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Is anti-Semitism a homogeneous construct?[2]

Abstract: The present paper investigates how the distinction of different facets of anti-Semitism is to be understood from a methodological point of view. Does it mean that there is a unique (quantitative) dimension of anti-Semitism on which the participants can be ordered due to a variety of expressions of anti-Semitic prejudice, or does it imply that these facets are independent dimensions of anti-Semitism, which combine themselves into (qualitatively) different syndromes of anti-Semitism?
After discussing various methodological approaches to the analysis of homogeneity vs. inhomogeneity of tests or questionnaires, the paper applies these methodologies to data from an anti-Semitism survey by Petzold (2004) and comes to the conclusion that the facets are no independent constructs. All of them are indicators of one and the same anti-Semitic attitude whose expression is partly modified during the strengthening of anti-Semitic prejudice, however.

1 Introduction

1.1 Facets of anti-Semitism

In the newer literature various facets of anti-Semitism are distinguished. Among others, *manifest or classical anti-Semitism* which refers to defamation that is openly expressed and draws on traditional prejudices held against Jews as Jews by non-Jews (e.g., Heyder et al., 2005; Frindte, Wammetsberger & Wettig, 2005a,b; Frindte, 2006, Zick & Küpper, 2007); s*econdary anti-Semitism* (Schönbach, 1961) which concerns how Germans deal with the Nazi past, the Holocaust and the question of guilt and responsibility (Frindte, Wammetsberger & Wettig, 2005a,b; Frindte, 2006); and *latent anti-Semitism* (Bergmann & Erb, 1991a,b) which is expressed in attempts to not publicly speak of intentionally committed discrimination against Jews as Jews (Frindte, Wammetsberger & Wettig, 2005a,b; Frindte, 2006).

(Not only) for the methodologist, this raises the question, how these various facets of Anti-Semitism are to be understood.

- Does the distinction of different facets mean that there is a unique (quantitative) dimension of anti-Semitism on which the participants can be ordered due to a variety of expressions of anti-Semitic prejudice, which ranges from open expression of dislike of Jews via the expression of traditional anti-Jewish prejudices and the demand to end the discussion of coming to terms with the German past up to the refusal to speak about Jews? (Assumption 1).
- Or does it imply that these facets are (more or less) independent constructs, which combine themselves into (qualitatively) different syndromes or patterns of anti-Semitism? (Assumption 2)

1.2 Methodology

Usually, anti-Semitism is measured by means of questionnaires where the participants respond to a number of k anti-Semitic statements on an m-point Likert-scale ranging from disagreement to agreement. The standard method which is applied in order to investigate whether questionnaire items form a homogeneous scale (cf. assumption 1) or whether it is to be broken down into more or less independent (homogeneous) sub-scales (cf. assumption 2) is the method of Principal Components Analysis (PCA) which dates back to Hotelling (1933). As we will see, this approach is not suited to decide between the two alternatives, however, and therefore we will have to fall back on other methods.

Principal Components Analysis

Principal Components Analysis displays the items as vectors in a k-dimensional space and the correlation of any two items i and i′ ($\rho_{ii'}$) as the angle ($\varphi_{ii'}$) between their respective vectors, so that

(1) $\rho_{ii'} = \cos\varphi_{ii'}$.

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The basic equation of PCA is

(2) $$x_{vi} = a_{i1}y_{v1} + \ldots + a_{ij}y_{vj} + \ldots + a_{ik}y_{vk}$$

where x_{vi} denotes a participant's (v) response to an item (i); ($a_{i1},\ldots,a_{ik}$) is the vector which displays the item's position in a k-dimensional system of orthogonal (= uncorrelated) coordinates or "factors" (j = 1,…,k) ; and the participant's factor values $y_{v1},\ldots,y_{vk}$ describe his or her position on these coordinates.

Since the so-called factor loadings $a_{ij} = \rho(X_{oi}, Y_{oj})$ are identical with the correlation between item i and factor j, homogeneity of a scale (cf. assumption 1) would imply that PCA results in the identification of one (main) factor on which all of the items load high, while the remaining factors describe minor deviations from this general dimension.

If the scale is to be broken down into a number of q more or less independent homogeneous sub-scales (cf. assumption 2), on the other hand, PCA should result in q main factors each of which can be assigned to one of the subscales so that the items which belong to the respective subscale load high on it, but not on the other factors.

However, the loading-matrix A = (a_{ij}) which results from PCA is unique up to multiplication with an orthogonal transformation matrix T only, so that any transformed loading Matrix $B = AT$ is an equally good description of the pair-wise item-correlations. In geometrical terms this means that there are infinitely many ways, how a k-dimensional space can be described by an orthogonal system of coordinates or, with other words: there are infinitely many ways, how a system of orthogonal coordinates can be rotated and still describe the same k-dimensional space and the same matrix of pair-wise correlations between the items. And there is no (formal) criterion, why one of these infinitely many orthogonal systems of coordinates should be favored. The only possible criteria are merely pragmatic.

- The un-rotated loading matrix defines the coordinates in a way, so that the first factor explains as much as possible of the variance of the response variables, the second factor describes as much as possible of the remaining variance, and so on. In geometrical terms, this means that all items are displayed by vectors which are as near as possible to the *first* coordinate of the system.
- The most common rotation-method is VARIMAX, which defines the coordinates in a way so that each of the items loads as high as possible on one of the factors and as low as possible on the others. In geometrical terms, this means that each item is displayed by a vector which is as near as possible to *one* of the coordinates.

Whether PCA supports the assumption of a homogeneous scale (assumption 1) or the alternative assumption of q more or less independent sub-scales (assumption 2), will therefore not (or at least not primarily) depend on the data, but on the arbitrarily chosen rotation method we apply.

- While the unrotated loading matrix will favor the assumption of one common dimension on which all items load high,
- the VARIMAX rotated loading matrix will favour the assumption of various sub-scales which are more-or less independent of each other.

Internal Consistency Analysis

Another common approach to analyze the homogeneity of a scale builds upon Classical Test Theory which dissects a participant's response to an item into two factors

(3) $$x_{vi} = \tau_{vi} + f_{vi},$$

one of which, the participant's true-score (τ_{vi}), is defined as the expected score $\tau_{vi} = E(X_{vi})$ while the other one (f_{vi}) is a measurement-error. One of the main aims of Classical Test Theory is to estimate the reliability of a (test or) questionnaire which is defined as the squared correlation between the test-scores

(4) $$x_{vt} = \sum_{i=1}^{k} x_{vi}$$

and the respective true-scores

(5) $$\tau_{vt} = \sum_{i=1}^{k} \tau_{vi}$$

and equals the proportion of systematic (true-score) variance in the variance of the observed scores

(6) $$\rho^2_{XT} = \frac{\sigma^2(T_{ot})}{\sigma^2(X_{ot})}.$$

Since the true-scores are non-observable (latent), the reliability cannot be computed directly, however, but only be estimated under certain additional assumptions (cf. Lord & Novick, 1968). The least restrictive of these additional assumptions is the concept of *essential τ-equivalence* which proposes that the items measure the same true-score variable but differ with respect to their difficulty so that the true-score difference between any two items (i and i') is a constant term $\tau_{vi} - \tau_{vi'} = c_{ii'}$ which describes the difficulty-difference of the items.

The most common way to estimate the reliability of a (test or) questionnaire is Cronbach's (1951) coefficient α which dates back to Guttman (1945) and is defined by

(7) $$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma^2(X_{oi})}{\sigma^2(X_{ot})}\right).$$

The popularity of the coefficient α is due to two of his properties: (1) In contrast to other reliability coefficients which may both, under-estimate or over-estimate the reliability if the additional assumptions do not hold (cf. Kempf, 2008), the coefficient α delivers in any case a lower bound of the reliability so that $\rho^2_{XT} \geq \alpha$, and it is equal to the reliability under quite weak assumptions, that is, if the items are essentially τ-equivalent.

- This has led to the common interpretation of coefficient α in terms of *internal consistency*, which operationalizes the homogeneity of a (test or) questionnaire by the essential τ-equivalence of the items: For any given reliability, coefficient α will be the higher, the more homogeneous the (test or) questionnaire is, and it will be the lower, the more the assumption of essential τ-equivalence is violated.
- However, since coefficient α depends on both, homogeneity and reliability, it is not a valid indicator of homogeneity or inhomogeneity of a (test or) questionnaire, either. Since reliability is the smaller, the less the participants differ with respect to their true-scores (small true-score variance; cf. equation 10), homogeneous tests may have small α-coefficients as well.

Ordinal homogeneity

Ordering the participants on a quantitative dimension implies less restrictive assumptions than essential τ-equivalence. We can already speak of a homogeneous (test or) questionnaire if (and only if) the responses to the various items imply the same rank order between the participants, so that for any pair of participants (v and v') and any pair of items (i and i')

(8) $$\tau_{vi} > \tau_{v'i} \Leftrightarrow \tau_{vi'} > \tau_{v'i'}.$$

If this is the case, we can speak of *ordinal homogeneity* of the scale. Since equation (8) must hold for any two single participants, it must hold for any two groups of participants (g and g') as well, so that

(9) $$\tau_{gi} > \tau_{g'i} \Leftrightarrow \tau_{gi'} > \tau_{g'i'},$$

where $\tau_{gi} = E(X_{gi})$ is the expected score within group g. In order to test whether ordinal homogeneity holds, we may therefore classify the participants into a number of g = 1,…,h distinct subsamples (classes of participants) and produce profile-lines as they are shown in Figures 1 and 2.

In order to do so, we estimate the expected item scores within the over-all sample $\tau_{oi} = E(X_{oi})$ and order the items according to them on the x-axis of the coordinate system so that the item with the highest over-all score is the first one and the item with the lowest over-all score is the last one (from left to right). Next we estimate the expected item scores within the classes of participants and display them on the y-axis. Finally we connect the expected item scores that belong to the same class with each other.

If the (test or) questionnaire is homogeneous, the resulting profile-lines must not intersect with each other (cf. Figure 1). Otherwise – if there is an intersection of profile lines – the (test or) questionnaire is inhomogeneous and (at least some of the items) imply different rank orders between the subsamples (cf. Figure 2).

Classification of participants into subsamples can either be based on some manifest criterion (like gender, age, or the participants' over-all scores τ_{vt}), or on a latent variable, which can be constructed by means of Latent Class Analysis (LCA).

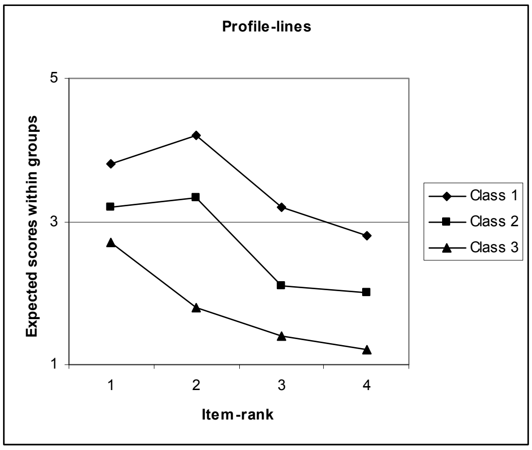

Figure 1: Necessary conditions for ordinal homogeneity

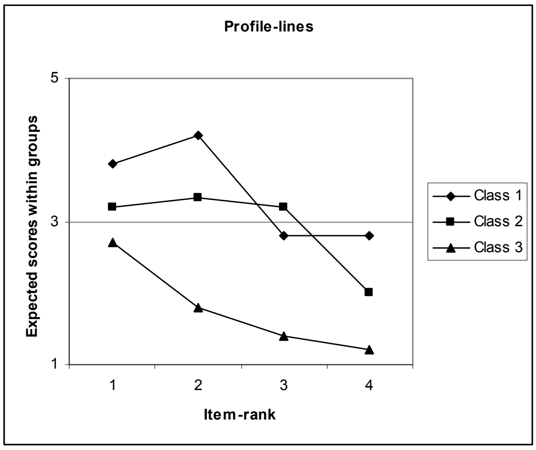

Figure 2: Inhomogeneity: the item with rank 3 implies a different rank-order between classes 1 and 2 than the other items

Latent Class Analysis

The LCA-method dates back to Lazarsfeld (1950) and describes the Likelihood of the participants' response Matrix X = $((x_{vi}))$ as a mixture-distribution of h latent classes of participants, so that

(10) $$L(X) = \prod_{v=1}^{n}\left(\sum_{g=1}^{h} p_g \text{ prob}\{(x_{v1},\ldots,x_{vk})|v \in g\}\right),$$

where p_g denotes the (relative) class-size and prob$\{(x_{v1},\ldots x_{vk})|v\in g\}$ is the probability with which a participant that belongs to class g produces exactly the response pattern $(x_{v1},\ldots,x_{vk})$ which he or she has actually produced. Assuming local independence, these class-specific pattern-probabilities can be computed from the class-specific category-probabilities $p_{gix} = \text{prob}(X_{vi} = x|v \in g)$ which describe the probability with which a participant that belongs to class g responds to item i in category x. For any given number of classes (h), the parameters p_g and p_{gix} can be estimated by means of the Maximum-Likelihood-Method and the number of classes which provides the best description of the data. This can be decided on the basis of information measures like Akaike's (1987) Information Criterion (AIC).

As compared with manifest classifications, LCA has the advantage to construct the classes in a way which provides an optimal description of the response matrix and which is most sensitive for possible inhomogeneities. Since it is based on the participants' response patterns, LCA also gives a much more detailed account of the data than Principal Components Analysis and/or Internal Consistency Analysis, which use only the participants' scores and – in case of PCA – their pair-wise correlations (PCA) as an empirical basis.

Strict homogeneity

Even though the condition in equation (8) is necessary and sufficient for the items to define the same rank order of participants, it cannot guarantee that the over-all score τ_{vt} contains the complete statistical information on a participant's position in this rank order.

If we claim that the over-all scores should be a sufficient statistics for the participants' ranks, another necessary condition must be fulfilled as well: not only the participants (cf. equation 8) but also the items must be uniquely ordered, so that for any pair of items (i and i') and any pair of participants (v and v')

(11) $$\tau_{vi} > \tau_{vi'} \Leftrightarrow \tau_{v'i} > \tau_{v'i'} .$$

Again, since this condition must hold for any two single participants, it must hold for any two groups of participants (g and g') as well, so that

(12) $$\tau_{gi} > \tau_{gi'} \Leftrightarrow \tau_{g'i} > \tau_{g'i'} .$$

Accordingly, the above defined profile-lines must not only be non-intersecting, but they must be monotonously falling as well (cf. Figure 3).

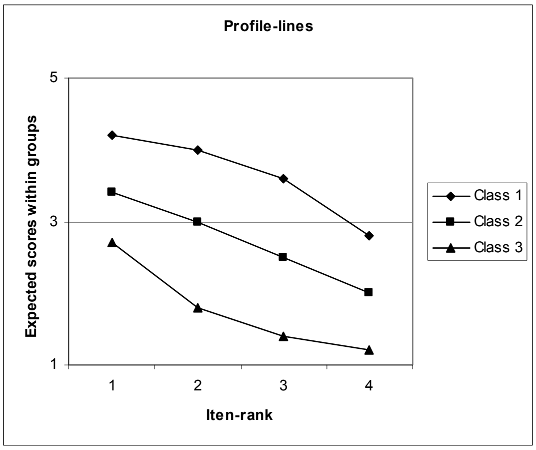

Figure 3: Necessary conditions for strict homogeneity

A necessary and sufficient condition for the sufficiency of the over-all score, states that the item-responses x_{vi} must be related to a latent dimension Θ on which both, the participants' latent trait (or attitude) (θ_v) and the difficulty of the item-response categories (δ_{ix}) can be measured, via the logistic function

(13) $$p_{vix} = \frac{\exp(x\theta_v - \delta_{ix})}{\sum_{y=0}^{m-1}\exp(y\theta_v - \delta_{iy})} \qquad \text{with } \delta_{i0} = 0$$

(cf. Figure 4), where $p_{vix} = \text{prob}(X_{vi} = x)$ denotes the probability with which a given participant (v) responds to item i in response category x, and the category difficulties δ_{ix} equal the sum of the thresholds α_{ij} which must be transgressed in order to respond in the respective category

(14) $$\delta_{ix} = \sum_{j=1}^{x}\alpha_{ij} \ .$$

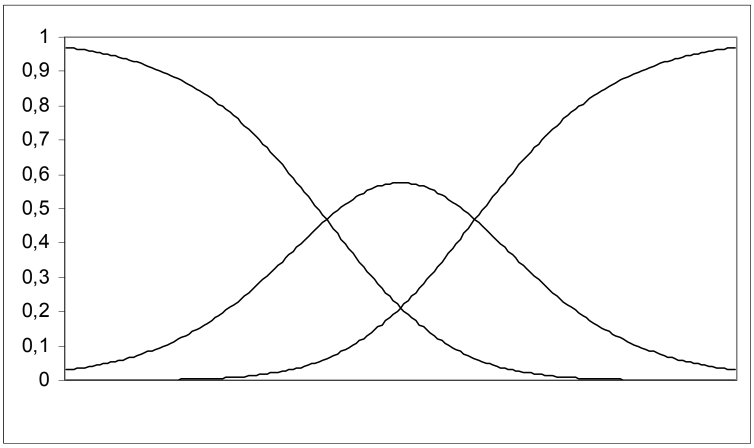

Figure 4: Necessary and sufficient conditions for strict homogeneity

The model in equations (13-14) dates back to the works of Rasch (1960) and Andrich (1978) and is known as the Rasch-model for ordered response categories x = 0,…,m-1. Whether the model fits the data can be tested by means of (conditional) Likelihood-Ratio-Tests (Andersen, 1973) and other methods (cf. Rost, 1996).

2. Method

Sample

The present paper applies this methodology to data from a study by Petzold (2004). The age of the N = 411 participants ranged from 18 to 83 years (M = 40.28, SD = 16.55). 57.7% of the participants were female, 42.1%

male. 25.1% of them were students, 15.3% academics, 13.1% retired, 12.2% service personnel , 8% civil servants, 8% social professions, 5.8% unemployed, 5.6% craftsmen and 6.9% other.

Subscales and items

A total of 12 items from Petzold's questionnaire were grouped into 4 subscales of 3 items each (cf. Table 1): two scales for measuring different aspects of manifest anti-Semitism (MA1: Dislike of the Jews; and MA2: Jewish conspiracy), a scale for measuring secondary anti-Semitism (SA: Ruling off the past) and a scale for measuring latent anti-Semitism (LA: Refusal to speak about the Jews).

The "positive" items (No. 1-8, 10-12) were scored on a five-point Likert scale from 1 = completely disagree via 2 = rather disagree, 3 = neither agree nor disagree and 4 = rather agree until 5 = completely agree. The "negative" item (No. 9) was scored the other way round. Accordingly, the higher an item score is, the more did a participant agree with the anti-Semitic pole. In Latent Class Analysis, missing data were treated as a response category of its own and scored as 0. In the other analyses which cannot handle nominal response categories, they were scored as 3 (neither agree nor disagree).

MA1: Dislike of Jews (Conbach-Alpha = 0.837)	
1	One shouldn't do business with Jews
2	I belong to those who dislike the Jews
3	It is preferable to have nothing to do with Jews
MA2: Jewish conspiracy (Cronbach-Alpha = 0.820)	
4	There exists a secret Jewish network which has a crucial influence on the political and economic processes in this world
5	A fundamental goal of Judaism is to safeguard supremacy in this world
6	The Jews have too much influence in this world
SA: Ruling off the past (Cronbach-Alpha = 0.777)	
7	Decades after the end of war, we shouldn't talk so much about the persecution of Jews and eventually rule off the past
8	One should ultimately put an end to the chitchat about our guilt vis-à-vis the Jews
9	The German people has a particular responsibility vis-à-vis the Jews
LA: Refusal to speak about Jews (Cronbach-Alpha = 0.469)	
10	I believe that many people do not dare to tell their real opinion of the Jews
11	The whole topic "Jews" is somehow unpleasant for me
12	I don't tell everybody what I think about the Jews

Table 1: The four subscales for manifest, secondary and latent anti-Semitism.

Data description

Analysis of Variance ($F_{3,1640} = 129.469$; $p < 0.001$) revealed a significant difference between the mean scores of the four scales, which are throughout below the neutral score of 9 (cf. Figure 5). The more obvious the anti-Semitic content of the subscales was, the less did the participants agree with it and, particularly the scale for dislike of Jews (MA1) had the least mean score. Whether this is due to the participants' sensitivity for anti-Semitic content or whether it is caused by a tendency towards social desirability cannot be easily decided.

Un-rotated PCA of the subscale-scores identified a general anti-Semitism factor on which all subtests show high positive loadings and which accounts for 61.46% of the total variance. The second factor is a bi-polar factor which accounts for 16.05% of the total variance and differentiates between secondary (SA) and latent anti-Semitism (LA). The third factor accounts for 12.35% of the total variance and differentiates between secondary and latent anti-Semitism (SA and LA) on the one hand side and manifest anti-Semitism (MA1 and MA2) on the other. The fourth factor accounts for 10.15% of the total variance and differentiates between the two aspects of manifest anti-Semitism: dislike of Jews (MA1) and the allegation of a Jewish conspiracy (MA2) (cf. Tables 2 and 3).

After VARIMAX rotation, each of the four factors accounts for approximately a quarter of the total variance and each of the subtests loads high on another of the four factors. Factor 1 correlates with latent anti-Semitism (LA) at 0.945; Factor 2 correlates with secondary anti-Semitism (SA) at 0.946; Factor 3 correlates with dislike of Jews (MA1) at 0.914; and Factor 4 correlates with the allegation of a Jewish conspiracy (MA2) at 0.903 (cf. Tables 4 and 5).

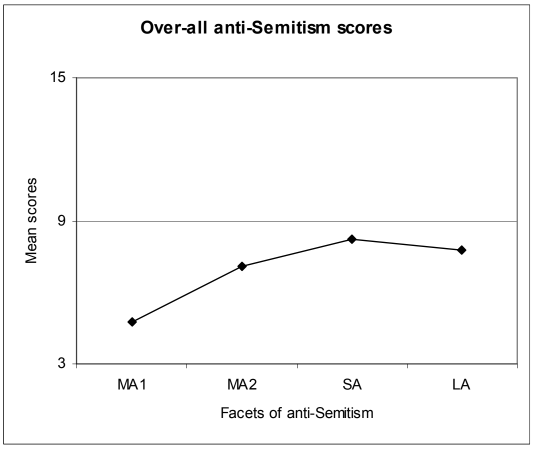

Figure 5: Mean scores of agreement with manifest, secondary and latent anti-Semitic statements in the over-all data

Factor	Initial eigenvalues	
	Total	Variance %
1	2.458	61.455
2	0.642	16.051
3	0.494	12.346
4	0.406	10.147

Table 2: Un-rotated PCA of the subtest-scores: explained variance

Subscale	Factor			
	1	2	3	4
MA1	0.819	0.056	-0.431	0.375
MA2	0.837	-0.048	-0.215	-0.501
SA	0.737	0.561	0.376	0.036
LA	0.737	-0.568	0.347	0.116

Table 3: Un-rotated PCA of the subtest-scores: factor loadings

Factor	Sum of squared loadings	
	Total	Variance %
1	1.019	25.463
2	1.018	25.450
3	0.990	24.753
4	0.973	24.334

Table 4: VARIMAX rotated PCA of the subtest-scores: explained variance

Subscale	Factor			
	1	2	3	4
MA1	0.210	0.225	0.914	0.263
MA2	0.243	0.227	0.271	0.903
SA	0.146	0.946	0.207	0.204
LA	0.945	0.146	0.194	0.217

Table 5: VARIMAX rotated PCA of the subtest-scores: factor loadings

Statistical data analysis

In order to infer whether there exists a unique dimension of anti-Semitism (assumption 1) or whether the different facets define more or less independent constructs that combine themselves into different patterns of anti-Semitism (assumption 2), a three step strategy of data analysis was employed.

1. As a first step, LCA was applied to each of the four subscales, and by inspecting the resulting profile-lines it was examined whether the participants can be ordered with respect to the associated facets of anti-Semitism.
2. If the results of step 1 spoke in favor of ordinal homogeneity, the subscales were analyzed by means of the Mixed Rasch Model (MRM; Rost, 1990), and in order to infer, whether the subtest-scores contain the complete statistical information on the participants' attitudes, the model in equation 13 was tested against the MRM.
3. As a third step, typical patterns into which the various facets of anti-Semitism combine themselves were identified by means of second-order LCA, and by examining the respective profile-lines it was determined which of the above named assumptions is more appropriate.

Both, in LCA and in MRM analysis, two criteria were used in order to determine the number of latent classes: (1) a minimal AIC, which defines an optimal compromise between accuracy and simplicity of the description of the data; and (2) a non-significant Likelihood-Ratio-Test against the so-called saturated model, which ensures that the description of the data is not substantially poorer than the best possible description. The goodness of fit statistics of the various models are documented in the appendix.

3. Results

3.1 Homogeneity of the subscales

Subscale MA1: Dislike of Jews

While all of the items of subscale MA1 have a very low level of agreement (cf. Figure 5), the expression of dislike of Jews seems to be the easier, however, the more seemingly factual reasons the respective statement contains: Item 1 ("One shouldn't do business with Jews") has the highest level of agreement (M = 1.77); item 3 ("It is preferable to have nothing to do with Jews") follows in the second place (M = 1.64), and item 2 ("I belong to those who dislike the Jews") finds the least support (M = 1.37).

Latent Class Analysis of the subscale identified four latent classes (cf. Appendix, Table 1) which are clearly ordered with respect to the participants' dislike of Jews (cf. Figure 6). Class 1 contains those 62.8% of the participants, who unequivocally reject the statements (M = 1.12). Class 2 (22.5%) rejects the statements less decidedly (M = 1.99). Class 3 (12.1%) is undecided whether to agree or disagree (M = 2.83) and the very small class 4 (2.6%) rather agrees with the statements (M = 4.1).

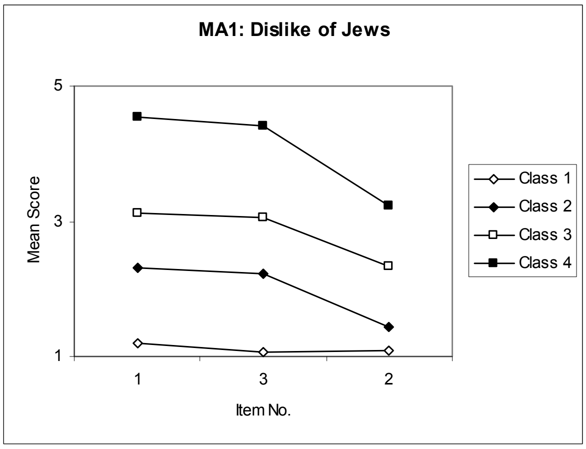

Figure 6: Profile-lines of subscale MA1

Although the profile-lines are non-intersecting and monotonously falling, the subtest-scores are not a sufficient statistic for the participants' underlying attitude, however. Testing the Rasch Model against the two-class solution of the MRM (cf. Appendix, Table 2) resulted in a significant Likelihood-Ratio (Chi-square = 46.78; df = 22; p <0.01).

Subscale MA2: Jewish conspiracy

The allegation of a Jewish conspiracy is rejected to a lesser degree than the blatant expression of dislike of Jews (cf. Figure 5). Again, agreement with the statements seems to be the easier, the more they are disguised as a rational argument: Item 4 ("There exists a secret Jewish network which has a crucial influence on the political and economic processes in this world") has the highest level of agreement (M = 2.64); item 6 ("A fundamental goal of Judaism is to safeguard supremacy in this world") follows in the second place (M = 2.29), and item 5 ("The Jews have too much influence in this world") finds the least support (M = 2.12).

Latent Class Analysis of the subscale identified four latent classes (cf. Appendix, Table 3) which are clearly ordered with respect to the participants' allegation of a Jewish conspiracy (cf. Figure 7). Class 1 contains those 33.9% of the participants, who reject the statements most strongly (M = 1.44). Class 3 (24.6%) rejects the statements as well, but to a lesser degree (M = 2.13). Class 2 (29.5%) is undecided whether to agree or disagree (M = 2.84) and class 4 (12.0%) rather agrees with the statements (M = 4.22).

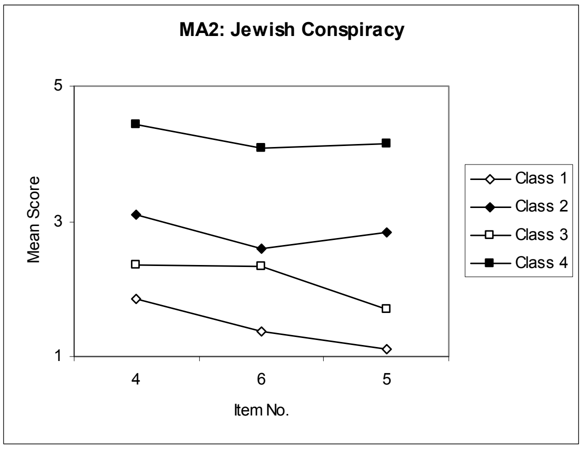

Figure 7: Profile-lines of subscale MA2

Although the profile-lines are non-intersecting, they are not monotonously falling, however. Unlike the other classes, participants in class 2 accuse the Jews of having too much influence in this world (item 5) to a stronger degree than they allege that safeguarding Jewish supremacy was a fundamental goal of Judaism to (item 6). This result which speaks in favour of ordinal homogeneity but rules out strict homogeneity of the subscale is also supported by testing the Rasch Model against the two-class solution of the MRM (cf. Appendix, Table 4) which resulted in a significant Likelihood-Ratio (Chi-square = 90.40; df = 22; p <0.001).

Subscale SA: Ruling off the past

All in all, these statements which express secondary anti-Semitism are supported to the highest degree (cf. Figure 5). Again, agreement with the statements seems to be the easier, the less obvious their anti-Semitic content is: Item 7 ("Decades after the end of war, we shouldn't talk so much about the persecution of Jews and eventually rule off the past") has the highest level of agreement (M = 3.02); item 8 ("One should ultimately put an end to the chitchat about our guilt vis-à-vis the Jews") follows in the second place (M = 2.69), and item 9 ("The German people (does not) have a particular responsibility vis-à-vis the Jews") finds the least support (M = 2.51).

Latent Class Analysis of the subscale identified five latent classes (cf. Appendix, Table 5) which are clearly ordered with respect to the participants' claim to rule off the past (cf. Figure 8). Class 3 contains those 19.5% of the participants, who reject the statements most strongly (M = 1.52). Class 2 (26.2%) rejects the statements as well, but to a lesser degree (M = 2.08). Class 4 (18.4%) is undecided whether to agree or disagree (M = 2.72). Class 1 (27.1%) rather agrees with the statements (M = 3.70), and class 5 (8.7%) supports them the strongest (M = 4.51).

Figure 8: Profile-lines of subscale SA

Similarly as in subscale MA2, the profile-lines are non-intersecting but not monotonously falling, and testing the Rasch Model against the three-class solution of the MRM (cf. Appendix, Table 6) yielded a significant Likelihood-Ratio (Chi-Square = 177.26; df = 44; p < 0.001). While participants who basically rejected the statements (classes 3 and 2) disagreed particularly with item 8 which discredits the issue of German responsibility as "chitchat", those participants who generally supported the statements (class 5), agreed with it even more than with the other ones.

Subscale LA: Refusal to speak about Jews

These statements which are designed to measure latent anti-Semitism are the second most supported ones (cf. Figure 5). Item 10 ("I believe that many people do not dare to tell their real opinion of the Jews") which does not necessarily unveil how a participant himself handles the issue has the highest level of agreement (M = 3.60); item 12 ("I don't tell everybody what I think about the Jews") which follows in the second place (M = 2.14) and item 11 ("The whole topic of "Jews" is somehow unpleasant for me") find distinctly less support (M = 1.99).

Latent Class Analysis of the subscale identified three latent classes (cf. Appendix, Table 7) which are ordered with respect to the participants' underlying attitude (cf. Figure 9). Class 1 contains 40.2% of the participants, who rather reject the statements (M = 2.14). Class 2 (38.3%) is undecided with a tendency towards rejecting the statements (M = 2.53), and class 3 (21.5%) is undecided with a tendency towards agreement (M = 3.50).

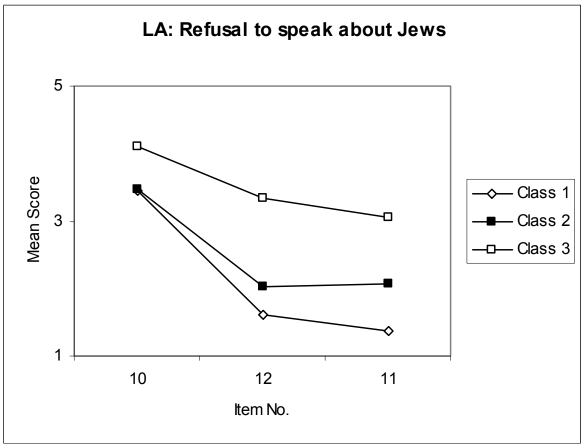

Figure 9: Profile-lines of subscale LA

Similarly as in Subscale MA1, the profile-lines are non-intersecting and mostly monotonous, but testing the Rasch Model against the three-class solution of the MRM (cf. Appendix, Table 8) yielded nonetheless a significant Likelihood-Ratio (Chi-square = 85.98; df = 22; $p < 0.001$). Accordingly, the subscale for latent anti-Semitism is not strictly homogeneous either.

3.2 Second order LCA

Summarizing the results so far, we may conclude that the four subscales fulfil the conditions of ordinal homogeneity. Nonetheless, they are not strictly homogeneous, however. Although the subscales define quantitative dimensions along which the participants can be ordered, the subscale-scores do not exploit all of the relevant statistical information. In order to examine whether and how the respective facets of anti-Semitism combine themselves into different syndromes of anti-Semitism, it is more appropriate, therefore, to base the second-order analysis on the participants' class-membership indices rather than on their subtest-scores.

Doing so, LCA identified four classes of participants (cf. Appendix, Table 9) which differ in their average degree of agreement with the various anti-Semitic statements (cf. Figure 10). Including 45.68% of the participants, class 1 rather disagrees with the statements (M = 1.89) and class 2 which includes 29.79% of the participants displays a tendency to disagree with them (M = 2.31). The 16.83% of participants who belong to class 3 are undecided whether to agree or not (M = 3.02) and the 7.70% of participants in class 4 tend to agree with them (M = 3.29).

Since the profile-lines of classes 3 and 4 are not completely monotonous (lack of strict homogeneity), these average scores display only part of the differences between the classes, however, and the slight intersection of their profile-lines is inconsistent with the assumption of ordinal homogeneity as well.

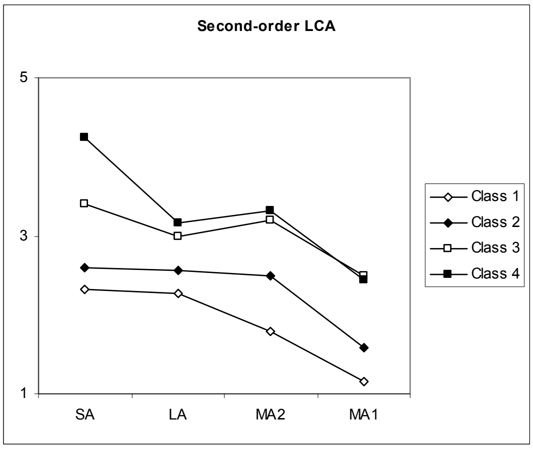

Figure 10: Profile-lines of the second-order LCA

Nonetheless, the profile-lines do not indicate qualitatively different patterns (or syndromes) of anti-Semitism into which the various facets are combined. Since each of the four subscales defines more or less the same rank order between the identified classes of participants, we may conclude that each of the facets – ruling off the past (SA), refusal to speak about Jews (LA), assumption of a Jewish conspiracy (MA2) and dislike of Jews (MA1) – is an expression of the same form of anti-Semitism pure and simple. However,

- the assumption of a Jewish conspiracy (MA2) is relatively more agreed with, the less the participants reject anti-Semitic statements in general (class 3) and even more so, the stronger their over-all agreement with anti-Semitic statements is (class 4),
- while it is relatively more rejected, the more the participants tend to reject anti-Semitic statements in general (classes 2 and 1).

Moreover, participants who tend to agree with anti-Semitic statements in general (class 4) disclaim their dislike of Jews (MA1) to a slightly higher degree than those who appear to be rather undecided in general (class 3).

4. Discussion

Although the analysed subscales are ordinally homogenous, the results of our study indicate that neither anti-Semitism in general nor the various facets of anti-Semitism can be measured on strictly homogenous scales. Both, the use of over-all scores and the use of subscale-scores, therefore, cause a considerable loss of statistical information which disguises the structure of anti-Semitic prejudice.

Nonetheless, the various facets of anti-Semitism are not independent constructs which combine themselves into qualitatively different patterns of anti-Semitism. Since each of the four subscales defines more or less the same rank order of participants, it can rather be assumed that each of them is an indicator of one and the same anti-Semitic attitude whose expression is partly modified during the strengthening of anti-Semitic prejudice, however.

- The stronger the prejudice becomes, the more do participants disclaim their dislike of Jews (MA1), and
- the more does the expression of anti-Jewish prejudice focus on the assumption of a Jewish conspiracy (MA2), while
- the more the prejudice is opposed, the more do participants focus on the rejection of this assumption.

Since anti-Semitism is discredited in the (German) public, anti-Semites obviously try to present themselves as not prejudiced and to disguise their averseness to Jews as a rational adjudgement. This interpretation is also supported by the following findings:

- Among the statements which were designed to measure latent anti-Semitism (subscale LA) the one item which does not necessarily unveil how a participant himself handles the issue (item 10) found distinctly more agreement than the other two items.
- Statements which "only" claim to rule off the past (subscale SA) were generally supported to the highest degree, and agreement with these statements was the stronger, the less obvious their anti-Semitic content was.

- The more obvious the anti-Semitic content of the subscales was, the less did the participants agree with. Particularly subscale MA1 (dislike of Jews) had the least mean score and support of the respective items was the weaker, the less seemingly factual reasons they contained.
- Also the allegation of a Jewish conspiracy (subscale MA2) was generally rejected to a lesser degree than the blatant expression of dislike of Jews, and agreement with the respective statements was generally the stronger, the more they were disguised as a rational argument.

Since the attempt to present one's averseness to Jews as resulting from rational adjudgement rather than prejudice effects different items in a different way, these factors reduce the homogeneity of the scales. Nonetheless, it is precisely these "irregularities" which add to their validity and, therefore, should not be treated as mere "measurement errors", however.

The same holds for another factor which may reduce the homogeneity of the scales as well. Already small semantic variations of how the same issue is addressed, can evoke a differential modulation of the participants' responses:

- While those classes of participants who generally opposed the claim to rule off the past (subscale SA), rejected the statement which discredits the issue of German responsibility as "chitchat" (item 8) more decidedly than the other ones,
- it was particularly this statement with which those participants who supported the claim agreed most strongly.

There can be no doubt: the claim to rule off the past is <u>not</u> a position which opposes anti-Semitism. However, if it is associated with discrediting the issue of German responsibility as "chitchat" it comes close to Holocaust denial and its anti-Semitic content becomes obvious.

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Appendix

Number of classes	Log-Likelihood	Number of parameters	Degrees of freedom	Likelihood-Ratio	p	AIC
1	-1234.20	13	136	532.20	< 0.001	2494.40
2	-1039.16	27	122	162.30	< 0.01	2132.32
3	-997.06	41	108	78.10	n.s.	2076.12
4	-978.15	55	94	40.28	n.s.	2066.30
5	-974.18	69	80	32.34	n.s.	2086.36
6	-968.87	83	66	21.72	n.s.	2103.74
Saturated M.	-958.01	149				2214.02

Table 1: Subscale MA1: Goodness of fit statistics of the LCA

Number of classes	Log-Likelihood	Number of parameters	Degrees of freedom	Likelihood-Ratio	p	AIC
1	-1001.93	23	101	90.61	n.s.	2049.86
2	-978.54	45	79	43.82	n.s.	2047.08
3	-966.54	67	57	19.83	n.s.	2067.08
4	-961.71	89	35	10.16	n.s.	2101.42
Saturated M.	-956.63	124				2161.25

Table 2: Subscale MA1: Goodness of fit statistics of the MRM

Number of classes	Log-Likelihood	Number of parameters	Degrees of freedom	Likelihood-Ratio	p	AIC
1	-1839.31	15	200	655.79	<0.001	3708.62
2	-1691.12	31	184	359.41	<0.001	3444.24
3	-1601.79	47	168	180.76	n.s.	3297.58
4	-1566.52	63	152	110.21	n.s.	3259.04
5	-1556.68	79	136	90.52	n.s.	3271.35
6	-1541.73	95	120	60.63	n.s.	3273.46
Saturated M.	-1511.41	215				3452.83

Table 3: Subscale MA2: Goodness of fit statistics of the LCA

Number of classes	Log-Likelihood	Number of parameters	Degrees of freedom	Likelihood-Ratio	p	AIC
1	-1534.24	23	101	147.87	<0.01	3114.48
2	-1489.04	45	79	57.47	n.s.	3068.08
3	-1485.50	67	57	50.38	n.s.	3104.99
4	-1469.14	89	35	17.67	n.s.	3116.28
Saturated M.	-1460.31	124				3168.61

Table 4: Subscale MA2: Goodness of fit statistics of the MRM

Number of classes	Log-Likelihood	Number of parameters	Degrees of freedom	Likelihood-Ratio	p	AIC
1	-1904.49	13	136	581.88	< 0.001	3834.98
2	-1746.76	27	122	266.42	< 0.001	3547.52
3	-1697.21	41	108	167.32	< 0.001	3476.42
4	-1671.45	55	94	115.80	~ 0.05	3452.90
5	-1643.27	69	80	59.44	n.s.	3424.54
6	-1636.77	83	66	46.44	n.s.	3439.54
7	-1631.61	97	52	36.12	n.s.	3457.22
Saturated M.	-1613.55	149				3525.10

Table 5: Subscale SA: Goodness of fit statistics of the LCA

Number of classes	Log-Likelihood	Number of parameters	Degrees of freedom	Likelihood-Ratio	p	AIC
1	-1728.14	23	101	231.95	< 0.001	3502.28
2	-1676.04	45	79	127.74	< 0.001	3442.08
3	-1639.51	67	57	54.68	n.s.	3413.02
4	-1628.18	89	35	32.04	n.s.	3434.36
5	-1618.57	111	13	12.80	n.s.	3459.14
Saturated M.	-1612.17	124				3472.34

Table 6: Subscale SA: Goodness of fit statistics of the MRM

Number of classes	Log-Likelihood	Number of parameters	Degrees of freedom	Likelihood-Ratio	p	AIC
1	-1700.01	15	200	246.02	<0.05	3430.02
2	-1653.76	31	184	153.52	n.s.	3369.52
3	-1629.62	47	168	105.24	n.s.	3353.24
4	-1616.22	63	152	78.44	n.s.	3358.44
5	-1607.41	79	136	60.82	n.s.	3372.82
Saturated M.	-1577.00	215				3584.00

Table 7: Subscale LA: Goodness of fit statistics of the LCA

Number of classes	Log-Likelihood	Number of parameters	Degrees of freedom	Likelihood-Ratio	p	AIC
1	-1638.03	23	101	152.04	< 0.001	3322.06
2	-1595.04	45	79	66.06	n.s.	3280.08
3	-1587.98	67	57	51.94	n.s.	3309.96
4	-1577.95	89	35	31.88	n.s.	3333.90
Saturated M.	-1562.01	124				3372.02

Table 8: Subscale LA: Goodness of fit statistics of the MRM

Number of classes	Log-Likelihood	Number of parameters	Degrees of freedom	Likelihood-Ratio	p	AIC
1	-2022.17	12	227	594.24	< 0.001	4068.34
2	-1879.9	25	214	309.7	< 0.001	3809.80
3	-1825.4	38	201	200.7	n.s.	3726.80
4	-1809.27	51	188	168.44	n.s.	3720.54
5	-1799.37	64	175	148.64	n.s.	3726.74
6	-1790.82	77	162	131.54	n.s.	3735.64
Saturated M.	-1725.05	239				3928.10

Table 9: Goodness of fit statistics of the second order LCA