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

Comparison across countries.

Pamela Isabel INOSTROZA FERNANDEZ

Supervisor: Prof. Femke De Keulenaer
Co-supervisor: Maria Magdalena Isac

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FACULTEIT WETENSCHAPPEN
Celestijnenlaan 200H bus 2100
3001 LEUVEN (HEVERLEE), BELGIË
tel. + 32 16 32 14 01
fax + 32 16 32 14 01
www.kuleuven.be

Preface

This work was very interesting to perform, it grant me the opportunity to study in a deeper sense the subpopulations that are hidden behind large-scale assessments. I learned that not only variable center studies can give important insights about the different profiles that each country is composed by. I had to study many topics regarding civic and citizenship attitudes, I can not express how grateful I am to my promotors, particularly Maria Magdalena Isac who provide me with the idea to research this topic along with many insights that I should focus on. Professor Femke de Keulenaer was a great teacher and mentor regarding the statistical techniques I should apply and analyze to achieve our main objective. Their support and involvement with this project were at the right level with the difficulty. They gave me the reasoning and interest to complete this research. I want to thank them and state that they will have my respect and gratitude for the work performed.

Summary

Civic education is an important subject for every citizen in our modern society. It is important that every individual acknowledge the importance of the civil rights and obligations of any citizen. One of the most commented topics is how society faces and behaves towards the great diversity of individuals and cultures. Students are a great population to be studied as they are forming their own mindset and attitudes. Using ICCS 2016, an international large-scale assessment, it is possible to identify which are the most common behaviors among students' attitudes considering different aspects of equality towards women and ethnic and racial groups. As expected, the most common pattern is composed of students that share a high chance to accept and promote equality towards women and ethnics groups. Nonetheless, there is a small number of students that tend to disagree with this equality. Another set of students shares a high level of agreement with both minorities' equal rights but do not agree with their political role in society. Student's endorsement towards woman's rights remaining pattern shares a high level of agreement towards equality in basic rights but favor towards men when competing for jobs or political roles. Another pattern identified towards ethnic groups is students that disagree with their equal right to have good jobs. These patterns are similar across the 14 countries studied in Europe but they differ in the number of individuals in each pattern.

List of abbreviations

ICCS: International Civic and Citizenship Education Study.
ILSA: International Large Scale Assessments
IEA: International Association for the Evaluation of Educational Achievement.
GLMM: Generalized Linear Mixed Model
LCA: Latent Class Analysis
CFA: Confirmatory Factor Analysis

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Chapter 1

Introduction

The development of civic values and attitudes of tolerance and respect for the rights of diverse social groups among youth is essential for sustainable democratic societies. These values are strongly promoted by families, educational systems and international organizations across the world. The measurements and comparison of these attitudes among youth can provide valuable information about their development in different societies.

International studies such as the International Civic and Citizenship Education Study (ICCS) provide extensive comparative information regarding these aspects. The ICCS study is a large-scale assessment (survey) applied in more than 25 educational systems during the last three cycles and focused on secondary education (representative samples of 8th graders, 14-year-olds in each country) addressing topics such as citizenship, diversity and social interactions at school.

Previous research using ICCS data has been largely focused on average country comparisons of attitudinal measures such as attitudes toward equal rights for immigrants, ethnic minorities and women, norms of good citizenship behavior and political participation. Most of these studies employed variable-centered analyses. Nevertheless, recent studies started to show the usefulness of person-centered approaches (i.e. latent class analysis, hereafter LCA) aimed at identifying profiles of young people's attitudes. For example, using ICCS 2009 data, (Hooghe, Oser, & Marien, 2016) compare profiles of good citizenship norms across 38 countries and distinguished distinctive subgroups of the population that share a common understanding of what constitutes good citizenship were identified (e.g. who express either engaged or duty-based citizenship norms).

Nevertheless, most of these studies employing LCA with ICCS data focused on patterns within a particular type of attitude described by individual items (e.g. citizenship norms) leaving space for investigations that aim to capture a wider set of attitudinal measures described by scores on different variables.

To address this gap, this research will approach the topic of tolerance and respect for the rights operationalized as a multifaceted set of attitudes toward equal rights for women and ethnic/race minorities. This topic was addressed by previous studies aimed at comparing these attitudinal measures mostly in isolation across countries and over time. However, to date, no studies addressed the potential interdependence in these attitudinal dimensions among different subgroups of people (e.g. highly tolerant, highly intolerant regarding all aspects, etc.). Therefore, the current study aims to fill this gap by addressing the following research questions:

- What profiles of attitudes towards gender equality are observed among adolescents?

- What profiles of tolerance and respect for equal rights of ethnic/race groups are observed among adolescents?
- Are these profiles comparable across countries?
- It is possible to state a confirmatory model for these profiles?

This research aims to answer these questions for an extensive set of countries, mainly European countries that had a variety of geographical locations, languages and economical backgrounds. This is important in order to avoid including external factors that can impact the clear interpretation of the results. This study will be focused on the last ICCS study available from 2016, including 14 European countries and two endorsement scales regarding attitudes towards gender equality and ethnic/race equal rights.

The study starts with a study of previous research performed in this matter and the statistical background that need to be considered in order to perform correctly this analysis. Subsequently, the analysis and summary of the results are discussed. Finally, results are discussed and a conclusion is given.

Chapter 2

Framework

Two main topics are relevant to go deep into this chapter, the scales that want to be evaluated and the methodology to be used. For this, first, large scales assessments are going to be learn, along with their main focus, data collection, and available information. The scales that are going to be used in this research were selected mainly because the promotion of tolerance is an important goal of European education policies focused on education for democratic citizenship and human rights. It is expected that civilians agree to equal rights for all the residents of the same country. Based on lately expressions of discrimination around the world, particularly in Europe is that this research will be focused in identifying which are the profiles of students according to their attitude towards these two groups of minorities (women and ethnic/race groups).

In order to achieve this goal, the correct technique should be used, taking into account not only the expected result but also the complexity of the information and the most suitable estimation technique. In this chapter, mixture models literature will be reviewed in order to identify the most suitable technique and statistics to consider when analyzing this data.

Mixed models will be learned, particularly Latent Class Analysis which is a model-based approach to cluster individuals/cases into distinctive groups, called latent classes, based on their responses to a set of observed categorical variables. The first LCA approach was improved by (Lazarsfeld & Henry, 1968) and (Goodman, 1974). This methodology requires multiple calculations that now, thanks to the increase of computing availability power and the creation of specialized software for mixture models, this technique is more accessible to be used.

2.1 International Large-Scale Assessments

International Large-Scale Assessments (ILSAs) have been used to draw comparisons among countries on a variety of topics in education and, more broadly, for example, in adolescent development (Isac, Palmerio, & Werf, 2019). These assessments can inform the public about influential factors on the micro and macro levels, foster interdisciplinary and international collaboration, and provide important data for studying the context and processes of education and development.

2.1.1 IEA - ICCS 2016

The International Association for the Evaluation of Educational Achievement (IEA) International Civic and Citizenship Education Study (ICCS) produces internationally comparative data collected via student, school and teacher questionnaires. Data from different waves of the ICCS survey is publicly available to researchers. The first time this study was applied was in 1999 to 28 countries and it was called CIVED, the second wave started using the name ICCS and was implemented in 2009 in 38 countries, the last study was performed in 2016 in 24 countries. The next cycle is scheduled for 2022 and 25 countries will participate. It focuses their research on how young people are prepared to undertake their roles as citizens in a range of countries in the second decade of the 21st century (Citizenship Education Study 2016, n.d.). ICCS study evaluates student's knowledge and understanding of civics and citizenship, as well as their attitudes, perceptions, and activities related to civics and citizenship.

ICCS 2016 addressed the following research questions:

1. The way civic and citizenship education is implemented in participating countries, including the aim and principles for this learning area, the curricular approaches chosen to provide it, and changes and/or developments since 2009.

2. The extent of student's knowledge and understanding of civics and citizenship, and the factors associated with its variation across and within countries.

3. Student's current and expected future involvement in civic-related activities, their perceptions of their capacity to engage in these activities, and their perception of the value of civic engagement.

4. Student's belief about contemporary civic and civic issues in society, including those concerned with civic institutions, rules and social principles (democracy, citizenship, and diversity), as well as their perceptions of their communities and threats to the world's future.

5. The ways in which schools organize civic and citizenship education, with a particular focus on general approaches, the processes used to facilitate civic engagement, interaction with their communities, and schools' and teacher's perceptions of the role of this learning area.

The 2016 study gathered data from more than 94.000 students in 8th grade in about 3800 schools from 24 countries. Also, data from more than 37.000 teachers in those schools and contextual data collected from school principals are included. An additional European questionnaire gathered data from almost 53.000 students in 14 European countries and a Latin American student questionnaire from more than 25.000 students from 5 Latin American countries.

Of all 24 participants countries, 16 are from Europe, 5 are from Latin America, and 3 from Asia. In two of the participant countries, a sub-national entity participate. In Belgium, ICCS 2016 was implemented only in the Flemish education system and North Rhine-Westphalia state in Germany participate as a benchmarking participant.
The student population is defined as students in 8th grade, in average 13.5 years of age in this study.

The schools samples were designed as stratified two-stage cluster samples, first schools were randomly selected at the first stage with probability proportional to the size and intact classrooms were sampled at the second stage. Each country has a sample size of 150 schools approximately and a sample of students around 3.000 and 4.500. Additionally, around 15 teachers teaching the target grade from each school were sampled.

The framework of the study consist of two parts:

- The civic and citizenship framework outlines the outcome measures addressed by the cognitive test and the international ans regional student questionnaires;

- The contextual framework maps the contextual factors expected to influence outcomes and explain their variation.

The assessment framework identified the different types of student perceptions and behaviors relevant to civics and citizenship along two affective-behavioural domains:

i. Attitudes: These refer to judgments or evaluations regarding ideas, persons, objects, events, situations, and/or relationships. This include the students' belief about democracy and citizenship, students' attitudes towards the rights and responsibilities of groups in society, and students' attitudes towards institutions.

ii. Engagement: Refers to students' civic engagement , students' expectations of future civic related action, and students' disposition to actively engage in society (interest, sense of efficacy). The sense of engagement also includes preparedness to participate in forms of civic protest, anticipated future political participation as adults, and anticipated future participation in citizenship activities.

2.1.2 Students' endorsement of equal rights and opportunities

Based on our research questions, Students' endorsement of equal rights and opportunities indicators from the attitudes domain are the most suitable scales to be studied.

ICCS 2016 scale *Students' endorsement of equal rights and opportunities* includes 2 different scales, attitudes towards gender equality and attitudes towards equal rights for all ethnic/racial groups as indicated in table A.1. These 11 items will be used in this study to identify the profiles of students towards equal rights and opportunities.

Accordingly to the technical report (Citizenship Education Study 2016, n.d.), a two dimensional model in a confirmatory latent class analysis (CFA) using the items of these indicators showed a good fit after controlling for the common residual variance between the negatively worded statements on gender equality. These two latent dimensions are highly correlated (0.63) and the measurement invariance was within acceptable ranges, this means that a certain degree of measurement invariance across countries was achieved when considering a variable-center approach.

The scales *Students' endorsement of gender equality* (S_GENEQL) and *Students' endorsement of equal rights for all ethnic/racial groups* (S_ETHRGHT) created by the consortium, consist of values ranging from 16.32 to 63.94 and 19.33 to 66.36 respectively. The distribution of these indicators can be observed in figure 2.1 for the 14 European countries. Here it is possible to identify that most countries averages values are similar to the European weighted average on both scales, nonetheless few countries performed below the European weighted average such as Bulgaria, Estonia, Latvia and the Netherlands in both scales. Lithuania performs below the average in gender equality scale but higher in ethnic/racial groups equality indicator. On the other hand, Norway and Sweden obtained indicators considerable higher than the European weighted average.

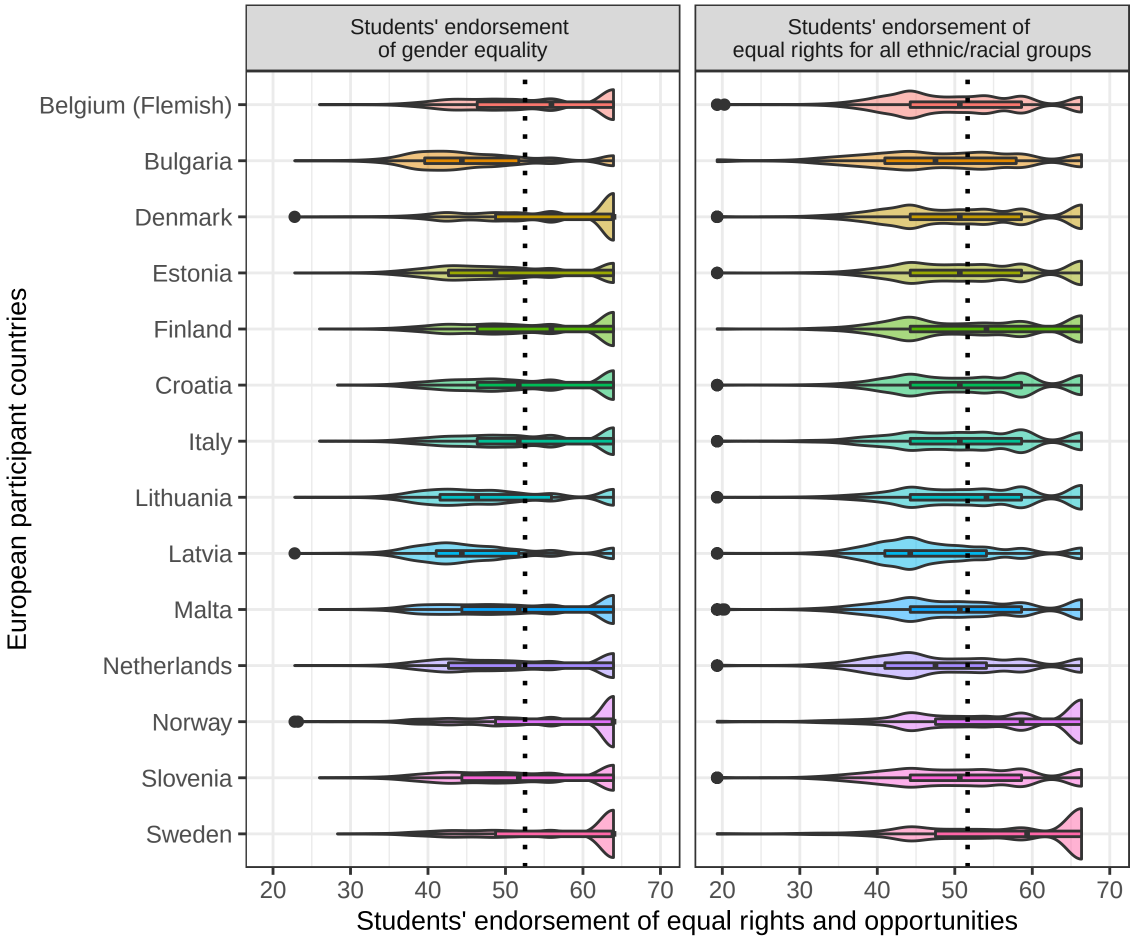

Figure 2.1: Distribution of derived scales Students' endorsement of equal rights and opportunities

CFA, a variable-center methodology, was performed to evaluate country invariance in (Isac, Palmerio, & Werf, 2019), which was achieve using additionally attitudes towards immigration indicator, this type of analysis is helpful to identify global behaviors of the whole population in the country and be able to compare them across countries. However, with this methodology it is not possible to dig deeper into different subpopulations in each country and explain those average values.

The rise of engaged citizenship study (Hooghe & Oser, 2015) used latent class analysis to identify groups supporting duty-based and engaged citizenship norms, based on 12 indicators. The research included 21 countries, although no invariance analysis was evaluated to compare this groups across countries. The analysis was performed both in 1999 and in 2009 scales and the sizes of the groups in both periods are compared globally and for each country.

Not much research using this particular indicators has been performed in order to identify how many subpopulations can be identified in each country regarding young people's beliefs about equal rights and opportunities for different groups in society based on gender and ethnic/racial background. Neither how are the patterns or behaviors of these subpopulations and which of them are representatives and comparable across countries.

2.2 Mixture models Latent Class Analysis

Parameters that describe a factor's effects in an ordinary generalized linear model are called fixed effects. Fixed effect applies to all categories of interest, gender, treatments or any other manifest grouping variable. By contrast, random effects apply to a sample of all possible categories. GLM extend ordinary regression by allowing nonnormal responses and a link function of the mean. The generalized linear mixed model (GLMM) is a further extension that permits random and fixed effects in the linear predictor.

In this type of analysis, a contingency table is treated as a finite mixture of unobserved tables generated under a conditional independence structure at categories of a latent variable (Agresti, 2013). A GLMM with discrete data create a mixture of linear predictor values using a latent variable, in this case, the unobserved random effect vector instead of being continuous and assumed to have a Normal distribution, it is a qualitative mixture distribution.

2.2.1 Person center approach

Meanwhile ANOVA, multiple regression, mixed models are variable-centered approaches that focus on relations among variables and assume that the sample studied come from a homogeneous population. Mixture models (finite mixture models) have taken the place of the framework for a person-center analytic approach. The difference between these two approaches is that person-centered approach focuses on identifying unobserved subpopulations comprised of similar individuals or cases, and involves modeling a mixture outcome distribution (usually a Normal distribution).

Commonly used to validate scales, Confirmatory Factor Analysis (CFA) focuses on grouping items, and thus is a variable-centered approach; in contrast, LCA focuses on grouping respondents or cases based on the patterns of item responses, and thus is a person-centered approach.

The most common technique to find homogeneous groups based on observed variables is cluster analysis. There are different methods that can be used to identify this groups of cases, but they are lacking in giving statistical indices and test for the optimal number of clusters. The most common techniques to determine the best number of groups are based on tabular o graphical output and the researcher's interpretation of these groups.

The mixture of different distributions indicates population heterogeneity; ie. sample observations arise from a finite number of unobserved subpopulations in the target populations.

Latent class and finite mixture models can be useful as a tool for building typologies (or clustering) based on dichotomous observed variables, this approach has more advantages over traditional cluster techniques such as k-means clustering.

Latent class modeling defines a model for the probability of having a particular response pattern. This probability is a weighted average (or mixture) of the class-specific probabilities for these patterns. The item responses of an individual are mutually independent given the individual's class membership. Similar to cluster analysis, it is possible to assign individuals to the latent classes. The probability of belonging to a particular class given the responses (posterior class membership probability) can be obtained by the Bayes' rule (Vermunt, 2014).

Mixture modeling provides an important complement to the traditional variable-centered analytical approaches. It offers the opportunity for researchers to identify unknown a priori homogeneous groups/classes of individuals based on the measures of interest, examine the features of heterogeneity across the groups/classes, evaluate the effects of covariates on the group/class membership, assess the relationship between the group/class membership and other outcomes, and study transitions between the latent group/ class memberships over time. As a matter of fact, person-centered approaches and variable-centered approaches can be integrated into a general mixture modeling framework so that one can better understand the relationships among variables and the pattern of such relationships (Muthen & Muthen, 2000).

2.2.2 Latent Class Analysis

As indicated previously a mixture model assumes that some of its parameters differ across unobserved subgroups, latent classes, or mixture components and particularly a latent class model is a mixture model for a set of categorical items.

A latent class model assumes the existence of a latent categorical variable such that the observed response variables are conditionally independent, given that variable. LCA treat a contingency table as a finite mixture of unobserved tables generated under a conditional independence structure of a latent variable. In other words, LCA can directly assess the theory that distinctive groups of people share specific attitudes. Depending on the response variable in the model, the analysis is called Latent Profile Analysis if is continuous (Normal) and Latent Class Analysis if the response variable is categorical (Multinomial).

The goal of LCA is to identify unobserved subgroups based on similar response patterns. In contrast with cluster analysis, LCA is a model-based approach to clustering. It identifies subgroups based on posterior membership probabilities rather than somewhat adhoc dissimilarity measures such as Euclidean distance. The general probability model underlying LCA allows for formal statistical procedures for determining the number of clusters, and more interpretable results stated in terms of probabilities.

LCA assumes conditional independence, that the observed categorical indicators are mutually independent once the categorical latent variable is conditioned out. Assuming the conditional independence, the joint probability of all observed indicator variables is described as:

$$P(u_1, u_1, ..., u_Q) = \sum_{k=1}^{K} P(C = k)P(u_1|C = k)P(u_2|C = k)...P(u_Q|C = k) \tag{2.1}$$

From Bayes' formula, the posterior probabilities for each individual to be in different classes are estimated as:

$$P(C = k|u_1, u_2, ..u_Q) = \frac{P(C = k)P(u_1|C = k)P(u_2|C = k)...P(u_Q|C = k)}{P(u_1, u_2, ..., u_Q)} \tag{2.2}$$

where $P(C = k)$ are the unconditional probabilities ($\sum_{k=1}^{K} P(C = k) = 1$) and $P(u_Q|C = k)$ are the conditional probabilities.

The unconditional probabilities are latent class probabilities, and the average of the probabilities can be interpreted as the prevalence of latent class (relative frequency of class membership) or the proportion of the population expected to belong to a latent class. The 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.

Conditional probabilities close to 1.0 indicate that members in the corresponding latent class endorse a category of the item; on the contrary, a very small probability indicates that they do not endorse the characteristic of the item. When a conditional item-response probability is close to $1/J$, where J is the number of categories in the item, the conditional probability is considered as random probability, thus the latent class membership is not predictive of the patterns of item response.

The conditional item-response probability is defined

$$P(u_q = u_{qj}|C = k) = \frac{1}{1 + exp(-L_{jk})} \tag{2.3}$$

and

$$L_{jk} = ln(\frac{P_{jk}}{1 - P_{jk}}) \tag{2.4}$$

which is the logit for u_{qj} given in latent class k. A logit of 0 means that the conditional item probability $P_{jk} = 0.5$, when the logit take an extreme value as -15 then $P_{jk} = 0$. On the contrary, a logit with a positive extreme value 15, $P_{jk} = 1$. These conditional item response probabilities provide information about how the latent classes differ from each other, for this reason, are used to define the estimated classes.

Number of classes

Determining the number of latent classes is the most important part of a Latent Class Analysis. This cannot be estimated directly from the data. To determine the optimal number of classes, a series of LCA models with an increasing number of latent classes should be fitted. The optimal number of classes will be obtained based on the comparison of the k-class model with the (k-1)class model iteratively.

It is important to consider other aspects before deciding the final number of classes, it is recommended to follow a series of step to identify the model that best fit the underlined classes.

a) Compare subsequent models by model fit indices.

b) Evaluate the quality of latent class membership.

c) Confirm that the size of the latent classes is reasonable.

d) Identify that the final classes are interpretable based on a theoretical grounding.

Model fit

In mixture models, multiple model fit statistics can be used to compare models. Information criterion indices, such as AIC, consistent AIC, BIC, aBIC, Lo-Mendell-Rubin likelihood ratio (LMR LR) test, adjusted LMR LR test and bootstrap likelihood ratio test (BLRT).

Akaike's Information Criterion

Akaike's Information Criteria called AIC, is one of the more important indicators to evaluate models performance, uses the formula

$$AIC(M) = -2\, log - likelihood_{max}(M) + 2\, length(M) \tag{2.5}$$

where $length(M)$ corresponds to the length of parameter vector of the model M. AIC penalizes the log-likelihood, generating a balance between a good fit (high value of log-likelihood) and complexity (simple models are preferable).

AIC prefers a model with few parameters but the fit of the model is good as well. Numerical results have shown that AIC has a tendency to overfit, it tends to pick models with more parameters than strictly necessary. It can be proven that this effect tends to vary in one parameter more than necessary. The corrected version of AIC can be express as the following.

$$AIC_c f(\theta) = AICf(.;\theta) + \frac{2\,length(\theta)(length(\theta)+1)}{n - length(\theta) - 1} \tag{2.6}$$

Bayesian information criterion

Based on the probability given the data it is possible to find the best model. This idea is based on Bayesian framework, involving prior probabilities on the candidate models along with prior densities on all parameters in the models.

$$BICf(.;\theta) = -2\,logL(\hat{\theta}) + log(n)length(\theta) \tag{2.7}$$

where n is the sample size and $length(\theta)$ the number of parameters.

Compared to AIC, BIC include a more severe penalty for complexity. Smaller values of information criterion indices indicate a better model fit.

Log-likelihood ratio test

The LR test based on model χ^2 statistic is not appropriate in this case, this is because the contingency table usually has a large number of zero cells, for this, the model χ^2 distribution is not correct. In addition, the model with (k-1)-classes is a special case of the k-classes model where the one latent class probability is set to zero, and the difference of the log-likelihood between these two models does not follow a χ^2 distribution.

Lo, Mendell, and Rubin developed the LMR LR test, which is not based on χ^2 distribution but on a correctly derived distribution. A significant P-value ($p < 0.05$) of the LMR LR when comparing model fit in a k-classes and (k-1)-class model indicates a significant improvement in model fit in the k-class model compared to the (k-1)-classes model. Then, if the test is statistically insignificant ($P \geq 0.05$) when comparing the (k+1)-class model with the k-class model, this means that there is no more significant improvement in model fit when including a new class, thus cannot reject the k-class model. Consequently, the optimal number of classes will be k.

LMR LR test may inflate Type I error when the sample size is small, for this adjusted LMR LR was proposed by adjusting the number of degrees of freedom and sample size. These two tests can perform identically.

An alternative LR test based on non-χ^2 distribution is the BLRT, Bootstrap log-likelihood ratio test where parametric bootstrapping was used to generate a set of bootstrap samples using the parameters estimates from the (k-1)-class model, and each of the bootstrap samples is analyzed for both k-class and (k-1)-class models. A distribution of the log-likelihood differences between the k-class and (k-1)-class model from all the bootstrap samples is constructed. The BLRT is applied following this empirical distribution of the log-likelihood differences. The P-values are interpreted in the same way as the LMR LR test.

Quality of latent class membership classification

Once the optimal number of classes is identified, the cases or individuals are classified into latent classes. The probability for an individual to be assigned to a specific latent class is measured by posterior class-membership probability given the individual's response pattern on the observed categorical indicators/items. The latent class memberships of individuals are not definitely determined but based on their highest posterior class-membership probabilities.

If the posterior probability of an individual is close to 1.0, then the class misclassification or uncertainty is small. The probability for correct class-classification for an individual is the highest probability to be in a class, and the probability of misclassification is the sum of the probability to be classified in the rest of the classes. Posterior probabilities for a specific class of 1.0 are unlikely, consequently zero for the rest of the classes. A rule of thumb for acceptable class classification is 0.70 or greater (Nagin, 2005).

For assessing the quality of class membership classification another criterion is Entropy, whose values range from 0 to 1 with smaller values indicating a better classification, which is defined as,

$$EN(k) = -\sum_{i=1}^{N}\sum_{k=1}^{K} P_{ik} ln P_{ik} \tag{2.8}$$

where P_{ik} is the posterior probability for the ith individual to be in class k.

Relative entropy

The relative entropy that is defined by (Kamakura & Wedel, 2000) as

$$REN(k) = 1 - \frac{EN(k)}{Nln(K)} \tag{2.9}$$

for a k-class model with a sample size of N. This rescaled version of entropy range from 0 to 1 and a value closer to 1.0 indicates better classification. A good classification can be defined as some researchers suggest with an entropy of 0.8 or higher, 0.6 is medium and 0.4 is low relative entropy.

When defining the final latent classes it is important to check the size of each class, the percentage of individuals in each class represents the prevalence of the corresponding subpopulation in the target population. To have a meaningful class classification, the sizes should not be too small. Latent classes must be theoretically meaningful and interpretable. The researcher needs to define and name the classes based on the patterns of item-response probabilities in that class. For this, the classes identified should make sense and if any class is not theoretically interpretable, the model will not be useful regardless of model fit.

After the number of latent classes is defined, the class classification should be checked and interpreted. Class counts are estimated based on the posterior class membership probabilities for each individual to be partially a member of all the classes. Another type of latent class count is estimated based on the most likely latent class membership, this means that each individual is assigned to the most likely class. If these two types of counts differ substantially indicated that the class membership misclassification is large. With a perfect classification (entropy = 1) the two counts would be identical.

Avoid local maxima

A well-known problem of any mixture modeling is that model estimation may not converge on the global maximum of the likelihood, but local maxima, providing incorrect parameter estimates (Goodman, 1974; B. Muthén & Shedden, 1999). The solution is to estimate the model with different sets of random values to ensure the best likelihood (McLachlan & Peel, 2000; L. K. Muthén & Muthén, 2012).

The software used automatically generates 10 random sets of starting values in the initial stage for all model parameters, and then maximum likelihood optimization is carried out for 10 iterations using each of the 10 random set starting values, and finally 2 starting values for the final stage optimizations. When more than 2 classes are specified it requests a larger number of random sets of starting values to avoid local maxima of the likelihood.

2.3 Measurement invariance

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 (e.g. gender, countries or time). Measurement invariance is an important prerequisite for using multi-indicator assessment instruments to examine group differences. If the measurement properties of an instrument differ between observed groups (non invariance), it is not possible to compare the differences between the groups (Białowolski, 2016; Kankaraš, Vermunt, & Moors, 2011; Vermunt, 2014).

The importance of cross-countries comparisons is at the heart of large-scale international surveys. Instruments that assess subjective attitudes (e.g. attitudes towards migrants) and also psychological traits such as perseverance, aims for the validity and comparability of survey results. Reflective latent constructs measured through self-reports, for example, are particularly affected by subtle linguistic differences in the translated questionnaires and by broader cultural differences. These may introduce variation in participants' understanding of survey questions, and therefore in the relationship between their responses and the target latent construct. Similarly, when confronted with Likert items (*Strongly Agree*, *Agree*, *Disagree*, *Strongly disagree*), or with subjective rating scales (*on a scale from 1 to 10*), cultural norms may mediate the response process of participants. As a result, international surveys may fall short of their objective to facilitate comparisons across countries (*Invariance analyses in large-scale studies*, 2019).

Multigroup Latent Class Analysis tests whether the number of classes is stable across the known groups and if the measurement part of the model is equivalent across these groups.

1. Heterogenous model

The first model to measure invariance is an *unconstrained model* in which the compared groups exhibit the same number of classes but the parameters defining those classes are freely estimated across groups. This means that assumes that the only similarity between groups is the number of classes identified and allows that response patterns (conditional probabilities) and class sizes vary among groups. Although the number of classes in all groups may be the same, direct between-country comparisons are not possible in this step because the meaning of latent classes may be substantially different. A completely unrestricted multi-group latent class model is equivalent to the estimation of a separate 3-class LC model for each group (Davidov, Schmidt, & Billiet, 2011).

$$\pi^{ABCDEX|G}_{ijklmt|g} = \pi^{X|G}_{t|g}\pi^{A|X,G}_{it|g}\pi^{B|X,G}_{jt|g}\pi^{C|X,G}_{kt|g}\pi^{D|X,G}_{lt|g}\pi^{E|X,G}_{mt|g} \tag{2.10}$$

Here, $\pi^{ABCDEX|G}_{ijklmt|g}$ denotes the conditional probability that an individual who belongs to the gth group will be at level (i, j, k, l, m, t) with respect to variables A, B, C, D, E, and X. The conditional probability of X taking on level t for a member of the gth group is denoted by $\pi^{X|G}_{t|g}$ which denotes determines the LC proportion for the gth group.

$\pi^{A|X,G}_{it|g}$ is the conditional probability of an individual taking level i of variable A, for a given level t of the latent variable X and for a given group membership g of the grouping variable G. Parameters $\pi^{B|X,G}_{jt|g}$, $\pi^{C|X,G}_{kt|g}$, $\pi^{D|X,G}_{lt|g}$, and $\pi^{E|X,G}_{mt|g}$ are similarly defined conditional probabilities. Indicator variables A, B, C, D and E are independent from each other, given the value of the latent variable X. This is usually referred to as the assumption of local independence (Lazarsfeld & Henry, 1968).

The latent class and conditional response probabilities are constrained to a sum of 1: $\sum \pi^{X|G}_{t|g} = 1$, $\sum \pi^{A|XG}_{it|g} = 1$, and so on.

$$\pi^{A|XG}_{it|g} = \frac{\exp(\lambda^{A}_{i} + \lambda^{AX}_{it} + \lambda^{AG}_{ig} + \lambda^{AXG}_{itg})}{\sum \exp(\lambda^{A}_{i} + \lambda^{AX}_{it} + \lambda^{AG}_{ig} + \lambda^{AXG}_{itg})} \tag{2.11}$$

2. Partial homogeneity

The second model to test is the *semi-constrained model* in which equality constraints are imposed across the observed groups. The measurement part of the model (conditional probabilities) are restricted to be equal in all observed groups. For each group, the meaning of latent classes is invariant of the group and cross-group comparisons are meaningful. Yet, the size of the classes (i.e. the relative importance of each class) may still vary. Most applicable and desirable in cross-cultural studies.

$$\pi^{ABCDEX|G}_{ijklmt|g} = \pi^{X|G}_{t|g}\pi^{A|X}_{it|g}\pi^{B|X}_{jt|g}\pi^{C|X}_{kt|g}\pi^{D|X}_{lt|g}\pi^{E|X}_{mt|g} \tag{2.12}$$

To test for invariance, the unconstrained model and the semi-constrained models are compared using the likelihood ratio test (LRT) and information criteria such as AIC, BIC, aBIC. A statistically significant LRT indicates a substantial decrease in model fit such that the semi-constrained model should be rejected. The model with the smallest AIC, BIC, aBIC value is selected as the best-fitting model.

If the semi-constrained model is rejected, this means, lower information criteria for the unconstrained model and LRT statistically significant, there is no evidence to assume measurement invariance. In this case, latent classes are characterized different across the observed groups and differences in the prevalence of the profiles across the groups cannot be meaningfully determined.

For invariance to exist, the semi-constrained model should show a better fit to the data than the unconstrained model. Only after establishing the stability of the classes definition across the different groups, it is possible to compare groups and evaluate the differences in class prevalence.

3. Complete homogeneity

The more strict level of invariance is where all parameters are constrained across countries, and the prevalence of latent classes are restricted to be equal across groups (i.e. the percentage of individuals assigned to different classes will be equal in all groups). This last assumption will imply that the identified groups of individuals with similar scoring patterns are identical in all the groups with identical numbers of individuals assigned to each group.

$$\pi^{X|G}_{t|1} = \pi^{X|G}_{t|2}, \; for\, t = 1, 2, 3 \tag{2.13}$$

If the fully constrained model fit best it can be concluded that there are no differences in how the known groups are represented in each profile. In contrast, if the fully constrained model is rejected but the semi-constrained model holds means that although the profiles have the same meaning in each group, there are differences in how the individuals are distributed across classes.

Meeting this last assumption ensures the highest level of cross-country comparability but may be difficult to achieve in cross-cultural studies.

When the number of observations per group is small, likelihood ratio tests have limited power; while with large groups, violations of invariance detected in such tests may be inconsequential for the substantive inferences (*Invariance analyses in large-scale studies*, 2019). The problem is compounded by the fact that in realistic settings (when violations of measurement invariance may be due to cultural or language specificities), the hypotheses are not independent, neither across items nor across groups.

In case that the fully constrained and semi-constrained models are rejected, it can be studied if some latent classes are measurement invariant or not and/or if some items are invariant or not. That means that the assumption of measurement invariance can be relaxed for some classes and/or items. This can be done successively until one finds such a less restrictive model that does not fit the data worse than the totally unrestricted model.

If the number of classes differs between groups, then it can be tested whether the classes that are present in all groups are measurement invariant or not. This means if one group has 2 classes and another group has 3 classes a 3-class multigroup model with full measurement invariance can be tested, where the size of the third class in the first group would be zero. This strategy is recommended for a small number of groups. When a large number of groups is tested another strategy is recommended as it will take so much time in computing and compare all parameters to identify the ones that are invariant or that should be free.

The appropriate strategy for a large number of groups is to conduct a multigroup LCA where full measurement invariance is assumed across the groups and that the number of classes does not differ across those groups. For this, the appropriate number of classes should be identified for each group and test if just one class is different between them, if this is rejected an extra class should be added to identify if there are two different classes among them. If the double of classes is found as the best fit means that none of the classes is measurement invariant, because different classes by country are needed. This strategy has the advantage to have a higher power to detect small classes that exist in several groups but that would not be detected in country-specific analysis because their size within a group might be too small.

Chapter 3

Methods

3.1 Methodological features

There are two different approaches to conduct a Latent Class Analysis, an exploratory and confirmatory approach. Both methodologies are valid for this analysis but their main difference resides in the hypothesis that wants to be tested.

When researchers do not have specific hypotheses but the goal is to identify how many classes are necessary to fit the data, an exploratory latent class analysis can be performed. In this case, several latent class models with an increasing number of classes should be computed. The best-fitting will be selected, this can be identified by which increasing the number of latent classes would not result in a model that fits the data significantly better than the previous model. Information criteria such as AIC, BIC and aBIC can be used to determine the best fit, the best model will have the lowest values of information criteria.

The confirmatory approach starts with specific hypotheses about the latent structure, the researcher can test if there is a defined number of classes that explained the associations between the observed variables and specific relations in the items for each class or across classes. Based on the conditional response probabilities and class sizes computed by the software, the expected frequencies can be estimated. These frequencies can be compared with the observed frequencies with a statistical test such as Pearson test or the LRT. If the test statistics show that the observed and expected frequencies do not differ significantly, the model is appropriate to explain the associations of the observed variables. The expected frequency of each possible response pattern should be at least 1 or even 5 to make sure that both statistics follow a χ^2 distribution and that p-values can be used for a valid decision. In case of sparse tables, bootstrapping goodness of fit is highly recommended (*Invariance analyses in large-scale studies*, 2019).

As mentioned before, studying measurement invariance is necessary to determine whether the number and nature of the latent profiles are the same across the different observed groups (Olivera-Aguilar & Rikoon, 2018). For this, multigroup LCA models are computed, and the relative fit of the unconstrained and semi-constrained models are compared using the LRT, AIC, BIC, and aBIC measures, Entropy and LL reduction is evaluated as well. Additionally, is needed to review any kind of response bias, the most common refers to "a systematic tendency to respond to a range of questionnaire items on some basis other than the specific item content" for example, extreme responses for agree/disagree (Kankaraš, Vermunt, & Moors, 2011).

3.2 Analytical strategy

In order to perform the analysis for this research the strategy to be used is based on performing firstly independent analysis for each selected country, this way it will be possible to identify the country-specific number of classes as a starting point.

Based on the optimal number of classes for each country, an independent analysis of the latent class will be performed in order to evaluate class membership, sizes and the interpretation of these classes for each country.

Once all the classes are identified for each country, all these classes will be compared between countries in order to identify similar and unique classes across countries. With this, a final number of optimal classes will be chosen for the total sample (including all the countries) in order to absorb all the possible different classes found in all the countries independently. If similar classes were found in more than one country this will count as one in the global model, if unique classes are identified this will count as a country-specific class. This country-specific class could be different across countries for that reason it will count as just one class. If one country or more have two or more country-specific classes, two or more classes will be included in the global model.

With the number of classes decided for the global model an exploratory latent class analysis is performed where a number of classes will be similar across countries and the remaining classes will differ across countries. The results from this model will be used to evaluate the model fit and the results will be compared between including/excluding one class.

The model with a good fit and the best interpretability will be chosen to evaluate the levels of invariance. First, the heterogeneous model will be analyzed, where all the parameters are freely estimated across countries. This will be similar to try different models for each country. This model is going to be compared to more restricted models. Next, some parameters will be fixed in order to test if partial invariance can be achieved, with this it will be tested if the classes patterns are comparable across countries. As a third step, the most restricted model is computed, where not only the patterns are assumed to be equal across countries but also the class membership.

Finally, confirmatory latent class analysis will be evaluated with some fixed conditional probabilities based on hypotheses obtained from the global and most invariant model identified.

In summary, this strategy will allow to identifying if there are some classes and how many of them can be compared across countries and how we can interpret them.

1. Independent exploratory LCA to identify the country-specific number of classes.
2. 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 the total number of classes identified in the general exploratory LCA model.

The analytical strategy will be performed using both software, R and Mplus. Mplus is the specialized software to perform Mixed models, especially with complex samples. This software allows to include weights, clustering and stratification variables. This is the core for modeling large scale assessment data. As Mplus can be used by creating automatized code in R, that allows to extract the output of the complex procedure performed and utilize R features to summarize and report the results. Most of the important code used for the different tasks are summarized in appendix A.3.

To avoid local maxima and obtain trustworthy estimations the number of random sets of starting values for initial stage optimization was set to 100, the number of random sets of starting values for final stage optimization to 25 (a quarter of the number of initial starting values) and the maximum number of iterations in optimization to 5.

To be completely sure that the model has reached the global maximum value of likelihood, Mplus perform the model by running the analysis multiple times and indicate if the global maxima is reached. When this is not the case is not possible to compare the results, this is clearly stated in the following chapter.

3.3 Study

In this section, the different scales used in the research are explained. Firstly, an explanation of the variables that conform every scale used in the analysis are described. Secondly, a summary and description of the data selected for the analysis, characteristics and size are given.

3.3.1 Variables

The first scale is composed of seven items, present also in ICCS 2009, ask about the roles of women and men in society. Students were asked to indicate their level of agreement (four levels ranging from "strongly agree" to "strongly disagree") with each statement. The six first items are used to form the scale *Students' endorsement of gender equality*. The first three items consult about the level of agreement with statements related to governmental, work and every way life with *"Men and women should have equal opportunities to take part in government"*, *"Men and women should have the same rights in every way"* and *"Men and women should get equal pay when they are doing the same jobs"*.

The last three items which are negatively worded consult for the level of agreement with the following statements, *"Women should stay out of politics"*, *"When not many jobs available, men should have more right to a job than women"* and *"Men are better qualified to be political leaders than women"*. These last items were inversely coded, this means that when an individual responded "Agree" to any of these items, this response was coded as "Disagree" and then the question should be interpreted inversely. In the analysis chapter, these items will appear with a "(r)" added at the end of the label to easily identify them. Higher values of this scale reflect stronger agreement with the notion of gender equality or stronger disagreement with negative views of gender equality.

The other set of questions is focused on the rights and responsibilities of all different ethnic/racial groups in society. Same as before students' indicate their level of agreement in the same range. This scale called *Students' endorsement of equal rights for all ethnic/racial groups* indicate with higher scores a greater degree of agreement with the idea that ethnic and racial groups should have the same rights as other citizens in society.

In this scale, also from ICCS 2009, the first two items are focused on evaluating the attitude towards equality in education and work with *"All ethnic and racial groups should have equal chance to get a good education"* and *"All ethnic and racial groups should have an equal chance to get good jobs"*. The third item is related to school education with *"Schools should teach* *students to respect members of all ethnic and racial groups"* and last two items are focused in politic equality and responsibilities with *"Members of all ethnic and racial groups should be encouraged to run in elections for political office"* and *"Members of all ethnic and racial groups should have same rights and responsibilities"*.

The original response categories for these items are based on four points agree/disagree scale, starting by the lower level of agreement "Strongly disagree" (1), "Disagree" (2), "Agree" (3), and "Strongly disagree" (4). For this analysis and to be able to reduce the complexity in the interpretation, these categories were recoded into two levels, "Disagree" (1) and "Agree" (2).

3.3.2 Sample

Multiple countries participate in the ICCS 2016 study, from different continents Europe, Asia, Latin America and the Caribbean mainly (detailed sample size of the participating countries can be found in Table A.2 in the appendix).

Only European countries were selected for this research, the decision was mainly based on work with countries with different backgrounds, where no characteristics such as language, geographical location, economic status or others could influence unwanted factors that could impact in the results.
Fourteen countries were chosen, from nordic, western, central, eastern and southern Europe. Each country sample size is different, the country with the highest student sample is Norway (6271), followed by Denmark (6254), and the countries with the lowest sample size are Netherlands (2812) and Slovenia (2844).

This research will be focused only on the 14 European countries that participated in the assessment, these countries can be organized by the following geographical grouping:

a) Nordic: Denmark, Finland, Norway, Sweden.

b) Western European: Belgium (Flemish), The Netherlands.

c) Central and Eastern European: Bulgaria, Estonia, Latvia, Lithuania, Croatia, Slovenia.

d) Southern European: Italy, Malta.

The complexity of the sample design of the study itself forces to apply this complexity into the analysis as well. Weights for each student are available in order to estimate correctly all the tests and statistics. Each individual in the sample not only include the sampling weight but also a senate weight associated, that sum up 1000 for each country, this means that each country will have the same participation in the analysis.

The need of using a complex sample design forces that the analysis to be even more complex as if there were no weights involved in the sample. Luckily, Mplus provides a set of tools that allows performing a latent class analysis and multigroup LCA considering not also the complexity of the sample design but the inclusion of the student senate weights in the estimation as well.

Regardless the software performs most of the analysis available, some test such as the bootstrap likelihood ratio difference test for comparing models differing in the number of classes is not possible to calculate when using sampling weights. This is a disadvantage when working with samples.

Chapter 4

Results

In this chapter, the relevant findings from every step performed are analyzed following the analytical strategy indicated in the previous chapter. First, latent class analysis for each country included in the sample selected is performed in order to identify the optimal number of classes for each country separately. Secondly, a global analysis is performed to identify how many latent classes are identified including all different countries, with this information it is possible to establish the number of classes that can be compared across countries. Finally, a multigroup latent class analysis is performed considering all the previous information. The multigroup analysis is constructed in multiple steps, the most restricted model until the less restricted model is evaluated. As a final step, a confirmatory latent class analysis is performed using some theoretical hypotheses that was defined based on the previous results.

This procedure is performed for the two scales that were used to create the Students' endorsement of equal rights and opportunities indicators separately.

For every analysis in this chapter, the model fit statistics table include all the statistics that are retrieved by MPLUS software. Here is a brief description of the meaning behind every column that will be shown. The first table with the model fit statistics for all different models indicate first the number of classes used in the model, the total number of parameters estimated, the final and best Log-likelihood, the values for information criteria AIC, BIC, aBIC. The entropy indicated in each table correspond to the relative entropy, where a perfect classification is 1, the table also indicates the log likelihood reduction (LL Reduction) from adding one class into the model. Two tests for model fit are indicated as well, the value of the statistic and the p-value associated with the Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR) and Lo-Mendell-Rubin adjusted LRT Test (LMR).

Conditional response probabilities plots are included as a summary for every independent model, the x-axis includes all the items included in the model, the y axis corresponds to the values of the probability to agree with that item, these values range from 0 to 1, where values close to 1 indicate that is highly likely to agree with that item, in contrast, values close to 0 indicate unlikely to agree to that item. On the other hand, values around 0.5 indicate randomness in the response, for this reason, is not possible to indicate a clear tendency to agree or to disagree. The different classes identified in the plots are colored differently but the colors remain the same when the response pattern is similar across countries. When a new class was identified a new color was used. The sample size for each class appears at the end of the x-axis colored with the same color as the class.

4.1 Students' endorsement of gender equality scale

As mentioned in the previous chapter, this scale is composed of 6 items, in the following tables and plots, these items were ordered from positive to negative items for an easier interpretation of the results. This ordering consider first all the items that were positive worded in the instrument *Men and women should have equal opportunities to take part in government (GND1)*, *Men and women should have the same rights in every way (GND2)* and *Men and women should get equal pay when they are doing the same jobs (GND5)*, followed by the three other items that are negatively worded *Women should stay out of politics (r) (GND3)*, *Not many jobs available, men should have more right to a job than women (r) (GND4)*, *Men are better qualified to be political leaders than women (r) (GND6)*. As mentioned before all these variables were recoded in two categories, Agree and Disagree. All 14 countries were analyzed independently and then pooled in the same dataset.

4.1.1 Analysis by country

Multiple latent class models with 1 to 6-classes[1] were performed in each country in order to evaluate the model fit of each one of them. The results are summarized in table 4.1. In most European countries, the best model fit based on the different criteria indicated previously are by including 3 or 4 latent classes.

For Belgium, Croatia, Denmark, Latvia and Netherlands there is no significant improvement in the log-likelihood from two to three latent classes. In this sense, BIC and aBIC simultaneously have the lowest values in the 3-class model.

On the other hand, in Bulgaria, Estonia, Malta, Slovenia, and Sweden according to the statistical tests, BIC, and aBIC criteria, the best model is a 4-class model. In Finland, Italy and Lithuania models, the BIC, aBIC differ from the statistical test indicating a better fit for the 3 class model.

Norway is the only country from the sample where the best model fit is the one with 5 latent classes according to the statistical tests and BIC and aBIC.

It is a common tendency in all the evaluated countries that the AIC value is lower in the models with one more class than the indicated by the statistical tests and BIC and aBIC statistics. That is consistent with the indication that this criterion tends to overfit the data.

Values of Entropy are higher when the tests are significant but consistent with a better fit of the data, the lower entropy found in the 4-class model is in Latvia (73.7%) and the highest value in Norway (96%). The log-likelihood reduction is consistent in all countries, where having more than 3 latent classes reduce the log-likelihood around 0.2% and 1%.

All models selected accomplish at least one or more of the criteria established for a good fit. The bivariate residuals were also analyzed, and all countries have residuals around the range of acceptable [-2 ; 2] as shown in the figure 4.1. There it can be seen that just one value is outside the ranges in Malta with a 4-class model.

[1] Summary with all models can be found in Appendix, table A.3.

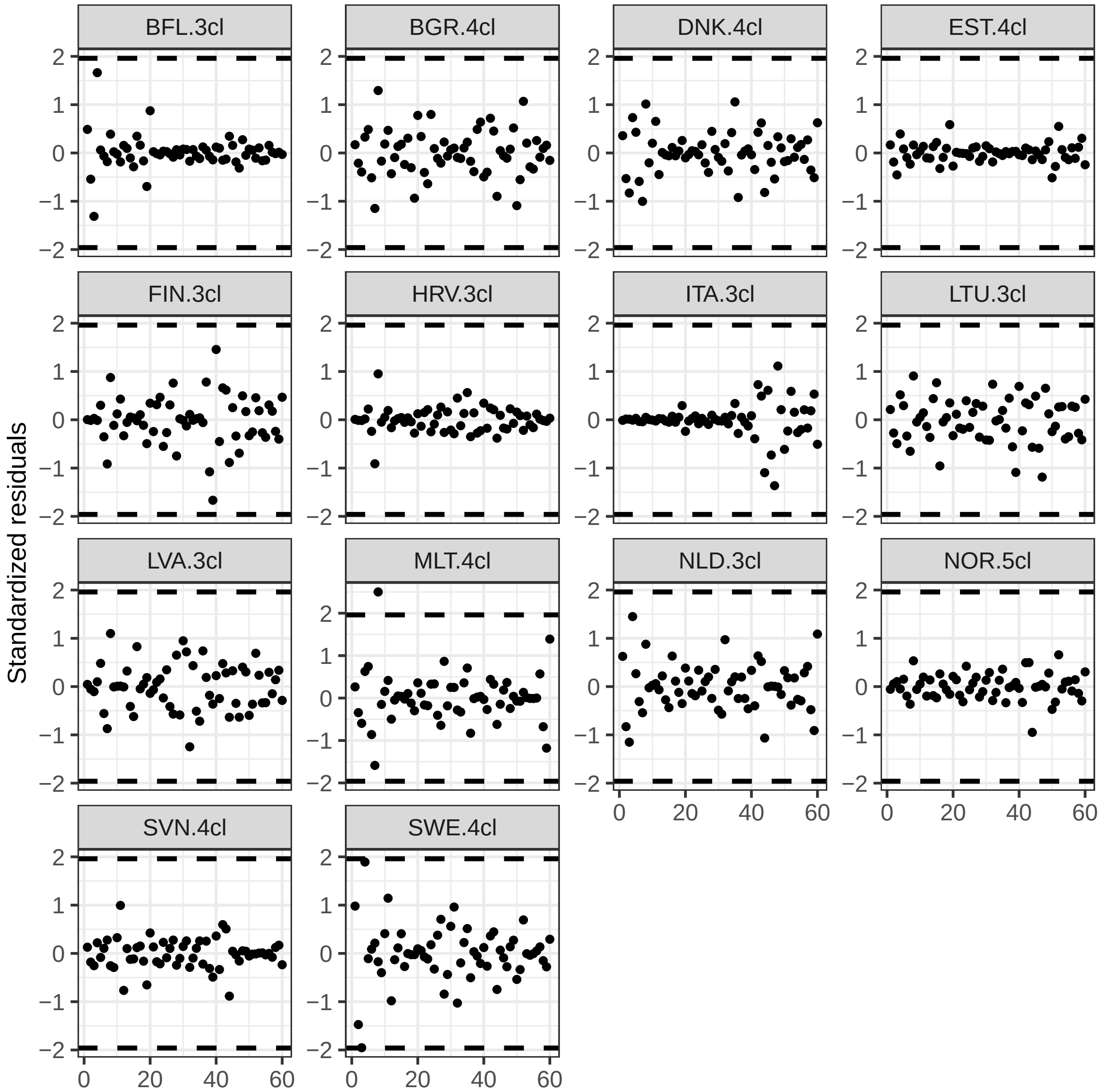

Figure 4.1: Bivariate standardized residuals individual country models for Students' endorsement of gender equality

Table 4.1: Best model, fit statistics individual country model Students' endorsement of gender equality

Country	N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
Belgium (Flemish)	3	20	-3812	7664	*7784*	*7721*	*88.2%*	0.8%	*62*	*0.323*	*61*	*0.327*
Bulgaria	4	27	-7523	15100	*15261*	*15175*	*75.2%*	0.4%	*60*	*0.077*	*59*	*0.08*
Croatia	3	20	-5368	10777	*10902*	*10838*	87.6%	0.9%	*98*	*0.085*	*96*	*0.088*
Denmark	4	27	-5914	11883	*12063*	11977	91.2%	0.6%	*74*	*0.174*	*73*	*0.178*
Estonia	4	27	-4974	*10001*	*10162*	*10076*	77.7%	0.6%	*57*	*0.183*	*56*	*0.189*
Finland	3	20	-3477	6993	*7114*	*7051*	90.7%	1.2%	86	0.037	84	0.039
Italy	3	20	-4830	9701	*9824*	*9760*	84.6%	1.5%	145	0	143	0
Latvia	3	20	-7993	16027	*16148*	*16085*	72.4%	0.8%	*121*	*0.052*	*119*	*0.055*
Lithuania	3	20	-7447	14934	*15058*	14994	*82.5%*	1.6%	248	0	244	0
Malta	4	27	-6204	12462	*12629*	*12543*	87.2%	0.5%	*65*	*0.235*	*64*	*0.238*
Netherlands	3	20	-4759	9557	*9676*	*9612*	87.0%	1.5%	*140*	*0.074*	*138*	*0.076*
Norway	5	34	-6035	12137	*12365*	*12257*	93.2%	0.5%	*66*	*0.281*	*65*	*0.286*
Slovenia	4	27	-4280	8614	*8774*	*8689*	*87.5%*	0.7%	*56*	*0.158*	*55*	*0.163*
Sweden	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

In figure 4.2, the classes of each independent model can be identified by looking at the conditional probabilities. In the figure, the conditional probabilities to agree to each item are shown and plotted for each class estimated in each country. From all the models, two classes that are similar across countries are identified in the figure, Fully egalitarian and Competition-driven sexism, green and purple line respectively.

A brief explanation of each class is described following.

- **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).

- **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 politically related items (light-green line)
  Conditional probabilities are 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).

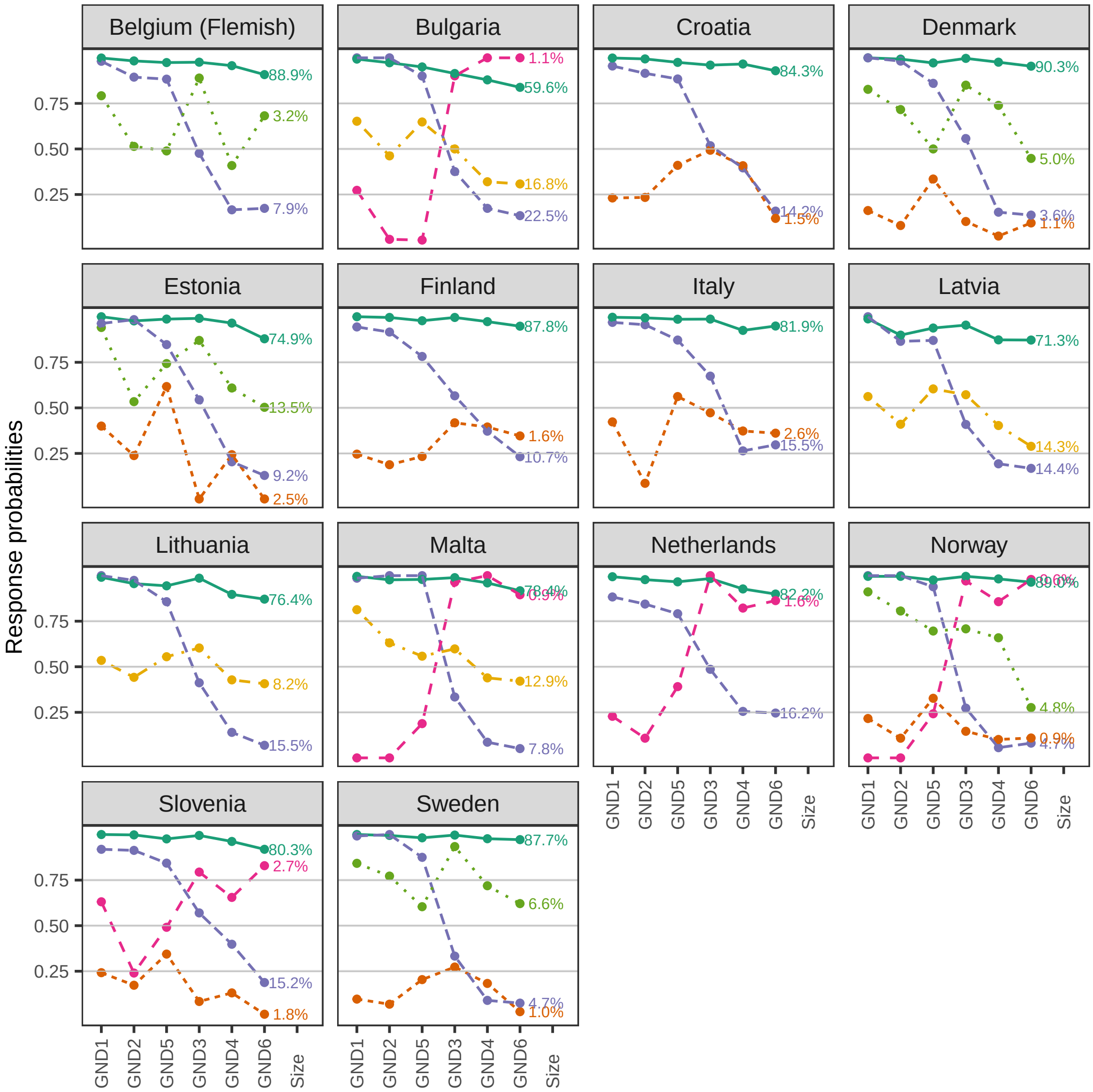

Figure 4.2: Classes for best individual country model for Students' endorsement of gender equality

The classes described before are not present in all countries, for this reason, a global model will be tested in the pooled sample considering not only the classes that are similar across more than one country but additional classes will be added in order to absorb the remaining different classes that the global model will identify.

In the following section, the global model will be tested using the pooled dataset.

4.1.2 General model

Table 4.2 show the results of each model using the pooled sample with all the countries. Models with 1 to 7 classes were computed and the model fit statistics were summarized in the table.

The model that includes a single class has the largest AIC (192,838), BIC (192,891), and ABIC (192,872) values for the pooled sample, indicating that this model fits data worse than all other models. In addition, the P-values for the VLMR test, and LMR in the 2-class model are all < 0.0001; this means that both tests reject the single-class model in favor of a model with at least two latent classes. In other words, there exists heterogeneity in the target population in regard to attitudes towards gender equality.

On the other hand, the LMR LR and VLMR tests for the 6-class model are not statistically significant ($P > 0.05$). That is, the two tests are in favor of at most 5 classes.

In contrast, BIC and aBIC values are all smaller in the 5-class model than those in the 6-class model; thus consider that the models with more than 5 classes are not preferred. AIC values reach the lowest value in the 7-class model, but based on the previous results this criteria will not be considered in this case due to the tendency to overfit the data.

The relative entropy given by Mplus software, decrease when including more than 4 classes and increase again with the 6-class model, this would suggest that a model with at least 6 class or 4 classes is preferred.

Together with the percentage of reduction in the log-likelihood value, that indicates that by adding two classes to the model the log-likelihood is reduced by 13.3%, this reduction is only increased by 1.2% if the model is a 3-class model and finally this value is reduced close to 0 if more than 5 classes are included.

Now, the preferred model must be either the 5-class or the 6-class model. Considering the residuals of each model, in figure 4.3 all values are around -1.96 and 1.96. But based on the parsimony principle a 4-class model can be considered as well as just one value of the residuals is outside the acceptable range.

Theoretically, we tend to determine that the 4-class LCA model is the preferred model. We will show later that the classes identified by the 4-class model are more interpretable and representatives than the rest of the models. And in particularly that two classes can be compared across countries.

Table 4.2: Model fit statistics LCA Students' endorsement of gender equality

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*

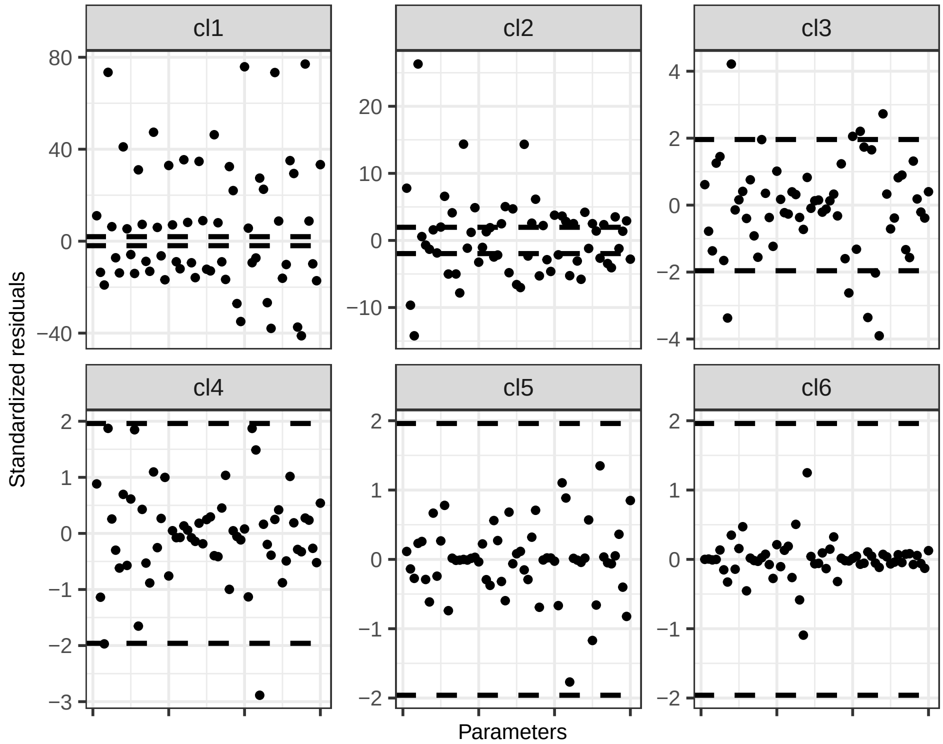

Figure 4.3: Bivariate model fit standardized residuals global model for Students' endorsement of gender equality

Three, four, five and six classes model were investigated profoundly. It is clear that is not easy to choose the best model fit without doing a full analysis. There are some patterns that can be clearly identified in all the models as can be seen in figure 4.4, Class 1 with 81%, 79.2%, 77% and 78.6% in each model respectively, the estimated probabilities to agree for this latent class, the **Fully egalitarian** group, for all six items *Men and women should have equal opportunities to take part in government*, *Men and women should have the same rights in every way*, *Men and women should get equal pay when they are doing the same job*, *Women should stay out of politics*, *Not many jobs available, men should have more right to a job than women* and *Men are better qualified to be political leaders than women* are higher than 0.92.

The second class (Class 2 in Figure 4.4) identified in all the models, called **Competition-driven sexism**. For this class, the estimated probabilities to agree to the first 3 items are close or higher than 0.9 in all models. For the last three items, the estimated probabilities to agree are not higher than 0.5 in all models. The class size differ in all four models, 11.3%, 11.5%, 12.8% and 8.6% in the 3, 4, 5, 6-class model respectively.

The third class that can be seen with a similar pattern in all the models is called **Non-egalitarian**, this class appears in the 4-class model. The pattern of this class is basically showing lower estimated conditional probabilities to agree to any of these statements, no greater than 0.4, with the exception of one item *Men and women should get equal pay when they are doing the same jobs* with an estimated probability to agree no higher than 0.55. The estimated sizes for this class are 7.7%, 7% and 5.8% in each model respectively.

The four, fifth and sixth classes identified in the models differ in all the countries, nevertheless, one class appears to be consistent in the 5-class model, where this class called **Reverse competition-driven sexism** has opposite conditional probabilities compared to the second class identified previously.

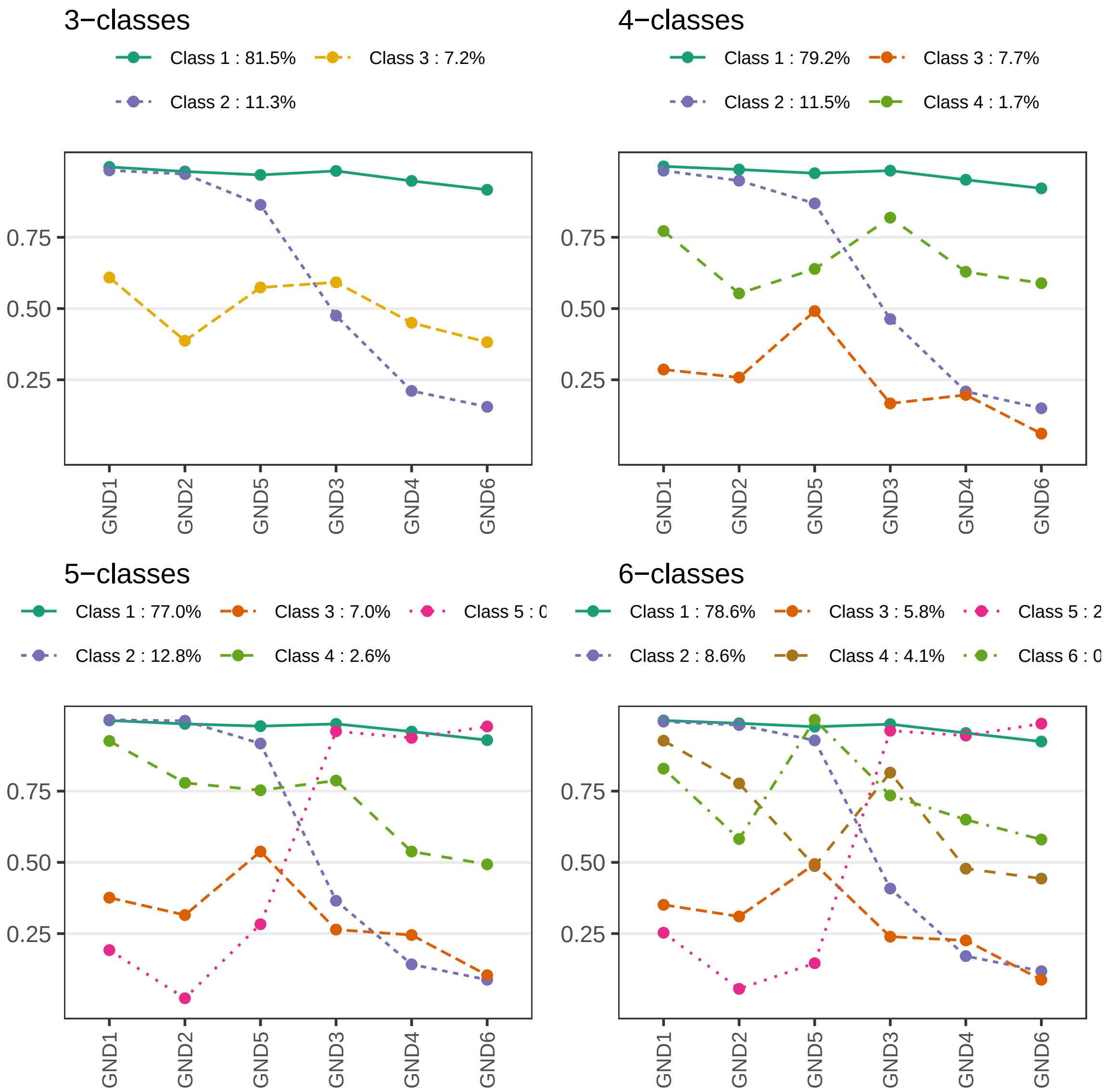

Figure 4.4: Comparative conditional probabilities to agree in 3 to 6 latent class global models for Students' endorsement of gender equality

The main two classes in the solutions with five and six classes does not strongly differ from other models, and the remaining classes are not informative at all or with a sample size very small, using this as a criterion, one can prefer a four-class solution.

In table 4.3 the conditional probabilities to agree with the fourth latent class model are shown. These values are very close to 1 for the first class, Fully egalitarian. Similar values are obtained for the positive items in the second class Competition driven-sexism, meanwhile, for third item GND3, conditional probabilities are close to 0.5, this would mean a random response, but the last two items have lower conditional probabilities close to 0.2, which would mean not likely to agree to the statements. Table 4.4 indicate the counts and proportions using the model estimated and the most likely probabilities.

Table 4.3: Probabilities to agree each item in the four-class global model for Students' endorsement of gender equality

param	Fully egalitarian	Competition-driven sexism	Non-egalitarian	Political egalitarian
GND1 - Men and women should have equal opportunities to take part in government	0.999	0.984	0.286	0.772
GND2 - Men and women should have the same rights in every way	0.988	0.949	0.258	0.553
GND5 - Men and women should get equal pay when they are doing the same jobs	0.975	0.869	0.491	0.639
GND3 - Women should stay out of politics (r)	0.984	0.463	0.167	0.819
GND4 - Not many jobs available, men should have more right to a job than women (r)	0.952	0.209	0.197	0.629
GND6 - Men are better qualified to be political leaders than women (r)	0.922	0.15	0.061	0.589

Table 4.4: Class sizes four-class global model for Students' endorsement of gender equality

	Model estimated		Most likely	
Class	Counts	Proportion	Counts	Proportion
Fully egalitarian	39924.2	79.2%	41508	82.3%
Competition- driven sexism	5782.2	11.5%	5258	10.4%
Political egalitarian	3864.7	7.7%	2969	5.9%
Non-egalitarian	859.9	1.7%	696	1.4%

4.1.3 Country comparability

To evaluate the country comparability, the classes that were found in the independent model were identified to later check how many of them could be tested for comparability using a multigroup latent class model.

The different classes identify according to each global model is summarized next, indicating in which countries the same class is present.

- Global three-class model:
  1. Fully egalitarian - ALL COUNTRIES
  2. Competition-driven sexism - ALL COUNTRIES
  3. Random response - BGR, LVA, LTU, MLT
- Global four-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
- Global five-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
- Global six-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 country models

With three classes, the random response class is not very interpretable. With six classes, a new no-identified class appears, which is not interpretable. With five classes, the reverse competition-driven sexism class is present in five countries but with class sizes lower than 1%, which would be not representative. With four classes, the four classes are identified across countries and two of them are present in all countries, which means is the best model for comparability.

Country multigroup analysis

In table 4.5 different models with multigroup analysis are tested, first the more restricted model is evaluated, complete homogeneity. In this model, all conditional and unconditional probabilities are fixed to be equal across the groups.

Then, the partial homogeneity is tested where only the conditional probabilities are constrained to be equal across the groups, and the class sizes are estimated freely. The second approach of partial homogeneity is tested, where only the conditional probabilities for the two common classes identified are constrained across groups, and the remaining are freely estimated along with the unconditional probabilities. Finally, the complete heterogeneous model is tested, where not only the unconditional probabilities are estimated freely but all the conditional probabilities as well. In the last two models the best log-likelihood is not replicated, this means that the solution may not be trustworthy due to local maxima. These results can not be considered valid.

Just by looking at the valid results, the partial homogeneity where all conditional probabilities are constrained to be equal across groups shows a better fit compared to the more restricted model, the complete homogeneity. With it is valid to indicate that the 4 classes identified do not share the same unconditional probabilities (class sizes) across the groups but the conditional probabilities can be considered as equal in all groups.

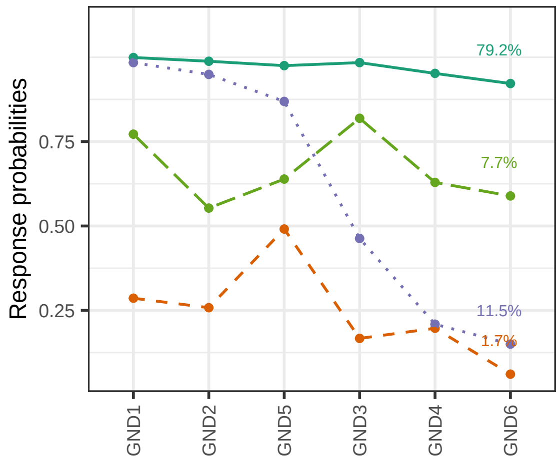

Figure 4.5: Conditional probabilities to agree in a 4-class complete homogeneous multigroup model for Students' endorsement of gender equality scale

Table 4.5: Multigroup model fit statistics global model with four-classes with Students' endorsement of gender equality

Ngroups	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	Δ LL	Δ DF	pvalue Δ
Four-class model										
Complete homogeneity										
14	40	*-215414*	430907	431260	431133	*94.0%*	-1.49%	-3158	-348	0
Partial homogeneity										
14	**79**	**-213195**	**426549**	***427246***	***426995***	**88.1%**	**-0.44%**	**-940**	**-308**	**0**
Complete heterogeneity										
14	391	-212256	*425293*	428745	427502	*94.0%*	*0.00%*			

Note:
The best loglikelihood value was not replicated for the following models:
[1] 4-class Complete heterogeneity model.

Figure 4.5 indicates the values for the patterns with the conditional probabilities fixed in all countries, but also the unconditional probabilities are constrained to be equal in all groups. Here can be observed that the patterns are similar to the ones identified in the independent models and the global model as well. But by constraining the class sizes the model fit is not optimal.

In the figure 4.6, partial homogeneity constrained the conditional probabilities to be equal but not the unconditional probabilities, with this the model fit improves compared to the complete homogeneous model.

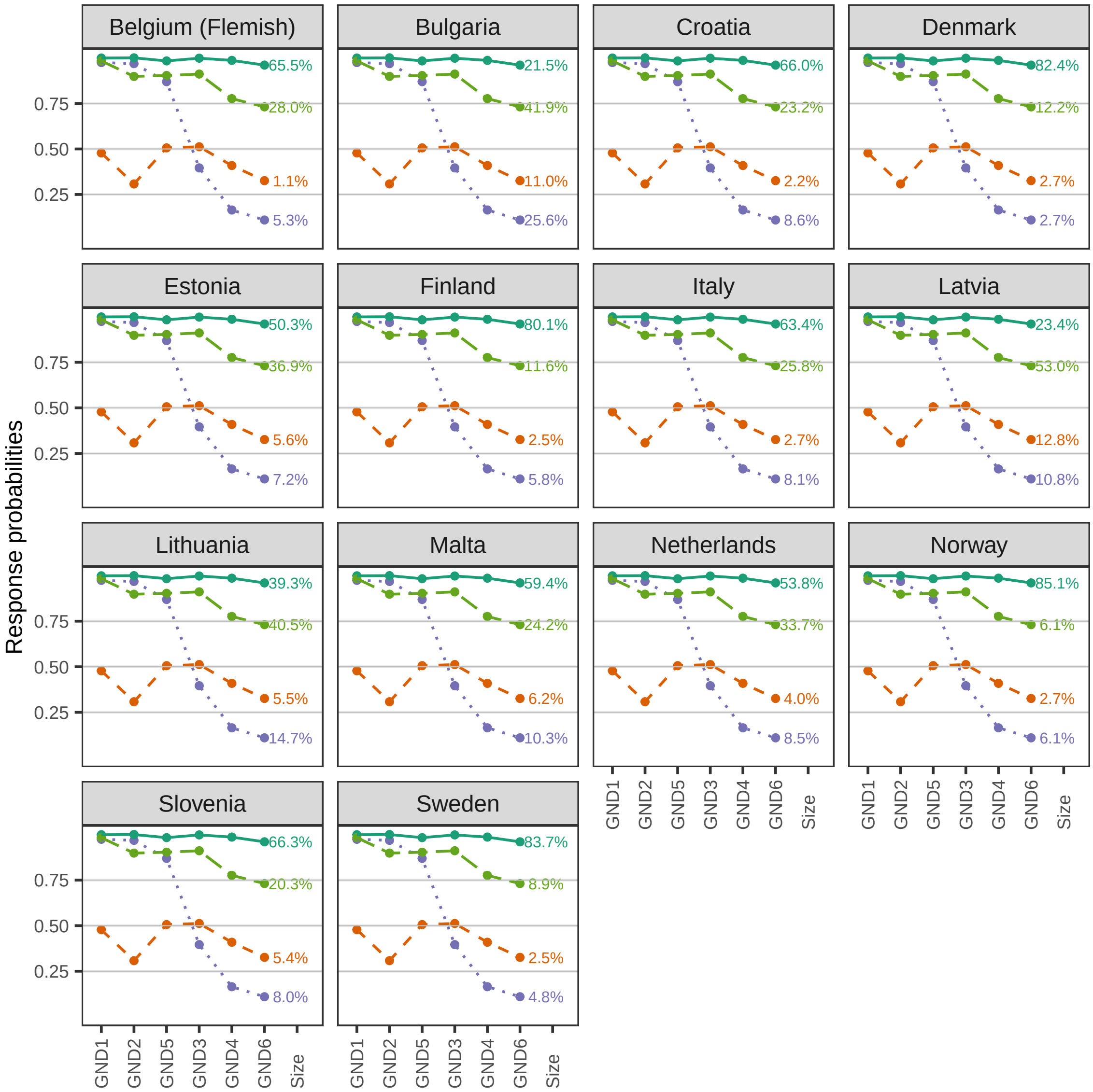

Figure 4.6: Conditional probabilities to agree in a 4-class partial homogeneous multigroup model for Students' endorsement of gender equality scale

4.1.4 Confirmatory Latent Class Analysis

The confirmatory model was performed by establishing some constraints based on the previous research. For the Students' endorsement of gender equality, the hypothesis was that the conditional probabilities for the first item in the Fully egalitarian class, is 1 and the probabilities to agree to the second and third item in the same class are equal to the probabilities of the first item in the Competition-driven sexism class. The third hypothesis is that the conditional probability of the third item in the Competition-driven sexism class is 0.5. The rest of the conditional probabilities were estimated freely as can be seen in table 4.7.

In table 4.6 the model fit statistics of this model indicate that do not differ considerable from the exploratory approach analyzed previously, only the AIC value is better in the exploratory model.

Table 4.6: Model fit statistics 4-class Confirmatory LCA for Students' endorsement of gender equality scale

Type	N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction
All countries								
Exploratory LCA	4	27	-82327	*164708*	164946	164861	*82.7%*	
Confirmatory LCA	4	23	*-82340*	164726	*164929*	*164856*	82.5%	*0.0%*

Values for the thresholds, class sizes and the probabilities to agree to each item can be found in the appendix table A.5.

Table 4.7: Probabilities to agree each item in a 4-class Confirmatory LCA for Students' endorsement of gender equality scale

param	Fully egalitarian	Competition-driven sexism	Non-egalitarian	Political egalitarian
GND1 - Men and women should have equal opportunities to take part in government	1	0.986	0.296	0.75
GND2 - Men and women should have the same rights in every way	0.986	0.941	0.272	0.552
GND5 - Men and women should get equal pay when they are doing the same jobs	0.975	0.864	0.495	0.638
GND3 - Women should stay out of politics (r)	0.986	0.5	0.181	0.817
GND4 - Not many jobs available, men should have more right to a job than women (r)	0.953	0.228	0.195	0.645
GND6 - Men are better qualified to be political leaders than women (r)	0.923	0.167	0.057	0.609

The confirmatory approach stated that students that would be classified into the Fully egalitarian class would highly agree (totally) *Men and women should have equal opportunities to take part in government* which is the first item in the scale. Also, they would agree equally to both items *Men and women should have the same rights in every way* and *Women should stay out of politics (r)*.

The confirmatory approach also stated that the students that belong to the second class Competition-driven sexism class would agree in the same level as the second most likely items in the first class (mentioned before) to the item *Men and women should have equal opportunities to take part in government*. The hypothesis also stated that students would not agree or disagree with the item *Women should stay out of politics (r)* which means that they will tend to give a medium response not having a clear attitude towards gender in this situation.

4.2 Students' endorsement of equal rights for all ethnic/racial groups scale

This scale is composed of 5 items, in the following results, these items were ordered in the output for an easier interpretation of the results. This ordering consider first *All ethnic and racial groups should have equal chance to get a good education (ETH1)*, *All ethnic and racial groups should have an equal chance to get good jobs (ETH2)*, *All ethnic and racial groups should have same rights and responsibilities (ETH5), and All ethnic and racial groups schools should teach students to respect (ETH3)*, followed by *All ethnic and racial groups should be encouraged to run in elections (ETH4)*. As mentioned before all these variables were recoded in two categories, as Agree and Disagree. All 14 countries were analyzed independently and then pooled in the same dataset.

4.2.1 Analysis by country

A latent class analysis with 1 to 6-class models was performed in each country in order to evaluate the model fit of each one of them[2]. The results are summarized in table 4.8. In most European countries, the best model fit based on the different criteria indicated previously are by including 3 or 4 latent classes.

For Belgium, Bulgaria, Estonia, Italy, Lithuania, Latvia, Slovenia, Netherlands, Norway, Slovenia and Sweden, according to the statistical tests, BIC, and aBIC criteria, the best model is a 3-class model.

On the other hand, Denmark and Malta have a better model fit in a 4-class model, consistently results between statistical test and BIC criteria.

In Croatia models, tests indicate that a 2-class model is better for their data, even though BIC indicates a 3-class model to have the lowest value.

Norway is the only country from the sample that the best model fit is the one with 5 latent classes according to the statistical tests and BIC and aBIC.

It is a common tendency in all the evaluated countries the AIC value is lower in the models with one more class than the indicated by the statistical tests and BIC and aBIC. This is consistent with the indication that this criterion tends to overfit the data.Values of Entropy are higher when the tests are significant, but consistent with a better fit of the data the lower entropy found in the 3-class model is in Belgium (60.5%)and the highest value in Sweden (90.2%). The log-likelihood reduction is consistent in all countries, where having more than 3 latent classes reduce the log-likelihood around 0.1% and 0.6%.

[2]Model fit statistics for each model can be found in the Appendix A.6

Table 4.8: Best model, fit statistics individual country model Students' endorsement of equal rights for all ethnic/racial groups

Country	N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
Belgium (Flemish)	3	17	-4019	8072	*8174*	*8120*	60.5%	0.8%	63	0.021	62	0.023
Bulgaria	3	17	-5354	10742	*10843*	10789	78.5%	1.8%	193	0	190	0
Croatia	3	17	-4507	9047	*9153*	9099	76.1%	0.9%	*84*	*0.416*	*82*	*0.422*
Denmark	4	23	-8282	*16610*	*16764*	*16691*	72.3%	0.3%	*54*	*0.059*	*53*	*0.062*
Estonia	3	17	-3254	6543	*6644*	*6590*	69.8%	1.3%	87	0.002	86	0.002
Finland	3	17	-3391	6815	*6918*	6864	80.8%	*2.9%*	200	0	196	0
Italy	3	17	-4354	8742	*8846*	8792	81.1%	1.6%	146	0	143	0
Latvia	3	17	-5353	10741	*10844*	*10790*	64.0%	1.1%	124	0.001	122	0.001
Lithuania	3	17	-4194	8423	*8528*	*8474*	84.8%	0.9%	75	0.016	74	0.017
Malta	4	23	-5691	11428	*11570*	*11497*	80.3%	0.7%	78	0.032	76	0.034
Netherlands	3	17	-4729	9493	*9593*	*9539*	69.7%	1.8%	170	0	166	0
Norway	3	17	-5448	10930	*11044*	10990	88.1%	1.9%	207	0	203	0
Slovenia	3	17	-4272	8578	*8679*	8625	77.5%	1.0%	87	0.027	85	0.029
Sweden	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

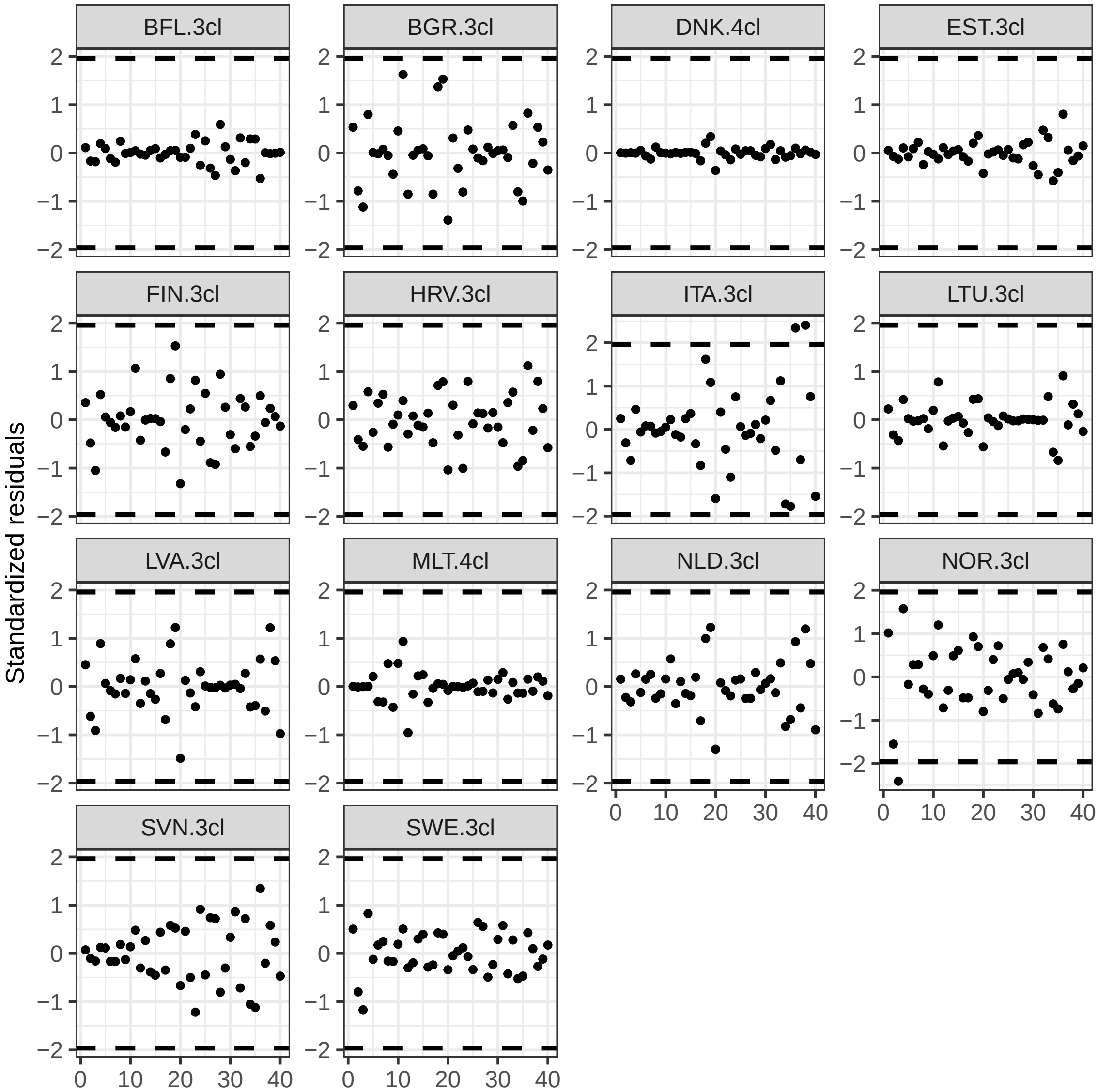

Figure 4.7: Bivariate standardized residuals for individual country models for Students' endorsement of equal rights for all ethnic/racial groups scale

In figure 4.8 the classes of each independent model can be identified. In the figure, the conditional probabilities for agree to each item are shown and plotted for each of the classes modeled in each country. Here can be identified two classes that are similar in all the models, the green and purple lines.

- **Fully egalitarian:** Most likely to agree to all items in the scale (green line)
  Conditional probabilities greater than 0.7 to agree, class sizes around 61.8% (Latvia) and 90% (Sweden)

- **Political non-egalitarian:** Most likely to agree to all items but a random answer to *All ethnic and racial groups should be encouraged to run in elections (ETH4)* item (orange line)
  Conditional probabilities to agree higher than 0.5 in all items but to the political item ($<$ 0.5), class sizes around 7.6% (Denmark) and 36% (Latvia).

- **Non-egalitarian:** Not likely to agree to any item in the scale (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: Not likely to agree to *All ethnic and racial groups should have an equal chance to get good jobs (ETH2)* item. Class size 8.3% (Malta)
  - Strong political non-egalitarian: Most likely to agree to most items in the scale but not likely to agree to *All ethnic and racial groups should be encouraged to run in elections (ETH4)* item. Class size 21.3% (Denmark).

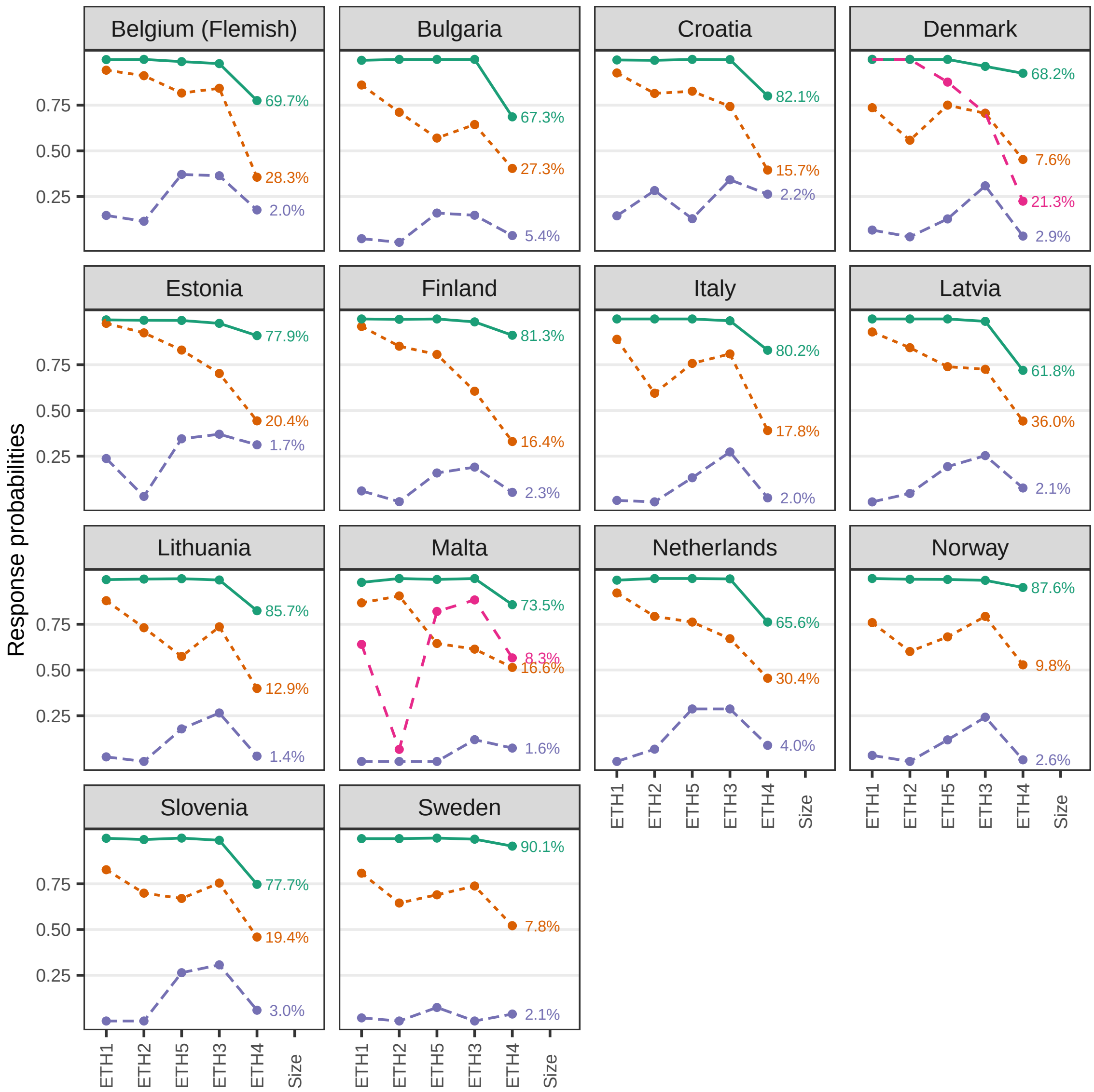

Figure 4.8: Classes for best individual country model for Students' endorsement of equal rights for all ethnic/racial groups

4.2.2 General model

The model with a single class has the largest AIC (159379), BIC (159423), and ABIC(159407) values for the European countries model in Table 4.9, indicating that this model fits data worse than all other models. In addition, the P-values of the VLMR test, and LMR in the 2-class model are all < 0.0001; this means that both tests reject the single-class model in favor of a model with at least two latent classes. In other words, there exists heterogeneity in the target population in regard to attitudes towards gender equality.

In the 6-class model, the LMR LR and VLMR are not statistically significant ($P > 0.05$). That is, the two tests are in favor of at most 5 classes. In contrast, AIC, BIC and aBIC values are all smaller in the 5-class model than those in the 6-class model; thus consider that the models with more than 5 classes are not preferred. The relative entropy given by Mplus software, decrease when including more than 4 classes and increase again with the 6-class model, this would suggest that a model with at least 6 class or 4 classes is preferred. Together with the percentage of reduction in the log-likelihood value, that indicates that by adding two classes to the model the log-likelihood is reduced by 12.1%, this reduction is only increased by 1.5% if the model is a 3-class model and finally this value is reduced close to 0 if more than 5 classes are included.

Now, the preferred model must be either the 4-class or higher model considering the residuals of each model in figure 4.9, where all values are around -1.96 and 1.96. Theoretically, we tend to determine that the 4-class LCA model is the preferred model. We will show later that the classes identified by the 4-class model are more interpretable and representatives than the rest of the models. And in particularly that 3-classes can be compared across countries.

Table 4.9: Model fit statistics LCA Students' endorsement of equal rights for all ethnic/racial groups 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	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*

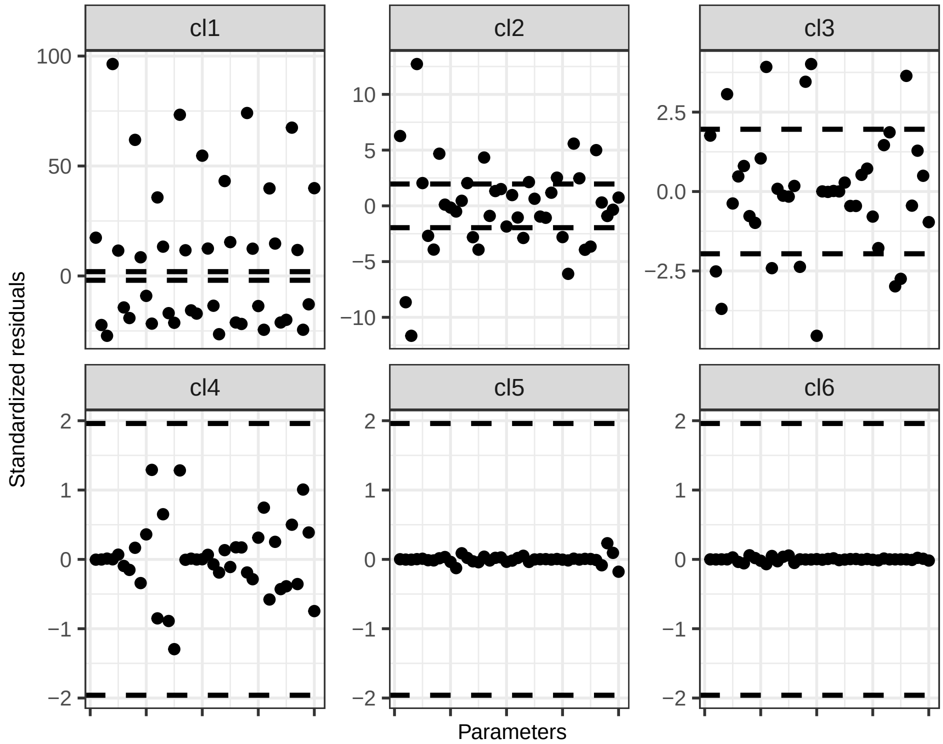

Figure 4.9: Bivariate model fit standardized residuals global model for Students' endorsement of equal rights for all ethnic/racial groups scale

Similarly to the previous scale, the three, four, five and six classes model were investigated profoundly. It is clear that is not easy to choose the best model fit without doing a full analysis. There are some patterns that can be clearly identified in all the models, Class 1 with 75.9%, 75.4%, 74% and 78.8% in each model respectively, the estimated probabilities to agree for this latent class, the **Fully egalitarian** group, for all four first items are higher than 0.99 and 0.83 for the item All ethnic and racial groups should be encouraged to run in elections.

The second class (Class 2 in figures in 4.10) identified in all the models, called **Political non-egalitarian**. For this class, the estimated probabilities to agree to the first 2 items are higher than 0.93 in all models. For the next two items, the estimated probabilities to agree are around 0.66 and 0.75 in all models and for the last item probabilities decrease to 0.5. The class size differs in all four models, 21.7%, 16%, 15% and 8.4% in the 3, 4, 5, 6-class model respectively.

The third class that can be seen with a similar pattern in all the models is called **Non-egalitarian**, this class appears from the 3-class model. The pattern of this class is basically showing lower estimated conditional probabilities to agree to any of these statements, no greater than 0.13. The estimated sizes for this class are 2.4%, 6.5%, 7.1% and 7% in each model respectively.

The fifth and sixth classes identified in the models differ in all the countries, nevertheless, one class appears to be consistent in the 5-class model, where this class called **Employment non-egalitarian** has low conditional probabilities to agree (0.2) to the item *All ethnic and racial groups should have an equal chance to get good jobs.*

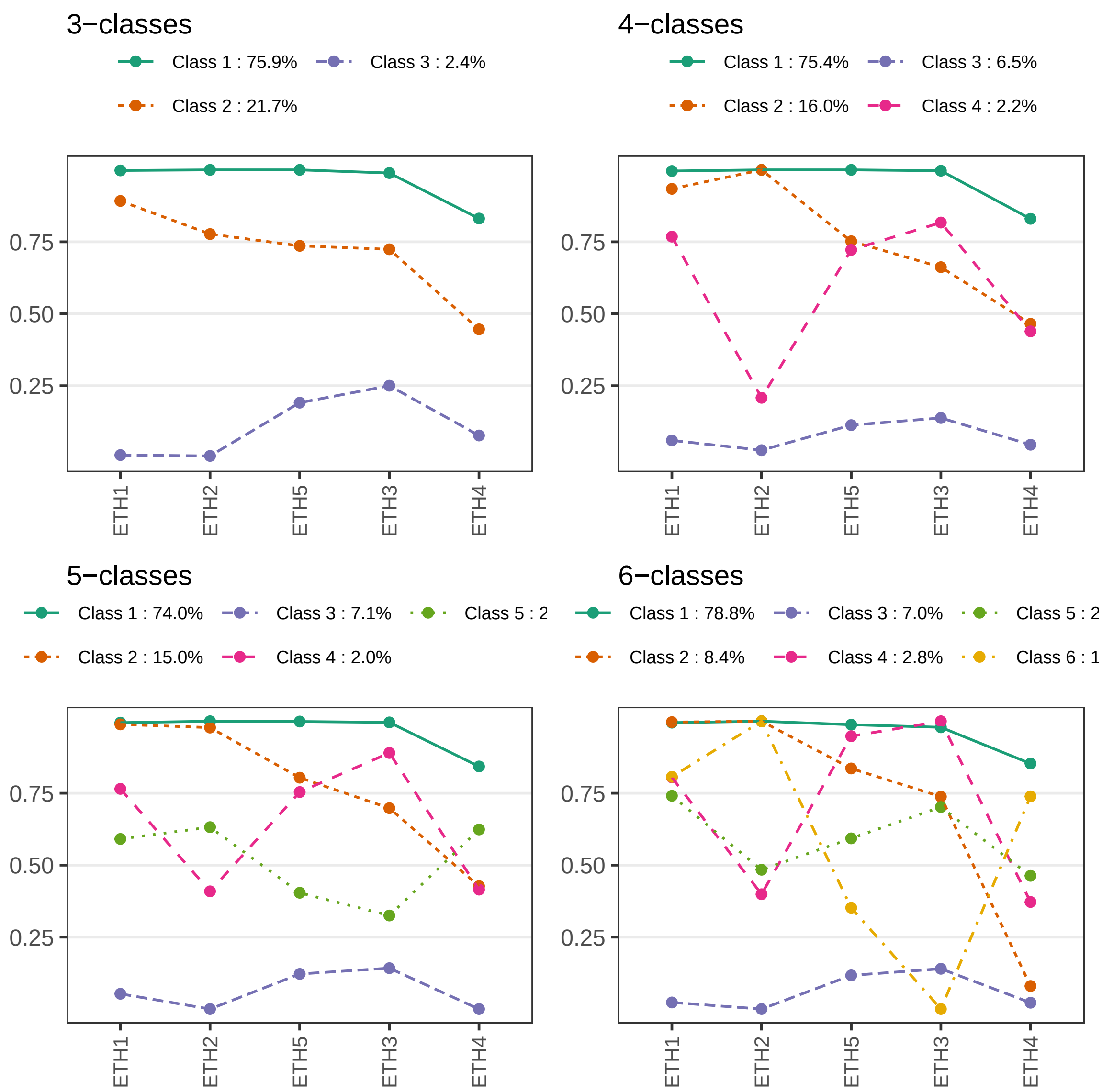

Figure 4.10: Comparative conditional probabilities to agree in 3 to 6 latent class global models for Students' endorsement of equal rights for all ethnic/racial groups

The main three classes in the solutions with three, four and five classes does not strongly differ from other models, and the remaining classes are not informative at all or very small, using this as a criterion, one can prefer a four-class solution. In table 4.10 the conditional probabilities to agree are shown. These values are very close to 1 in the first class, Fully egalitarian. Similar values are obtained for the first two items in the second class Political non-egalitarian, next three items start decreasing the conditional probability to agree from 0.76 to 0.46. Class sizes shown in 4.11 indicates that proportions of unconditional probabilities even though are not exactly the same, there are similar values among the Model estimated and Most likely classification.

Table 4.10: Probabilities to agree each item four-class global model for Students' endorsement of equal rights for all ethnic/racial groups scale

param	Fully egalitarian	Political non-egalitarian	Non-egalitarian	Employment non-egalitarian
ETH1 - All ethnic and racial groups should have equal chance to get good education	0.996	0.934	0.06	0.768
ETH2 - All ethnic and racial groups should have an equal chance to get good jobs	1	1	0.026	0.208
ETH5 - All ethnic and racial groups should have same rights and responsibilities	1	0.752	0.113	0.722
ETH3 - All ethnic and racial groups schools should teach students to respect	0.997	0.662	0.138	0.817
ETH4 - All ethnic and racial groups should be encouraged to run in elections	0.83	0.465	0.045	0.439

Table 4.11: Class sizes four-class global model for Students' endorsement of equal rights for all ethnic/racial groups scale

	Model estimated		Most likely	
Class	Counts	Proportion	Counts	Proportion
Fully egalitarian	37774.4	75.4%	41600	83.0%
Political non-egalitarian	8014.1	16.0%	4902	9.8%
Employment non-egalitarian	3257.5	6.5%	2521	5.0%
Non-egalitarian	1080.1	2.2%	1103	2.2%

4.2.3 Country comparability

To evaluate the country comparability, the classes that were found in the independent models were identified to later check how many of them could be tested for comparability using a multigroup latent class model.

- 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 country models

With 3 classes, all classes are very interpretable. With 5 classes, a random response class is identified, which is not interpretable. With 4 classes, the Employment non-egalitarian class is present in just one country, which is not representative.

With a 4-classes model, three main classes are identified across countries. All of the classes are present in all countries which means that is the best model for comparability. One remaining class can be freely estimated that variates in each country and/or with a class size of 0.

Country multigroup analysis

In table 4.12 different models with multigroup analysis are tested, first the more restricted model is evaluated, complete homogeneity. In this model, all conditional and unconditional probabilities are fixed to be equal across the groups. Then, the partial homogeneity is tested where only the conditional probabilities are constrained to be equal across the groups, and the class sizes are estimated freely.

The second approach of partial homogeneity is tested, where only the conditional probabilities for the three common classes identified are constrained across groups, and the remaining are freely estimated along with the unconditional probabilities.

Finally, the complete heterogeneous model is tested, where not only the unconditional probabilities are estimated freely but all the conditional probabilities as well. In the last two models the best log-likelihood is not replicated, this means that the solution may not be trustworthy due to local maxima. These results can not be considered valid.

Just by looking at the valid results, the partial homogeneity where all conditional probabilities are constrained to be equal across groups shows a better fit compared to the more restricted model, the complete homogeneity. With it is valid to indicate that the 4 classes identified do not share the same unconditional probabilities (class sizes) across the groups but the conditional probabilities can be considered as equal in all groups.

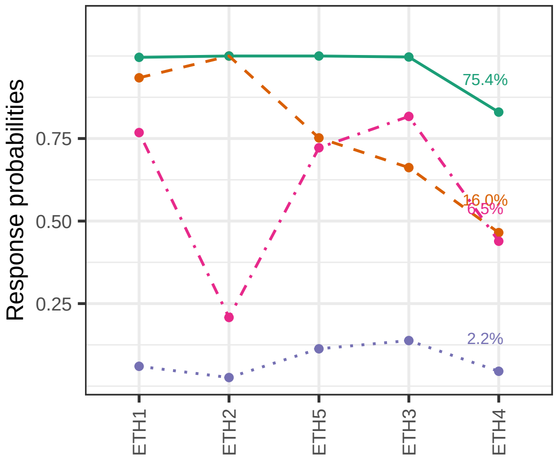

Figure 4.11: Conditional probabilities to agree in a 4-class complete homogeneous multigroup model for Students' endorsement of equal rights for all ethnic/racial groups scale

Table 4.12: Multigroup model fit statistics, global model with four-classes for Students' endorsement of equal rights for all ethnic/racial groups scale

Ngroups	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	Δ LL	Δ DF	pvalue Δ
Four-class model										
Complete homogeneity										
14	36	*-201088*	402248	402566	402451	92.2%	-1.20%	-2383	-299	0
Partial homogeneity										
14	**75**	**-199422**	**398994**	***399656***	***399418***	**88.9%**	**-0.36%**	**-717**	**-261**	**0**

Table 4.12: Multigroup model fit statistics, global model with four-classes for Students' endorsement of equal rights for all ethnic/racial groups scale *(continued)*

Ngroups	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	Δ LL	Δ DF	pvalue Δ
Complete heterogeneity										
14	335	-198705	*398081*	401036	399972	*93.2%*	*0.00%*			

Note:
The best loglikelihood value was not replicated for the following models:
[1] 4-class Complete heterogeneity model

Figure 4.11 indicates the values for the patterns with the conditional probabilities fixed in all countries, but also the unconditional probabilities are constrained to be equal in all groups. Here can be observed that the patterns are similar to the ones identified in the independent models and the global model as well. But by constraining the class sizes the model fit is not optimal.

In the figure 4.12, partial homogeneity constrained the conditional probabilities to be equal but not the unconditional probabilities, with this the model fit improves compared to the complete homogeneous model and lower values for BIC and aBIC are obtained.

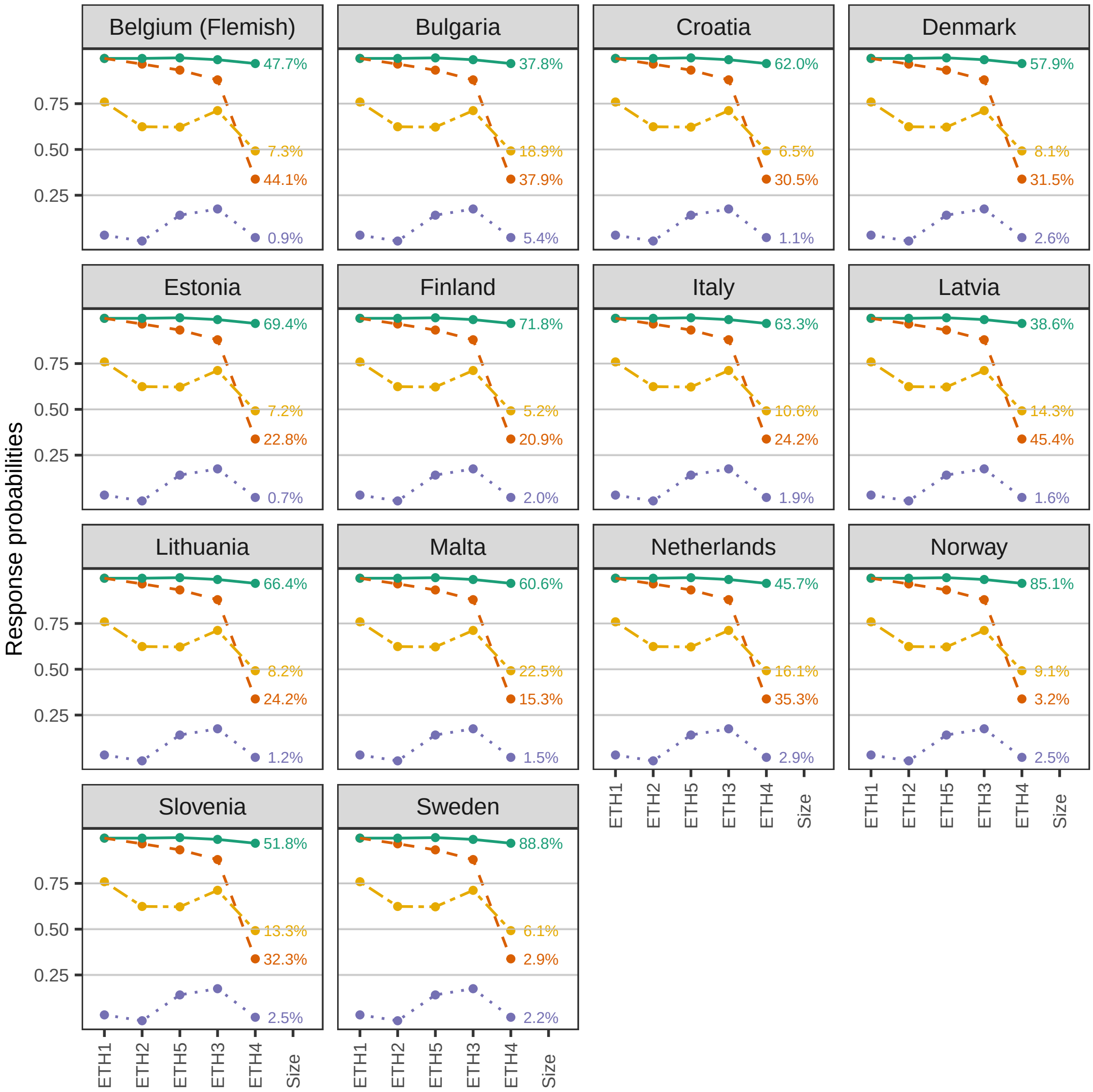

Figure 4.12: Conditional probabilities to agree in a 4-class partial homogeneous multigroup model for Students' endorsement of equal rights for all ethnic/racial groups scale

4.2.4 Confirmatory Latent Class Analysis

The confirmatory model was performed by establishing some constraints based on the previous research. For the Students' endorsement of equal rights for all ethnic/racial groups scale, two hypotheses were tested.

First, as stated in table 4.7 that the conditional probabilities for the first latent class Fully egalitarian, are the opposite to the ones in the third class Non-egalitarian. The second was that the first two conditional probabilities are equal in Class 1 and Class 2.

The rest of the conditional probabilities were estimated freely. In table 4.13 the model fit statistics of this model do not differ considerably from the exploratory approach analyzed previously.

Table 4.13: Model fit statistics Confirmatory LCA Students' endorsement of equal rights for all ethnic/racial groups scale

Type	N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction
All countries								
Exploratory LCA	4	23	-68807	*137660*	*137863*	*137790*	*77.5%*	
Confirmatory LCA	4	16	*-68911*	137854	137995	137945	73.0%	*-0.2%*

Table 4.14: Probabilities to agree each item 4-class Confirmatory LCA Students' endorsement of equal rights for all ethnic/racial groups scale

param	Fully egalitarian	Political non-egalitarian	Non-egalitarian	Employment non-egalitarian
ETH1 - All ethnic and racial groups should have equal chance to get good education	0.995	0.995	0.005	0.668
ETH2 - All ethnic and racial groups should have an equal chance to get good jobs	0.993	0.993	0.007	0.414
ETH5 - All ethnic and racial groups should have same rights and responsibilities	1	0.806	0	0.647
ETH3 - All ethnic and racial groups schools should teach students to respect	1	0.697	0	0.734
ETH4 - All ethnic and racial groups should be encouraged to run in elections	0.843	0.474	0.157	0.375

The confirmatory approach here stated that students would agree to *All ethnic and racial groups should have equal chance to get good education* and *All ethnic and racial groups should have an equal chance to get good jobs* items equally in the Fully egalitarian and Political non-egalitarian classes. But students belonging to the Non-egalitarian class would have the remaining probability to agree to these items, which would mean not be likely to agree.

Chapter 5

Discussion and conclusion

This research started without having any previous hypotheses, the research questions were based on exploring the different possible profiles of students that could be found in ICCS 2016 study regarding the student' endorsement of equal rights and opportunities. Despite the complexity of identifying reliable and interpretable profiles for the sample, the analysis provided strong evidence to identify the most common profiles across countries. This would be of great help for next researchers who intend to identify more specific profiles of students or even when including more countries in the polled sample.

The person-centred approach gives the possibility to explore how different the indicators that were calculated by the consortium are. With this, now is not only possible to compare the countries in a general level of the students' attitudes toward equal rights but also it is possible to learn how each country is composed, by which subgroups of students.

Latent Class Analysis was a great tool for identifying these profiles based on a statistical approach, with tests and statistics that give strong evidence to state why those profiles should be identified.

As expected by the variable-centre results, most countries indicators values for the student' endorsement of equal rights and opportunities are high, this means, that a high level of agreement with the notion of gender and ethnic/race equality is shown. But this approach does not give information about the differences between students that achieve a high score and medium score. With this research, it was possible to expand that group into groups of students with different attitudes towards this subject.

It was also interesting to identify that while most of the profiles are similar across countries, the number of students that relate to those profiles is not similar across countries. And particularly, that country-specific profiles could be observed.

As a first conclusion, it is clear to say that complete comparability is not assured when we look at subpopulations patterns when analyzing Large Scale Assessments. Even though is it confirmed that at a variable level this comparison is straightforward, this does not apply necessary when comparing all different groups that can be identified within a country with another country.

If the objective is to compare the groups that can be found in more than one country the best strategy is to conduct independent country models, this way the analysis will allow to identify and select common patterns in LSA scales. Not only similar groups or subpopulations can be found, but also unique (country-specific) groups can be found. With this, particular realities (patterns) can be distinguished when performing individual models.

One of the most interesting parts of this research was that it could be tested if the patterns are invariant across countries. With it, was possible to state that the profiles were similar across countries but not the class sizes, as they differ across countries when complete homogeneity was not achieved, this would mean that even though the patterns of the conditional probabilities are equal, the unconditional probabilities can not be assumed to be equal across countries. This would mean that the classes exist in most of the countries but the number of respondents estimated to have that attribute differs across countries.

For the Students' endorsement of gender equality scale, it was clear that two classes are highly similar across countries, Fully egalitarian and Competition-driven sexism. And it was established that these can be compared across countries, but only by the conditional probabilities. The class sizes (unconditional probabilities) can not be compared.

When looking at the visualization of the response patterns it is clear that some neighbouring countries can share some patterns. But as indicated before not clearly in class size but in the level of agreement with the items.

The confirmatory approach gives a clear interpretation of the strong agreement with gender equality based on opportunities in the government, along with the relation that the second-highest probability to agree is shared by two items in the Fully egalitarian class and by one item in the Competitive-driven sexism class equally. Most interesting is that students in the Competition-driven sexism class would not have a clear attitude towards women in politics.

For the Students' endorsement of equal rights for all ethnic/racial groups, three classes are found as highly similar across countries, Fully egalitarian, Political non-egalitarian and Non-egalitarian. In contrast to the previous scale, not more clear patterns are identified across countries. Some particular patterns are found but not with sustainable class size.

A clear pattern of random response can be identified not only in this scale but for gender equality as well. Even though the size of this class is not greater than 10% in most countries, some of them are around 20% (Malta), meaning that some students are not engaged either positive or negative in having an opinion about these matters.

The confirmatory approach gives a clear interpretation of the relation between the level of agreement between the Fully egalitarian and Political non-egalitarian classes. And how this relation is contrary to the Non-egalitarian class.

One of the limitations of this research is that it is not clear if there is an impact of inverse worded items in these patterns. Particularly the competition-driven sexism class in gender equality scale shows a clear change pattern regarding negative wording. It would very interesting to study how students pay attention to the reasoning behind the negative meaning of the item.

An advantage for this type of research is that based on statistical analysis, the profiles can be defined without hard theoretical background as an exploratory approach. Later on, with the specialist in the topic, those profiles could be cleaned or optimized.

This research can be used as a starting point in future researches, to evaluate different hypotheses to be tested. It also is of great help for other researchers that want to perform the same analysis but for different cycles of the study, as it was mentioned that these scales are present in the study from 2009 and they will be present in the next cycle of 2022. In the case of researchers interested in other countries, these results can be used for comparative purposes.

As a recommendation for future research, I would suggest having an ordered strategy to analyze the data, as more countries are added into the analysis more complex the analysis gets. Choose wisely the countries included in order to avoid external factors in the results.

Appendix A

Appendix

A.1 Complementary tables

Table A.1: Items for students' endorsement of equal rights and opportunities. ICCS 2016

Item	Description
Gender equality	
IS3G24A	Men and women should have equal opportunities to take part in government
IS3G24B	Men and women should have the same rights in every way
IS3G24E	Men and women should get equal pay when they are doing the same jobs
IS3G24C	Women should stay out of politics (r)
IS3G24D	Not many jobs available, men should have more right to a job than women (r)
IS3G24F	Men are better qualified to be political leaders than women (r)
Equal rights for all ethnic and racial groups	
IS3G25A	All ethnic and racial groups should have equal chance to get good education
IS3G25B	All ethnic and racial groups should have an equal chance to get good jobs
IS3G25C	Schools should teach students to respect members of all ethnic and racial groups
IS3G25D	Members of all ethnic and racial groups should be encouraged to run in elections
IS3G25E	Members of all ethnic and racial groups should have same rights and responsibilities

Table A.2: Countries sample sizes that participate in ICCS 2016

AlphaCode	Country	Participating schools	Participating students
BFL	**Belgium (Flemish)**	**162**	**2931**
BGR	**Bulgaria**	**147**	**2966**
CHL	Chile	178	5081
TWN	Chinese Taipei	141	3953
COL	Colombia	150	5609
HRV	**Croatia**	**175**	**3896**
DNK	**Denmark**	**184**	**6254**
DOM	Dominican Republic	141	3937
EST	**Estonia**	**164**	**2857**
FIN	**Finland**	**179**	**3173**
HKG	Hong Kong SAR	91	2653
ITA	**Italy**	**170**	**3450**
KOR	Korea, Republic of	93	2601
LVA	**Latvia**	**147**	**3224**
LTU	**Lithuania**	**182**	**3631**
MLT	**Malta**	**47**	**3764**
MEX	Mexico	213	5526
NLD	**Netherlands**	**123**	**2812**
NOR	**Norway**	**148**	**6271**
PER	Peru	206	5166
RUS	Russian Federation	352	7289
SVN	**Slovenia**	**145**	**2844**
SWE	**Sweden**	**155**	**3264**

Note:

Bold countries were selected for this research

A.2 Detailed output

Table A.3: Model fit statistics LCA by country Students' endorsement of gender equality

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
Belgium (Flemish)											
1	6	*-4246*	8504	8540	8521						
2	13	-3843	7713	7790	7749	84.8%	*9.5%*	806	0	791	0
3	**20**	**-3812**	**7664**	***7784***	***7721***	***88.2%***	**0.8%**	***62***	***0.323***	***61***	***0.327***
4	27	-3795	*7645*	7806	7721	68.9%	0.4%	*34*	*0.237*	*33*	*0.24*
5	34	-3789	7646	7849	7741	74.3%	0.2%	*13*	*0.392*	*13*	*0.394*
6	41	-3785	7653	7898	7768	81.8%	0.1%	*7*	*0.64*	*7*	*0.641*
Bulgaria											
1	6	*-8369*	16749	16785	16766						
2	13	-7710	15446	15524	15483	63.6%	*7.9%*	1317	0	1294	0
3	20	-7553	15146	15265	15202	69.8%	2.0%	315	0	309	0
4	**27**	**-7523**	**15100**	***15261***	***15175***	***75.2%***	**0.4%**	***60***	***0.077***	***59***	***0.08***
5	34	-7508	15083	15287	15179	71.2%	0.2%	*30*	*0.445*	*30*	*0.45*
6	41	-7500	*15083*	15328	15198	73.7%	0.1%	*15*	*0.458*	*14*	*0.46*
Croatia											
1	6	*-6227*	12466	12503	12484						
2	13	-5417	10860	10942	10901	84.8%	*13.0%*	1619	0	1592	0
3	20	-5368	10777	*10902*	*10838*	87.6%	0.9%	*98*	*0.085*	*96*	*0.088*
4	**27**	**-5353**	***10759***	**10929**	**10843**	**90.8%**	**0.3%**	***31***	***0.081***	***31***	***0.084***
5	34	-5349	10765	10978	10870	91.9%	0.1%	*8*	*0.46*	*8*	*0.464*

Table A.3: Model fit statistics LCA by country Students' endorsement of gender equality *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
6	41	-5346	10774	11031	10900	*94.1%*	0.0%	*5*	*0.787*	*5*	*0.789*
Denmark											
1	6	*-7273*	14557	14597	14578						
2	13	-6043	12111	12198	12157	*91.7%*	*16.9%*	2460	0	2420	0
3	20	-5951	11943	12077	12013	90.2%	1.5%	*182*	*0.077*	*179*	*0.08*
4	**27**	**-5914**	**11883**	***12063***	**11977**	**91.2%**	**0.6%**	***74***	***0.174***	***73***	***0.178***
5	34	-5894	11856	12084	*11975*	86.7%	0.3%	*41*	*0.386*	*40*	*0.39*
6	41	-5876	*11833*	12108	11978	84.7%	0.3%	*38*	*0.52*	*37*	*0.523*
Estonia											
1	6	*-5754*	11520	11556	11537						
2	13	-5044	10115	10192	10151	79.1%	*12.3%*	1419	0	1394	0
3	**20**	**-5002**	**10045**	**10164**	**10100**	**80.8%**	**0.8%**	**84**	**0.011**	**83**	**0.012**
4	27	-4974	*10001*	*10162*	*10076*	77.7%	0.6%	*57*	*0.183*	*56*	*0.189*
5	34	-4968	10004	10206	10098	78.9%	0.1%	*11*	*0.54*	*11*	*0.541*
6	41	-4965	10012	10256	10125	*81.5%*	0.1%	*7*	*0.521*	*6*	*0.522*
Finland											
1	6	*-4273*	8558	8594	8575						
2	13	-3520	7065	7144	7102	89.3%	*17.6%*	1506	0	1480	0
3	**20**	**-3477**	**6993**	***7114***	***7051***	**90.7%**	**1.2%**	**86**	**0.037**	**84**	**0.039**
4	27	-3461	6975	7139	7053	*92.3%*	0.5%	*32*	*0.57*	*31*	*0.574*
5	34	-3450	6968	7173	7065	91.3%	0.3%	*22*	*0.212*	*21*	*0.215*
6	41	-3442	*6966*	7214	7084	90.2%	0.2%	*15*	*0.417*	*15*	*0.42*

Table A.3: Model fit statistics LCA by country Students' endorsement of gender equality *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
Italy											
1	6	*-5615*	11242	11279	11260						
2	13	-4903	9832	9912	9870	80.9%	*12.7%*	1424	0	1399	0
3	**20**	**-4830**	**9701**	***9824***	***9760***	**84.6%**	**1.5%**	**145**	**0**	**143**	**0**
4	27	-4821	*9695*	9861	9775	*87.5%*	0.2%	*19*	*0.246*	*19*	*0.251*
5	34	-4814	9696	9904	9796	84.6%	0.1%	*14*	*0.539*	*14*	*0.542*
6	41	-4810	9703	9955	9824	73.5%	0.1%	*7*	*0.356*	*6*	*0.358*
Latvia											
1	6	*-8765*	17542	17578	17559						
2	13	-8054	16134	16213	16172	68.4%	*8.1%*	1421	0	1397	0
3	**20**	**-7993**	**16027**	***16148***	***16085***	**72.4%**	**0.8%**	***121***	***0.052***	***119***	***0.055***
4	27	-7977	16009	16172	16086	73.7%	0.2%	*32*	*0.416*	*32*	*0.42*
5	34	-7963	15994	16200	16092	77.7%	0.2%	*29*	*0.752*	*29*	*0.754*
6	41	-7955	*15992*	16241	16110	*78.6%*	0.1%	*15*	*0.458*	*15*	*0.459*
Lithuania											
1	6	*-8481*	16973	17011	16991						
2	13	-7571	15168	15249	15207	78.3%	*10.7%*	1819	0	1788	0
3	**20**	**-7447**	**14934**	***15058***	**14994**	***82.5%***	**1.6%**	**248**	**0**	**244**	**0**
4	27	-7421	14895	15062	*14977*	78.0%	0.4%	*53*	*0.167*	*52*	*0.172*
5	34	-7409	*14885*	15096	14988	77.3%	0.2%	*24*	*0.456*	*23*	*0.46*
6	41	-7403	14888	15142	15012	71.5%	0.1%	*11*	*0.755*	*11*	*0.755*
Malta											

Table A.3: Model fit statistics LCA by country Students' endorsement of gender equality *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
1	6	*-7383*	14779	14816	14797						
2	13	-6378	12782	12862	12821	78.5%	13.6%	2011	0	1977	0
3	20	-6236	12513	12637	12573	84.2%	*2.2%*	283	0.028	278	0.029
4	**27**	**-6204**	**12462**	***12629***	***12543***	**87.2%**	**0.5%**	***65***	***0.235***	***64***	***0.238***
5	34	-6190	12449	12660	12552	*88.9%*	0.2%	*27*	*0.394*	*26*	*0.396*
6	41	-6181	*12443*	12698	12567	88.7%	0.2%	*20*	*0.481*	*19*	*0.483*
Netherlands											
1	6	*-5373*	10757	10793	10774						
2	13	-4829	9683	9760	9719	75.9%	*10.1%*	1088	0	1068	0
3	**20**	**-4759**	**9557**	***9676***	***9612***	**87.0%**	**1.5%**	***140***	***0.074***	***138***	***0.076***
4	27	-4742	9539	9699	9613	*87.1%*	0.3%	*32*	*0.435*	*32*	*0.438*
5	34	-4728	*9525*	9726	9618	77.8%	0.3%	*28*	*0.543*	*28*	*0.546*
6	41	-4723	9527	9770	9640	75.9%	0.1%	*12*	*0.556*	*11*	*0.557*
Norway											
1	6	*-7878*	15767	15807	15788						
2	13	-6289	12603	12691	12649	91.8%	*20.2%*	3178	0	3126	0
3	20	-6104	12247	12382	12318	95.3%	2.9%	370	0	364	0
4	27	-6068	12189	12371	12285	*96.0%*	0.6%	72	0.039	71	0.041
5	**34**	**-6035**	**12137**	***12365***	***12257***	**93.2%**	**0.5%**	***66***	***0.281***	***65***	***0.286***
6	41	-6024	*12130*	12406	12276	93.7%	0.2%	*21*	*0.373*	*20*	*0.376*
Slovenia											
1	6	*-5202*	10416	10451	10432						

Table A.3: Model fit statistics LCA by country Students' endorsement of gender equality *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
2	13	-4369	8764	8841	8800	84.2%	*16.0%*	1666	0	1637	0
3	20	-4308	8656	8775	8711	85.5%	1.4%	122	0.018	120	0.02
4	**27**	**-4280**	**8614**	***8774***	***8689***	***87.5%***	**0.7%**	***56***	***0.158***	***55***	***0.163***
5	34	-4271	*8610*	8812	8704	86.9%	0.2%	*18*	*0.507*	*18*	*0.51*
6	41	-4264	8611	8855	8724	86.9%	0.1%	*13*	*0.297*	*13*	*0.298*
Sweden											
1	6	*-3877*	7766	7802	7783						
2	13	-3155	6336	6415	6373	90.6%	18.6%	1444	0	1419	0
3	20	-3080	6200	6321	6258	*94.3%*	*2.4%*	150	0.004	147	0.004
4	**27**	**-3049**	**6152**	***6316***	**6230**	**89.2%**	**1.0%**	***62***	***0.398***	***61***	***0.402***
5	34	-3022	*6113*	6319	*6211*	89.7%	0.9%	*54*	*0.133*	*53*	*0.136*
6	41	-3016	6114	6362	6232	89.9%	0.2%	*13*	*0.513*	*13*	*0.515*

Note:

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

[1] Croatia, 6 classes model

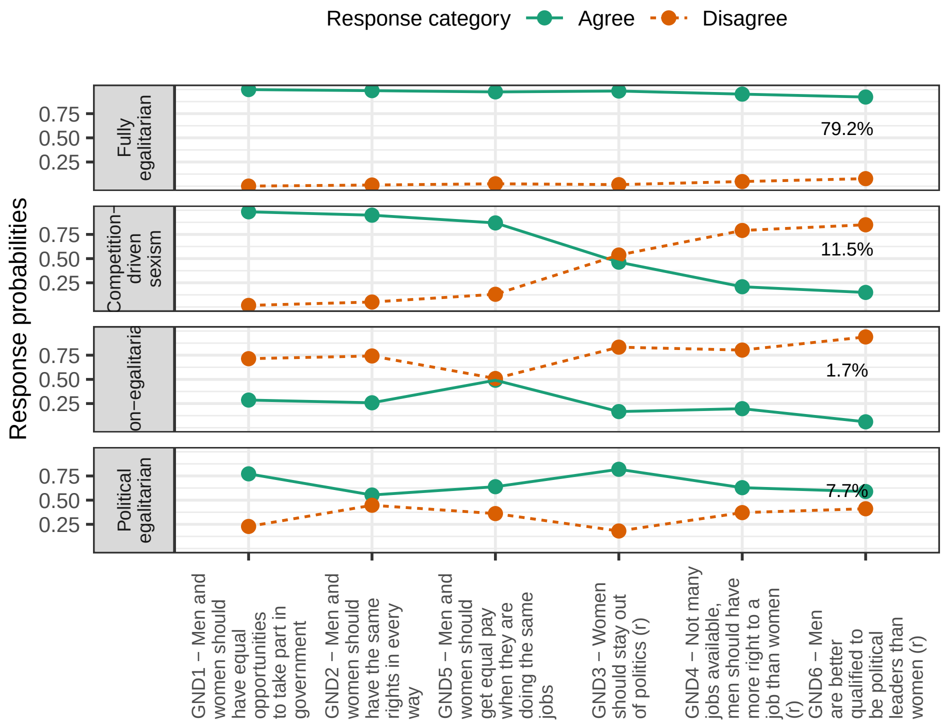

Figure A.1: Response categories probabilities and class size for 4-classes global model for Attitude towards gender equality scale

Table A.4: Thresholds 4-class Confirmatory LCA Students' endorsement of gender equality

Parameter	Fully egalitarian	Competition-driven sexism	Non-egalitarian	Political egalitarian
GND1$1	15.000	4.228	-0.867	1.099
GND2$1	4.228	2.777	-0.983	0.211
GND5$1	3.668	1.852	-0.021	0.568
GND3$1	4.228	0.000	-1.507	1.494
GND4$1	3.014	-1.217	-1.419	0.595
GND6$1	2.488	-1.604	-2.806	0.442
Means	2.404	0.541	-1.390	

Table A.5: Class sizes 4-class Confirmatory LCA Students' endorsement of gender equality

	Model estimated		Most likely	
Class	Counts	Proportion	Counts	Proportion
Fully egalitarian	39769.2	78.9%	41486	82.3%
Competition- driven sexism	6172.5	12.2%	5476	10.9%
Political egalitarian	3593.9	7.1%	2699	5.4%
Non-egalitarian	895.4	1.8%	770	1.5%

Table A.6: Model fit statistics LCA by country Students' endorsement of equal rights for all ethnic/racial groups scale

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
Belgium (Flemish)											
1	5	*-4321*	8653	8683	8667						
2	11	-4051	8123	8189	8154	85.1%	*6.3%*	542	0	530	0
3	**17**	**-4019**	**8072**	***8174***	***8120***	**60.5%**	**0.8%**	**63**	**0.021**	**62**	**0.023**
4	23	-4011	*8068*	8205	8132	61.8%	0.2%	*16*	*0.231*	*16*	*0.235*
5	29	-4009	8076	8249	8157	60.9%	0.1%	*4*	*0.451*	*4*	*0.453*
6	35	-4008	8086	8295	8184	*88.2%*	0.0%	*1*	*0.627*	*1*	*0.627*
Bulgaria											
1	5	*-6406*	12822	12852	12836						
2	11	-5451	10923	10989	10954	84.7%	*14.9%*	1910	0	1871	0
3	17	-5354	10742	*10843*	10789	78.5%	1.8%	193	0	190	0
4	**23**	**-5335**	**10717**	**10854**	***10781***	**82.3%**	**0.3%**	***37***	***0.192***	***36***	***0.198***
5	29	-5325	*10708*	10882	10790	*88.3%*	0.2%	*20*	*0.385*	*20*	*0.39*
6	35	-5322	10714	10923	10812	87.7%	0.1%	*6*	*0.506*	*6*	*0.508*
Croatia											
1	5	*-5101*	10213	10244	10228						
2	11	-4548	9119	9188	9153	*87.6%*	*10.8%*	1106	0	1084	0
3	17	-4507	9047	*9153*	9099	76.1%	0.9%	*84*	*0.416*	*82*	*0.422*
4	**23**	**-4491**	**9027**	**9171**	***9098***	**82.8%**	**0.4%**	***32***	***0.126***	***31***	***0.128***
5	29	-4479	*9016*	9197	9105	79.0%	0.3%	*23*	*0.206*	*23*	*0.211*
6	35	-4478	9027	9246	9134	86.6%	0.0%	*1*	*0.618*	*1*	*0.618*
Denmark											

Table A.6: Model fit statistics LCA by country Students' endorsement of equal rights for all ethnic/racial groups scale *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
1	5	*-9787*	19585	19618	19602						
2	11	-8519	17061	17134	17099	86.9%	13.0%	2536	0	2488	0
3	17	-8309	16652	16766	16712	68.6%	*2.5%*	421	0	413	0
4	**23**	**-8282**	***16610***	***16764***	***16691***	**72.3%**	**0.3%**	***54***	***0.059***	***53***	***0.062***
5	29	-8280	16617	16811	16719	*88.2%*	0.0%	*5*	*0.583*	*5*	*0.584*
6	35	-8278	16625	16859	16748	84.8%	0.0%	*4*	*0.545*	*4*	*0.546*
Estonia											
1	5	*-3577*	7165	7195	7179						
2	11	-3298	6618	6684	6649	82.8%	*7.8%*	559	0	547	0
3	**17**	**-3254**	**6543**	***6644***	***6590***	**69.8%**	**1.3%**	**87**	**0.002**	**86**	**0.002**
4	23	-3245	*6537*	6674	6601	74.9%	0.3%	*18*	*0.638*	*18*	*0.643*
5	29	-3243	6545	6717	6625	75.2%	0.1%	*4*	*0.344*	*4*	*0.345*
6	35	-3242	6553	6761	6650	*97.3%*	0.1%	*4*	*0.428*	*4*	*0.429*
Finland											
1	5	*-4186*	8382	8412	8396						
2	11	-3491	7003	7070	7035	88.9%	16.6%	1391	0	1363	0
3	**17**	**-3391**	**6815**	***6918***	**6864**	**80.8%**	***2.9%***	**200**	**0**	**196**	**0**
4	23	-3370	*6786*	6925	*6852*	87.3%	0.6%	41	0.008	40	0.009
5	29	-3365	6788	6964	6872	*93.6%*	0.1%	*9*	*0.367*	*9*	*0.372*
6	35	-3364	6797	7009	6898	88.0%	0.0%	*3*	*0.517*	*3*	*0.519*
Italy											
1	5	*-5113*	10235	10266	10250						

Table A.6: Model fit statistics LCA by country Students' endorsement of equal rights for all ethnic/racial groups scale *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
2	11	-4427	8876	8943	8909	85.8%	*13.4%*	1371	0	1344	0
3	**17**	**-4354**	**8742**	***8846***	**8792**	**81.1%**	**1.6%**	**146**	**0**	**143**	**0**
4	23	-4330	8706	8847	*8774*	81.6%	0.6%	*48*	*0.114*	*47*	*0.119*
5	29	-4319	*8696*	8874	8781	85.2%	0.3%	*22*	*0.082*	*22*	*0.086*
6	35	-4316	8702	8917	8806	*88.8%*	0.1%	*5*	*0.63*	*5*	*0.632*
Latvia											
1	5	*-5794*	11599	11629	11613						
2	11	-5416	10853	10920	10885	77.5%	*6.5%*	757	0	742	0
3	**17**	**-5353**	**10741**	***10844***	***10790***	**64.0%**	**1.1%**	**124**	**0.001**	**122**	**0.001**
4	23	-5341	10728	10867	10794	71.3%	0.2%	*25*	*0.357*	*24*	*0.362*
5	29	-5335	*10728*	10903	10811	78.5%	0.1%	*12*	*0.426*	*12*	*0.428*
6	35	-5333	10736	10948	10837	*87.8%*	0.0%	*3*	*0.592*	*3*	*0.593*
Lithuania											
1	5	*-4822*	9654	9685	9669						
2	11	-4232	8486	8554	8519	87.9%	*12.2%*	1180	0	1156	0
3	**17**	**-4194**	**8423**	***8528***	***8474***	**84.8%**	**0.9%**	**75**	**0.016**	**74**	**0.017**
4	23	-4188	*8422*	8565	8492	88.9%	0.1%	*12*	*0.514*	*12*	*0.518*
5	29	-4183	8424	8603	8511	90.9%	0.1%	*11*	*0.498*	*10*	*0.501*
6	35	-4181	8433	8649	8538	*93.0%*	0.0%	*3*	*0.533*	*3*	*0.534*
Malta											
1	5	*-6393*	12796	12827	12811						
2	11	-5798	11619	11687	11652	72.0%	*9.3%*	1189	0	1166	0

Table A.6: Model fit statistics LCA by country Students' endorsement of equal rights for all ethnic/racial groups scale *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
3	17	-5730	11493	11599	11545	74.1%	1.2%	138	0.002	135	0.002
4	**23**	**-5691**	**11428**	***11570***	***11497***	**80.3%**	**0.7%**	**78**	**0.032**	**76**	**0.034**
5	29	-5684	*11425*	11605	11512	78.4%	0.1%	*15*	*0.381*	*14*	*0.385*
6	35	-5680	11429	11646	11535	*83.2%*	0.1%	*8*	*0.515*	*8*	*0.517*
Netherlands											
1	5	*-5359*	10727	10757	10741						
2	11	-4814	9650	9715	9680	*79.6%*	*10.2%*	1089	0	1067	0
3	**17**	**-4729**	**9493**	***9593***	***9539***	**69.7%**	**1.8%**	**170**	**0**	**166**	**0**
4	23	-4718	9482	9618	9545	73.8%	0.2%	*23*	*0.358*	*22*	*0.365*
5	29	-4711	*9480*	9651	9559	77.6%	0.2%	*14*	*0.548*	*14*	*0.552*
6	35	-4709	9487	9695	9583	77.7%	0.0%	*4*	*0.483*	*4*	*0.484*
Norway											
1	5	*-7290*	14590	14623	14607						
2	11	-5551	11125	11199	11164	*94.7%*	*23.8%*	3477	0	3412	0
3	17	-5448	10930	*11044*	10990	88.1%	1.9%	207	0	203	0
4	23	-5426	*10897*	11052	*10978*	90.0%	0.4%	*45*	*0.057*	*44*	*0.06*
5	**29**	**-5421**	**10900**	**11094**	**11002**	**91.2%**	**0.1%**	***9***	***0.773***	***9***	***0.775***
6	35	-5419	10908	11143	11031	92.2%	0.0%	*4*	*0.293*	*4*	*0.294*
Slovenia											
1	5	*-4916*	9841	9871	9855						
2	11	-4315	8652	8718	8683	*86.7%*	*12.2%*	1201	0	1176	0
3	17	-4272	8578	*8679*	8625	77.5%	1.0%	87	0.027	85	0.029

Table A.6: Model fit statistics LCA by country Students' endorsement of equal rights for all ethnic/racial groups scale *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
4	**23**	**-4255**	**8556**	**8693**	***8620***	**83.9%**	**0.4%**	***34***	***0.101***	***33***	***0.105***
5	29	-4248	*8555*	8727	8635	81.3%	0.2%	*13*	*0.388*	*13*	*0.393*
6	35	-4246	8563	8771	8660	85.7%	0.0%	*4*	*0.541*	*4*	*0.543*
Sweden											
1	5	*-3175*	6360	6390	6374						
2	11	-2379	4780	4847	4812	*95.8%*	25.1%	1592	0	1560	0
3	17	-2306	4646	*4749*	*4695*	90.2%	*3.1%*	147	0.011	144	0.012
4	**23**	**-2299**	**4643**	**4783**	**4710**	**92.4%**	**0.3%**	***14***	***0.427***	***14***	***0.43***
5	29	-2292	*4642*	4818	4726	93.2%	0.3%	*13*	*0.432*	*13*	*0.434*
6	35	-2291	4651	4863	4752	95.2%	0.1%	*3*	*0.543*	*3*	*0.543*

Note:

The best loglikelihood value was not replicated for the following models

[1] Denmark - 6-classes complete heterogeneity;

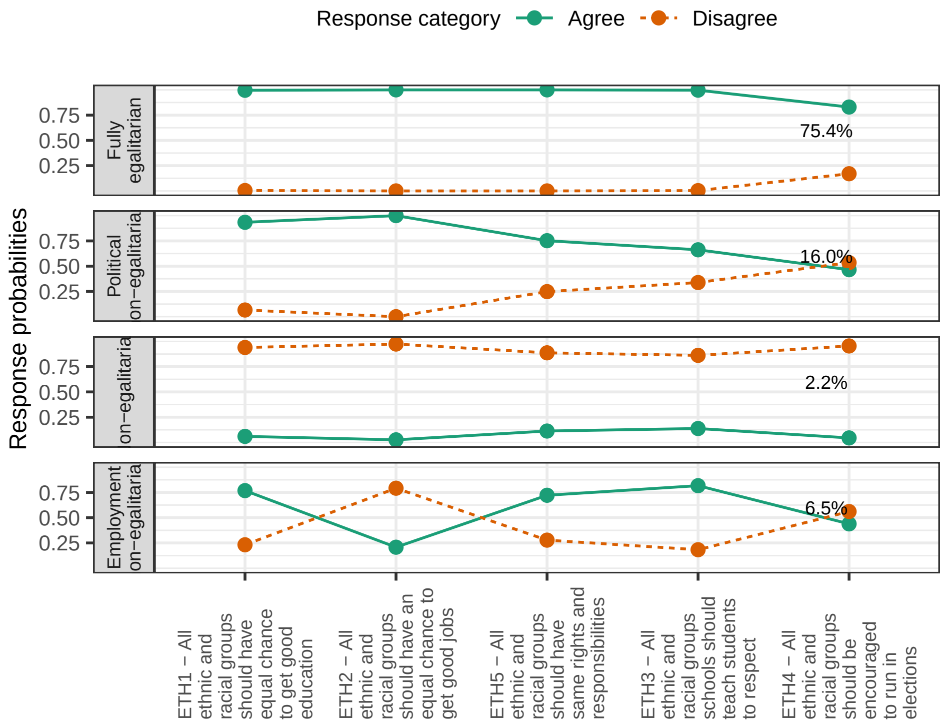

Figure A.2: Response categories probabilities and class size for 4-classes global model for Attitude towards ethnic and race equal rights scale

Table A.7: Thresholds 4-class Confirmatory LCA Attitude towards ethnic and race equal rights scale

Parameter	Fully egalitarian	Political non-egalitarian	Non-egalitarian	Employment non-egalitarian
ETH1$1	5.265	5.265	-5.265	0.699
ETH2$1	5.026	5.026	-5.026	-0.346
ETH5$1	24.196	1.424	-24.196	0.606
ETH3$1	17.167	0.831	-17.167	1.016
ETH4$1	1.678	-0.102	-1.678	-0.509
Means	2.112	0.576	-1.815	

Table A.8: Class sizes 4-class Students' endorsement of equal rights for all ethnic/racial groups scale

	Model estimated		Most likely	
Class	Counts	Proportion	Counts	Proportion
Fully egalitarian	36968.5	73.8%	41874	83.5%
Political non-egalitarian	7955.2	15.9%	4053	8.1%
Employment non-egalitarian	4474.0	8.9%	3420	6.8%
Non-egalitarian	728.3	1.5%	778	1.6%

A.3 Syntax

Packages used

```
library(thesisdown)
library(plyr)
library(tidyverse)
library(knitr)
library(kableExtra)
library(MplusAutomation)
library(gridExtra)
library(grid)
library(scales)
library(RColorBrewer)
```

MplusAutomation syntax

```
library(MplusAutomation)
ds_lc <- data_model %>%
  dplyr::select(all_of(sample), all_of(Scales), IDSTUD, COUNTRY, CYCLE)

remlabclass <- function(ces){
  for (each in colnames(ces)){
    if ("labelled" %in% class(ces[[each]])){
      class(ces[[each]]) = c("numeric")
      attr(ces[[each]], "levels") <- NULL
    }
    attr(ces[[each]], "label") <- NULL
  }
  return(ces)
}
ds_lc0 <- remlabclass(ds_lc)

#----------------By country scales together by CYCLE ----------------------
for (j in 3:3) { #input file for each CYCLE 1:3
  data1 <- ds_lc0 %>%  filter(CYCLE == paste0("C",j)) %>%
    dplyr::select(all_of(sample), all_of(ScalesGND), IDSTUD, COUNTRY) %>%
    mutate_if(is.factor, ~ as.numeric(.x)) %>%
    data.frame()

  cnt <- unique(data1[,c("COUNTRY","id_k")]) %>%
    arrange(as.character(COUNTRY))

  data1 <- data1  %>% dplyr::select(-COUNTRY)
  prepareMplusData(df = data1,
             filename = paste0("data/MplusModels/ByCountry/GNDDtaC",j,".dat"),
             interactive =FALSE)
```

```
for(c in 1:nrow(cnt)){
  data <- data1 %>%  filter(id_k == cnt$id_k[c])

  lapply(1:6, function(k) { #input file for different number of classes
    fileConn <- file(paste0("data/MplusModels/ByCountry/GNDlca_",
                            cnt$COUNTRY[c],"_C",j,"cl",
                            sprintf("%d", k),".inp"))
    writeLines(c(
      paste0("TITLE: ", cnt$COUNTRY[c], "GND LCA - C", j,
             " with ", k ," classes;"),
      "DATA: ",
      paste0("FILE = GNDDtaC",j,".dat;"),
      "",
      "VARIABLE: ",
      paste0("NAMES = ", paste(colnames(data), collapse = "\n"),";"),
      "IDVARIABLE = IDSTUD;",
      paste0("USEVARIABLES = ",
             paste(colnames(data)[grepl('^GND', colnames(data))],
                   collapse = "\n"),";"),
      paste0("USEOBSERVATIONS ARE id_k EQ ", cnt$id_k[c], ";"),
      paste0("CATEGORICAL = ",
             paste(colnames(data)[grepl('^GND', colnames(data))],
                   collapse = "\n"),";"),
      "MISSING = .;",
      paste0("CLASSES = ",sprintf("c(%d);", k)),
      "WEIGHT = ws;",
      "STRATIFICATION = id_s;",
      "CLUSTER = id_j;",
      " ",
      "ANALYSIS:",
      "TYPE = COMPLEX MIXTURE;",
      "PROCESSORS = 4;",
      "STARTS = 1000 250;",
      "STITERATIONS = 20;",
      "STSEED = 288;",
      "",
      "MODEL:",
      "%OVERALL%",
      " ",
      "OUTPUT: ",
      "TECH10",
      "TECH11",
      "SVALUES",
      ";",
      "",
      "SAVEDATA:",
```

```
      paste0("FILE = Prob_", cnt$COUNTRY[c] ,
             "_GNDlca_C", j,"cl", k,".dat;"),
      "SAVE = CPROBABILITIES;"

    ), fileConn)
    close(fileConn)
  })
 }
}

runModels(target = "data/MplusModels/ByCountry", recursive = TRUE,
          replaceOutfile = "never") #modifiedDate
ByCountry_GND <- readModels(target = "data/MplusModels/ByCountry",
                            recursive = TRUE,
                            filefilter = "GNDlca_[A-Z]{3}_C3cl")
ByCountry_ETH <- readModels(target = "data/MplusModels/ByCountry",
                            recursive = TRUE,
                            filefilter = "ETHlca_[A-Z]{3}_C3cl")

save(ByCountry_GND,
     ByCountry_ETH,
     file = "data/MplusModels_ByCountry.RData")
```

Automatized R code

```
#------Add label to variables----------
VarClass <- function(lc, orden = c(1:length(levels(factor(lc$param))))){
  b <- levels(factor(lc$param))
  b <- b[order(b)[orden]]
  labels <- NULL
  i = 0
  for (each in b){
    i = i + 1
    labels[each] <- paste0(b[i]," - ",attr(data_model[[each]], "variable.label"))
  }
  lc$param <- factor(lc$param, levels = b, labels = labels)
  return(lc)
}

#------Class barplot----------
graphclass <- function(cmodel = NULL, nclass = NULL,
                       orden = c(1:length(levels(factor(cmodel$param)))),
                       title = NULL, leg = FALSE){
  a <- levels(factor(cmodel$param))
  a <- a[order(a)[orden]]
  labels <- NULL
```

```
  for (each in a){
    labels[each] <- attr(data_model[[each]], "variable.label")
  }

  labels2 <- NULL
  n <- 0
  for (each in levels(cmodel$category)){
    n <- n + 1
    labels2[each] <- paste(each, "-", attr(data_model[[a[1]]], "levels")[n])
  }

  cmodel$paramf <- factor(cmodel$param, levels = a, labels = labels)
  cmodel$categoryf <- factor(cmodel$category, levels = levels(cmodel$category),
                             labels = labels2)

  zp1 <- ggplot(data = subset(cmodel),
         aes(x = paramf, y = value, fill = categoryf)) +
    geom_bar(stat = "identity", position = "stack") +
    ggtitle(title) +
    labs(x = "Items", y = "Response probabilities", fill ="Response category") +
    scale_fill_grey() + theme_bw() +
    theme(legend.position = "top",
          title = element_text(size=9),
          strip.text.y = element_text(size = 7),
          axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 0, size = 6),
          axis.text.y = element_text(size = 7),
          axis.title = element_text(size = 7),
          axis.ticks.y=element_blank(),
          panel.grid.major.y=element_blank(), legend.title = element_text(size = 8),
          legend.key.size = unit(0.3, "cm"),
          legend.text = element_text(size = 8)) +
    scale_x_discrete(label = function(x) str_wrap(x,25)) +
    guides(fill=guide_legend(nrow=1,byrow=TRUE)) +
    scale_y_continuous(breaks = c(0.25,0.5,0.75)) +
    geom_hline(yintercept=c(0.25,0.5,0.75), linetype = "dashed", size = 0.3,
               color = "gray") +
    facet_grid(. ~ Class, labeller = label_wrap_gen(20))

  print(zp1)
}

#------Models fit summary----------
Modelfit <- function(Modellist, title ="", fontn = 9){
  resultsbyallo <- mixtureSummaryTable(eval(parse(text=paste0(Modellist))),
                  keepCols = c("Title", "NLatentClasses", "Parameters", "LL",
                               "AIC", "BIC", "aBIC","Entropy",
                               "T11_VLMR_2xLLDiff", "T11_VLMR_PValue",
```

```
                             "T11_LMR_Value", "T11_LMR_PValue"))

resultsbyallo <- resultsbyallo %>%
  mutate(Type = Title,
    Cycle = substr(Title,str_locate(Title, "C[0-9]+")[1],
                   str_locate(Title, "C[0-9]+")[2]+1),
    Year = ifelse(Cycle == "C1", 1999, ifelse(Cycle == "C2", 2009,
                              ifelse(Cycle == "C3", 2016, NA)))) %>%
  arrange(Year)


resultsbyall <- resultsbyallo %>% dplyr::arrange(Year) %>%
  dplyr::group_by(Year) %>%
  dplyr::mutate(
    Reduction = scales::percent(ifelse(is.na(lag(LL)), NA,
                                (lag(LL)-LL)/lag(LL)),accuracy = 0.1),
    LL = cell_spec(round(LL,0), italic = ifelse(LL == min(LL),
                                                TRUE, FALSE)),
    AIC = cell_spec(round(AIC,0), italic = ifelse(AIC == min(AIC),
                                                  TRUE, FALSE)),
    BIC = cell_spec(round(BIC,0), italic = ifelse(BIC == min(BIC),
                                                  TRUE, FALSE)),
    aBIC = cell_spec(round(aBIC,0), italic = ifelse(aBIC == min(aBIC),
                                                    TRUE, FALSE)),
    Entropy = ifelse(is.na(Entropy), "",
                      cell_spec(scales::percent(Entropy,accuracy = 0.1),
                        italic = ifelse(Entropy == max(Entropy, na.rm = T),
                                               TRUE, FALSE))),
    Reduction = ifelse(is.na(Reduction),"",cell_spec(Reduction,
                      italic = ifelse(Reduction == max(Reduction, na.rm = T),
                                            TRUE, FALSE))),
    T11_VLMR_2xLLDiff = ifelse(is.na(T11_VLMR_2xLLDiff), "",
                               cell_spec(round(T11_VLMR_2xLLDiff,0),
                                italic = ifelse(T11_VLMR_PValue > 0.05,
                                                TRUE, FALSE))),
    T11_VLMR_PValue = ifelse(is.na(T11_VLMR_PValue), "",
                             cell_spec(round(T11_VLMR_PValue,3),
                                italic = ifelse(T11_VLMR_PValue > 0.05,
                                                TRUE, FALSE))),
    T11_LMR_Value = ifelse(is.na(T11_LMR_Value), "",
                           cell_spec(round(T11_LMR_Value,0),
                                italic = ifelse(T11_LMR_PValue > 0.05,
                                                TRUE, FALSE))),
    T11_LMR_PValue = ifelse(is.na(T11_LMR_PValue), "",
                            cell_spec(round(T11_LMR_PValue,3),
                                      italic = ifelse(T11_LMR_PValue > 0.05,
                                                      TRUE, FALSE)))) %>%
```

```
    ungroup()

  resultsbyall <- resultsbyall[,c("Year", "NLatentClasses", "Parameters", "LL",
                                 "AIC",  "BIC",  "aBIC", "Entropy", "Reduction",
                                 "T11_VLMR_2xLLDiff", "T11_VLMR_PValue",
                                 "T11_LMR_Value", "T11_LMR_PValue")] %>%
    setNames(c("Year", "N Latent\n Classes", "Param", "Log-Likelihood",
               "AIC",   "BIC",  "aBIC", "Entropy", "LL\n Reduction",
               "VLMR\n 2*LL Dif", "VLMR\n PValue", "LMR\n Value", "LMR\n PValue"))
  tableSumm <- resultsbyall %>% select(-Year) %>%
    kbl(caption = paste0(title),
        booktabs = TRUE, longtable = TRUE, row.names = FALSE, escape = FALSE) %>%
    kable_classic_2(full_width = F) %>%
    kable_styling(latex_options = c("repeat_header", "HOLD_position"),
                  font_size = fontn) %>%
    column_spec(c(1,2), width = "3em") %>%
    column_spec(c(3:12), width = "4em") %>%

  return(tableSumm)
}


#------Class highest probabilities----------
HighProb <- function(lc5, siz5, title = NULL,
                     orden = c(1:length(levels(factor(lc5$param)))),
                     longsize = 11){

  labels_x <- NULL
  for (each in levels(lc5$param)){
    labels_x[each] <- paste0(each," - ",attr(data_model[[each]], "variable.label"))
  }
  labels_x <- unlist(labels_x)

  lc5f <- lc5 %>%  mutate(Class = str_remove(Class,"\n"))
  siz5f <- siz5 %>%
    mutate(Class = str_remove(Class,"\n"),
           param = levels(lc5$param)[orden][length(levels(lc5$param))],
           category = "2")
  siz <- left_join(lc5f, siz5f, by = c("param", "category", "Class")) %>%
    arrange(Class, param) %>%
    group_by(param) %>% mutate(dif = abs(value - lag(value))) %>% ungroup() %>%
    mutate(Class = factor(Class, levels = str_remove(levels(lc5$Class),"\n")),
           param = factor(param, levels = levels(lc5$param), labels = labels_x))

  siz$paramf <- factor(siz$param, levels = levels(siz$param)[orden])
  pc5 <- siz %>%
    ggplot() +
```

```
    geom_point(aes(x = paramf, y = value, group = category, color = category),
               size = 2) +
    geom_line(aes(paramf, value, group = category, linetype = category,
                  color = category)) +
    scale_fill_grey() + theme_bw() #+
    #ggtitle(title)

  pc5 <- pc5 +
    geom_text(aes(x = paramf, y = 0.5, label = scales::percent(per, accuracy = 0.1)),
              size = 2.5, nudge_x = -0.15, nudge_y = 0.1) +
    facet_grid(Class ~ ., switch = "y", labeller = label_wrap_gen(6)) +
    theme(legend.position = "top", legend.box="vertical",
          strip.text.y = element_text(size = 7),
          legend.spacing.y = unit(-0.2, 'cm'),
          title = element_text(size = 9),
          axis.title.x = element_blank(),
          axis.text.y = element_text(size = 8),
          legend.title = element_text(size = 8),
          legend.text =  element_text(size = 8),
          axis.text.x = element_text(angle = 90, size = 7,
                                     vjust = 0.5, hjust = 0)) +
    scale_y_continuous(breaks = c(0.25,0.5,0.75)) +
    labs(y="Response probabilities", linetype = "Response category",
         color = "Response category")  +
    scale_linetype_discrete(labels = c("Agree", "Disagree")) +
    scale_color_brewer(type = "qual", palette = "Dark2",
                       labels = c("Agree", "Disagree")) +
    scale_shape(solid = FALSE, guide = FALSE) +
    scale_x_discrete(label = function(x) str_wrap(x,15))
  return(pc5)
}

#------Comparative highest probabilities----------
ClassGraph <- function(lc5f, siz5, title = NULL,
                       orden = c(1:length(levels(factor(lc5f$param)))),
                       selected = c(1:length(levels(factor(siz5$Class))))){

  labels_x <- NULL
  for (each in levels(lc5f$param)){
    labels_x[each] <- paste0(each," - ",attr(data_model[[each]],
                                            "variable.label"))
  }
  labels_x <- unlist(labels_x)

  siz5f <- siz5 %>% arrange(desc(per)) %>% cbind(row = c(1:nrow(siz5))) %>%
    mutate(Class = factor(as.numeric(Class)),
           ClassesSizes = paste("Class", row,":",
```

```
                              scales::percent(per, accuracy = 0.1)))

  siz <- lc5f %>%
    arrange(Class, param) %>%
    group_by(param) %>% mutate(dif = abs(value - lag(value))) %>%
    ungroup()

  siz$paramf <- factor(siz$param, levels = levels(siz$param)[orden])

  pc5 <- siz %>% filter(category == 1) %>%
    ggplot() +
    geom_point(aes(x = paramf, y = value, group = Class, color = Class),
               size = 1.5) +
    geom_line(aes(paramf, value, group = Class, linetype = Class, color = Class)) +
    scale_fill_grey() + theme_bw() +
    ggtitle(title) +
    theme(legend.position = "top",
          legend.direction = "vertical",
          strip.text.y = element_text(size = 8),
          legend.spacing.x = unit(0.2, 'cm'),
          legend.spacing.y = unit(-0.2, 'cm'),
          legend.margin=margin(t = 0, unit='cm'),
          title = element_text(size = 9),
          panel.grid.minor.y = element_blank(),
          panel.grid.major.x = element_blank(),
          panel.grid.minor.x = element_blank(),
          axis.title.x = element_blank(),
          axis.title.y = element_blank(),
          legend.title = element_blank(),
          legend.text = element_text(size = 7),
          axis.text.x = element_text(angle = 90, size = 8,
                                     vjust = 0.5, hjust = 0)) +
    guides(linetype = guide_legend(nrow = 2)) +
    scale_y_continuous(breaks = c(0.25,0.5,0.75), limits = c(0,1)) +
    labs(y="Response probabilities", linetype = "Latent Classes",
         color = "Latent Classes")  +
    scale_linetype_discrete(labels = siz5f$ClassesSizes) +
    scale_colour_manual(values=cbPalette[selected],
                        labels = siz5f$ClassesSizes) +
    scale_shape(solid = FALSE, guide = FALSE) +
    scale_x_discrete(label = function(x) str_

#----GND 4 groups----
classes4GND <- c("Fully egalitarian",
                "Competition- driven sexism",
                "Non-egalitarian",
                "Political egalitarian")
```

```
orden4GND <- c(2,4,3,1)
lcaGND_C3cl4 <- lcaGND$GND_lca_C3cl4.out$parameters$probability.scale %>%
  rename_with(~ c("Class", "value")[which(c("LatentClass", "est") == .x)],
              .cols = c("LatentClass", "est")) %>%
  mutate_at( c("param", "category", "Class"), ~ as.factor(.x)) %>%
  mutate(Class = factor(Class, levels = orden4GND, labels = classes4GND))

counts4GND <- full_join(lcaGND$GND_lca_C3cl4.out$class_counts$modelEstimated,
                        lcaGND$GND_lca_C3cl4.out$class_counts$mostLikely,
                        by = c("class"))

lcaGND_C3cl4$orden = rep(c(1,2,4,5,3,6), each = 2)
VarClass(lcaGND_C3cl4) %>% group_by(Class, param) %>%
  filter(category == 1) %>%
  select(orden, param, Class, value) %>%
  mutate(value = cell_spec(value, color = ifelse(value >= 0.75, "Myblue",
                ifelse(value < 0.75 & value >= 0.25, "Mygreen","Myred")))) %>%
  reshape2::dcast(orden + param ~ Class) %>% arrange(orden) %>% select(-orden) %>%
  kbl(caption = "Probabilities to agree each item 4-class Gender equality model",
      booktabs = TRUE, longtable = TRUE, align = c("l", rep("r",4)),
      row.names = FALSE, digits = 3, escape = FALSE) %>%
  kable_classic_2(full_width = F) %>%
  kable_styling(latex_options = c("repeat_header", "HOLD_position"),
                font_size = 9) %>%
  column_spec(1, width = "15em") %>%
  column_spec(2:5, width = "5em") %>%
  collapse_rows(1, valign = "top") %>%
  print()

counts4GND  %>%
  mutate(class = factor(class, levels = orden4GND, labels = classes4GND),
         proportion.x = scales::percent(proportion.x,accuracy = 0.1),
         proportion.y = scales::percent(proportion.y,accuracy = 0.1)) %>%
  arrange(desc(count.y)) %>%
  kbl(col.names = c("Class", "Counts", "Proportion", "Counts", "Proportion"),
      caption = paste0("Class sizes 4-class Gender equality model"),
      booktabs = TRUE, longtable = TRUE, align = c("l", rep("r",4)),
      row.names = FALSE, digits = 1, escape = TRUE) %>%
  kable_classic_2(full_width = F) %>%
  kable_styling(latex_options = c("repeat_header", "HOLD_position"),
                font_size = 9) %>%
  add_header_above(c(" " = 1 , "Model estimated" = 2, "Most likely" = 2))

sizelca4_GND <- lcaGND$GND_lca_C3cl4.out$class_counts$modelEstimated %>%
  dplyr::select(-count) %>%
  rename_with(~ c("Gender", "Class")[which(c("proportion", "class") == .x)],
              .cols = c("proportion", "class")) %>%
```

```
  mutate(Class = factor(Class, levels = orden4GND, labels = classes4GND)) %>%
  reshape2::melt(id.vars = c("Class"), variable.name = "Group") %>%
  dplyr::arrange(Group) %>%
  dplyr::group_by(Group) %>%
  dplyr::mutate(countT= sum(value, na.rm = TRUE)) %>%
  dplyr::group_by(Class) %>%
  dplyr::mutate(per=value/countT) %>%
  dplyr::select(Group, Class, per)

HighProb(lcaGND_C3cl4, sizelca4_GND,  orden = c(1,2,5,3,4,6),
         title = "Response categories probabilities and class size
         for\n 4-classes Gender equality model")
```

Mplus syntax

Latent Class model with 4 classes

```
TITLE: LCA C3 GND with 4 classes;
DATA:
FILE = GND_Dta_C3.dat;

VARIABLE:
NAMES = id_i id_j id_r id_s
id_k wt ws
GND1 GND2 GND3 GND4 GND5 GND6
IDSTUD;
IDVARIABLE = IDSTUD;
USEVARIABLES = GND1
GND2 GND3 GND4 GND5 GND6;
CATEGORICAL = GND1
GND2 GND3 GND4 GND5 GND6;
MISSING = .;
CLASSES = c(4);
WEIGHT = ws;
STRATIFICATION = id_s;
CLUSTER = id_j;

ANALYSIS:
TYPE = COMPLEX MIXTURE;
PROCESSORS = 4;
STARTS = 100 50;
STITERATIONS = 5;
STSEED = 288;

OUTPUT:
TECH10
TECH11
TECH14;
```

```
SVALUES
;

SAVEDATA:
FILE = GND_Prob_C3cl4.dat;
SAVE = CPROBABILITIES;
```

Complete homogeneous multigroup latent class model with 4 classes

```
TITLE:C.Hom MG Country LCA GND C3 with 4 classes;
DATA:
FILE = GND_DtaC3.dat;

VARIABLE:
NAMES = id_i id_j id_r
id_s id_k wt ws
GND1 GND2 GND3 GND4 GND5 GND6
IDSTUD;
IDVARIABLE = IDSTUD;
USEVARIABLES = GND1
GND2 GND3 GND4 GND5 GND6;
CATEGORICAL = GND1
GND2 GND3 GND4 GND5 GND6;
MISSING = .;
CLASSES = g(14) c(4);
KNOWNCLASS = g(id_k =
 1    !    BFL
 2    !    BGR
 3    !    DNK
 4    !    EST
 5    !    FIN
 6    !    HRV
 7    !    ITA
 8    !    LTU
 9    !    LVA
 10   !    MLT
 11   !    NLD
 12   !    NOR
 13   !    SVN
 14   !    SWE
);
WEIGHT = ws;
STRATIFICATION = id_s;
CLUSTER = id_j;

ANALYSIS:
```

```
TYPE = COMPLEX MIXTURE;
PROCESSORS = 4;
STARTS = 1000 250;
STITERATIONS = 20;
STSEED = 288;

MODEL:
%OVERALL%
Model c:

                    %c#1%
 [GND1$1-GND6$1] (91-96);
                    %c#2%
         [GND1$1-GND6$1];
                    %c#3%
         [GND1$1-GND6$1];
                    %c#4%
         [GND1$1-GND6$1];

OUTPUT:
TECH10
SVALUES
;

SAVEDATA:
FILE = GND_Prob_MGCntry_C3cl4_3CHom.dat;
SAVE = CPROBABILITIES;
```

Partial homogeneous multigroup latent class model with 4 classes

```
TITLE: P.Hom MG Country LCA GND C3 with 4 classes;
DATA:
FILE = GND_DtaC3.dat;

VARIABLE:
NAMES = id_i id_j id_r id_s
id_k wt ws
GND1 GND2 GND3 GND4 GND5 GND6
IDSTUD;
IDVARIABLE = IDSTUD;
USEVARIABLES = GND1
GND2 GND3 GND4 GND5 GND6;
CATEGORICAL = GND1
GND2 GND3 GND4 GND5 GND6;
MISSING = .;
```

```
CLASSES = g(14) c(4);
KNOWNCLASS = g(id_k =
 1    !    BFL
 2    !    BGR
 3    !    DNK
 4    !    EST
 5    !    FIN
 6    !    HRV
 7    !    ITA
 8    !    LTU
 9    !    LVA
 10   !    MLT
 11   !    NLD
 12   !    NOR
 13   !    SVN
 14   !    SWE
);
WEIGHT = ws;
STRATIFICATION = id_s;
CLUSTER = id_j;

ANALYSIS:
TYPE = COMPLEX MIXTURE;
PROCESSORS = 4;
STARTS = 1000 250;
STITERATIONS = 20;
STSEED = 288;

MODEL:
%OVERALL%
c ON g;

      %g#1.c#1%
  [GND1$1] (1);
  [GND2$1] (2);
  [GND3$1] (3);
  [GND4$1] (4);
  [GND5$1] (5);
  [GND6$1] (6);
      %g#1.c#2%
  [GND1$1] (7);
  [GND2$1] (8);
  [GND3$1] (9);
 [GND4$1] (10);
 [GND5$1] (11);
 [GND6$1] (12);
      %g#1.c#3%
```

```
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
     %g#1.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);
     %g#2.c#1%
 [GND1$1] (1);
 [GND2$1] (2);
 [GND3$1] (3);
 [GND4$1] (4);
 [GND5$1] (5);
 [GND6$1] (6);
     %g#2.c#2%
 [GND1$1] (7);
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
     %g#2.c#3%
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
     %g#2.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);

.
.
.

    %g#14.c#1%
```

```
  [GND1$1] (1);
  [GND2$1] (2);
  [GND3$1] (3);
  [GND4$1] (4);
  [GND5$1] (5);
  [GND6$1] (6);
     %g#14.c#2%
  [GND1$1] (7);
  [GND2$1] (8);
  [GND3$1] (9);
 [GND4$1] (10);
 [GND5$1] (11);
 [GND6$1] (12);
     %g#14.c#3%
 [GND1$1] (13);
 [GND2$1] (14);
 [GND3$1] (15);
 [GND4$1] (16);
 [GND5$1] (17);
 [GND6$1] (18);
     %g#14.c#4%
 [GND1$1] (19);
 [GND2$1] (20);
 [GND3$1] (21);
 [GND4$1] (22);
 [GND5$1] (23);
 [GND6$1] (24);

OUTPUT:
TECH10
SVALUES
;

SAVEDATA:
FILE = GND_Prob_MGCntry_C3cl4_2PHom.dat;
SAVE = CPROBABILITIES;
```

Complete heterogeneous multigroup latent class model with 4 classes

```
TITLE: C.Het MG Country LCA GND C3 with 4 classes;
DATA:
FILE = GND_DtaC3.dat;

VARIABLE:
NAMES = id_i id_j id_r id_s
```

```
id_k wt ws
GND1 GND2 GND3 GND4 GND5 GND6
IDSTUD;
IDVARIABLE = IDSTUD;
USEVARIABLES = GND1
GND2 GND3 GND4 GND5 GND6;
CATEGORICAL = GND1
GND2 GND3 GND4 GND5 GND6;
MISSING = .;
CLASSES = g(14) c(4);
KNOWNCLASS = g(id_k =
 1    !    BFL
 2    !    BGR
 3    !    DNK
 4    !    EST
 5    !    FIN
 6    !    HRV
 7    !    ITA
 8    !    LTU
 9    !    LVA
 10   !    MLT
 11   !    NLD
 12   !    NOR
 13   !    SVN
 14   !    SWE
);
WEIGHT = ws;
STRATIFICATION = id_s;
CLUSTER = id_j;

ANALYSIS:
TYPE = COMPLEX MIXTURE;
PROCESSORS = 4;
STARTS = 1000 250;
STITERATIONS = 20;
STSEED = 288;

MODEL:
%OVERALL%
c ON g;

      %g#1.c#1%
  [GND1$1] (1);
  [GND2$1] (2);
  [GND3$1] (3);
  [GND4$1] (4);
  [GND5$1] (5);
```

```
 [GND6$1] (6);
     %g#1.c#2%
 [GND1$1] (7);
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
     %g#1.c#3%
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
     %g#1.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);
     %g#2.c#1%
[GND1$1] (25);
[GND2$1] (26);
[GND3$1] (27);
[GND4$1] (28);
[GND5$1] (29);
[GND6$1] (30);
     %g#2.c#2%
[GND1$1] (31);
[GND2$1] (32);
[GND3$1] (33);
[GND4$1] (34);
[GND5$1] (35);
[GND6$1] (36);
     %g#2.c#3%
[GND1$1] (37);
[GND2$1] (38);
[GND3$1] (39);
[GND4$1] (40);
[GND5$1] (41);
[GND6$1] (42);
     %g#2.c#4%
[GND1$1] (43);
[GND2$1] (44);
[GND3$1] (45);
```

```
 [GND4$1] (46);
 [GND5$1] (47);
 [GND6$1] (48);

 .
 .
 .

     %g#14.c#1%
[GND1$1] (313);
[GND2$1] (314);
[GND3$1] (315);
[GND4$1] (316);
[GND5$1] (317);
[GND6$1] (318);
     %g#14.c#2%
[GND1$1] (319);
[GND2$1] (320);
[GND3$1] (321);
[GND4$1] (322);
[GND5$1] (323);
[GND6$1] (324);
     %g#14.c#3%
[GND1$1] (325);
[GND2$1] (326);
[GND3$1] (327);
[GND4$1] (328);
[GND5$1] (329);
[GND6$1] (330);
     %g#14.c#4%
[GND1$1] (331);
[GND2$1] (332);
[GND3$1] (333);
[GND4$1] (334);
[GND5$1] (335);
[GND6$1] (336);

OUTPUT:
TECH10
SVALUES
;

SAVEDATA:
FILE = GND_Prob_MGCntry_C3cl4_1CHet.dat;
SAVE = CPROBABILITIES;
```

Confirmatory latent class model with 4 classes for Students' endorsement of gender equality scale

```
TITLE: ConfLCA C3 GND with 4 classes;
DATA:
FILE = GND_Dta_C3.dat;

VARIABLE:
NAMES = id_i id_j id_r
id_s id_k wt ws
GND1 GND2 GND3 GND4 GND5 GND6
IDSTUD;
IDVARIABLE = IDSTUD;
!subpopulation is (id_k == 1);
USEVARIABLES = GND1
GND2 GND3 GND4 GND5 GND6;
CATEGORICAL = GND1
GND2 GND3 GND4 GND5 GND6;
MISSING = .;
CLASSES = c(4);
WEIGHT = ws;
STRATIFICATION = id_s;
CLUSTER = id_j;

ANALYSIS:
TYPE = COMPLEX MIXTURE;
PROCESSORS = 4;
STARTS = 100 50;
STITERATIONS = 5;
STSEED = 288;


MODEL:
%OVERALL%
%C#1%
[GND1$1*15] (p1);
[GND2$1*4.3] (p2);
[GND3$1*4.2] (p2);
[GND4$1*3.2] (p4);
[GND5$1*3.8] (p5);
[GND6$1*2.6] (p6);

%C#2%
[GND1$1*6] (p2);
[GND2$1*6] (p8);
[GND5$1*2.4] (p9);
```

```
[GND3$1*0] (p10);
[GND4$1*-1.8] (p11);
[GND6$1*-2.3] (p12);

%C#3%
[GND1$1] (p13);
[GND2$1] (p14);
[GND5$1] (p15);
[GND3$1] (p16);
[GND4$1] (p17);
[GND6$1] (p18);

%C#4%
[GND1$1] (p19);
[GND2$1] (p20);
[GND5$1] (p21);
[GND3$1] (p22);
[GND4$1] (p23);
[GND6$1] (p24);

MODEL CONSTRAINT:
p1 = 15;
p10 = 0;


OUTPUT:
TECH10
TECH11
TECH14;
SVALUES
;

SAVEDATA:
FILE = GND_ConfProb_C3cl4.dat;
SAVE = CPROBABILITIES;
```

Confirmatory latent class model with 4 classes for Students' endorsement of equal rights for all ethnic/racial groups scale

```
TITLE: ConfLCA C3 ETH with 4 classes;
DATA:
FILE = ETH_Dta_C3.dat;

VARIABLE:
NAMES = id_i id_j id_r
```

```
id_s id_k wt ws
ETH1 ETH2 ETH3 ETH4 ETH5
IDSTUD;
IDVARIABLE = IDSTUD;
USEVARIABLES = ETH1
ETH2 ETH3 ETH4 ETH5;
CATEGORICAL = ETH1
ETH2 ETH3 ETH4 ETH5;
MISSING = .;
CLASSES = c(4);
WEIGHT = ws;
STRATIFICATION = id_s;
CLUSTER = id_j;

ANALYSIS:
TYPE = COMPLEX MIXTURE;
PROCESSORS = 4;
STARTS = 100 50;
STITERATIONS = 5;
STSEED = 288;


MODEL:
%OVERALL%
%C#1%
[ETH1$1*5.3] (p1);
[ETH2$1*15] (p2);
[ETH3$1*5.5] (p3);
[ETH4$1*1.7] (p4);
[ETH5$1*6.7] (p5);

%C#2%
[ETH1$1*4.5] (p1);
[ETH2$1*3.7] (p2);
[ETH3$1*0.8] (p8);
[ETH4$1*-0.3] (p9);
[ETH5$1*1.4] (p10);

%C#3%
[ETH1$1*-2.9] (p11);
[ETH2$1*-15] (p12);
[ETH3$1*-1.8] (p13);
[ETH4$1*-15] (p14);
[ETH5$1*-2] (p15);

%C#4%
[ETH1$1] (p16);
```

```
[ETH2$1] (p17);
[ETH3$1] (p18);
[ETH4$1] (p19);
[ETH5$1] (p20);

MODEL CONSTRAINT:
p1=-p11;
p2=-p12;
p3=-p13;
p4=-p14;
p5=-p15;

OUTPUT:
TECH10
TECH11
TECH14;
SVALUES
;

SAVEDATA:
FILE = ETH_ConfProb_C3cl4.dat;
SAVE = CPROBABILITIES;
```

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