KU LEUVEN

Profiles of tolerance and respect for the rights of diverse social groups among youth.

Comparisons across countries.

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0 Table of Contents

- 1 Introduction
- 2 Framework
- Methods
- 4 Results
- 6 Conclusion
- **6** Further steps?

1 Outline

- Introduction
- 2 Framework
- Methods
- 4 Results
- 6 Conclusion
- **6** Further steps?

1 Introduction

International studies such as the International Civic and Citizenship Education Study (ICCS) provides extensive comparative information regarding attitudes among youth.

Many studies focused on average country comparisons of attitudinal measures based on a variable-centred approach. Focused on the relations among variables and assumes that the sample comes from a homogeneous population, such as Confirmatory Factor Analysis.

Recent studies started to show the usefulness of person-centred approaches.

No studies addressed the potential interdependence in these attitudinal dimensions among different subgroups of people.

1 Research questions

- 1 What profiles of attitudes toward diverse groups equality can be distinguished among adolescents in different countries?
- 2 Are these profiles comparable across countries?
- 3 What individual and contextual factors are associated with profile membership?

2 Outline

- 1 Introduction
- 2 Framework

Mixture models Large scale assessments Methodological features Study

- 3 Methods
- 4 Results
- 6 Conclusion

Framework Mixture models



2 Mixture models

Is an extension of Generalized Linear Models (GLM), where random as well as fixed effects are allowed in the linear predictor.

Generalized Linear Mixture Model (GLMM) assumes that some of its parameters differ across unobserved subgroups, latent classes, or mixture components.

This is very helpful when we do not know if the population is homogeneous. The mixture of different distributions indicates population heterogeneity.

2 Person-centred approach

Clustering tool for categorical variables (similar to k-means clustering for continuous variables). Also known as probabilistic cluster analysis.

Classify respondents into one or more groups (latent classes)

- ▶ Identify unobserved subpopulations with similar individuals.
- ▶ Define a model for the probability of having a response pattern.
- Using the probability of belonging to a class, assign individuals to the latent classes.

2 Latent Class Analysis

A latent class model is a mixture model for a set of categorical items.

LCA assumes conditional independence, that the observed categorical indicators are mutually independent once the categorical latent variable is conditioned out.

- Unconditional probabilities are latent class probabilities, the proportion of the population expected to belong to a latent class.
- Conditional probabilities are conditional item-response probabilities, measurement parameters, representing the likelihood of endorsing specific characteristics of the observed items, given a specific class membership.

2 How identify the number of classes?

An important step in the analysis, different aspects must be considered:

- Compare subsequent models by model fit indices.
- Evaluate the quality of latent class membership.
- Confirm that the size of the latent classes is reasonable.
- Identify that the final classes are interpretable based on a theoretical grounding.

2 Model fit

- Akaike's information criterion:
 - · Lower value, tendency to overfit
- Bayesian information criterion:
 - Lower value, more severe penalty for complexity
- ► Relative entropy:
 - Perfect classification (entropy = 1)
- Log-likelihood ratio test (LR, BLRT, Bootstrap¹)
 - Significant model fit improvement comparing a k-classes and (k-1)-class model
- Bivariate residuals
 - Residuals values should be close to zero [-1.96 1.96]

¹not available for weighted data

2 Multigroup latent class analysis

Measurement invariance can be defined as a conditional independence property of the measurement model with respect to a set of sub-populations within the parent population.

- ▶ Complete heterogeneous model: same number of classes but the parameters defining those classes are freely estimated across groups.
- Partial homogeneous model: equality constraints are imposed across the observed groups, classes are invariant of the group but the size may vary.
- ➤ Complete homogeneous model: all parameters are constrained across groups, and the prevalence of latent classes are restricted to be equal across groups.

Framework Large scale assessments

2 IEA ICCS 2016

The International Civic and Citizenship Education Study (ICCS)

Research:

- The way civic and citizenship education is implemented in participating countries
- Student's belief about contemporary civic and civic issues in society

Population:

- more than 94.000 students in 8th grade
- about 3800 schools
- more than 37.000 teachers in those schools
- 24 countries
- Complex sample design: stratified two-stage cluster samples
 - Schools randomly selected (probability proportional to size)
 - Intact classrooms sampled at the second stage
- Complex assessment design: Booklets, plausible values

Framework Methodological features

2 Methodological features

- **Exploratory LCA:** No specific hypothesis but the goal is to identify how many classes are necessary to fit the data.
- Confirmatory LCA: Starts with a specific hypothesis, expected frequencies can be estimated and compared with the observed frequencies, if the test indicates that they do not differ significantly the model is appropriate.
- Multigroup LCA: If the measurement properties differ between observed groups (non-invariance), it is not possible to compare the differences between the groups.

Framework Study

2 Student's endorsement of equal rights and opportunities

A two dimensional model in a CFA with two scales showed a good fit after controlling for the common residual variance between the negatively worded statements on gender equality².

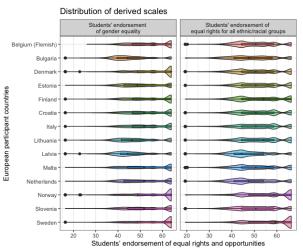
Level of agreement: ranging from strongly disagree to strongly agree.

- ▶ Attitudes towards gender equality: Higher values of this scale reflect stronger agreement with the notion of gender equality or stronger disagreement with negative views of gender equality.
- ▶ Attitudes towards equal rights for all ethnic/racial groups: Higher scores indicate a greater degree of agreement with the idea that ethnic and racial groups should have the same rights as other citizens in society.

²ICCS 2016 Technical Report

2 Derived scales

Two latent dimensions are highly correlated (0.63) and the measurement invariance was within acceptable ranges³.



³ICCS 2016 Technical Report

3 Outline

- 1 Introduction
- 2 Framework
- Methods
 Sample
 Variables
 Analytical strategy
- 4 Results
- Conclusion

Methods Sample



3 Sample

Students in 8th grade from European participant countries

Country	Sample size
Belgium (Flemish)	2931
Bulgaria	2966
Denmark	6254
Estonia	2857
Finland	3173
Croatia	3896
Italy	3450
Lithuania	3631
Latvia	3224
Malta	3764
Netherlands	2812
Norway	6271
Slovenia	2844
Sweden	3264

Methods Variables



3 Items

Level of agreement (dichotomised into agree and disagree).

Attitudes towards gender equality scale

- GND1: Men and women should have equal opportunities to take part in government
- GND2: Men and women should have the same rights in every way
- GND5: Men and women should get equal pay when they are doing the same jobs
- GND3: Women should stay out of politics (r)
- GND4: Not many jobs available, men should have more right to a
 job than women (r)
- **GND6:** Men are better qualified to be political leaders than women (r)

3 Items

Level of agreement (dichotomised into agree and disagree).

Equal rights for all ethnic and racial groups

- **ETH1:** All ethnic and racial groups should have equal chance to get good education
- ETH2: All ethnic and racial groups should have an equal chance to get good jobs
- ETH3: All ethnic and racial groups schools should teach students to respect
- ETH5: All ethnic and racial groups should have same rights and responsibilities
- **ETH4:** All ethnic and racial groups should be encouraged to run in elections

Methods Analytical strategy

3 Analytical strategy

- Independent exploratory LCA to identify country-specific number of classes.
- Independent analysis to identify country-specific latent class membership, sizes and interpretability.
- 3 Identify similar classes across countries.
- 4 Exploratory LCA with all groups to check if the total number of classes remains.
- 5 Evaluate different levels of measurement invariance for the number of comparable classes across countries.
- 6 Establish a confirmatory analysis with the conditional probabilities and total number of classes identified in the general exploratory LCA model.

4 Outline

- Introduction
- 2 Framework
- Methods
- 4 Results

Attitudes towards gender equality Attitudes towards race and ethnic rights

- 6 Conclusion
- **6** Further steps?

Results Attitudes towards gender equality

4 Independent exploratory LCA by country

Best model fit statistics Individual Gender equality scale models

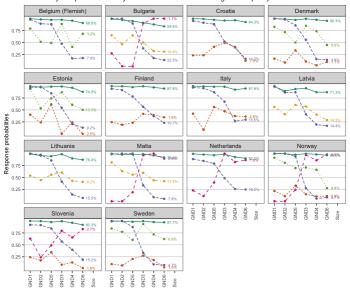
Country	N Latent Classes	Param	Log- Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
BFL	3	20	-3812	7664	7784	7721	88.2%	0.8%	62	0.323	61	0.327
BGR	4	27	-7523	15100	15261	15175	75.2%	0.4%	60	0.077	59	0.08
DNK	4	27	-5914	11883	12063	11977	91.2%	0.6%	74	0.174	73	0.178
EST	4	27	-4974	10001	10162	10076	77.7%	0.6%	57	0.183	56	0.189
FIN	3	20	-3477	6993	7114	7051	90.7%	1.2%	86	0.037	84	0.039
HRV	3	20	-5368	10777	10902	10838	87.6%	0.9%	98	0.085	96	0.088
ITA	3	20	-4830	9701	9824	9760	84.6%	1.5%	145	0	143	0
LTU	3	20	-7447	14934	15058	14994	82.5%	1.6%	248	0	244	0
LVA	3	20	-7993	16027	16148	16085	72.4%	0.8%	121	0.052	119	0.055
MLT	4	27	-6204	12462	12629	12543	87.2%	0.5%	65	0.235	64	0.238
NLD	3	20	-4759	9557	9676	9612	87.0%	1.5%	140	0.074	138	0.076
NOR	5	34	-6035	12137	12365	12257	93.2%	0.5%	66	0.281	65	0.286
SVN	4	27	-4280	8614	8774	8689	87.5%	0.7%	56	0.158	55	0.163
SWE	4	27	-3049	6152	6316	6230	89.2%	1.0%	62	0.398	61	0.402

Note:

Best model based on the lowest value of BIC

4 Independent exploratory LCA by country

Classes by independent country models for attitudes towards gender equality scale



4 Classes identified in Attitudes towards gender equality scale

- ► Fully egalitarian: Most likely to agree to all items (green line)
 - Conditional probabilities greater than 0.75 to agree, class sizes around 60% (Bulgaria) and 90% (Denmark).
- ► Competition-driven sexism: Most likely to disagree to gender competitive items in favor of women (purple line).
 - Conditional probabilities greater than 0.75 to agree to positive views of gender equality and generally lower than 0.5 to agree to reversed negative views, class sizes around 3.6% (Denmark) and 22.5% (Bulgaria).
- ▶ Non-egalitarian: Not likely to agree to any item (orange line)
 - Conditional probabilities lower to 0.5 to agree to any item, class sizes around 0.9% (Norway) and 2.6% (Italy).

4 Classes identified in Attitudes towards gender equality scale

- ► Reverse competition-driven sexism: Most likely to agree to gender competitive items in favor of women (pink line)
 - Conditional probabilities lower than 0.25 to agree to positive views of gender equality and generally greater than 0.75 to agree to reversed negative views, class sizes around 0.6% (Norway) and 1.6% (Netherlands).
- Political egalitarian: Likely to agree to political related items (light-green line)
 - Conditional probabilities greater than 0.75 in political equality items, class sizes around 3.2% (Belgium) and 1.4% (Estonia).
- Random response: Not defined attitude (yellow line)
 - Conditional probabilities between 0.25 and 0.75 to agree all items, class sizes around 2.7% (Slovenia) and 16.8% (Bulgaria).

4 Exploratory approach - General model

Model fit statistics LCA attitudes towards gender equality scale

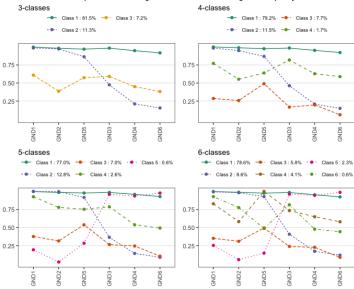
N Latent Classes	Param	Log- Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
All countries											
1	6	-96413	192838	192891	192872						
2	13	-83617	167261	167376	167334	80.5%	13.3%	25591	0	25258	0
3	20	-82592	165223	165400	165336	84.5%	1.2%	2051	0	2025	0
4	27	-82327	164708	164946	164861	82.7%	0.3%	529	0	522	0
5	34	-82163	164394	164694	164586	81.1%	0.2%	328	0	324	0
6	41	-82136	164355	164717	164586	82.5%	0.0%	53	0.246	52	0.252
7	48	-82116	164328	164752	164600	82.1%	0.0%	40	0.244	40	0.247

4 Best model fit

- ▶ AIC, a 7-class model has the lower value but tendency to overfit suggest to select a lower number of classes model
- ▶ **BIC**, considering the penalty for complexity a 5-class model should be selected
- ▶ Log-likehood ratio test, a model with 5 classes would indicate a better fit, as the 6-class model do not show a significant improvement in the model fit.
- ▶ **Relative entropy**, more than 80% of the membership is correctly classified based on the model estimated, 3-class has the highest value 84.5%.
- ▶ Bivariate residuals, all residuals values in the acceptable range from 5-class model on, just 1 value outside range in the 4-class model.

4 Best model fit

Conditional probabilities to agree to attitudes towards gender equality scale



4 Profiles identified for comparability

3-class model:

- 1 Fully egalitarian ALL COUNTRIES
- 2 Competition-driven sexism ALL COUNTRIES
- 3 Random response BGR, LVA, LTU, MLT

4-class model:

- 1 Fully egalitarian ALL COUNTRIES
- 2 Competition-driven sexism ALL COUNTRIES
- 3 Non-egalitarian HRV, DNK, EST, FIN, ITA, NOR, SLV, SWE
- 4 Political egalitarian BFL, DNK, EST, NOR, SWE

4 Profiles identified for comparability

5-class model:

- 1 Fully egalitarian ALL COUNTRIES
- 2 Competition-driven sexism ALL COUNTRIES
- 3 Non-egalitarian HRV, DNK, EST, FIN, ITA, NOR, SLV, SWE
- 4 Political egalitarian BFL, DNK, EST, NOR, SWE
- 5 Reverse competition-driven sexism BGR, MLT, NLD, NOR, SLV

6-class model:

- 1 Fully egalitarian ALL COUNTRIES
- 2 Competition-driven sexism ALL COUNTRIES
- 3 Non-egalitarian HRV, DNK, EST, FIN, ITA, NOR, SLV, SWE
- 4 Political egalitarian BFL, DNK, EST, NOR, SWE
- 5 Reverse competition-driven sexism BGR, MLT, NLD, NOR, SLV
- 6 Pro-women pay/job Not defined in individual models

4 Interpretability

- ▶ With 3 classes: random response class is not very interpretable.
- ▶ With 6 classes, a new no identified class appears, not interpretable.
- ▶ With 5 classes, reverse competition-driven sexism class is present in 5 countries but with class sizes lower than 1%, not representative.
- With 4 classes, four main classes are identified across countries. Two of them are present in all countries. Best model for comparability.
- ► Two remaining classes can be freely estimated that variates in each country and/or with a class size of 0.

4 Multigroup Latent Class Analysis

Multigroup model fit statistics, Attitudes towards gender equality

Туре	Ngroups	Param	Log- Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	ΔLL	$_{\rm DF}^{\Delta}$	pvalue Δ
4-classes											
Complete homogeneity	14	40	-215414	430907	431260	431133	94.0%	-1.49%	-3158	-348	0
Partial homogeneity all classes	14	79	-213195	426549	427246	426995	88.1%	-0.44%	-940	-308	(
Partial homogeneity 2 classes	14	223	-212710	425866	427834	427126	85.6%	-0.21%	-454	-168	0
Complete heterogeneity	14	391	-212256	425293	428745	427502	94.0%	0.00%	0	0	

Note

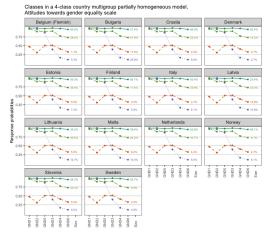
The best loglikelihood value was not replicated for the following models:

¹ Partial homogeneity 2 classes;

² Complete heterogeneity;

4 Multigroup LCA 4-classes

Partial homogeneity: Conditional probabilities to be equal across countries



Results Attitudes towards race and ethnic rights

4 Independent exploratory LCA by country

Best model fit statistics Individual Ethnic and race rights equality scale models

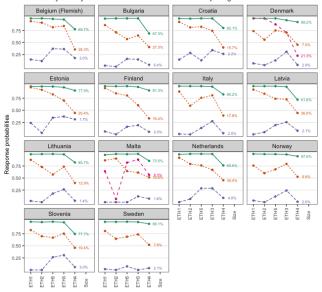
Country	N Latent Classes	Param	Log- Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
BFL	3	17	-4019	8072	8174	8120	60.5%	0.8%	63	0.021	62	0.023
BGR	3	17	-5354	10742	10843	10789	78.5%	1.8%	193	0	190	0
DNK	4	23	-8282	16610	16764	16691	72.3%	0.3%	54	0.059	53	0.062
EST	3	17	-3254	6543	6644	6590	69.8%	1.3%	87	0.002	86	0.002
FIN	3	17	-3391	6815	6918	6864	80.8%	2.9%	200	0	196	0
HRV	3	17	-4507	9047	9153	9099	76.1%	0.9%	84	0.416	82	0.422
ITA	3	17	-4354	8742	8846	8792	81.1%	1.6%	146	0	143	0
LTU	3	17	-4194	8423	8528	8474	84.8%	0.9%	75	0.016	74	0.017
LVA	3	17	-5353	10741	10844	10790	64.0%	1.1%	124	0.001	122	0.001
MLT	4	23	-5691	11428	11570	11497	80.3%	0.7%	78	0.032	76	0.034
NLD	3	17	-4729	9493	9593	9539	69.7%	1.8%	170	0	166	0
NOR	3	17	-5448	10930	11044	10990	88.1%	1.9%	207	0	203	0
SVN	3	17	-4272	8578	8679	8625	77.5%	1.0%	87	0.027	85	0.029
SWE	3	17	-2306	4646	4749	4695	90.2%	3.1%	147	0.011	144	0.012

Note:

Best model based on the lowest value of BIC

4 Independent exploratory LCA by country

Classes by country for attitudes towards Ethnic and race equal rights scale



4 Classes identified - Attitudes towards race and ethnic rights

- ► Fully egalitarian: (green line)
 - Conditional probabilities greater than 0.7 to agree, class sizes around 61.8% (Latvia) and 90% (Sweden)
- ▶ Political non-egalitarian: (orange line)
 - Conditional probabilities to agree higher than 0.5 in all items but political item (< 0.5), class sizes around 7.6% (Denmark) and 36% (Latvia).
- ► Non-egalitarian: (purple line)
 - Conditional probabilities lower than 0.5 to agree all items, class sizes around 1.4% (Lithuania) and 5.4% (Bulgaria).
- Country specific class: (pink line)
 - Employment non-egalitarian: Class size 8.3% (Malta)
 - Strong political non-egalitarian: Class size 21.3% (Denmark).

4 Exploratory approach - General model

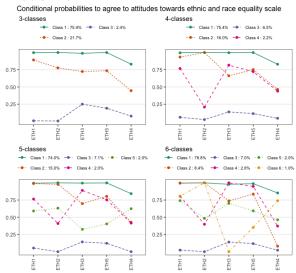
Model fit statistics LCA attitudes towards ethnic and race equal rights scale

N Latent Classes	Param	Log- Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
All countr	ries										
1	5	-79684	159379	159423	159407						
2	11	-70046	140115	140212	140177	84.7%	12.1%	19276	0	18984	0
3	17	-68984	138003	138153	138099	75.4%	1.5%	2124	0	2091	0
4	23	-68807	137660	137863	137790	77.5%	0.3%	355	0	350	0
5	29	-68755	137568	137824	137732	74.0%	0.1%	104	0	102	0
6	35	-68754	137578	137887	137775	80.8%	0.0%	2	0.541	2	0.542
7	41	-68754	137589	137951	137821	82.0%	0.0%	1	0.528	1	0.528

4 Best model fit

- ► AIC, lower value for the 5-classes model.
- BIC, 5-classes considering penalty for complexity.
- ► Log-likehood ratio test, 5-classes model has better fit compared to the 6-classes model
- ▶ **Relative entropy**, 77.5% is correctly classified in a 4-class model.
- ▶ **Bivariate residuals**, no values out of range from a 4-class model on.

4 Best model fit



4 Profiles identified for comparability

- 3-class model:
 - 1 Fully egalitarian: ALL COUNTRIES
 - 2 Political non-egalitarian: ALL COUNTRIES
 - 3 Non-egalitarian: ALL COUNTRIES

4-class model:

- 1 Fully egalitarian: ALL COUNTRIES
- 2 Political non-egalitarian: ALL COUNTRIES
- 3 Non-egalitarian: ALL COUNTRIES
- 4 Employment non-egalitarian: MLT

► 5-class model:

- 1 Fully egalitarian: ALL COUNTRIES
- 2 Political non-egalitarian: ALL COUNTRIES
- 3 Non-egalitarian: ALL COUNTRIES
- 4 Employment non-egalitarian: MLT
- 5 Random response: Not identified in individual models

4 Interpretability

- Three main classes found in every model are similar in all countries.
- Country specific classes for Malta if more classes are added.
- ▶ A 4-class model is the better fit to identify three comparable classes and one that variates in each country and/or with size of 0.

4 Multigroup Latent Class Analysis

Country multigroup model Ethnic and race rights equality fit statistics

Туре	Ngroups	Param	Log- Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	ΔLL	Δ DF	pvalue Δ
4-classes											
Complete homogeneity	14	36	-201088	402248	402566	402451	92.2%	-1.20%	-2383	-299	0
Partial homogeneity all classes	14	75	-199422	398994	399656	399418	88.9%	-0.36%	-717	-261	0
Complete heterogeneity	14	335	-198705	398081	401036	399972	93.2%	0.00%	0	0	

Notes:

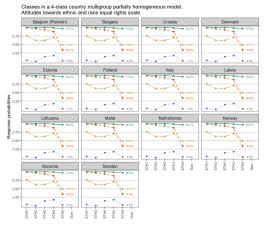
The best loglikelihood value was not replicated for the following models



^{1 4-}classes complete heterogeneity;

4 Multigroup LCA 4-classes

Partial homogeneity: Conditional probabilities to be equal across countries



5 Outline

- Introduction
- 2 Framework
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- **5** Conclusion
- **6** Further steps?

5 Conclusions

General

- 1 Comparability is not assured when we look at subpopulations patterns when analysing Large Scale Assessments.
- 2 A independent country analysis is the best strategy to identify common patterns in LSA scales.
- 3 Different country-specific subpopulations were found.
- 4 Some of the patterns are invariants across countries.

5 Conclusions

- Attitudes towards gender equality
 - 1 Fully egalitarian and Competition-driven sexism are the classes that can be compared across countries.
 - 2 Neighbouring countries can share some patterns.
 - 3 Not clear if there is an impact of inverse worded items in these patterns, the relation with competition-driven sexism class could be forced by wording?.
- Attitudes towards ethnic and race equal rights.
 - 1 Fully egalitarian, Political non-egalitarian and Non-egalitarian are the classes that can be compared across countries.
 - 2 Not many patterns are identify in every country (3-4).

6 Outline

- Introduction
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- **6** Further steps?

6 Further steps?

- Partial homogeneity using conditional probabilities predefined (confirmatory approach) for comparable classes.
- ► Evaluate LCA for all Student's endorsement of equal rights and opportunities items? (Gender and Ethnic items together)
- Respond to third research question for comparable classes.

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Thank you for your feedback!