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Unobserved Heterogeneity between Individuals in Group-Focused Enmity

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Group-focused enmity (GFE) and related research have mostly focused on variable-centred analyses such as structural equation modelling and factor analysis, implicitly assuming that the results apply uniformly to all participants in the sample. Person-centred research questions and analysis methods, which investigate unobserved heterogeneity in the sample, have been lacking in GFE research. Nonetheless, initial evidence exists from research on Islamophobia and GFE that various unobserved latent classes (i.e., subgroups) differing in their average prejudice can be identified within one dataset. In this manuscript, we applied factor mixture modelling to investigate unobserved heterogeneity using the data of the German GFE survey 2011. We found two latent classes of equivalent factor-analytical composition with consistently high versus low expressions of target-specific prejudice. No comparison of latent GFE means was possible. Membership in the high prejudice latent class was associated with higher age, right-wing political orientation, high right-wing authoritarianism and high social dominance orientation. Our findings demonstrate the importance of exploring unobserved heterogeneity in attitudes research and outline how person-centred research can complement variable-centred research in order to understand social-psychological phenomena.[1]

Keywords: Group-Focused Enmity, Generalised Prejudice, Unobserved Heterogeneity, Factor Mixture Models

Target-specific prejudice against different ethnic, religious, or national groups (e.g., xenophobia, homophobia, sexism; in the following called target-specific prejudice elements) have often been researched and discussed as separate phenomena (Zick et al. 2008). Nonetheless, there is some early theorising (Adorno et al. 1950; Allport 1954) and strong empirical support (e.g., Ekehammar et al. 2004; Heyder and Schmidt 2003) for the notion that these prejudice elements are substantially interrelated: Individuals who reject one outgroup also tend to reject other outgroups. In addition, there is empirical evidence supporting the idea

[1] The manuscript contains online supplementary materials, which are provided on the homepage of the International Journal of Conflict and Violence. The Mplus output files contain both analysis code and detailed outputs and can be viewed using the free Mplus demo version (https://www.statmodel.com/demo.shtml).

that different prejudice elements originate from common causes and lead to similar consequences (Meeusen et al. 2018; Zick et al. 2008). Group-Focused Enmity (GFE) has been introduced as a syndrome of generalised (i.e., not target-specific) antipathy against different outgroups (Bergh and Akrami 2016; Heitmeyer 2002; Zick et al. 2008), which assists in explaining the aforementioned phenomena. In brief, GFE is theorised to be a structure of substantially interrelated prejudice elements that is rooted in an ideology of inequality (Zick et al. 2008). GFE has been researched broadly in large-scale surveys and panels (e.g., Heitmeyer 2002), focussing for instance on the syndrome's structure, its composition concerning different target-specific prejudice elements, its stability, and its (prejudice elements') trajectories over time (e.g., Davidov et al. 2011; Zick et al. 2008). The prejudice elements that have been under scrutiny vary, but often include anti-refugee attitudes, antisemitism, antiziganism, devaluation of disabled people, devaluation of homeless people, devaluation of long-term unemployed people, devaluation of newcomers, homophobia, Islamophobia, racism, sexism, and xenophobia (Heitmeyer et al. 2013; Küpper and Zick 2014; Zick et al. 2008).

One important feature of the above-mentioned previous research on GFE is that the research questions and analysis methods usually, and often implicitly, assumed the sample to be homogeneous (i.e., the findings were expected to apply uniformly to all individuals in the sample; Lubke and Muthén 2005; Muthén 1989). This so-called variable-centred perspective bears the risk of overlooking potentially existing unobserved heterogeneity between individuals, or in other words, the possibility that distinct unknown subgroups (i.e., latent classes) of individuals exist within one dataset showing quantitative and/or qualitative differences in GFE. Such research questions are the focus of person-centred research perspectives, which have become more prominent in intergroup relations and attitudes research in recent years (Osborne and Sibley, 2017; see also Adelman and Verkuyten 2020; Bamberg and Verkuyten 2021; Dangubic, Verkuyten, and Stark 2020; Meeusen et al. 2018; for an instructive introduction to the methodology, see Ferguson, Moore, and Darrell 2019). Given the many additional insights these approaches offer, we follow the recent call for the application of person-centred approaches in social psychological research generally, and prejudice research in particular (Bamberg and Verkuyten 2021; Osborne and Sibley 2017).

Heterogeneity between individuals might be expressed through qualitative variations in the interrelation of target-specific prejudice elements between latent classes (which might result in unequal measurement models, i.e., measurement non-invariance, between latent classes) or by quantitatively different average levels of GFE or target-specific prejudice elements between latent classes. These differences may in turn cause variations in relevant outcomes. Consequently, from a methodological perspective, person-centred approaches extend and complement the established variable-centred GFE focus by considering not only information concerning the correlational structure, but also the mean structure of different GFE elements, and by not assuming linear relations between variables (Meeusen et al. 2018).

Unobserved heterogeneity has only recently come to the attention of GFE and prejudice research (on Islamophobia see Adelman and Verkuyten 2020, and Dangubic, Verkuyten, and Stark 2020; on GFE Meeusen et al. 2018). All studies found substantial unobserved heterogeneity in Islamophobia and GFE elements in Dutch and Belgian samples, but the results varied with regard to the number and characteristics of the identified latent classes and the applied analytical procedure. These findings indicate that further investigation of unobserved heterogeneity in other research contexts (i.e. Germany) and using different, potentially more informative methods (i.e. factor mixture modelling) is a promising and fruitful endeavour for subsequent GFE research.

1 Research aims and hypotheses

This research addresses the mentioned research gap by investigating unobserved heterogeneity in German GFE survey data. Our study explores the extent of unobserved heterogeneity in GFE data as well as the existence of qualitative and quantitative differences between latent GFE classes. Like in all reports in this special section, all our research questions and analytic procedures were preregistered with the editors (see online supplementary materials for the original and revised research proposal). Our research goals are:

(I) to examine whether unobserved heterogeneity can be found in GFE; if so,

(II) to identify the adequate number of latent classes to account for this unobserved heterogeneity;

(III) to describe qualitative (i.e., potential differences in the GFE measurement models of the different latent classes which would result in configural or metric measurement non-invariance) and quantitative differences (i.e., variations in the average levels of GFE or its target-specific prejudice elements between the different latent classes);

(IV) and to explore whether these latent classes can be characterised by covariates found in previous GFE research.

We will do so by applying factor mixture modelling (FMM, Lubke and Muthén 2005), which is more informative about potential differences between latent classes compared to previously published works on unobserved heterogeneity in GFE and Islamophobia, which employed latent class or latent profile analysis (Adelman and Verkuyten 2020; Dangubic, Verkuyten, and Stark 2020; Meeusen et al. 2018). Compared to these previously used methods, FMM provides additional insights because it also examines the underlying measurement models (i.e., exploring potential qualitative differences in GFE between latent classes) and because it has more realistic theoretical assumptions by accounting for variance in GFE and its elements within the latent classes (i.e., survey participants assigned to one latent class are not assumed to have the exact same average GFE and target-specific prejudice element levels; Clark et al. 2013; Lubke and Muthén 2005).

Based on previous findings in prejudice research (Adelman and Verkuyten 2020; Dangubic, Verkuyten, and Stark 2020; Meeusen et al. 2018), we expect to find unobserved heterogeneity between respondents, which is expressed in a significant factor variance parameter in the GFE confirmatory factor analysis model as well as the preferred number of latent classes being more than one (Expectation E1). We use FMM as an explicitly explorative and context-dependent approach to person-centred research, which is why we cannot present any expectation regarding the number of latent GFE classes or their potential qualitative difference. Nonetheless, previous research has unanimously found two latent classes expressing generally high or low prejudice levels across all indicators of GFE or Islamophobia (Adelman and Verkuyten 2020; Dangubic, Verkuyten, and Stark 2020; Meeusen et al. 2018). Consequently, we expect to replicate these two latent classes of respondents with generally high or low GFE levels in our data (E2). Moreover, Meeusen et al. (2018) found in their Belgian sample that GFE was based on differential patterns of ethnic and symbolic prejudice. Ethnic prejudice was directed at target groups that were perceived as foreign or ethnically different (i.e., immigrants, North Africans, Eastern Europeans, and Roma in Meeusen et al. 2018), while symbolic prejudice was targeted at groups perceived as deviating from moral, religious or other social norms (i.e., homosexuals, Jews, the other linguistic group in Belgian society in Meeusen et al. 2018). These differences were also expressed in the patterns of unobserved heterogeneity, meaning that two latent classes evolved which described participants with elevated levels on either ethnic or symbolic prejudice and low levels on the respective other prejudice. Consequently, we expect to find latent classes with differing average levels on target-specific prejudice elements relating either to ethnic or symbolic prejudice (E3).

For the further characterisation of these latent classes on the basis of theoretically founded covariates, we will focus on the following constructs and their expected relations with GFE:

a. Previous research has shown that the demographic information age, level of education, and the political orientation predict differential GFE latent class membership (Meeusen et al. 2018). This was also shown by Davidov et al. (2011) regarding differences in the trajectories of GFE target-specific prejudice elements. Davidov et al. (2011) also presented living in the territory of the former East or West Germany as a relevant predictor of GFE elements. In accordance with previous findings, we expect that – if we do find latent classes differing in their average GFE or target-specific prejudice element levels (see E2) – higher age, lower level of education, living in the eastern part of Germany, and comparatively right-wing political orientation will be associated with higher expressions of prejudice. Consequently, the covariates age, level of education, region and political orientation should differentiate between the different latent classes in GFE (E4).

b. Additionally, the individual characteristics right-wing authoritarianism (RWA; i.e., submissiveness to authority figures, aggressive behaviour in the name of authorities, and conformist behaviour and thought; Altemeyer 1981) – and social dominance orientation (SDO; i.e., support for social hierarchy and desire for one's own group to be superior to other groups; Sidanius and Pratto 1999) – have been found to be both positively related to GFE levels (Zick et al. 2008) and to differentiate between latent classes in GFE (Meeusen et al. 2018) and islamophobia (Adelman and Verkuyten 2020). Consequently, we expect RWA and SDO to significantly predict latent class membership (E5). Based on the dual process motivational model (Duckitt and Sibley 2010), which posits that RWA is particularly linked to symbolic prejudice and SDO particularly to ethnic prejudice, we additionally expect RWA levels to be especially elevated in latent classes characterised by high symbolic prejudice levels, while SDO levels should be especially high in latent classes with high ethnic prejudice levels (E6).

2 Methods

2.1 Data

To test our assumptions, we analysed the data from the German “Gruppenbezogene Menschenfeindlichkeits-Survey 2011” (Heitmeyer et al. 2013). This cross-sectional large-scale survey was administered to N = 2000 German-speaking participants aged 16 years and above (M_{Age} = 51.43 years, SD_{Age} = 16.12, Min = 16, Max = 94) living in private households in Germany. Demographic information about the sample is displayed in Table 1.

Data were collected in May and June 2011 using computer-assisted telephone interviews (CATI; for more information, see tns infratest 2011). The survey assessed, among other things, a broad variety of target-specific prejudice elements of GFE: anti-refugee attitudes, antisemitism, antiziganism, devaluation of disabled people, devaluation of homeless people, devaluation of long-term unemployed people, devaluation of newcomers, homophobia, Islamophobia, racism, sexism, and xenophobia (each element measured with at least two indicators on a four-point scale, see Table 2; Heitmeyer et al. 2013). Additionally, it included measures of RWA (four indicators) and SDO (three indicators) as well as a variety of demographic variables, such as age, level of education, living in the eastern or western part of Germany, and political orientation (see variable overview in the Online Supplementary Materials).

We used SPSS Version 25 to recode all prejudice elements' indicators so that higher scale values represent higher levels of antipathy. Unlike Zick et al. (2008) and Davidov et al. (2011), we did not exclude participants with migration background from analysis. For one, this was done because we were interested in sample heterogeneity – reducing demographic background heterogeneity would thus have been counterproductive. Additionally, excluding participants with a certain background is normally done in prejudice research to ensure that participants exclusively rate outgroups. However, in our case, excluding participants with migration background would not have achieved this goal, given the many other prejudice elements under scrutiny for which we had no available control measures (e.g., sexual orientation for homophobia) or for which participant exclusion would have resulted in major concerns of generalisability (e.g., excluding females for sexism). Thus, we used the entire sample. Missing values in the relevant indicators ranged between 0% and about 46% of all values per person (M = 0.85, SD = 1.90) and Little's MCAR test showed that the missing completely at random assumption had to be rejected, χ^2 (8722) = 9793.027, p < .001. We thus used a robust maximum likelihood (MLR) estimator in all subsequent analyses to account for missing values.

As we acknowledge the advantages of presenting open code in the reporting of scientific findings (Martins, 2021), we report all detailed outputs of our analyses in the Online Supplementary Materials. The GMF survey 2011 data are available upon request from the GESIS Leibnitz Institute for Social Sciences (see https://search.gesis.org/research_data/ZA5576).

Table 1: Sample composition in terms of gender, educational background, nationality, migration background, and living in eastern versus western Germany

	Total	Percentage
Gender		
Female	1073	53.7
Male	927	46.4
Educational Background[1]		
No school leaving certificate	17	0.9
8th grade leaving certificate	27	1.4
9th grade leaving certificate	297	14.9
10th grade leaving certificate	672	33.6
University entrance qualification	398	19.9
University degree	567	28.3
Missing	22	1.1
Nationality		
Only German	1929	96.5
German and another nationality	20	1.0
Non-German	51	2.6
Migration background[2]		
Yes	262	13.1
No	1738	86.9
Living in eastern versus western Germany		
Eastern Germany	670	33.5
Western Germany including Berlin	1330	66.5

Note: 1 For the subsequent analysis, educational background was dichotomised into "maximum ten years of schooling" (n = 1013) and "more than ten years of schooling" (n = 965).[2] In this study, participants with migration background were defined as people who have at least one parent or grandparent who is not German (excluding those whose non-German grandparents are/were Polish and/or Russian).

2.2 Factor Analysis

We fitted all factor analysis models and FMM in Mplus Version 8.3 (Muthén and Muthén 1998 – 2017) or higher. We used a stepwise procedure to generate a good-fitting model of the group-focused enmity (GFE) factor:

1. Following Zick et al. (2008), we ran confirmatory factor analyses for each target-specific prejudice element to identify the two indicators with the highest standardised factor loading (i.e., the two most reliable indicators). Where only two indicators per GFE element were available, we tested whether these two indicators loaded on one factor in a simultaneous confirmatory factor analysis by examining the results for substantial (i.e., standardised factor loading > .4; Brown 2015) and significant factor loadings.
2. The two identified indicators per GFE element were combined to a prejudice element mean score, which served as observed indicator for a unidimensional first-order GFE factor model,[2,3] which we modelled using confirmatory factor analysis (CFA). We evaluated the CFA model fit, considering RMSEA ≤ .08, SRMR ≤ .10 and CFI ≥ .95 to be adequate (Schermelleh-Engel, Moos-

[2] In previous research, GFE has often been modelled as a second-order factor with first-order factors for each GFE element (for an example, see Zick et al. 2008). We refrained from doing so to reduce model complexity, which might ultimately have hindered the convergence of the factor mixture models (Lubke and Muthén 2005).

[3] Meeusen et al. (2018) recently found an alternative bi-dimensional model of GFE (ethnic versus symbolic prejudice) rather than a unidimensional structure in Belgian data. Consequently, we examined our assumed unidimensional GFE model in exploratory factor analysis. The oblique exploratory factor analysis identified two factors with eigenvalues > 1 (factor 1: 4.677, factor 2: 1.179), whereby the two-factorial model fitted the data substantially better than the unidimensional model (MLR-corrected $\chi^2(11)$ = 347.463, p < .001). Nonetheless, the two-factorial model was limited in its interpretability, as two GFE elements did not show any substantial factor loading (i.e., |standardised factor loading| > .4) on any of the two factors and ten out of the twelve GFE elements showed significant cross-loadings. Moreover, the found variable clusters did not represent the assumed ethnic versus symbolic prejudice as proposed by Meeusen et al. (2018). The unidimensional model showed substantial and significant factor loadings for all GFE elements and adequate model fit for all indices except the CFI, which is why we preferred the unidimensional GFE model. The detailed results of the exploratory factor analysis are presented in the Online Supplementary Materials.

brugger and Müller 2003). If the GFE factor model including all elements showed unacceptable model fit, we adapted the measurement model by excluding GFE elements with insubstantial or insignificant factor loadings (see above) and by introducing theoretically plausible residual covariances between elements (Zick et al. 2008) based on standardised residual covariances and modification indices (Brown 2015). The adequately fitting GFE model was examined for significant GFE factor variance, which indicates substantial variation (i.e., unobserved heterogeneity) and thus forms the precondition for performing FMM. If the GFE factor variance was significant, this model was subjected to FMM analysis.

2.3 Factor Mixture Modelling and Covariate Analysis

To explore the character of the unobserved heterogeneity, we applied FMM, which models data as continuous latent variables (i.e., factor analysis), but simultaneously allows for categorical differences (i.e., different latent class memberships, different factor loadings, indicator intercepts, and residual (co-)variances between the measurement models of the latent classes; Lubke and Muthén 2005). We fitted models with increasing numbers of latent classes to the data, starting with two and ending with five latent classes (because five was the largest number of latent classes that was found in previous examinations of population heterogeneity in attitudes and generalised prejudice research; Dangubic, Verkuyten, and Stark 2020; Meeusen et al. 2018). For each number of latent classes, we specified four models with differing levels of measurement invariance (for detailed information on measurement invariance assessment, see Boer, Hanke and He 2018; Davidov et al. 2014): The most restricted model assumed *strict* measurement invariance, meaning that the factor loadings, indicator intercepts, residual variances, and residual covariances for identical indicators were set equal across latent classes. In a strict measurement invariance model, the latent mean values of the GFE factor are estimated freely and can be meaningfully compared across latent classes. However, due to the equality restrictions, no differences between the target-specific prejudice elements are modelled. Additionally, GFE is measured with identical reliability in all latent classes. The *scalar* measurement invariance model releases the assumption of equal residual variances and covariances, while keeping up all other mentioned equality constraints. Thus, scalar measurement invariance allows for meaningful mean value comparisons of the GFE factor, which is, however, measured with varying reliability across latent classes. The *metric* measurement invariance model additionally releases the assumption of equal indicator intercepts across latent classes. In such a model, the latent GFE factors' average levels cannot be meaningfully compared, but differences in the target-specific prejudice elements can be interpreted. Metric measurement invariance models allow for correlational comparisons of GFE between latent classes. Finally, the *configural* measurement invariance model additionally relaxes the assumption of equal factor loadings across latent groups. This model assumes that all parameters in the GFE measurement model are freely estimated between latent classes, and thus, the GFE factors might be conceptually, but not empirically, comparable across latent classes. Differences in the factor loadings of identical prejudice elements between different latent classes might indicate potential qualitative differences (e.g., in the case of non-significant factor loadings, which would indicate that a certain prejudice element does not express GFE in one latent class).

As a technical necessity to avoid an erroneous identification of local instead of global extrema in the estimation of the models, we computed each model with two sets of starting values (2000 500 and 4000 1000; see also Lubke and Muthén 2005, 32). To determine the optimal model with regard to number of latent classes and level of measurement invariance, we applied the following criteria: successful convergence, parsimony and interpretability of the latent class results, no less than 1 percent of total sample count in one latent class, low Bayesian Information Criterion (BIC), a significant Bootstrap Likelihood Ration (BLRT) test, high entropy (near 1), and high posterior probabilities (near 1; Jung and Wickrama 2008; Lubke and Muthén 2005). To describe the differences between the resulting latent classes, we focused on the

GFE measurement model, the latent GFE mean levels (if possible according to the level of measurement invariance), and the GFE elements' average levels (i.e., the indicator intercepts of the measurement model, if possible according to the level of measurement invariance).

The finally selected FMM was further subjected to covariates analyses using the R3STEP procedure (Asparouhov and Muthén, 2014), which is based on logistic regression. With this procedure, we examined whether the covariates age, level of education, living in the territory of the former East or West Germany, political orientation, RWA and SDO predict latent class membership.

3 Results

3.1 Measurement Model of Group-Focused Enmity

As a first step in preparation of the FMM, we specified CFAs for every GFE element to identify the two indicators with the highest factor loading. The results are displayed in Table 2.

Next, we averaged the two indicators per GFE element and used the resulting mean scores as indicators for the unidimensional GFE confirmatory factor analysis model, which we subsequently adapted to improve model fit. The results of these analyses are presented in Table 3.

The initial CFA model showed an adequate model fit for all indices but the CFI. To increase model fit, we examined the modification indices for theoretically plausible residual covariances (i.e., relations between the GFE elements that are not explained by the underlying syndrome of GFE). We identified five residual covariances which substantially improved model fit: (I) A positive residual covariation between *xenophobia* and *Islamophobia*, which can be explained by the fact that when thinking about foreigners, most Germans tend to think of Turkish migrants, who are predominantly Muslims (Asbrock et al. 2014; Wasmer and Hochman 2019). (II) A positive residual covariation between *sexism* and *homophobia*, whose indicators both relate strongly to conservative and inflexible gender roles (Black, Oles, and Moore 1998; Stark 1991) and which have been summarised in recent GFE research as a heterosexist attitude pattern (Herek 2000; Zick, Berghan, and Mokros 2019). These two residual covariances have also been reported by Zick et al. (2008). (III) A negative residual covariation between *racism* and *anti-refugee attitudes*, which could be due to the fact that one of the indicators measuring racism included the preferential treatment of resettlers in migration policies, and therefore the hierarchical ideas of immigration could explain the conceptual overlap. (IV) A positive residual covariation between *antiziganism* and *devaluation of homeless people*, which could be caused by the indicators of both GFE elements discussing the presence of these groups in city centres and pedestrian precincts. (V) A positive residual covariation between *anti-refugee attitudes* and *xenophobia*, which can be explained by the indicators of both elements referring to state policies and the social system. The resulting GFE measurement model showed good model fit, $\chi^2(49) = 284.538$, $p < .001$, RMSEA = .049 [90% CI: .044, .055], CFI = .955, SRMR = .035. The standardised model parameters are depicted in Figure 1. The variance of the GFE factor was highly significant, $\varkappa_{GFE} = .141$, $p < .001$. This allows us to transfer the measurement model to the subsequent FMM analyses and confirms the first part of expectation E1, in which we assumed to find unobserved heterogeneity between respondents expressed in a significant variance parameter in the GFE factor model (as well as the number of latent classes being more than one).

3.2 Factor Mixture Model Analyses

We fitted FMM including two to five latent classes as well as strict, scalar, metric and configural measurement invariance assumptions between latent classes. The results are summarised in Table 4. All FMM showed lower BIC value (which prefers the model with the lowest value) than the initial one-factorial CFA model, which confirms the second part of E1 (i.e., that the number of latent classes is larger than one).

Based on BIC and entropy criteria, two FMM are to be preferred: The metric measurement invariance model with two latent classes has the lowest BIC value, and the configural measurement invariance model with two latent classes has the highest entropy value. Both models showed high posterior probabilities, i.e., a high likelihood for participants to be classified into the correct latent class. For the metric model,

Table 2: Standardised factor loadings (λ) of the indicators of the Group-Focused Enmity elements

GFE Element	Wording	Standardised λ
Anti-refugee attitudes	When examining applications for asylum, the state should be generous.†	.529***
	Most asylum seekers are not really afraid of being persecuted in their home countries.†	.583***
Antisemitism	Jewish people have too much influence in the world.†	.753***
	As a result of their behaviour, Jewish people are not entirely without blame for being persecuted.	.677***
	Many Jewish people try to gain personal advantage today from what happened during the Nazi era.†	.758***
	I am angry that the Germans are still blamed for the crimes against Jews.	.490***
Antiziganism	I would have a problem with Sinti and Romani being present in my area.†	.853***
	Sinti and Romani should be banned from the city centres.†	.799***
	Sinti and Romani tend to be criminal.	.692***
Devaluation of disabled people	In Germany, we make too much effort for disabled people.	.686***
	I think many demands of disabled people are excessive.†	.827***
	Disabled people receive too many benefits.†	.808***
Devaluation of homeless people	Begging homeless people should be removed from pedestrian precincts.†	.681***
	The homeless in the towns are unpleasant.†	.673***
	Most homeless people are unwilling to work.	.533***
Devaluation of long-term unemployed people	Most long-time unemployed people are not really interested in finding work.†	.776***
	Long-term unemployed people who don't find work are themselves responsible for their situation.	.750***
	I think it's outrageous when long-time unemployed people enjoy their lives at the expense of the society.†	.784***
	Long-time unemployed people should be forced to do community service.	.625***
	Long-time unemployed people should only receive money from the state if they are willing to take any work.	.635***
Devaluation of newcomers	Those who are new somewhere should be content with less.†	.627***
	Those who have always lived here should have more rights than those who arrive later.†	.773***
Homophobia	Marriages between two women or between two men should be permitted.	.763***
	It is disgusting when homosexuals kiss in public.†	.796***
	Homosexuality is immoral.†	.796***
Islamophobia	The many mosques in Germany are a sign that even here Islam will enlarge its power.	.663***
	With so many Muslims here in Germany, I sometimes feel like a stranger in my own country.†	.733***
	The Muslim culture fits absolutely into our Western world.	.688***
	Immigration to Germany should be forbidden for Muslims.†	.767***

	I am distrustful with people of Muslim religion.	.656***
	Islamic and Western European values can be combined.	.607***
Racism	German re-settlers should be better off than foreigners because they are of German origin.†	.647***
	It is right that whites are leading in the world.†	.622***
Sexism	Discrimination against women is still a problem in Germany.	.173***
	Current employment policy discriminates against women.	.179***
	Women should concentrate more on their role as wives and mothers.†	.814***
	It is more important for a wife to help her husband's career than to have one herself.†	.678***
Xenophobia	The foreigners who live in Germany are a burden on the social welfare system.†	.766***
	There are too many foreigners living in Germany.†	.889***
	If the jobs get scarce, the foreigners living in Germany should be sent home.	.764***

Notes: The indicators marked with † represent the two indicators with the highest factor loadings (i.e., the most reliable indicators) for each element. These two indicators were subsequently used to model the GFE factor. *** *p*- value < .001.

Table 3: Model fit indices for the unidimensional GFE factor and the subsequent model adaptations

Model	BIC	χ^2	df	*p*	RMSEA	CFI	SRMR
1-factor model	49,649.437	633.722	54	< .001	.073 [.068 .078]	.889	.049
1-factor model with model adaptation 1	49,494.549	507.283	53	< .001	.065 [.060 .071]	.913	.045
1-factor model with model adaptation 2	49,363.504	399.151	52	< .001	.058 [.053 .063]	.934	.041
1-factor model with model adaptation 3	49,307.578	348.117	51	< .001	.054 [.049 .059]	.943	.039
1-factor model with model adaptation 4	49,272.664	314.417	50	< .001	.051 [.046 .057]	.949	.037
1-factor model with model adaptation 5	49,241.674	284.538	49	< .001	.049 [.044 .055]	.955	.035

Notes. Model adaptations introduced: 1 = residual covariance between *xenophobia* and *islamophobia*; 2 = residual covariance between *sexism* and *homophobia*; 3 = residual covariance between *racism* and *anti-refugee-attitudes*; 4 = residual covariance between *antiziganism* and *devaluation of homeless people*; 5 = residual covariance between *anti-refugee attitudes* and *xenophobia*.

the correct classification was observed in 90.5–92.7% of all cases; for the configural model, the correct classification was observed in 90.7–93.1% of all cases. The differences in BIC, entropy value and posterior probabilities as well as in the final class counts based on the most likely latent class membership are negligible, so we assume both models to fit the data equally well. In both cases, the BLRT test, which tests whether the FMM assuming two classes fits the data better than a one-class-model, was highly significant, *p*s < .001. In the following, we describe the results of the more parsimonious metric measurement invariance model, which assumes equal factor loading of similar GFE elements across latent classes. However, we also ran the analyses for the configural measurement invariance model, the results of which are highly comparable and can be found in the online supplementary materials.

The metric measurement invariance level of the model indicates that the factor loadings of similar indicators are set equal across latent classes, while indicator intercepts and residual (co)variances are estimated freely. As a consequence, GFE is conceptualised sufficiently equal across the two latent classes to allow for comparative correlational or regression analysis, but it does not allow for any comparison of the latent GFE mean values (Davidov et al. 2014). Instead, for our interpretation, we focused on the differences in the target-specific prejudice elements' mean values (i.e., the indicator intercepts). As these are observed parameters, they can be interpreted and compared between the two latent classes without any requirements of a specific measurement invariance level (Brown 2015). Figure 2 shows the average levels of all GFE elements in the two latent classes.

To summarise, we identified two latent classes, one characterised by less agreement to all GFE indicators (latent class # 1, a "low prejudice class"), and one characterised by stronger agreement (latent class # 2, a "high prejudice class"). This finding supports our expectation E2 concerning the existence of two latent classes with generally high and low GFE levels, respectively. At the same time, this finding disconfirms our expectation E3, as we did not find any additional latent classes with differing levels on target-specific prejudice elements relating either to ethnic or symbolic prejudice. The two latent classes are approximately equal in size, with the low prejudice class including 953 survey participants (47.65%) and the high prejudice class including 1047 survey participants (52.35%). The mean differences between the latent classes are highly significant for all GFE elements, *p*s $< .001$. The two latent classes showed the largest differences regarding the agreement to the xenophobia and Islamophobia indicators. The differences between the two latent classes were lowest regarding the agreement to the devaluation of disabled people indicators.

3.3 Analyses of Covariates

Based on the clear differences on all GFE elements between the two latent classes, we were able to substantiate two expectations concerning the covariates. We expected that higher age, lower levels of education, living in the eastern (vs. western) part of Germany, and stronger right-wing political orientations should enhance the probability for people to fall into latent class # 2 (i.e. the "high prejudice class") compared to latent class # 1 (i.e., the "low prejudice class") (E4). Additionally, higher average RWA and SDO levels were expected to increase the likelihood for people to fall into the "high prejudice class" (latent class # 2) compared to the "low prejudice class" (latent class # 1) (E5). As we did not find a latent class with varying levels of ethnic and symbolic prejudice, we discarded E6.

As Table 5 displays, when controlling for all respective other covariates in a multinominal logistic regression, lower level of education, higher age, right-wing political orientation, higher RWA and higher SDO values made it more likely to fall into latent class # 2 ("high prejudice class") compared to # 1 ("low prejudice class"). However, in contrast to our predictions, controlling for all other covariates, living in eastern Germany did not significantly predict latent class membership.

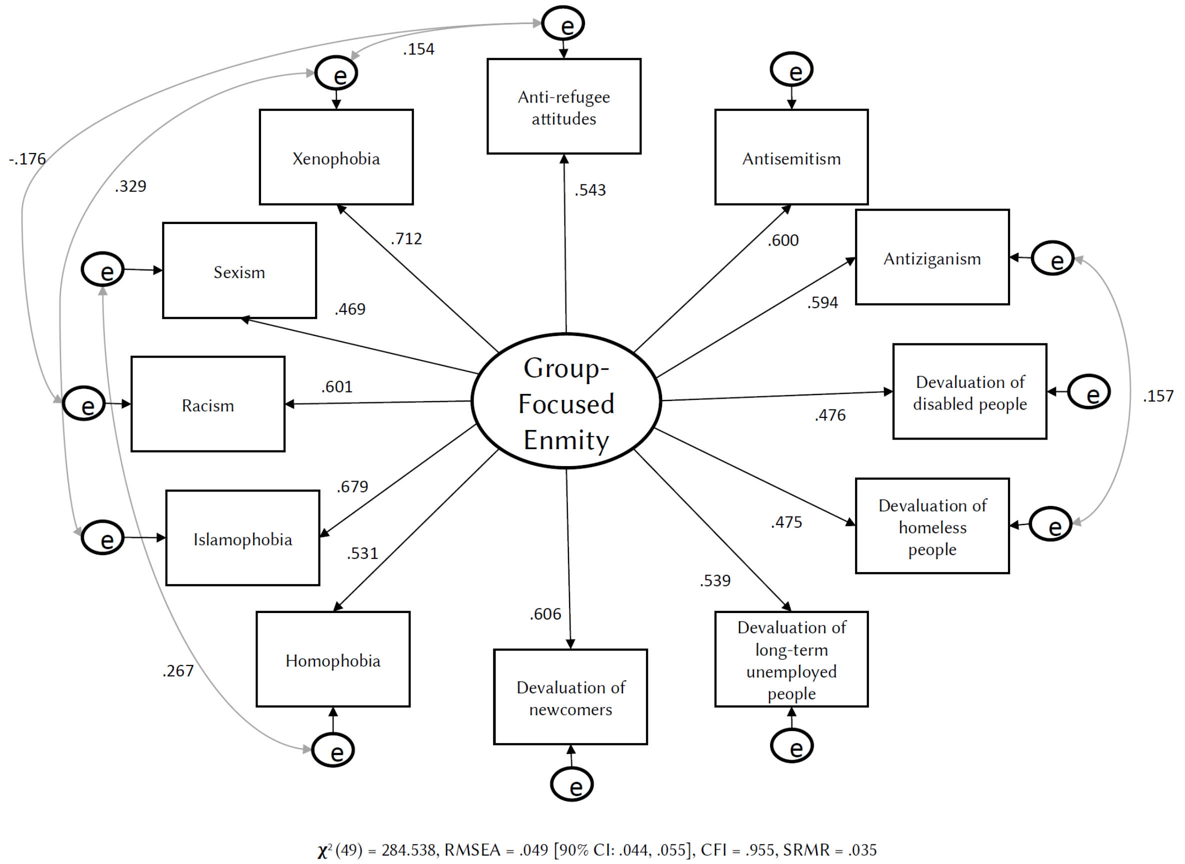
4 Discussion

In this study, we explored the extent of unobserved heterogeneity in GFE data focussing on potential qualitative and quantitative differences between latent GFE classes. As such, this work answers the recent calls in social psychology and beyond to extend and complement variable-centred prejudice research with person-centred approaches (Lubke and Muthén 2005; Meeusen et al. 2018; Osborne and Sibley 2017).

We expected and found substantial unobserved heterogeneity between respondents expressed in a significant latent variance of the GFE factor model as well as the number of latent classes being more than one (E1). These findings are in line with previous findings in prejudice research (e.g., Adelman and Verkuyten 2020; Dangubic, Verkuyten, and Stark 2020; Meeusen et al. 2018) and suggest that there are distinct subgroups of individuals that can be clearly differentiated and that have different patterns of prejudice towards various target groups. In line with (E2) and prior research (Adelman and Verkuyten 2020; Dangubic, Verkuyten, and Stark 2020; Meeusen et al. 2018), we found two subgroups: One latent class consisting of participants that generally scored low on all target-specific prejudice elements (latent class # 1, ca. 46% of the sample), and one that scored consistently high (latent class # 2, ca. 54% of the sample). Since those were the only subgroups that we found, both E3, which postulated subgroups that particularly devalued either ethnic target groups or those target groups that violate social norms (Meeusen et al. 2018), and E6, which postulated covariates associated with these classes, were disconfirmed.

One of our main contributions is that we applied factor mixture modelling to arrive at these results, which goes beyond previous variable-centred, but also person-centred approaches in prejudice research in important ways. Beyond other advantages, this method allowed us to examine similarities and differences in the underlying measurement models of the two latent classes. With regard to the measurement model and measurement invariance, that is, the extent to which the latent classes can be meaningfully compared, the highest level our model obtained was metric measurement invariance. This means that whereas correlations of the latent GFE factor with third variables can be meaningfully compared across classes, latent GFE means cannot be compared without bias. This is because the necessary precondition of equal intercepts across classes, or equal "points-of-zero" (Boer, Hanke, and He 2018, 176), is not given. This finding extends the existing discussion of comparability of prejudice and attitude scores across different units of observed groups, such as countries (Davidov et al. 2014; Zercher et al. 2014), measurement time points (Kotzur et al. 2022), and experimental groups (Friehs et al. 2022), to the comparability of unobserved latent classes within one dataset. Indeed, recent (mostly variable-centred) literature comparing average prejudice and attitudes levels across observed units shows that comparability is more often assumed

Figure 1: Measurement model of the Group-Focused Enmity (GFE) factor



Note: We report standardised parameters.

Table 4: Results of the Factor Mixture Models with differing numbers of latent classes and levels of measurement invariance

# Latent classes	MI level	BIC	Entropy	Replication with different starting values succeeded	Final class counts based on most likely latent class membership					Comments
					1	2	3	4	5	
2	strict	49,249.09	.300	Yes	544	1456				
2	scalar	47,504.56	.692	Yes	866	1134				
2	**metric**	**47,397.03**	**.714**	**Yes**	**953**	**1047**				
2	configural	47,411.51	.717	Yes	963	1037				
3	strict	49,226.56	.655	Yes	658	134	1208			
3	scalar	/	.000	Yes	988	473	539			A
3	metric	/	.604	Yes	566	812	622			A
3	configural	/	.609	Yes	623	755	622			A
4	strict	49,230.42	.639	Yes	820	626	111	443		
4	scalar	/	.000	Yes	977	327	337	359		A
4	metric	/	.482	Yes	560	355	415	670		A
4	configural	/	.486	Yes	630	325	383	662		A
5	strict	49,239.59	.650	Yes	741	463	100	386	310	B
5	scalar	/	.000	Yes	986	236	237	267	274	A
5	metric	/	.573	Yes	199	666	463	391	281	A
5	configural	/	.589	No	251	621	465	331	332	A

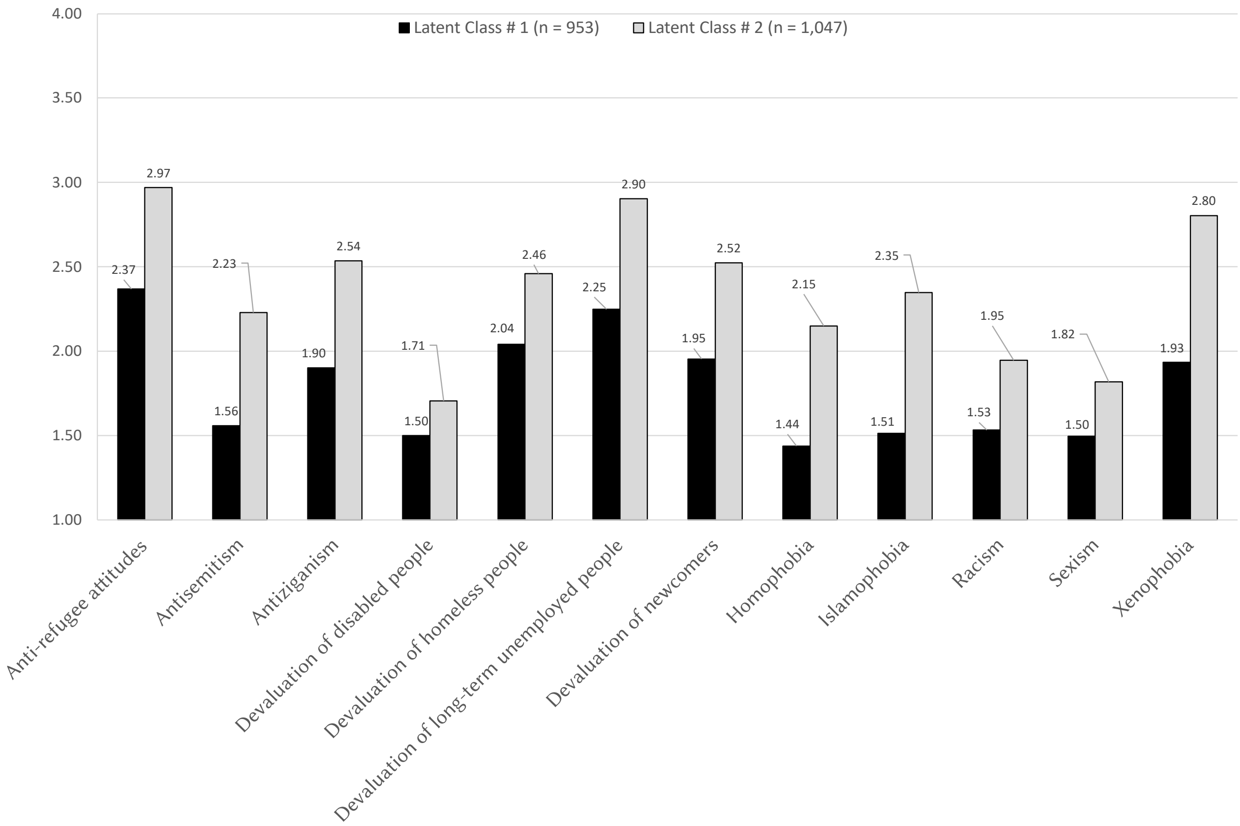
Notes. MI = Measurement Invariance; BIC = Bayesian Information Criterion; A = model estimation resulted in the following warning: "The model estimation did not terminate normally. Estimates cannot be trusted." B = Implausible parameter estimates: All factor loadings for one latent class were zero. Bold print indicates the best fitting model.

Table 5: Multinomial logistic regression of most likely class membership on covariates

	b	*p*-value	*OR*
Eastern Germany	0.195	.106	1.215
More education	-0.261	.043	0.770
Age	0.018	< .001	1.018
Right-wing political orientation	0.435	< .001	1.545
Right-wing authoritarianism	1.725	< .001	5.615
Social dominance orientation	0.682	< .001	1.978

Notes: Logistic regression was conducted using the auxiliary R3STEP command in Mplus. Latent class # 1 (i.e., the "low prejudice class") was used as reference class. *b* = estimated logit/log odds; *p* = one-tailed p-value; *OR* = odds ratio. Eastern Germany was coded as 2 vs. 1 for western Germany. More education was coded as 2 vs. less education as 1.

Figure 2 Estimated mean values (i.e., indicator intercepts) of the two latent classes for all target-specific prejudice elements



Note: The response scale for all items ranged from 1 – agree not at all to 4 – completely agree.

than fulfilled (Friehs et al. 2022). Thus, our findings stress the importance of carefully testing the measurement properties when comparing the mean values of different observed or unobserved groups to avoid systematically biasing the findings, e.g. by carefully considering measurement (non-)invariance between observed and unobserved groups, context and time points.

The found metric measurement invariance allows us to compare observed differences in the means of target-specific prejudice elements (i.e., the indicators of the GFE factor; Brown 2015). Due to the unequal indicator intercepts, metric measurement invariance suggests that GFE items are perceived and answered somewhat differently by those in the high prejudice latent class compared to those in the low prejudice latent class. Methodologically, this translates into different item difficulties or differential item functioning (Penfield and Camilli 2006). Given the explorative and highly sample-dependent nature of our statistical approach, these findings should be carefully replicated before generalising to other contexts. Nonetheless, if different studies found such differential item functioning to be a systematic pattern, that would be worth investigating more systematically.

A first indication of how participants in the two classes might differ is provided by our theoretically founded covariates analysis. Consistent with our expectations and previous research (Davidov et al. 2011; Meeusen et al. 2018), we found that a lower level of education, higher age and a comparatively right-wing political orientation were more likely to be found in the high prejudice latent class (E4). Additionally, RWA and SDO expectedly predicted latent class membership (E5) in the way that those belonging in the class with higher expressions of prejudice elements scored higher on RWA and SDO than those belonging to the low prejudice class. These findings are also in line with previous research (Adelman and Verkuyten 2020; Meeusen et al. 2018; Zick et al. 2008). The only unexpected finding is the non-significant effect of living in eastern compared to western Germany (e.g., Zick et al., 2008), which however descriptively confirmed the expected "direction" and would have been significant if it were used as the single predictor in a logistic regression. This indicates that most likely, this effect is not driven by the mere place of residence, but rather by psychological variables, such as attitudes and education, which predict GFE.

One potential reason for the limited invariance of the high versus low target-specific prejudice models may for instance be that participants that have a certain trait associated with high levels of target-specific prejudice, such as high RWA and/or SDO, might understand certain GFE items differently from those scoring low on these traits. Such processes are proposed in Duckitt and Sibley's dual process motivational model, which states that individuals high in SDO perceive the world as a "competitive jungle", while individuals high in RWA rather focus on signs of danger in their surroundings (Duckitt and Sibley, 2010, 1868). Statistically, such differences in understanding might manifest themselves in non-invariance. As one avenue for future studies, researchers could further explore such possibilities. Importantly, newly-proposed covariates of GFE, such as market-based values, self-concept and value orientation, should also be considered (Lee, Choi, and Travaglino 2022; Nickel 2022). This issue might be addressed using a mixed methods approach combining survey data with qualitative methods such as cognitive interviewing or online probing (Benítez and Padilla 2014; Meitinger et al. 2020).

Our findings complement, rather than conflict with the previous literature on GFE. The commonly presented approaches of examining large-scale GFE survey data's dimensionality, hierarchical measurement structure, stability (e.g., Zick et al. 2008), change (Davidov et al. 2011) or cross-country comparability (Küpper and Zick 2014) represent important research questions. Nonetheless, all of these approaches are exclusively variable-centred and (implicitly) assume the data to be homogeneous. Thus, potentially existing subgroups with differences in these processes within the data remain unnoticed if such research is not accompanied by examinations of unobserved heterogeneity. Therefore, we stress the potential and value of person-centred approaches in general, and of FFM in particular. These methods allow novel and unexpected insights and thereby stimulate new directions of research (Osborne and Sibley 2017).

Our research shows a number of strengths, including that we preregistered our research prior to conducting it, that we provided extensive open code, that we based our study on a large heterogenous sample (N = 2,000), and that we used sophisticated methods to address our research questions (FMM). Future research can build on this by replicating and extending our results. Dutch and Belgian data on GFE and Islamophobia found four or five latent classes with substantially more differentiated data patterns than we found (Adelman and Verkuyten 2020; Dangubic, Verkuyten, and Stark 2020; Meeusen et al. 2018). Therefore, replication studies could inform us whether the two consistently differing "high" vs. "low GFE" latent classes are singular to the used dataset or country context, and a number of large-scale data sets are available to test such assumptions.

Prior theorising (Zick et al. 2008) and research (Davidov et al. 2011) additionally suggests that the concept of GFE may change over time. Such changes may result from contextual changes, for instance increased migration or media coverage of the phenomenon, of changing narratives on specific groups shaping people's attitudes towards them. Thus, future research using longitudinal GFE data to focus on the stability of findings may shed light on the questions of stability and change in heterogeneity in GFE. Whereas, to the best of our knowledge, all research that explores unobserved heterogeneity in prejudice research is based on cross-sectional data, various methodological approaches to apply mixture modelling to repeated cross-sectional and longitudinal data also exist. Such methodological approaches could inform us whether the number and characteristics of latent classes remain stable over time and how large the proportion of participants is that remains within the same latent class or changes latent classes across time (O'Donnell et al 2021). In the case of German data on GFE, we have additionally observed a change of the constructs' components in the last years, as current surveys newly include for instance the devaluation of trans* people and the overarching construct of anti-genderism (Zick and Küpper 2021). Thus, it remains an open question whether we would find similar findings to ours using current data, and whether these findings are robust across multiple waves of measurement.

5 Conclusion

Investigating unobserved heterogeneity in GFE, we found two latent classes with metric measurement invariance (allowing for comparative correlational analyses of GFE) to describe our data best. These classes described generally less-prejudiced individuals (ca. 46% of the sample) and generally more-prejudiced individuals (ca. 54%) with substantial differences in the average levels of all group-specific prejudice elements. Similar to previous variable-centred research, these differences corresponded with distinct socio-demographic and ideological characteristics between groups. Our findings demonstrate the importance of exploring unobserved heterogeneity in attitudes research and outline how person-centred research approaches can complement variable-centred research in order to understand social-psychological phenomena.

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