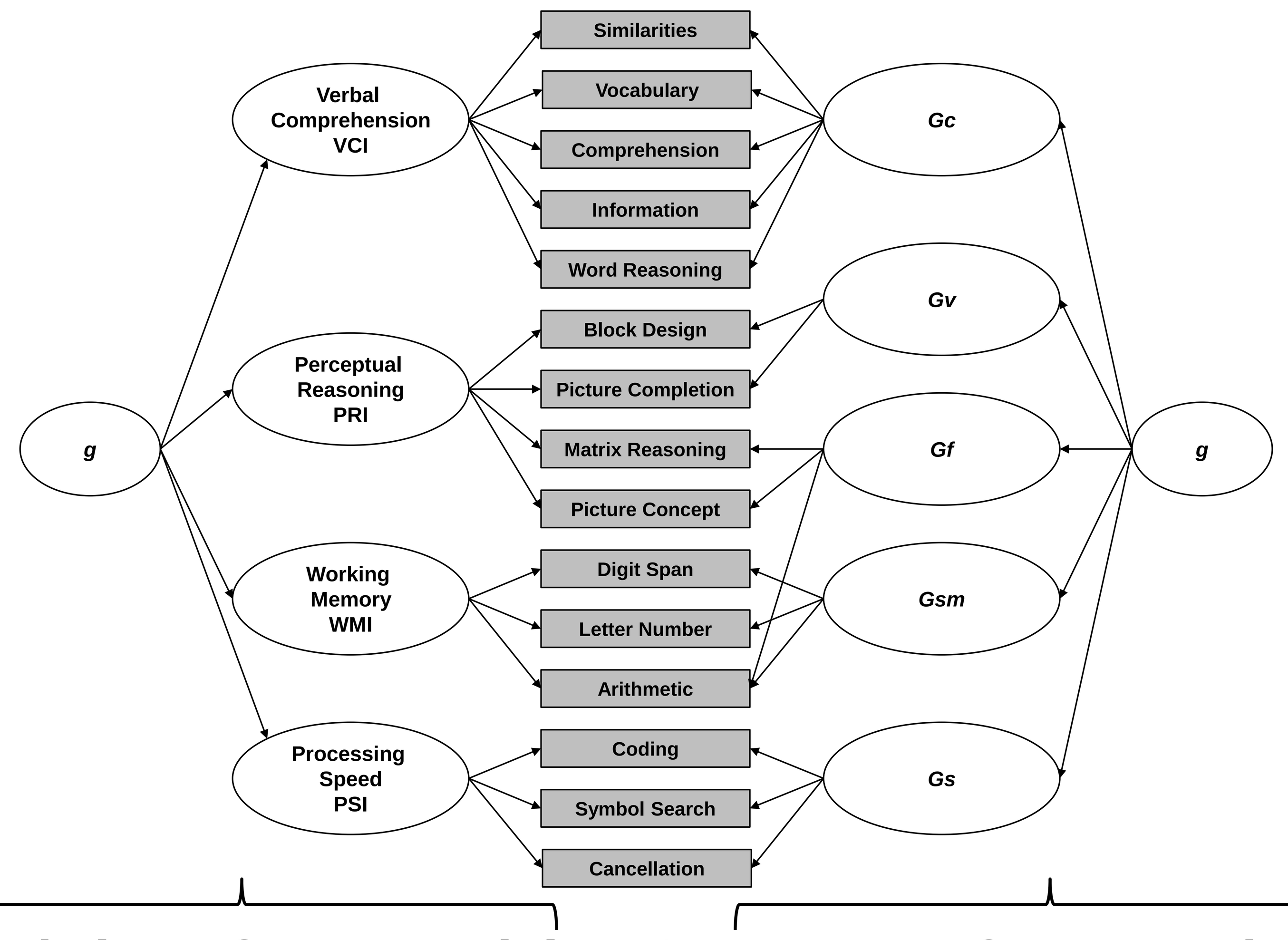
Philippe Golay[1,2], Isabelle Reverte[1], Jérôme Rossier[3], Nicolas Favez[1,2] & Thierry Lecerf[1,2]

[1]Faculty of Psychology and Educational Sciences, University of Geneva, [2]Distance Learning University, Switzerland, [3]Institute of Psychology, University of Lausanne

UNIVERSITÉ DE GENÈVE
FACULTÉ DE PSYCHOLOGIE ET DES SCIENCES DE L'ÉDUCATION

INTRODUCTION

• The Wechsler Intelligence Scale for children, 4th edition (WISC-IV) remains the most widely used test in the field of intelligence assessment.
• The interpretation of the WISC-IV is based on a 4-factor model which is only partially compatible with the mainstream Cattell-Horn-Carroll (CHC) model of intelligence measurement. Several confirmatory factor analytic studies (CFA) have shown that CHC-based models were more adequate than the 4-factors model.
• Some controversy also remains on the exact nature of constructs measured by each subtest (e.g. what does *Arithmetic* measure ?).



Wechsler 4 factor model **VS** ***CHC 5 factor model***

LIMITATIONS OF CONFIRMATORY FACTOR ANALYSIS (CFA)

- For model identification purpose, the majority of cross-loadings needs to be fixed to zero.
- Inappropriate zero loadings can contribute to poor model fit, distorted factors and biased factor correlations (Marsh, et al., 2010).
- After rejection of the initial model (inappropriate fit), the researcher can be tempted to try a series of modifications to achieve acceptable fit to the data.

"A number of writers have cautioned that extensive specification searches can lead to unjustified overfitting of data, with loss of meaning for indices of statistical significance" (Carroll, 1995)

- However, small but nonzero loadings could be equally compatible with theory.

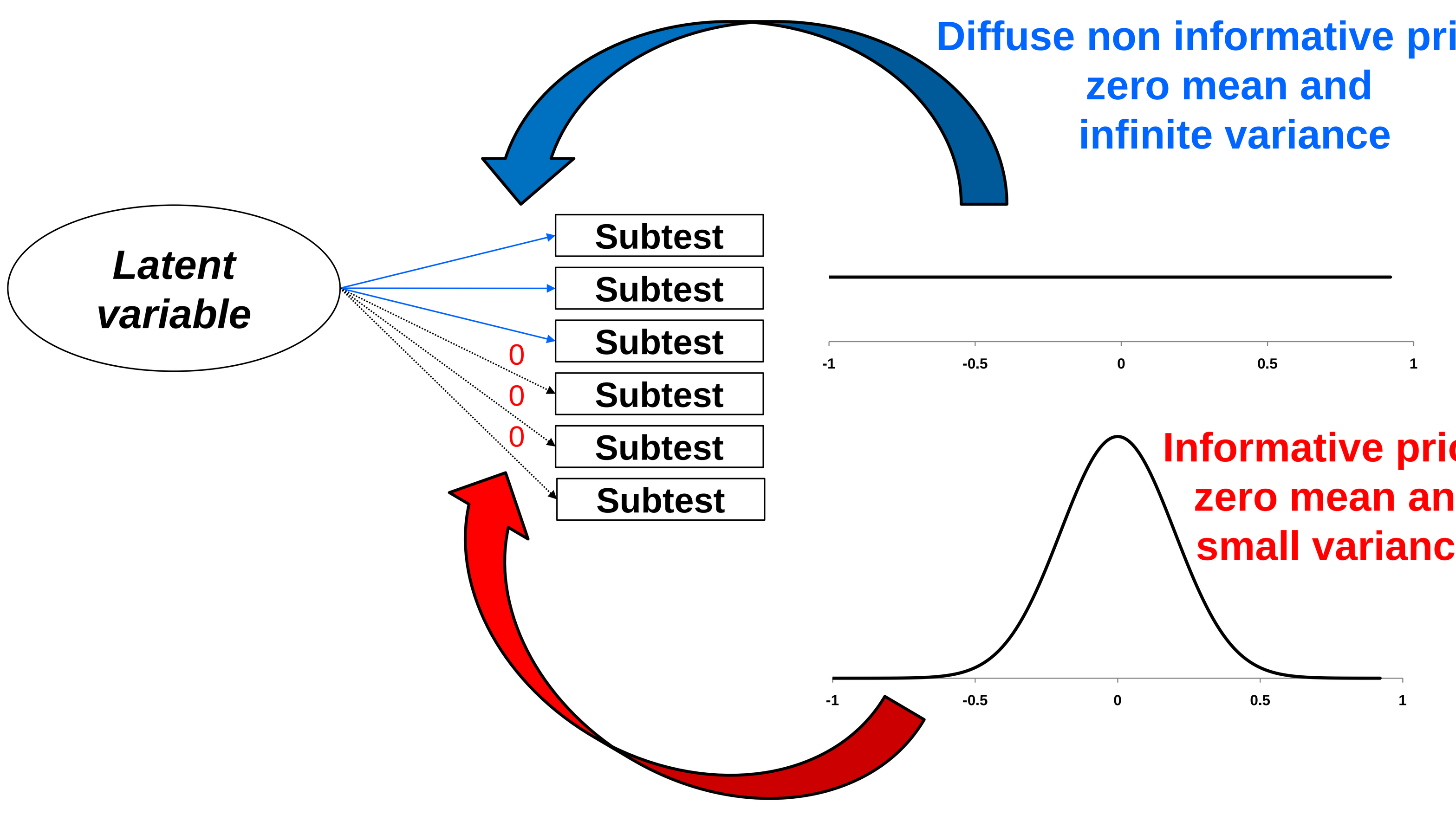
"These zero loadings can be considered as unnecessary strict restrictions to reflect the researchers' hypotheses" (Muthén & Asparouhov, 2011)

GOALS OF THE PRESENT STUDY AND METHODOLOGY

o **The first goal of this study was to compare CHC-based models to the classical 4-factors structure on the French WISC-IV.**

o **The second goal was to address the limitations of traditional maximum likelihood CFA using Bayesian structural equation modeling (BSEM).**

➢ Within the Bayesian framework, parameters are seen as variables rather than constants.
➢ Zero-fixed loadings are replaced by **approximate** zeros based on informative, small-variance priors.
➢ All parameters are freed and estimated simultaneously. Every cross-loadings will be tested in a single step process.
➢ BSEM can be seen as an "in-between" CFA and EFA approach. BSEM is less restrictive than CFA although still strongly theory driven.



SAMPLE DESCRIPTION

• 249 children from 8 to 12yr – schools from Geneva.

French-speaking Swiss children	N	Mean Age (SD)
Boys	124	9.69 (1.18)
Girls	125	9.78 (1.20)
Total sample	249	9.73 (1.19)

• The 10 core and the 5 supplemental subtests were administered.

Parents SES :	Executive	Self employed	Employee/ middle manager	Worker	Miscellaneous	Total
Girls	34	8	48	34	1	125
Boys	20	7	50	45	2	124
Total	54	15	98	79	3	249
%	22	6	39	32	1	100

RESULTS – MODELS COMPARISONS

➢The posterior distribution of Bayesian estimation was achieved through Markov Chain Monte Carlo (MCMC) algorithm with the Gibbs sampler Method.
➢Three MCMC chains with 50'000 iterations were used with different starting values and different random seeds.
➢The prior variance was 0.04 which results in 95% credibility interval of $\pm$ 0.39 (small to moderate cross-loadings).

Model	Number of free parameters	Posterior Predictive P-Value	Difference between observed & replicated X² 95% C.I.		DIC	Estimated number of parameters
			Lower 2.5%	Upper 2.5%		
1. WISC-IV 4 factor model	49	0.01	13.26	90.29	9645.04	47.34
2. WISC-IV 4 factor model with cross-loadings (variance of priors = 0.4)	94	0.46	-39.38	43.38	9616.23	68.98
3. CHC 5 factor model	50	0.01	9.47	85.21	9641.56	48.27
4. CHC 5 factor model with cross-loadings (variance of priors = 0.4)	**110**	**0.57**	**-45.55**	**36.63**	**9585.44**	**44.43**

o Higher Posterior Predictive P-Value and Lower DIC indicates better fit to the data.

o The CHC 5 factor model with small cross-loadings showed the better fit overall.

RESULTS – CHC 5 FACTOR MODEL WITH CROSS-LOADINGS

First order loadings	Gc	Gc 95% C.I.		Gv	Gv 95% C.I.		Gf	Gf 95% C.I.		Gsm	Gsm 95% C.I.		Gs	Gs 95% C.I.	
Similarities	0.624	0.455	0.783	0.125	-0.041	0.315	0.071	-0.072	0.270	0.017	-0.139	0.180	-0.001	-0.138	0.139
Vocabulary	0.797	0.647	0.969	-0.061	-0.236	0.116	0.022	-0.134	0.199	0.060	-0.098	0.225	0.023	-0.115	0.164
Comprehension	0.719	0.564	0.903	-0.114	-0.296	0.056	-0.011	-0.185	0.151	0.053	-0.103	0.221	-0.006	-0.149	0.136
Information	0.750	0.589	0.934	0.145	-0.023	0.338	-0.046	-0.241	0.104	0.012	-0.143	0.175	-0.001	-0.138	0.141
Word Reasoning	0.652	0.492	0.811	0.041	-0.132	0.215	0.054	-0.092	0.257	0.010	-0.147	0.165	-0.036	-0.178	0.099
Block Design	-0.066	-0.257	0.130	0.670	0.432	0.943	0.002	-0.209	0.177	0.039	-0.164	0.225	0.125	-0.045	0.291
Picture Completion	0.108	-0.085	0.297	0.522	0.278	0.806	0.027	-0.137	0.223	-0.098	-0.292	0.069	0.002	-0.156	0.153
Matrix Reasoning	0.050	-0.167	0.251	0.150	-0.079	0.366	0.469	0.103	0.895	0.032	-0.174	0.216	-0.024	-0.185	0.127
Picture Concept	0.048	-0.161	0.239	-0.062	-0.281	0.125	0.476	0.176	0.810	0.080	-0.114	0.259	0.035	-0.118	0.184
Digit Span	-0.032	-0.212	0.141	-0.090	-0.290	0.100	0.031	-0.131	0.230	0.646	0.444	0.877	0.017	-0.141	0.177
Letter Number Sequencing	0.018	-0.173	0.205	0.027	-0.174	0.236	0.001	-0.176	0.189	0.748	0.530	1.016	-0.113	-0.280	0.042
Arithmetic	0.153	-0.011	0.320	0.023	-0.148	0.207	0.020	-0.145	0.199	0.440	0.251	0.642	0.114	-0.028	0.261
Coding	-0.078	-0.25	0.092	-0.006	-0.203	0.200	0.002	-0.172	0.180	0.042	-0.134	0.235	0.629	0.455	0.809
Symbol Search	0.004	-0.171	0.179	0.108	-0.088	0.317	-0.016	-0.190	0.160	0.039	-0.140	0.221	0.657	0.482	0.864
Cancellation	0.051	-0.111	0.214	0.017	-0.166	0.214	0.027	-0.135	0.207	-0.134	-0.309	0.030	0.494	0.326	0.669

Second order loadings	General factor *g*	95% C.I	
Gc	0.720	0.247	0.911
Gv	0.686	0.225	0.931
Gf	0.860	0.350	0.994
Gsm	0.643	0.274	0.891
Gs	0.385	-0.080	0.711

➢ Parameters are considered to have substantive backing when the 95% credibility interval of the parameter does not cover zero.

CONCLUSIONS

1. Results on a sample of 249 French-speaking Swiss children (8-12 yr) showed that the CHC-based model fit was better than the 4-factor solution.
2. Models including small cross-loadings were more adequate.
3. Because every parameters were estimated, we got better insight on the nature of constructs measured by each subtest. Additionally, no further modifications needed to be tested. Thus, the BSEM model may have greater generalizability than extensively modified CFA models.
4. Because with ill-specified CFA models the correlations of first-order factors tend to be positively biased, the second order loadings are often overestimated (e.g. the loading of *Gf* on g is often found to be unitary). It was not the case with the BSEM model.

**This work was supported by Grant 100014_118248 awarded by the Swiss National Science Foundation*
(Analysis of the French WISC-IV structure according to the Cattell-Horn-Carroll Narrow ability classification, Lecerf, Favez & Rossier)

Contact: Philippe.Golay@unige.ch

12TH CONGRESS OF THE SWISS PSYCHOLOGICAL SOCIETY, UNIVERSITY OF FRIBOURG, SEPTEMBER 12TH-13TH, 2011