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Testing Measurement Invariance for a Second-Order Factor. A Cross-National Test of the Alienation Scale

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Abstract

Multiple group confirmatory factor analysis has become the most common technique for assessing measurement invariance. However, higher-order factor modeling is less frequently discussed in this context. In particular, the literature provides only very general guidelines for testing measurement invariance of second-order factor models, which is a prerequisite for conducting meaningful comparative research using higher-order factors. The current paper attempts to fill this gap. First, we explicate the constraints required for identification of the invariance levels in a multiple group second-order factor model. Second, in addition to the conventional interpretation of the results of this assessment, we suggest an alternative view on the invariance properties of a second-order factor as evidence of structural rather than measurement invariance. Third, we present an empirical application of the test which builds on Seeman's alienation scale and utilizes data from eight countries collected in 2008-2009. We found empirical support for metric invariance of both the first- and second-order factors, but no support for scalar invariance of the first- and second-order factors. However, we find pairs of countries where scalar invariance for both the first- and second-order factors is supported by the data. We finalize with a discussion of the results and their interpretation.

Keywords: higher-order factors, measurement invariance, multiple group confirmatory factor analysis, anomie, Seeman's alienation scale

Introduction*

Measurement invariance is the degree to which the measurement model of a latent variable is the same across groups involved in the analysis. It is considered to be one important indicator of population homogeneity. In recent years, various studies have emphasized that the assessment of measurement invariance is necessary in studies involving latent variables and multiple samples, especially in cross-national survey research (Davidov, Meuleman, Cieciuch, Schmidt, & Billiet, 2014; Davidov, Schmidt, & Billiet, 2011). There are several approaches to assess measurement invariance of latent variables; these include lenient ones such as multidimensional scaling and exploratory factor analysis, and stricter ones such as multiple group confirmatory factor analysis (MGCFA: Jöreskog, 1971) or multiple group latent class analysis (McCutcheon, 1987). Since its introduction for the assessment of measurement invariance (Meredith, 1993), MGCFA has become very popular (Davidov et al., 2014) as demonstrated by its inclusion in numerous textbooks and statistical guides, with hundreds of published papers demonstrating its applicability for invariance testing.

Different extensions of the basic MGCFA model have also been discussed in the literature. However, one variant of the MGCFA model, namely, its application to second-order and higher-order factor models, has received considerably less attention. A second-order factor model implies an ordinary factor model in which covariances of latent variables (i.e. first-order factors) are determined by one or more higher-order latent variables (i.e. second-order factors, see Figure 1). In cases of three or more second-order factors, third-order factor models are possible, although such models are rarely used (for an exception, see e.g., Cieciuch, Davidov, Vecchione, & Schwartz, 2014).

* This article is dedicated to Melvin Seeman of UCLA, the pioneer of theoretically driven empirical alienation research, in honor of his 100 birthday on February 5, 2018! He is still going strong in his work on the topic and is now focusing on alienation and health.

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Measurement models with second-order factors are good representations of second-order concepts (Rindskopf & Rose, 1988). For example, the popular Big Five personality traits structure (Costa & McCrae, 1990) was modeled as a set of second-order factors of Cattell's 16 first-order factors (John & Srivastava, 1999). A general intelligence, or Spearman's g-factor, can similarly be seen as a second-order factor where verbal, mathematical, and other kinds of intellectual abilities act as first-order factors (Jensen, 1998). Basic human values are structured hierarchically as well: There are specific values and higher-order values (Schwartz et al., 2012). Finally, alienation can be expressed as a higher-order concept for powerlessness, meaninglessness, and isolation (Seeman, 1991). We will go into more detail about this concept below in the empirical part of the study.

A second-order factor model mimics the logic of the first-order factor models. First-order factor models represent the reflective relations between observed indicators and an underlying factor (latent variable) (Boorsbom, Mellenbergh, & van Heerden, 2003; Costner, 1969; Hempel, 1973). Similarly, second-order factor models represent the reflective relations between first-order factors and an underlying second-order factor (which is also a latent variable). However, when it comes to testing the measurement invariance of second-order factors in multiple groups, various complications occur. Despite the growing number of substantive papers (over 500)[1] addressing second-order factor measurement invariance, very few of these attempted to describe the strategies and complications of this method. Chen, Sousa, and West (2005) provided general guidelines for testing measurement invariance of second-order factor models. Dimitrov (2010) followed their approach and presented an empirical example using the software package Mplus (Muthén & Muthén, 1998-2016). Strasheim (2011) explicated this approach using matrix notation and supplemented it with a technical description of the possible levels of measurement invariance for second-order factors, including the ones that are rarely used (e.g., invariance of residuals).

The purpose of the current paper is twofold. First, we provide a simple, non-technical yet comprehensive description of procedures involved in the assessment of measurement invariance of second-order factor models, embedding these into the context of cross-country surveys. Second, we demonstrate the procedure on real data and test for measurement invariance of a second-order factor. This second-order factor represents alienation, an important concept in sociological literature (Seeman, 1983). We test its measurement invariance properties across eight countries. Thus, rather than presenting a novel procedure, the added value of the paper focuses on guiding the reader through the process of assessing measurement invariance of second-order factors, providing a step-by-step description of the procedure, implementing the method on data across a number of countries, and presenting the

1 This is the number of papers citing Chen et al. (2005) paper in Google Scholar as of February 25, 2017, most of which test second-order factor invariance in some form.

example codes. Furthermore, we suggest an alternative interpretation of second-order factors across groups as a manifestation of structural rather than measurement parameters.

In the next section, we first describe different hierarchical levels of measurement invariance tests and how they apply to second-order factor models. Next, we discuss identification issues and different possible interpretations of the hierarchical factor structure. Finally, we present a cross-national measurement invariance test of alienation in a second-order multigroup factor model.

Assessment of Measurement Invariance

Measurement Invariance of First-Order Factor Models

A common way to assess measurement invariance is to specify an MGCFA model across groups, such as countries, cultures, language groups, or any other nominal variable (Davidov et al., 2014). MGCFA models are fitted to the data using different sets of specific constraints that correspond to the specific level of measurement invariance. Researchers typically differentiate between three levels of measurement invariance that are sufficient for conducting most comparative survey data analyses: configural, metric, and scalar invariance (Vandenberg & Lance, 2000; but see, e.g., Meredith, 1993, for additional levels of invariance).

Configural invariance means that approximately the same concept is measured across groups. It does not guarantee that a construct is measured on the same scale with the same zero point, but it indicates whether higher factor values correspond to higher levels of a concept measured in several groups. Support for configural invariance allows meaningful between-group comparison of *signs* of correlations or regression coefficients, which describe association of the latent variable with exogenous (i.e., external to the measurement model) variables. Configural invariance is met when the general factor structure is the same across groups, including the number of factors and the general pattern of factor loadings. Testing for configural invariance does not involve any parameter constraints across groups except those required for model identification (discussed below). Therefore, configural invariance may also be assessed with “lenient” methods, including multidimensional scaling (e.g., Schwartz & Bilsky, 1990) or exploratory factor analysis (Horn & McArdle, 1992; Lorenzo-Seva & Ten Berge, 2006). These methods provide statistical criteria on the degree of similarity between factor loadings across groups but are not methods considered to be strict tests. Testing for higher levels of measurement invariance is strict albeit necessary when researchers are interested in comparisons of latent variables’ degree of association or means across groups.

Metric invariance represents a second and higher level of measurement invariance. It means that the constructs are measured by the same measurement units across groups. Nevertheless, it does not guarantee that the zero point of the scales is the same across groups. Metric invariance implies that any difference in one unit of a latent variable results in the same differences of the observed indicator variables in all groups. It follows that when metric invariance is present, covariances and unstandardized regression coefficients involving latent variables can be meaningfully compared across groups. Metric invariance is met when the factor loadings are the same across groups. It is assessed by fixing factor loadings to be equal across groups and checking whether the model fit significantly decreases in comparison to the configural model.

Scalar invariance represents the third level of measurement invariance and means that the latent variables' scales are measured with the same units and have the same zero point for all the groups included in the analysis. It implies that the levels of the latent variables correspond to the same levels of the manifest variables across groups. Therefore, in addition to covariances and unstandardized regression coefficients, the means of the latent variables (the latent means) may be meaningfully compared across groups. Scalar invariance is met when intercepts of the observed indicator variables (in addition to the factor loadings) are the same across groups. Consequently, it is assessed by constraining the intercepts of the same items across different groups to equality.

One may rely on partial metric or partial scalar invariance in situations where not all the factor loadings and/or intercepts are the same across groups. Partial invariance would require at least two items with equal factor loadings (for partial metric invariance) and at least two items with equal factor loadings and intercepts per factor (for partial scalar invariance) to be invariant (Byrne, Shavelson, & Muthén, 1989). Partial metric or scalar invariance has the same implications as the corresponding full metric or full scalar invariance (but for criticisms on this approach, see, e.g., Steinmetz, 2011). Similarly, partial invariance may be applicable also for higher-order factors as discussed below.

Measurement Invariance of Second-Order Factor Models

Assessment of measurement invariance of second-order factor models follows basically the same logic as the assessment of measurement invariance of first-order models but with minor differences.

Before testing for measurement invariance of a second-order factor, it is necessary to establish invariance of the first-order factors. Metric invariance of the first-order factors is a prerequisite for the assessment of configural and metric invariance of the second-order factor. Scalar invariance of the first-order factors is a prerequisite to assess scalar invariance of the second-order factor. This determines the sequence of the models when assessing measurement invariance.

The metric invariance model of the first-order factors serves as the model where configural invariance of the second-order factor is tested for the following reason: If metric invariance of the first-order factors is supported by the data, it implies that covariances between the first-order factors are comparable. Therefore, the loadings of the second-order factors can be meaningfully compared across groups. Researchers can then examine the second-order factor loadings to determine whether their structure is also similar across countries. This can be done by fixing the second-order loadings to equality across groups.

The model parameter constraints used to test for second-order scalar invariance are similar to those applied in testing for scalar invariance of first-order factors (see Table 1) with slight differences. To test for scalar invariance of the second-order factor, scalar invariance of the first-order factors is necessary. It will imply that the means of the first-order factors are comparable and one may meaningfully test if they can be constrained to equality across groups.

Partial invariance of a second-order factor model may also be tested if full metric or scalar invariance is not supported by the data for the second-order factor. Following Byrne et al.'s (1989) suggestions for assessing partial invariance of first-order factors, a similar logic may be applied to second-order factors. According to this logic, two invariant first-order factors (with equal loadings on the second-order factor and equal intercepts) may be sufficient for guaranteeing partial invariance of the second-order factor. As this suggestion of implementing the idea of partial invariance on second-order factors is rather new, it requires further exploration using simulation studies that do not only focus on first-order factors (e.g., de Beuckelaer & Swinnen, 2011) but also on partial invariance of second-order factors.

A point worth mentioning is that measurement invariance of higher-order (e.g., of third- or fourth-order) factors follows a similar logic as the one for testing measurement invariance of second-order factors, because factors are continuous on all levels. While metric invariance is a prerequisite for configural and metric invariance on the higher factor level, and scalar invariance is a prerequisite for scalar invariance on the next higher factor level, it may make sense to consider testing first for metric invariance on all factor levels before assessing scalar invariance. By doing so, a differentiation between covariance and mean structures can be achieved.[2]

2 We would also like to indicate that this paper does not consider invariance of errors (the so-called strict invariance) for two reasons. First, this test is rarely conducted in cross-national applied research (see, e.g., Steinmetz, Schmidt, Tina-Booh, Wieczorek, & Schwartz, 2009). Second, equal errors across groups imply equal variances of their corresponding indicators or factors, a situation which is highly unlikely to occur.

Model Identification

Identification of a variance-covariance structure of the first-order factors may be achieved in three interchangeable ways (Little, Slegers, & Card, 2006): fixing the factor variances to 1, fixing the sum of the factor loadings to 1 (“effect coding”), or fixing one factor loading per factor to 1 (“marker indicator”). Likewise, models with a mean structure can be identified either by fixing one intercept per factor to 0, the latent mean in one group to 0, or the sum of the intercepts to 0.

These identification methods differ in their suitability for measurement invariance testing. There is no reason to assume that variances of latent variables should be equal across groups when testing for configural, metric, or scalar invariance. Therefore, it may be problematic to fix factor variances to 1 in all groups. Constraining the sum of factor loadings to be equal across groups makes it difficult to detect model misspecifications, especially when some factor loadings differ across groups. Therefore, constraining one factor loading per factor to 1 is a preferred way of identification of the covariance part of first-order factors. A disadvantage of this approach is that, in the context of modeling multiple groups, this constraint implies equality of the corresponding parameter across groups; thus, a factor loading fixed to 1 is assumed to be invariant across groups a priori, even in the unconstrained configural model. If the fixed loading is in fact not invariant, other truly invariant loadings might be represented by noninvariant factor loading estimates to compensate for the misspecified model. Therefore, special attention should be paid to the selection of the indicator whose loading is fixed to 1. For example, one should try different marker indicators for identifying the model and examine the patterns of loading differences across groups. Researchers are recommended to choose the most reliable and invariant item to serve as a marker. Ideally, this item would also be conceptually closest to the latent variable underlying the different items. An improper selection of a marker variable may lead to incorrect detection of the invariance level when only partial invariance is given in the data (Johnson, Meade, & DuVernet, 2009; Jung & Yoon, 2017). A proper selection of the marker indicator would enable researchers to meaningfully interpret both factor loadings and latent means.

When testing for scalar invariance, the mean structure is easy to identify by constraining the first-order factor means in one reference group to 0. Another technique requires constraining the intercept of a reference indicator to 0 (the “marker indicator method”). We do not apply the former method, because the first-order factor means serve as (latent) intercepts for the second-order factors. When testing for scalar invariance of second-order factors, latent intercepts are constrained to be equal across groups, and being constrained to 0 in one group implies constraining them to zero in all the groups. It leads to the test of latent intercepts' being zero instead of desired test of their equality across groups. Therefore, when testing for scalar invariance of second-order factors, we find it more appropriate to use the "marker method" by fixing one indicator intercept per first-order factor to 0. This allows first-order factor means to be freely estimated in all groups, and it is necessary for testing them for equality when assessing second- order factor scalar invariance.

When the latter method (i.e., the marker method) is used, an intercept fixed to 0 is assumed to be invariant across groups a priori, even in the unconstrained configural model, without empirically testing it. Just like with factor loadings, special attention should be paid to the selection of the indicator whose intercept is fixed to 0. For example, one may examine the modification indices to find out how the fit of the model would change if the marker indicator's intercept was not assumed to be invariant.

The identification of the second-order part of the model follows a similar rationale. For the variance-covariance structure one could either fix the second-order factor variance(s) or one of the second-order factor loading(s) to 1. Alternatively, one may fix the sum of the second-order factor loadings to 1 ("effect coding"). Also, in the context of group comparisons of second-order factors, it is not plausible to assume a cross-group equality of second-order factor variances. Therefore, a common way to identify the second-order part of the model is to choose one first-order factor to serve as an anchor and provide the metric for the second-order factor. Its loading to the second-order factor is constrained to 1. Again, attention should be paid to the selection of the metric, that is, the first-order factor, whose loading is fixed.

The means structure of the second-order factor may be identified by constraining the second-order factors' means in one group to 0. Alternatively, one may constrain the intercept of one reference ("marker") first-order factor to 0. We believe that identifying the second-order factor's mean by constraining it in one group to 0 is preferable and more convenient to implement, because its "indicators" (i.e., the first-order factors) are latent variables themselves whose means may be of interest for researchers. Consequently, it is reasonable to try to avoid constraining the intercept of one of them to 0 across groups.[3]

Testing Procedure

There are two strategies for testing these sequences of constraints. The top-down strategy requires first testing the most restrictive model, and then constraints are

3 When items are considered ordinal rather than continuous, in addition to factor loadings and intercepts one has to consider also a new type of parameters – thresholds (see, e.g., Davidov, Datler, Schmidt, & Schwartz, 2011). The issue of measurement invariance in the case of ordinal responses has not been fully clarified yet (see, e.g. Millsap, 2011, p. 129; Wu & Estabrook, 2016) and is beyond the scope of the current paper.

relaxed until an appropriate fit is achieved (Horn & McArdle, 1992). The bottom-up approach first tests the least restrictive models (i.e., configural invariance), and then factor loadings and intercepts are constrained in a stepwise manner. When working with second-order factor models, it is easier (and therefore preferable) to use the bottom-up strategy, because second-order factor models are complex and, in this way, it becomes easier to detect misspecifications (Brown, 2015, p. 290).

The sequence and specific sets of the constraints tested during the test for measurement invariance of the second-order factor models are listed in Table 1 and summarized below. First, configural invariance of the first-order factors is tested, followed by tests of first-order and second-order metric invariance. These are necessary preconditions to finally test for first- and second-order scalar invariance. Whereas tests of metric invariance on both levels require only information about the variance and covariance structure of the data, tests of scalar invariance on both levels require additional information on the mean structure of the data. Thus, one begins by testing for both first- and second-order metric invariance, and afterwards proceeds with testing for both types of scalar invariance. Such a sequence is reasonable because it allows differentiating in the invariance test between the covariance and the mean structures. Metric invariance on the second level is not a necessary requirement for scalar invariance on the first level. However, logically it makes sense to first examine whether metric invariance holds on both levels, and then expand the test using also information on the means and test for scalar invariance on both levels. As a general guideline, the logic of comparisons is not necessarily to choose the best-fitting model, but to select the most parsimonious one (i.e., the most constrained, with a highest possible level of invariance) which is still well-fitting (Brown, 2015). Such a model will allow more types of cross-group comparisons (as discussed previously). To achieve this, one can begin by comparing the fit of more constrained models with the less constrained ones. If the fit decreases considerably, we have to reject the model with a higher level of invariance, and if there is no considerable decrease in model fit, we can accept the model with a higher level of invariance.

What is a considerable decrease in model fit? The chi-square (χ^2) difference test (also known as the likelihood ratio test) is often applied to compare adjacent pairs of nested models, but it is known to reject models even when violations are minor, particularly when the sample size is large (Chen, 2007). Therefore, Chen (2007) and Cheung and Rensvold (2002) proposed to complement it with alternative criteria. They suggest that if the sample size is large, (>300), a comparative fit index (CFI) difference not larger than 0.01 across models implies that the model fit does not deteriorate considerably. In addition, one could use the sample-adjusted Bayesian information criterion (SABIC), whose values do not supply a significance level but are sensitive to measurement noninvariance; usually the most parsimonious yet well-fitting model has a lower SABIC (Van de Schoot, Lugtig, & Hox,

Table 1 Testing for Measurement Invariance and Possible Parameter Constraints in Multiple Group Confirmatory Factor Analysis with a Second-Order Factor

	First-order factors			Second-order factor	
	Factor loadings	Item intercepts	Latent means/ intercepts	Factor loadings	Latent means
1. Configural	Free, but one per factor is fixed to 1	Free, but one per factor is fixed to 0	Free	Free, but one per factor is fixed to 1	Fixed to 0
2. First-order metric	Set equal across groups and one per factor is fixed to 1	Free, but one per factor is fixed to 0	Free	Free, but one per factor is fixed to 1	Fixed to 0
3. First- and second-order metric	Set equal across groups and one per factor is fixed to 1	Free, but one per factor is fixed to 0	Free	Set equal across groups and one per factor is fixed to 1	Fixed to 0
4. First-order scalar	Set equal across groups and one per factor is fixed to 1	Set equal across groups and one per factor is fixed to 0	Free	Set equal across groups and one per factor is fixed to 1	Fixed to 0
5. First- and second-order scalar	Set equal across groups and one per factor is fixed to 1	Set equal across groups and one per factor is fixed to 0	Set equal across groups	Set equal across groups and one per factor is fixed to 1	Free, but fixed to 0 in one group

Note. The variances of all factors and residuals are freely estimated in all models. The models are based on the marker indicator approach (Little et al., 2006).

2012). Note that beside these criteria, the fit of each model should be acceptable on its own, that is, every model should fit the data well (but to a different degree). We consider a model fit as acceptable when the CFI value is at least as high as 0.90 (soft criterion) or 0.95 (very good fit), and the root mean square error of approximation (RMSEA) is not larger than 0.08 with the upper bound of its confidence interval not higher than 0.10 (but see, e.g., Hu & Bentler, 1999; Marsh, Hau, & Wen, 2004, or West, Taylor, & Wu, 2012, for a vivid discussion on this topic). Thus, and given that χ^2 testing leads too often to significant falsification, one may accept a model with a higher level of invariance if the model deterioration (e.g., in terms of CFI and RMSEA) is not too large and within the recommended criteria.

Interpreting Second-Order Factor Models in a Multiple Group Comparison

We suggest viewing measurement invariance of second-order factors using different perspectives. These perspectives rely on the two differing approaches on how to view second-order factors in the context of multiple group comparisons. The deductive and most popular approach assumes that the logic applied to first-order factor models (Costner, 1969; Hempel, 1973) should be transferred also to second-order factors (Chen et al., 2005; Dimitrov, 2010; Strasheim, 2011). From this point of view, scalar invariance for the second-order factor is necessary to compare its means across groups meaningfully.

The second interpretation originates from the realization of the fact that first-order factors are not observed variables; hence, they should not be treated in the same manner as indicators. Second-order factors might be treated as compensatory, that is, any combination of the invariant first-order factors is indicative of the general higher-order latent variable. The logic behind this view suggests that second-order factors based on invariant first-order factors reflect *structural* relations between the second- and the first-order factors rather than *measurement* relations. In other words, the relative importance of first-order factors may vary across societies or over time without changing the nature of the second-order factor. Thus, even if the structure (the relations between the first- and the second-order factors) slightly varies across groups, second-order factors may still be functionally equivalent across groups and could be compared (Hui & Triandis, 1985; Van de Vijver & Leung, 1997). Indeed, this view may be regarded as problematic, because strictly speaking, if measurement invariance of a second-order factor is not given, its means may be noncomparable. However, we believe it is worthwhile to consider the fact that the measurement structure of second-order factors may vary slightly across societies and over time even when they in fact tap into the very same general concept. One could take this into account by examining approximate (rather than exact) measurement invariance (Van de Schoot et al., 2013).[4]

4 An interesting alternative to the model with the single second-order factor is a bifactor model, which has a single factor loading on all of the items and has zero correlations with the other factors (Chen, West, & Sousa, 2006). Such a general factor might represent a method effect (e.g., response style) and can be easily confused with the second-order factor structure, especially in cross-national surveys. One can test the difference in fit of the second-order factor model and bifactor model, as they are nested, to determine which one represents the data better (Yung, Thissen, & McLeod, 1999).

This distinction corresponds to the difference between the etic and emic approaches in cross-cultural studies (Van de Vijver & Leung, 1997). Etic means that one postulates general statements which should hold in any culture, whereas the emic position assumes that relationships always vary depending on culture. Thus, etic corresponds to our first interpretation and emic to our second one. One should note, however, that this argument may also be used for interpreting the relation between items and first-order factors.

It may be of great interest to determine whether a higher-order construct has similar subdimensions with equal loadings across cultures or over time. This may be considered a major issue of investigation in comparative sociology for different types of concepts. Thus, when first-order factors display measurement invariance but second-order factors do not, it may not necessarily imply that the measurement of the items and their operationalization are problematic or that they are inadequate for comparative research. Instead, noninvariance of a second-order factor may imply that it has a different content across groups. Such an implication can be of great interest for theoreticians. In the following empirical example, we demonstrate how invariance of the second-order factor model is tested and interpreted.

Empirical Illustration

For the empirical illustration we use data measuring the concept of alienation, which is a concept of major importance in sociology. Initially defined by Karl Marx as "the surrender of control over work and its products, and the worker's disengagement from both work and fellow workers" (Seeman, 1991, p. 291), it denotes an individual's isolation, estrangement, and sense of being lost within the society (e.g., Seeman, 1959, 1991; see also Dean, 1961). The most stringent and also popular theoretical models of alienation were developed by Seeman (1959) who considered alienation as a combination of five subdimensions: feeling of powerlessness, meaninglessness, normlessness, isolation, and self-estrangement. A series of scales were developed based upon his model. Studies applying these scales connected the five subdimensions with the value-expectancy theory (see Robinson, 1973; Schmidt, 1990; Seeman, 1991) and applied them in several contexts (e.g., Dean, 1961; Huschka & Mau, 2006; McClosky & Schaar, 1965; Middleton, 1963). However, the validity and cross-national reliability of these scales have not been assessed yet (for an exception, see a German-American comparison of some of the items of the scales by Krebs & Schuessler, 1989). In addition, alienation was never specified and tested as a second-order factor model, although the underlying theoretical conceptualization would require this (Schmidt, 1990). Due to data constraints (see the next section), we employ and test the measurement of only three of the five subdimensions of alienation in the analysis. The definitions of the three subdimensions are presented in Table 2. In the following section, we will test for measurement invariance of alienation using a shortened version of McClosky and Schaar's (1965) alienation scale across several European countries.

Data and Measures

We employ data from the project "Group-Focused Enmity" carried out in 2008/2009 by the Institute for Interdisciplinary Research on Conflict and Violence (Bielefeld University, Germany) with its European partners[5] in eight countries: France, Germany, Great Britain (England, Scotland, Wales, but not Northern Ireland), Hungary, Italy, the Netherlands, Poland, and Portugal. These countries were chosen because they represent old and new EU member states and different geographical regions in Europe (Küpper et al., 2010; Zick et al., 2011). The countries differ in various characteristics such as the level of economic prosperity, level of inequality, history of democracy, or their citizens' well-being. These features may contribute not only to different levels of alienation, but also to a different measurement structure of alienation. We expect countries with a longer history of democracy, longer EU membership, a stronger economy, and a higher level of democratic participation of citizens to have lower levels of alienation.

Data were collected via computer-assisted telephone interviews with a representative sample of about 1,000 respondents aged 16 years and above in each country. A representative random sample was drawn from the national telephone master samples (stratified according to a regional allocation of the population). After choosing a household, the target person was selected by either picking the household member whose birthday was next or last, or by the Kish grid method where a table of preassigned random numbers is used to choose a respondent (Kish, 1949). Response rates were rather low and varied across countries, ranging between 4.5% in Italy to 33% in Germany. In the final sample, 48% of respondents were male and 52% were female, and the mean age was 47 years. In each country sample, about 1,000 respondents were interviewed, but only about half of them were asked all the questions included in the scale. Thus, the actual sample size in each country used in our study was approximately 500 (see Appendix A). These samples do not differ systematically from the full samples in their sociodemographic characteristics such as age and gender. Missing values were handled with the full information maximum likelihood algorithm during model estimation (Arbuckle, 1996).

The alienation scale in the data included six indicators which measured three first-order concepts: powerlessness, meaninglessness, and social isolation. The

5 The project was financially supported by the Compagnia di San Paolo, the Freudenberg Stiftung, the Groeben Stiftung, the Volkswagen Stiftung, and two other private foundations. For further details on data collection and documentation, see Zick, Küpper, and Hövermann (2011) and Küpper, Wolf, and Zick (2010).

items represented a short version of the McClosky and Schaar (1965) scales, and their question wording is presented in Table 2. No measures for normlessness and self-estrangement were included in the data. However, we consider these three subdimensions of alienation, that is, powerlessness, meaninglessness, and social isolation, to be the very core of alienation (Dean, 1961, p. 754; Seeman, 1959, p. 787; Seeman, 1991, p. 339). All items were measured on an agree-disagree scale ranging from 1 to 4 and then recoded so that 1 indicated "strongly disagree" and 4 indicated "strongly agree." Alienation was modeled in each country sample as a second-order factor reflecting the three subdimensions, which were in turn measured by two items each (see Figure 1). The replication data are listed in Appendix E.

In the following section, we will explore whether scalar invariance of the alienation measurement model is given in the data. However, there are various potential sources for an eventual lack of measurement invariance. Such sources threatening the invariance of the scale may result, for example, from suboptimal translations, a different understanding of various question items, or cultural variations in response style. We present the results of the invariance test below.

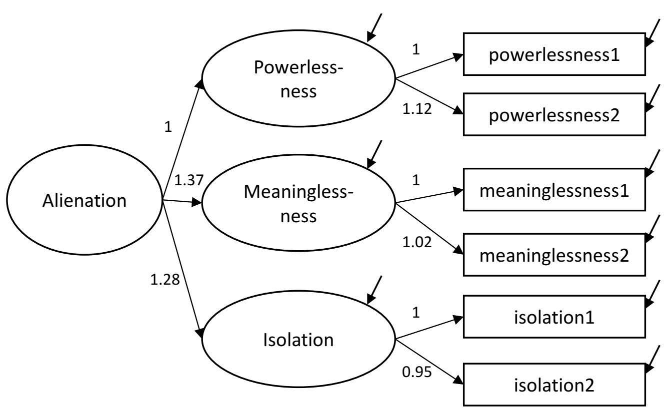

Figure 1 The second-order factor measurement model of alienation. The numbers are invariant unstandardized factor loadings as estimated in a second-order metric invariance model (corresponding to Model 3 in Table 3).

Table 2 Indicators of Alienation Used in the "Group-Focused Enmity" Survey

Second-order concept	First-order concept	Definition (Seeman, 1959)	Questionnaire items, each with four response options: 1 – "Strongly agree" 2 – "Somewhat agree" 3 – "Somewhat disagree" 4 – "Strongly disagree"
Alienation	Powerlessness	individual's sense of influence over socio-political events	1) Politicians do not care what people like me think 2) People like me do not have any say about what the government does
	Meaninglessness	when the individual is unclear on what s/he ought to believe – when the individual's standards for clarity in decision making are not met	1) Nowadays things are so confusing that you sometimes do not know where you stand 2) Nowadays things are so complex that you sometimes do not know what is going on
	Social Isolation	alienation from reigning goals and standards	1) Finding real friends is becoming more and more difficult nowadays 2) Relationships are getting more and more unstable

Method

To check whether we can compare the alienation scale across countries, we first specified a second-order confirmatory factor analysis model. It is depicted in Figure 1.

One loading of each first- and the second-order factor was fixed to 1 in order to identify the covariance structure part of the model (applying the marker item method). As we do not assess partial measurement invariance, the selection of marker indicators did not require any additional test of the adequacy of the chosen item. However, during the analysis we paid special attention to whether the modification indices suggest that the marker item's parameters are not equal across groups. As markers we selected the indicator "Politicians do not care what people like me think" for the powerlessness factor, the indicator "Nowadays things are so confusing that you sometimes do not know where you stand" for the meaninglessness factor, and the indicator "Finding real friends is becoming more and more difficult nowadays" for the social isolation factor. For the second-order factor, powerlessness was chosen to be the marker of the alienation factor because this first-order factor was treated as the very core of alienation in a number of studies (e.g., Geis & Ross, 1998; Neal & Seeman, 1964). Of all subdimensions, this one has been the most extensively studied (Seeman, 1975, p. 94). Moreover, Seeman (1959, p. 784) linked this concept to the original formulation of the alienation concept by Marx. Since our indicators had only four response options, the parameters were estimated using the maximum likelihood robust (MLR) estimator. In order to simplify the description, we treated these indicators as continuous.[6] All the models were tested using the software Mplus 7.3 (Muthén & Muthén, 1998-2016). The syntax codes are provided in Appendix D.

We began by fitting the CFA model in each country separately (not reported).[7] The model demonstrated an acceptable fit in all countries with the exception of Portugal. Consequently, we decided to exclude Portugal from further analysis. We checked invariance in five steps (as described in previous sections) according to the constraints listed in Table 1.

Results

Table 3 displays the fit measures of the five models we tested. Model 1, which included no cross-groups constraints, displayed a very good fit. Thus, we could conclude that each construct was measured by the same items in each of the countries included in the analysis. Also Model 2, which tested for metric invariance of the first-order factors, demonstrates a good fit. The χ^2 difference test suggested that there is no significant deterioration in the model fit compared to Model 1. In addition, the difference in CFI did not exceed 0.01. This indicates that the first-order factor loadings could be considered invariant across countries. Similarly, also Model 3, where we tested for metric invariance of the second-order factor, demonstrated a good fit. A comparison with Model 2 revealed no significant deterioration in the χ^2 value or in the CFI value. Therefore, we could conclude that the second-order factor loadings are invariant across countries as well. This finding implies the equal meaning of alienation across countries.

6 An examination of the item distributions did not detect any severe nonnormalities. In order to check the robustness of the results, we reanalyzed the model while accounting for the ordinal nature of the observed items using the WLSMV estimator in Mplus (see, e.g., Davidov et al., 2011). The model was identified using the constraints suggested by Millsap and Yun-Tein (2004), the second-order scalar invariance model was identified by constraining the latent intercepts to 0 in all groups and the second-order factor's mean to 0 in one group. The model fit indices are listed in Appendix B and demonstrate that our conclusions remain essentially the same.

7 The output may be obtained from the first author upon request.

Models 4 and 5 tested for full scalar invariance of the first- and second-order factors in the model. Imposed scalar invariance of the first-order factors in Model 4 showed a substantial deterioration in model fit both in terms of the χ^2 and the CFI. This finding implies that there is no first-order scalar invariance across all countries and, consequently, no second-order scalar invariance. However, for illustrative purposes, we also fitted a model testing for scalar invariance of the second-order factor in Model 5. As expected, this model showed a poor fit to the data. Thus, the best model in this sequence was Model 3, which demonstrated both first- and second-order metric invariance. Supporting these conclusions, the SABIC displayed the smallest value in this model as well.

As scalar invariance was not evidenced for both the first- and second-order factors in the model, means of the three first-order factors of alienation as well as the mean of the second-order factor of alienation may not be compared with confidence across countries. Since we only had two items measuring each first-order factor, and as partial scalar invariance requires that at least two items per factor display equal factor loadings and intercepts, it was not possible for us to test for partial scalar invariance.

Lack of evidence of scalar measurement invariance does not necessarily imply that no comparisons can be performed. It could well be the case that although the first- and second-order factors of alienation may not be comparable across all eight countries, there are pairs or triads of countries where they are comparable and where scalar invariance can be supported by the data. For example, we found full scalar invariance of this model between Italy and Germany (the fit indices are listed in Appendix C). The mean alienation in Italy was 0.344 and significant, whereas in Germany the mean was fixed to 0. Thus, the level of alienation was significantly higher in Italy than in Germany. Furthermore, we found empirical support for partial scalar invariance across Poland and France. In this model, the latent intercept of the first-order factor of meaninglessness was freed, whereas the intercepts of the first-order factors powerlessness and isolation were constrained to equality. The mean alienation in Poland was 0.471 and significant, whereas in France the mean was fixed to 0. In line with our expectations, the level of alienation is significantly higher in Poland than in France. Likewise, we found partial scalar invariance for Germany and the United Kingdom. In the model for these two countries we had to relax intercepts of the observed indicator of the first-order factor isolation, as well as the latent intercept of isolation itself. In the United Kingdom the latent mean of alienation was fixed to 0, whereas in Germany it was estimated as -0.160 and highly significant, indicating that the level of alienation was higher in the United Kingdom. Researchers interested in studying specific countries in these data would need to conduct the analysis we presented for these particular countries to determine whether they exhibit full or partial invariance.

Table 3 Results of Invariance Tests of a Second-Order Factor Model of Alienation

	$\chi^2(df)$	Scaled χ^2 difference	CFI	CFI difference	RMSEA	SRMR	SABIC
1) Configural invariance	49.5 (42)		0.998		0.019 [a]	0.014	51295
2) Metric invariance of the first-order factors	71 (60)	21.6	0.997	0.001	0.019 [a]	0.025	51231
3) Metric invariance of the first and second-order factors	79.8 (72)	8.6	0.997	0.001	0.015 [a]	0.029	51181
4) Scalar invariance of the first-order factors	417.2 (90)*	337.4*	0.917	0.080	0.085	0.063	51483
5) Scalar invariance of the first- and second-order factors	691.9 (102)*	274.2*	0.850	0.063	0.107	0.094	51740

Note. *df* – degrees of freedom; scaled $\chi 2$ difference is a difference between -2log-likelihood corrected with a scaling factor applied with maximum likelihood robust estimator; CFI – comparative fit index; delta CFI – difference in CFI from the previous model in the sequence; RMSEA – root mean square error of approximation, SABIC – sample-adjusted Bayesian information criterion, SRMR – standardized root mean square residual.

* significant at $p < 0.01$.

a – RMSEA is equal or lower than 0.05 at $p < 0.05$ level of significance.

Summary and Conclusions

Measurement invariance is a necessary condition to allow meaningful comparisons across groups. The last two decades have witnessed a significant increase in the number of cross-cultural studies which tested for measurement invariance across groups such as cultures, countries, or language groups (Davidov et al., 2014). MGCFA is currently one of the most common techniques used for assessing measurement invariance. However, higher-order factor modeling was only seldom discussed. In particular, the literature has provided only very general guidelines for testing measurement invariance of second-order factor models (and of higher-order factors in general). This is unfortunate, because measurement invariance is also a prerequisite for conducting meaningful comparative research when second- (or higher-) order factors are included in a study. In an attempt to fill this gap, the current paper first presents a nontechnical explanation of the constraints required for the identification of models and the different steps that are taken when testing for measurement invariance of second-order factors in a multiple-group model. Second, it provides a practical application of how to test for measurement invariance of a second-order factor using data drawn from eight European countries. It measures the second-order concept of alienation with its three first-order dimensions: powerlessness, meaninglessness, and social isolation.

The empirical example was performed using the concept of alienation as a second-order factor, where meaninglessness, powerlessness, and isolation served as first-order factors, each measured by two indicators. We found support for first- and second-order metric invariance among seven countries (excluding Portugal), but no support for scalar invariance across countries. Does it imply that alienation may not be compared across all countries? Strictly speaking, at least partial scalar invariance for the first- and second-order factors is necessary to guarantee that mean comparisons of alienation across countries are meaningful. However, we suggest that differences in the structural parameters for the second-order factors (e.g., differences in the intercepts of the first-order factors across countries) may reveal that the concept of alienation bears somewhat different connotations and content across countries. This could be a useful starting point for substantive researchers to examine reasons for the revealed parameter differences across countries.

The criteria described in this paper to test for measurement invariance require exact equality of factor loadings and intercepts. In recent times, however, this approach has often been regarded as too strict. For this reason, novel and more lenient forms of measurement invariance methods such as approximate Bayesian invariance (Muthén & Asparouhov, 2013) or alignment (Asparouhov & Muthén, 2014) are gaining popularity. Although these new methods are very promising, they are beyond the scope of the current paper. These newer procedures may suggest that scales are (approximately and sufficiently) invariant even when exact measurement invariance tests fail to do so. Such approximate invariance tests can also take into account parameters differences across countries in a more flexible way than our approach does. As we are not aware of any studies that have applied these procedures on second- or higher-order factors, a task for future studies is to do so and to provide illustrations of how to assess approximate measurement invariance for higher-order factors.

The study has several limitations related both to our measurements and the criteria used to assess measurement invariance. Measures were only available for three of the five subdimensions of our second-order factor of alienation. Thus, we could test its measurement invariance properties while only reflecting a part of its subdimensions. In addition, each first-order factor was measured by only two items. Thus, it was not possible for us to test whether partial (rather than full) scalar invariance was given in the data for the first-order factors. A test of partial invariance requires having at least three indicators to measure each first-order factor. However, the data we used also offered several advantages. In particular, the data represent a realistic and common situation in survey research in which we have only two items to measure each latent variable (see, e.g., the case of the value measurements in the European Social Survey). Second, the simplicity of the data allows for a clearer illustration of the procedure. Third, the illustration presented here uses data on an important concept in sociological and social psychological literature. Fourth, the data allow for testing a second-order factor across a large number of countries. An additional limitation we would like to acknowledge is that it is not clear whether the criteria we used to determine whether measurement invariance models are supported by the data, such as exploring differences in CFI across models (Chen, 2007; see also Cheung & Rensvold, 2002), apply also for models testing for measurement invariance of *second-order* factors. These criteria were developed originally for models with first-order factors. Future simulation studies may assess whether these criteria also apply for the test of measurement invariance of second-order factors. In spite of these limitations, we believe that testing for measurement invariance of a second-order factor is essential when using data from multiple samples and comparing these latent variables across countries. We hope that the nontechnical presentation of this method reported in this article will help researchers in their endeavor to study second- (or higher-) order factors from a cross-cultural perspective.

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Appendix A

Sample Characteristics

Country	Response rate, %	Sample size	Percentage females	Average age
France	10.2	531	53.4	46.0
Great Britain	24.6	519	50.6	46.8
Germany	33.0	495	50.2	47.9
Hungary	8.8	477	50.9	46.9
Italy	4.5	499	50.6	49.9
Netherlands	11.8	513	49.4	46.9
Portugal	7.3	483	52.9	45.4
Poland	15.5	501	52.3	43.1

Appendix B

Fit Indices of a Measurement Invariance Test of the Second-Order Factor of Alienation while Accounting for Ordinality of the Items (Using the WLSMV Estimator)

	$\chi^2(df)$	χ^2 difference	CFI	CFI difference	RMSEA	RMSEA upper boundary
1) Configural invariance	63.1 (42)		0.999		0.032	0.047
2) Metric invariance of the first-order factors	138.1 (60)	62.4*	0.993	0.007	0.051	0.062
3) Metric invariance of the first- and second-order factors	149.1 (72)	19.0	0.994	0.001	0.046	0.057
4) Scalar invariance of the first-order factors	634.5 (126)	519.1*	0.978	0.016	0.090	0.097
5) Scalar invariance of the first- and second-order factors	1122.4 (138)	309.2*	0.949	0.031	0.119	0.126

Note. * significant at $p < 0.01$ as estimated by *DIFFTEST* procedure in Mplus.

Appendix C

Fit Indices of the Second-Order Factor Models of Alienation in Italy and Germany

	$\chi^2(df)$	Scaled χ^2 difference	CFI	CFI difference	RMSEA	SRMR	SABIC
1) Configural invariance	15.0 (12)		0.997		0.023	0.015	14370
2) Metric invariance of the first-order factors	21.7 (15)	6.62	0.996	0.001	0.024	0.027	14367
3) Metric invariance of the first- and second-order factors	22.0 (17)	0.37	0.994	0.002	0.030	0.027	14360
4) Scalar invariance of the first-order factors	29.6 (20)	7.59	0.992	0.002	0.031	0.031	14357
5) Scalar invariance of the first- and second-order factors	35.2 (22)	5.62*	0.989	0.003	0.035	0.034	14356

* significant at $p < 0.01$.

Appendix D

Mplus Codes

1. Configural invariance model

```
DATA:
  FILE IS alienation7countries.dat;

VARIABLE:
  NAMES ARE country power1 power2 meaning1 meaning2 isolat1 isolat2;
  MISSING IS power1 power2 meaning1 meaning2 isolat1 isolat2 (5);
  GROUPING IS country (1=GB 2=GE 3=HU 4=IT 5=NE 7=PL 8=FR);

ANALYSIS:
  ESTIMATOR = MLR;

MODEL:
  POWER   BY power1@1 power2;
  ISOLAT  BY isolat1@1 isolat2;
  MEANING BY meaning1@1 meaning2;
  ALIENAT BY POWER@1 ISOLAT MEANING;

MODEL GB: !This block is repeated for each country
  POWER   BY power2;
  ISOLAT  BY isolat2;
  MEANING BY meaning2;

  [power1@0 power2 isolat1@0 isolat2 meaning1@0 meaning2];

  ALIENAT BY ISOLAT MEANING;
  [POWER ISOLAT MEANING];
  [ALIENAT@0];
```

2. Metric invariance of the first-order factors. Data, variable, and analysis blocks are the same as in the configural model). Hereafter, the additions to the code of the preceding model are in bold.

```
MODEL GB: !This block is repeated for each country
  POWER   BY power2  (load1);
  ISOLAT  BY isolat2 (load2);
  MEANING BY meaning2(load3);

  [power1@0 power2 isolat1@0 isolat2 meaning1@0 meaning2];

  ALIENAT BY ISOLAT MEANING;
  [POWER ISOLAT MEANING];
  [ALIENAT@0];
```

3. Metric invariance of the first- and second-order factors

```
MODEL GB: !This block is repeated for each country
  POWER   BY power2  (load1);
  ISOLAT  BY isolat2 (load2);
  MEANING BY meaning2(load3);

  [power1@0 power2 isolat1@0 isolat2 meaning1@0 meaning2];

  ALIENAT BY ISOLAT MEANING (load4 load5);
  [POWER ISOLAT MEANING];
  [ALIENAT@0];
```

4. Scalar invariance of the first-order factors

```
MODEL GB: !This block is repeated for each country
  POWER   BY power2  (load1);
  ISOLAT  BY isolat2 (load2);
  MEANING BY meaning2(load3);

  [power1@0 power2 isolat1@0
  isolat2 meaning1@0 meaning2] (intcpt1-intcpt6);

  ALIENAT BY ISOLAT MEANING (load4 load5);
  [POWER ISOLAT MEANING];
  [ALIENAT@0];
```

5. Scalar invariance of the first- and second-order factors.

```
MODEL GB: !This block is repeated for each country
  POWER   BY power2  (load1);
  ISOLAT  BY isolat2 (load2);
  MEANING BY meaning2(load3);

  [power1@0 power2 isolat1@0
  isolat2 meaning1@0 meaning2](intcpt1-intcpt6);

  ALIENAT BY ISOLAT MEANING (load4 load5);
  [POWER ISOLAT MEANING](intcpt7-intcpt9);
  [ALIENAT@0]; ! This line should be [ALIENAT*] in all the other
groups, i.e. latent mean is freely estimated except for one group.
```

Appendix E

Replication data. Variances and covariance matrices and means for the manifest variables in each country.

	POWER1	POWER2	MEANING1	MEANING2	ISOLAT1	ISOLAT2
Great Britain						
POWER1	0.88					
POWER2	0.58	0.99				
MEANING1	0.25	0.31	0.92			
MEANING2	0.19	0.25	0.62	0.87		
ISOLAT1	0.22	0.24	0.27	0.27	1.12	
ISOLAT2	0.20	0.18	0.29	0.22	0.35	0.81
Means	2.86	2.84	2.90	2.95	2.26	2.91
Germany						
POWER1	0.91					
POWER2	0.54	0.97				
MEANING1	0.30	0.29	0.86			
MEANING2	0.29	0.31	0.67	0.88		
ISOLAT1	0.30	0.30	0.37	0.43	1.01	
ISOLAT2	0.20	0.24	0.27	0.31	0.40	0.75
Means	2.87	2.77	2.60	2.64	2.67	2.84
Hungary						
POWER1	0.80					
POWER2	0.25	1.31				
MEANING1	0.24	0.31	1.04			
MEANING2	0.28	0.25	0.65	0.94		
ISOLAT1	0.21	0.16	0.31	0.29	0.98	
ISOLAT2	0.19	0.16	0.37	0.34	0.55	0.91
Means	3.27	2.43	2.97	3.08	3.17	3.21
Italy						
POWER1	0.72					
POWER2	0.36	0.77				
MEANING1	0.24	0.21	1.02			
MEANING2	0.20	0.22	0.63	0.83		
ISOLAT1	0.13	0.26	0.28	0.25	1.00	
ISOLAT2	0.18	0.24	0.26	0.23	0.54	0.79
Means	3.19	3.32	3.06	3.13	3.08	3.13

	POWER1	POWER2	MEANING1	MEANING2	ISOLAT1	ISOLAT2
Netherlands						
POWER1	0.84					
POWER2	0.57	0.88				
MEANING1	0.15	0.17	0.78			
MEANING2	0.15	0.20	0.50	0.74		
ISOLAT1	0.17	0.21	0.25	0.20	0.88	
ISOLAT2	0.18	0.21	0.20	0.22	0.42	0.79
Means	2.19	2.36	2.67	2.71	2.14	2.62
Poland						
POWER1	0.68					
POWER2	0.38	0.80				
MEANING1	0.12	0.15	0.64			
MEANING2	0.15	0.14	0.46	0.70		
ISOLAT1	0.12	0.17	0.21	0.25	0.83	
ISOLAT2	0.15	0.14	0.18	0.19	0.29	0.55
Means	3.36	3.31	3.28	3.13	3.12	3.34
France						
POWER1	0.96					
POWER2	0.58	1.18				
MEANING1	0.26	0.27	0.79			
MEANING2	0.30	0.36	0.54	0.79		
ISOLAT1	0.28	0.29	0.32	0.34	1.21	
ISOLAT2	0.31	0.32	0.34	0.33	0.86	1.15
Means	2.91	2.69	3.18	3.08	2.52	2.77