PERSEVAL: A Framework for Perspectivist Classification Evaluation

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Abstract

Data perspectivism goes beyond majority vote label aggregation by recognizing various perspectives as legitimate ground truths. However, current evaluation practices remain fragmented, making it difficult to compare perspectivist approaches and analyze their impact on different users and demographic subgroups. To address this gap, we introduce PERSEVAL, the first unified framework for evaluating perspectivist models in NLP. A key innovation is its evaluation at the individual annotator level and its treatment of annotators and users as distinct entities, consistently with real-world scenarios. We demonstrate PERSEVAL's capabilities through experiments with both Encoder-based and Decoder-based approaches, as well as an analysis of the effect of sociodemographic prompting. By considering global, text-, trait- and user-level evaluation metrics, we show that PERSEVAL is a powerful tool for examining how models are influenced by user-specific information and identifying the biases this information may introduce.

1 Introduction

Recently, part of the Natural Language Processing (NLP) community has seen what Cabitza et al. (2023) called a *perspectivist turn*. Researchers have increasingly questioned data harmonization techniques such as majority vote in favor of considering multiple perspectives as legitimate ground truths (Basile, 2020; Plank, 2022a). Perspectivist models thus leverage annotator disagreement to better account for user diversity (Prabhakaran et al., 2021) and adopt evaluation strategies capable of embracing disagreement (Uma et al., 2021b).

This framework assumes that part of the disagreement observed in annotation can be explained by the background and beliefs of the annotators, who might have different perspectives on the phenomena under study. For example, in a sensitive and difficult (Röttger et al., 2021) task such as hate speech detection, annotator specific modeling improved classification performance (Mostafazadeh Davani et al., 2022).

Evaluation practices in perspectivism vary widely. Inspired by early work on understanding and predicting annotator disagreement, one popular approach treats annotators' judgments separately, training with their individual labels (Fleisig et al., 2024). Another common practice is to consider all annotators as known at training time (Mostafazadeh Davani et al., 2022). While this represents a reasonable research scenario, it remains unclear how it would translate to real-world applications, where users are unknown during training, and adaptation occurs through limited interactions or feedback. To this end, some works in the perspectivist realm also account for unseen annotators (Deng et al., 2023; Orlikowski et al., 2025).

Given the diversity of assumptions and approaches, the developed models are not directly comparable, and quantifying their performance on different tasks remains hard. Moreover, the impact of using perspectivist models on new users and texts, together with the possible biases introduced remains underexplored.

With the overarching goal of rationalizing perspectivist evaluation and quantifying its impact, this paper presents a framework for Perspectivist Evaluation (PERSEVAL). To mirror real-world scenarios, we consider annotators, who provide the bulk of the annotation for training models, as disjoint from system users, for which performance is tested. Relaxing our working hypothesis, we also define two scenarios for which minimal test users' annotations are available, for example from user feedback or human-in-the-loop approaches. The first, inspired by Kocoń et al. (2021b), accounts for cases in which only a little information about test users' preferences is available during training; the model can thus use this information to learn a user-specific bias. The second scenario assumes

a system has been already trained and deployed, and allows using test user information for adaptation. All the variants of PERSEVAL are explained in Section 3.

Moreover, we consider two scenarios depending on the availability of explicitly-defined user characteristics: users can either be known by their identifier only, or they can be represented as a set of metadata, for example, describing their sociodemographic information or declared preferences.

Evaluation within PERSEVAL occurs at the individual annotation level and incorporates both global and fine-grained metrics—evaluating at the user, text, and trait levels (Section 5). This enables a comprehensive comparison and analysis across different perspectivist models.

We showcase our evaluation framework on encoder- and decoder-based models, considering five disaggregated datasets focused on phenomena such as irony and offensive speech detection or AI safety and with diverse designs concerning the number of annotators and the provided demographics. By performing evaluation at the individual annotation level, on the one hand, we can compare multiple perspectivist systems and the impact of explicitly modeling perspectives on their performance; on the other, we measure which point of view is privileged, e.g., by taking into account demographic data when available.

In summary, our contributions are the following: (1) We present PERSEVAL, an evaluation framework for perspective systems. We rationalize the user representation, the user splitting, and the evaluation functions. (2) We collect and harmonize five disaggregated datasets with diverse domains, classification tasks, and user representations. (3) We test several models and compare their performance in the proposed settings. (4) We carefully analyze the evaluation results, focusing on whether the models can bias their prediction following annotator-specific sociodemographic information and whether this introduced bias improves models' performance. (5) We develop and share a user-friendly library providing functionalities facilitating the comparison and analysis of different perspectivist approaches.

2 Related works

Perspectivism *Data perspectivism* aims at leveraging disaggregated annotations to model human perspectives in NLP (Frenda et al., 2024). The traditional approach towards annotators' disagreement "solves" it through data harmonization. However, aggregating annotations may result in an increasing bias toward specific groups, often minorities (Prabhakaran et al., 2021; Goyal et al., 2022). Perspectivist approaches, instead, challenge the assumption of a single ground truth (Aroyo and Welty, 2015) and consider the coexistence of different standpoints. These perspectives are defined differently depending on the task and the data: tied to cultural backgrounds (Akhtar et al., 2021), demographic information (Frenda et al., 2023; Casola et al., 2024), a combination of attitudes and behavior (Chulvi et al., 2023), a set of psychological characteristics (Mieleszczenko-Kowszewicz et al., 2023) or beliefs (Kazienko et al., 2023), moving in a continuum from a group-based to an individual perspective (Kocoń et al., 2021a).

Demographic data as perspectives A considerable body of work is exploring the influence of demographics in annotators' choices (Al Kuwatly et al., 2020; Larimore et al., 2021; Sap et al., 2022; Biester et al., 2022; Kumar et al., 2021; Davani et al., 2023; Jaggi et al., 2024). Encoding users' explicit traits has been an effective strategy when working with individual annotations (Milkowski et al., 2021; Wan et al., 2023), and it is increasingly investigated to evaluate generative models' cultural alignment (Cao et al., 2023; Tao et al., 2024; Casola et al., 2024). Sociodemographic prompting has been explored also to simulate human responses, showing mixed results (Argyle et al., 2023; Wang et al., 2025). Recent works have systematically studied both the potential and limitations of this approach, in zero-shot settings (Beck et al., 2024) as well as with fine-tuned generative models (Orlikowski et al., 2025).

Perspectivist evaluation Given the differences in disaggregated dataset design, number of annotators, available metadata, and corpus size (Plank, 2022b)[1,2], researchers have developed different ways to modeling and evaluating annotator perspectives. Works in the middle of the continuum between data- and human-centric approaches focus on modeling and evaluating groups of annotators (Akhtar et al., 2021; Frenda et al., 2023; Casola et al., 2023; Lo and Basile, 2023; Mostafazadeh Davani et al., 2024). Moving towards individuals,

[1] https://github.com/mainlp/awesome-human-label-variation

[2] https://pdai.info/

Mostafazadeh Davani et al. (2022) propose a multi-task approach, where the goal is to predict each annotator's label. Recent studies increasingly follow this line of research, experimenting in active-learning settings (Wang and Plank, 2023), proposing personalized methods. Personalization techniques have been used for modeling annotators (Plepi et al., 2022), often inspired by recommender systems methods (Kazienko et al., 2023; Heinisch et al., 2023), also being particularly attentive to annotators' demographics (Gordon et al., 2022) and minority voices (Mokhberian et al., 2024). A structured framework of evaluation comes from LeWiDi (Uma et al., 2021a; Leonardelli et al., 2023), which evaluates the impact of disagreement via cross-entropy. Nevertheless, this approach does not address the challenge of evaluating the models' ability to capture human perspectives. To the best of our knowledge, the only previous benchmark in this field of research is The Inherent Disagreement 8 dataset (TID-8) by Deng et al. (2023), a collection of 8 language-understanding disaggregated datasets with a varying number of annotators. In this work, we cover a larger diversity of approaches with a systematization of the possible splits, reporting a set of metrics to evaluate models also at the user, text and metadata level, and benchmarking encoder- and decoder-based models for perspectives classifications.

3 PERSEVAL: the Framework

We propose a conceptual framework for the evaluation of perspectivist text classification models. According to our framework, each instance is a <*text, user*> pair. We make this choice to better understand the impact of explicitly modeling perspectives (e.g., in terms of sociodemographic traits) on individual users. This choice is fundamentally different from traditional evaluation methodologies in NLP where instances are typically just textual. This difference has implications for several aspects that we discuss in the following sections.

3.1 Data Split

Previous research on disaggregated datasets has taken different approaches to data splitting. Most perspectivist evaluation practices rely on a fixed set of annotators, who typically annotate every text in the corpus; a standard text-based split is then adopted. This approach is useful from a theoretical standpoint, but does not reflect real-world scenarios and implications. In practice, a system is typically trained on data provided by one group of individuals (the *annotators*), while its inference is run on a set of instances encoding the perspectives of a distinct set of individuals (the *users*).

We conceptualize the data split in PERSEVAL under the assumption that annotators, who provide the training annotations, are disjoint from the test users. When explicit knowledge about the users is available — for example, in the form of sociodemographic information or preferences —, a model can attempt to learn biases toward such characteristics. When no such information is available, however, inferring preferences for completely unknown users is unfeasible. As a consequence, we define two adaptation scenarios:

- **Adaptation at training time (T)**: we assume minimal annotation from users has been obtained before training the system. A few annotations from test users are thus included in the training split.
- **Adaptation at inference time (I)**: we assume an already trained system has to be adapted to new users. A few test users instances can thus be used adapt an existing model.

In both cases, we assume that a minimal amount of annotations from users in the test set (e.g., collected through user interaction with the system or human-in-the-loop approaches.) is available.

3.2 User representation

The degree of user information available varies across datasets. When metadata are available, we represent the user through a set of traits, which may include sociodemographic or other explicit information. This representation enables models to learn user-specific perspectives based on these traits. We refer to this as the ***Named*** representation. With our proposed data split separating training and test users, the challenge is to learn annotator perspectives and generalize them to unseen users using only their traits. This setting is motivated by a well-established body of research examining the influence of annotators' demographic backgrounds on their choices, yielding both positive and contentious findings (Section 2).

To address scenarios where user metadata is unavailable, we also define a setting where users are represented solely by unique identifiers. While this

restricts the model's ability to personalize predictions, it is a common scenario in many real-world applications. We call this representation ***Unnamed***. In the *Unnamed* perspectives task, the model must classify perspectives without any explicit knowledge of the user's characteristics. This variant necessitates adaptation to infer user perspectives from the available annotations: the strict hypothesis for which test users are completely disjoint from training annotators must be relaxed (Section 3.1). As a consequence, the *Named* classification task can be performed with and without adaptation, while the *Unnamed* task requires some form of adaptation. Table 1 summarized the available variants.

Task	Adaptation	Adapt. Phase
Named	No adaptation	Never
	Adaptation-T	At training time
	Adaptation-I	At inference time
Unnamed	Adaptation-T	At training time
	Adaptation-I	At inference time

Table 1: Task variants proposed in PERSEVAL.

3.3 Extended training set

Since instances in PERSEVAL are <*text, users*> pairs, training and test instances could, in principle, share the same text, associated with labels from different users. This is the approach adopted in previous work when an annotor-level split was performed, for example by Orlikowski et al. (2025). However, this behavior is not always desirable, as the knowledge learned by a model from a training text may affect the inference on an instance with the same text in unpredictable ways.

To ensure fair evaluation and avoid data leakage, we follow standard practice and exclude any text instances in the test split that have been annotated by the training annotators. However, we also explore a variant where texts that appear in both training and test sets but are annotated by different users, are allowed in the training data (*extended*). This variant tests the model's ability to learn from systematic disagreements among users who annotate the same text differently, capturing the diversity of perspectives inherent in the data.

All task variants can use the extended training set. While they differ in training splits—and in some cases include additional sets for adaptation at inference time—the test set remains consistent to ensure fair performance comparison.

4 Datasets

PERSEVAL incorporates a diverse range of datasets, varying in task, domain and annotator information. Table 2 summarizes the dataset characteristics. A description of each dataset and the available metadata are available in Appendix A and B.

5 Evaluation metrics

Our evaluation setting is inspired by previous work in personalization. Given predicted labels and true annotations for each <*text, user*> pair, we compute standard classification metrics, i.e., precision, recall, and F1-score (referred to as *global metrics)*.

Moreover, the annotator-based characteristic of the disaggregated labels allows us to gain further insights into the models' capability to learn from diverse human perspectives. Inspired by Mokhberian et al. (2024), we report *user-level* metrics. These metrics are computed individually for each test user and then averaged; they provide a fairer evaluation regardless of the contribution in terms of annotations of each annotator to the dataset. We also report *text-level* metrics, computed individually for each text and averaged. The analysis of these metrics helps understand whether some texts are easier to classify for a given model and whether having instances with the same textual content (but different users, and thus, different annotations, in the extended version of the dataset), helps the model in the classification. Finally, for the named task, we also report *trait-level* metrics. These metrics, computed for each trait and then averaged for each dimension, are meant to describe if the preference of all groups of people is fairly learned by the model or if the model underperforms when considering users with certain characteristics.

6 Models

We benchmarked a series of approaches for perspectivist classification, using Encoder- and Decoder-based models, covering all task variants proposed in Section 3.

Due to the different settings supported by each approach, we test a subset of settings with each model. In particular, when working with the Encoder-based model, we did not include inference-time adaptation since this architecture does not support it. On the other hand, performing zero- and few-shot learning by prompting the Decoder-based model, we did not cover the *Adaptation-T*variant for the *Named* or the *Unnamed* Task.

Dataset	Reference	Task	#Annot.	#Texts	#Inst.	Source	Label	Positive Class	Metadata
BREXIT	Akhtar et al. (2021)	Abusive Language	6	1,120	3,872	Twitter	Binary	Offensiveness	Target and control group
EPIC	Frenda et al. (2023)	Irony	74	3,000	14,172	Twitter, Reddit	Binary	Irony	Gender, Nationality, Age/Generation
MHS	Sachdeva et al. (2022)	Hate Speech	7,912	39,565	135,556	YouTube, Twitter, Reddit	Binary	Hate Speech	Gender, Age/Generation, Education, Income
MD-Agreement	Leonardelli et al. (2023)	Offensiveness	819	10,753	53,765	Twitter	Binary	Offensiveness	—
DICES	Aroyo et al. (2024)	AI Safety	123	350	43,050	Human-chatbot conversations	Non-binary	Harmful	Gender, Age/Generation, Education, Ethnicity

Table 2: Overview of the datasets used in social media text classification tasks.

6.1 Encoder-based Model

We fine-tuned RoBERTa (Zhuang et al., 2021)[3], customized implementing Focal Loss (Lin et al., 2017) to prevent overfitting in case of unbalanced datasets. All splitting and training parameters are reported in Appendix C. Inspired by the personalized User-ID model from Ferdinan and Kocoń (2023), we added identifiers and traits of the annotators to the text embedding as a special token. The input thus concatenates the annotator ID, a special token for each of the annotator's traits, and the input text to classify. The special tokens explicitly encode the annotator's identity and characteristics and are used by the model to learn annotator- and trait-specific features in the classification. The model is then trained with a classification head to predict the binary label. We also computed a baseline without any additional special token.

6.2 Decoder-based Models

For the Decoder-based model, we focus on open-source models and benchmark the performance of Mixtral-8 7B[4] and Llama-3.1 8B[5], both instruction tuned. We consider several settings:

Base-zero We prompt the models to classify the test set examples, with no additional information.

Perspective Inspired by work on role-based sociodemographic prompting (Cheng et al., 2023), we ask the models to impersonate each user's trait. To do so, we prepend the given trait to the prompt (for example *You are a person from Generation X.*). We use this variant to test models without adaptation with a named user representation. We prompt the model for each available user trait.

[3]FacebookAI/roberta-base
[4]Mixtral-8x7B-Instruct-v0.1
[5]meta-llama/Llama-3.1-8B

In-Prompt Augmentation (IPA) We reproduced Salemi et al. (2024)'s approach, using In-Prompt Augmentation (*IPA*). It consists of prompting the model with user-specific input selected via retrieval augmentation, a framework which extracts pertinent texts, relevant to the classification of the unseen test case. Using the authors' terminology, given a sample (x_i, y_i) and a user u, a query generation function ϕ_q transforms the input x_i into a query q for retrieving the user profile P_u (i.e. the user's historical data) from the Adaptation set. To do so, we used the Contriever model (Izacard and Grave, 2021), a pre-trained dense retrieval model $\mathcal{R}(q, P_u, k)$ that retrieves the k most pertinent entries. Finally, the prompt construction function ϕ_p assembles the personalized prompt. Specifically, we selected 5 examples per user. We used this approach both giving information about the user's trait value (*Named* with *Adaptation-T*) and without providing demographic information.

When some outputs could not be properly parsed — such as when the model refused to provide an answer, particularly for datasets related to hate speech — we assigned an additional uncorrect label.

In the *Named* task, we prompt the model separately for each available user trait and determine the final label through a majority vote across the outputs of the trait-specific models. The prompts used for each setting are detailed in Appendix D.

7 Results

In this section, we present the results for the Encoder-based and Decoder-based Models. In all cases, we report metrics related to the positive class, with the exception of DICES, the only multi-class dataset, for which we present the macro-averaged metrics. To gain more insights into the effect of sociodemographic prompting, we performed an in

depth analysis (Section 7.3).

7.1 Encoder-based Model

Table 3 shows the results on the datasets with binary labels. We notice that when considering the *non-extended training set* — i.e., the case in which the text to be annotated has not been seen by the model at training time — the baseline tends to have higher scores in terms of global F1. With the *extended training set*, instead, providing sociodemographic traits leads to improved results over the baseline. This indicates a mild tendency of the model to learn the relation between latent features of the text and the users labeling them, although marginal.

The user and text-based F1 scores highlight the benefit of including demographic traits at training time, especially in the setting without adaptation set (*Adaptation-None*). When demographics are not available, such as for MD-Agreement, providing the user ID still results in being beneficial.

The trait-based F1 scores show that some traits are more informative than others, e.g., *Nationality* for EPIC, coherently with its focus on differences in the perception of irony across language varieties. This pattern is consistent in all settings. As for MHS, the model tends to be fairer to annotators grouped based on their education. The same score is obtained based on *Generation* and *Income* in the *Named* task with *Adaptation-T* for the *extended* and *non-extended* versions respectively.

Results for DICES are in Table 4. Providing demographics confirms a positive impact, with improved results in all settings in terms of global, user- and text-level F1 scores. Moreover, adaptation helps the performance across all the metrics.

In all settings, the model presents a higher trait-based F1 score on *Generation*, showing its influence during training, which aligns with intuition for a task related to human-AI conversations.

7.2 Generative Models

Table 5 presents the results for the Decoder-based models using the ensembling strategy described in Section 6. Across all datasets, all the approaches outperform the baseline, except for Mixtral on MHS. Focusing on *Named* tasks, we notice that adding annotators' demographics consistently helps the model. As expected, the *Unnamed* task is harder, however the user-based selection of few-shot examples of *IPA* significantly outperforms the baseline. Indeed, *IPA* is the most effective strategy for perspective classification with generative models, except on BREXIT. We speculate this is due to the high polarization of the annotations in this dataset, and the narrow characterization of the annotators. The same pattern can observed on DICES (Table 6), where *IPA* is the best approach with both models. The positive influence of sociodemographic information is also confirmed using IPA-Llama. *IPA-Mixtral* presents higher scores in the *Unnamed* setting, demonstrating the effectiveness of providing user-specific examples alone.

Examining the trait-based F1 scores, for both the *Perspective* and *IPA* approaches, the most informative traits are *Nationality* in EPIC (consistently with results on the Encoder). This is consistent when using LLama and Mixtral and aligns with intuition, given the dataset focuses on various linguistic varieties. A similar pattern is observed for *Generation* in MHS when using Llama. With Mixtral, *IPA* exhibits greater fairness toward annotators grouped by education. This result is consistent with the encoder, suggesting that these traits are particularly influential on the models' predictions.

7.3 Analysis

Given the importance of evaluating sociodemographic prompting (Beck et al., 2024), we investigate the extent to which demographic traits inform the models and whether the learned biases align with existing annotation.

Q1: What is the contribution of each trait when ensembling the model's outputs? We conducted an ablation study by ensembling model outputs across all possible combinations of traits. Since BREXIT has only one trait, and MD lacks information about the annotators, we computed the results for EPIC, MHS and DICES, reported in Appendix E.1 On EPIC, raters' *Generation* is the most informative trait in *Perspective* settings on both Llama and Mixtral; combining it with *Nationality* also shows a positive impact. These results are consistent with the dataset design and discussion by Frenda et al. (2024), where annotators' generation is one of the most polarizing demographic dimensions. The same pattern can be found for *IPA-Llama*. In DICES, *Education* is an important factor in *Perspective* settings with both models, an interesting result considering the focus on AI-safety. On the other hand, when models can see examples, *Generation* and *Gender* are more positively influential for Llama and Mixtral respectively. MHS is the only dataset where ensembling more traits

Dataset		Adapt	Extended	Global F1	User F1	Text F1	Traits F1s				
							Gender	Nationality	Generation	-	-
EPIC	baseline	-	No	**.555**	**.538**	**.376**	-	-	-		
	Named	None	No	.542	.527	.364	.520	.547	.527		
		Train	No	.550	.534	.371	.531	.556	.538		
	Unnamed	Train	No	.534	.518	.352	-	-	-		
							Group	-	-	-	-
BREXIT	baseline	-	No	**.567**	.519	.403	-				
	Named	None	No	.558	**.524**	**.416**	.524				
		Train	No	.544	.512	.405	.512				
	Unnamed	Train	No	.514	.484	.378	-				
							Gender	Generation	Education	Income	Ideology
MHS	baseline	-	No	.691	.643	.521	-	-	-	-	-
	Named	None	No	**.694**	**.727**	**.526**	.676	.692	.695	.676	.693
		Train	No	.685	.639	.511	.662	.683	.686	.686	.683
	Unnamed	Train	No	.681	.634	.504	-	-	-	-	-
MD	baseline	-	No	**.665**	.591	**.500**					
	Unnamed	Train	No	**.665**	**.597**	.499					
							Gender	Nationality	Generation	-	-
EPIC	baseline	-	Yes	.579	.559	.405	-	-	-		
	Named	None	Yes	.575	.560	**.567**	.555	.591	.560		
		Train	Yes	.578	.564	.398	.560	.589	.556		
	Unnamed	Train	Yes	**.586**	**.571**	.405	-	-	-		
							Group	-	-	-	-
BREXIT	baseline	-	Yes	**.592**	.543	.427	-				
	Named	None	Yes	.587	**.557**	**.455**	.557				
		Train	Yes	.540	.509	.424	.509				
	Unnamed	Train	Yes	.554	.524	.436	-				
							Gender	Generation	Education	Income	Ideology
MHS	baseline	-	Yes	**.698**	**.652**	.528	-	-	-	-	-
	Named	None	Yes	**.698**	.649	.528	.671	.698	.699	.698	.695
		Train	Yes	**.698**	.650	**.532**	.675	.700	.700	.698	.698
	Unnamed	Train	Yes	.696	.647	.527	-	-	-	-	-
MD	baseline	-	Yes	.667	.603	.495					
	Unnamed	Train	Yes	**.681**	**.620**	**.518**					

Table 3: Encoder model's global F1 score, and user-, text-, trait- level F1 for the positive class for binary datasets.

	Adapt	Extended	Global F1	User F1	Text F1	Traits F1s			
						Gender	Generation	Education	Race
baseline	-	No	.340	.311	.245				
Named	None	No	.400	.391	.361	.401	.400	.388	.397
	Train	No	.420	.407	.373	.419	.422	.408	.414
Unnamed	Train	No	**.434**	**.424**	**.389**	-	-	-	-
baseline	-	Yes	.440	.448	.335				
Named	None	Yes	.453	.439	.378	.452	.454	.436	.447
	Train	Yes	**.457**	.445	**.389**	.457	.457	.439	.454
Unnamed	Train	Yes	.456	**.446**	.388	-	-	-	-

Table 4: Macro-averaged global F1 score, and user-, text-, trait- level F1 for the Encoder model with DICES.

is beneficial in the *IPA* setting with both models, suggesting a less clear-cut influence of traits than in other settings and datasets. In fact, the *IPA* approach shows smaller F1 score differences across traits compared to the *Perspective* setting, as models benefit from personalized examples rather than relying solely on demographics.

Q2: Which demographic trait most significantly impacts models' labels? We filtered out texts annotated by only one subgroup. Then, we computed the impact of changing the demographic variable in the prompt on the models' label (Appendix E.2). Results in the *Perspective* approach tend to be consistent across the two models. For EPIC, *Nationality* and *Generation* are the most influential traits, while in MHS *Ideology* tends to make the model change the label. These are the same traits resulting to be most influential in the ablation study (Q1), consistently with the dataset task. On the other hand, *IPA* shows a higher percentage of cases where the model changes the label, confirming the positive effect of providing user-specific examples. Finally, DICES presents a very low label change compared to the other datasets.

Q3: How similar are the distribution of models' predictions and that of the annotators' chosen labels? Leveraging soft evaluation metrics (Rizzi et al., 2024), we measured the alignment between models and annotators' labels using Jensen-Shannon Divergence (JSD) (Uma, 2021). Taking

Model	Dataset	Approach		Adapt	Global F1	User F1	Text F1	Traits F1s				
								Gender	Nationality	Generation		
Llama	EPIC	Base-zero	Baseline	-	.529	.511	.363	-	-	-		
		Perspective	Named	None	.484	.467	.322	.465	.492	.463		
		IPA	Named	Test	**.547**	.528	**.387**	.515	.543	.532		
			Unnamed	Test	.546	**.530**	.386	-	-	-		
								Group				
	BREXIT	Base-zero	Baseline	-	.502	.476	.340	-				
		Perspective	Named	None	**.527**	**.502**	**.371**	.502				
		IPA	Named	Test	.364	.362	.238	.362				
			Unnamed	Test	.330	.319	.231	-				
								Gender	Generation	Education	Income	Ideology
	MHS	Base-zero	Baseline	-	.593	.543	.425	-	-	-	-	-
		Perspective	Named	None	.513	.452	.352	.418	.520	.515	.513	.510
		IPA	Named	Test	**.637**	.537	**.467**	.587	.648	.640	.637	.638
			Unnamed	Test	.626	**.570**	.456	-	-	-	-	-
	MD	Base-zero	Baseline	-	.556	.515	.381					
		IPA	Unnamed	Test	**.613**	**.535**	**.451**					
								Gender	Nationality	Generation		
Mixtral	EPIC	Base-zero	Baseline	-	.487	.477	.305	-	-	-		
		Perspective	Named	None	.507	.494	.328	.501	.515	.493		
		IPA	Named	Test	**.554**	.521	**.380**	.528	.551	.543		
			Unnamed	Test	.534	**.523**	.356	-	-	-		
								Group				
	BREXIT	Base-zero	Baseline	-	.255	.235	.128	-				
		Perspective	Named	None	.344	.323	.193	.323				
		IPA	Named	Test	.406	.382	.263	.382				
			Unnamed	Test	**.448**	**.410**	**.313**	-				
								Gender	Generation	Education	Income	Ideology
	MHS	Base-zero	Baseline	-	**.648**	**.599**	**.483**	-	-	-	-	-
		Perspective	Named	None	.643	.593	.479	.655	.647	.646	.643	.648
		IPA	Named	Test	.634	.569	.459	.621	.639	.643	.633	.634
			Unnamed	Test	.632	.571	.457	-	-	-	-	-
	MD	Base-zero	Baseline	-	**.538**	**.495**	**.678**					
		IPA	Unnamed	Test	.531	.398	.643					

Table 5: Decoder-based approach global F1 score, and user-, text- and trait- level F1 scores for the positive class.

Models	Dataset	Approach		Adapt	Global F1	User F1	Text F1	Traits F1s			
								Gender	Generation	Education	Race
Llama	DICES	Base-zero	Baseline	-	.290	.282	.310	-	-	-	-
		Perspective	Named	None	.298	.290	.289	.297	.295	.300	.297
		IPA	Named	Test	**.365**	**.354**	**.428**	.367	.363	.352	.362
			Unnamed	Test	.355	.340	.425	-	-	-	-
Mixtral	DICES	Base-zero	Baseline	-	.232	.228	.402	-	-	-	-
		Perspective	Named	None	.256	.323	.412	.297	.311	.310	.304
		IPA	Named	Test	.303	.350	**.448**	.302	.303	.309	.300
			Unnamed	Test	**.306**	**.356**	.443	-	-	-	-

Table 6: Macro-averaged global F1, user-, text- and trait- level F1 scores for the Decoder-based models with DICES.

each trait separately and filtering texts annotated by only one demographic group, we calculated the similarity of the distributions of each demographic variable by text and averaged (see also Appendix E.3). Results show that in BREXIT, the models asymmetrically present a higher alignment with the control group in almost all cases except for IPA-Mixtral.

On DICES, *Race* is the most aligned trait. DICES and MHS present higher alignment on the *Perspective* approach than *IPA*. Overall, while in the previous analysis we saw that *IPA* ensures a higher label variability in the predictions at the text level, this does not necessarily correlate with a higher alignment with the label distributions.

8 Conclusion

We introduced PERSEVAL, the first unified framework for the evaluation of perspectivist text classification. We assume train annotators and test users are different, and design a *Named* perspectivist classification task where users are represented by their explicit traits and an *Unnamed* task where only their identifier is available. We included five datasets and implemented three baseline models, presenting a robust benchmark for complex real-world applications. Results show that the fine-tuned Encoder benefits more from learning latent user-specific biases. For Decoder-based models, within the *Perspective* approach models appear particularly sensitive to specific demographic cues, which vary according to the dataset and its task. Conversely, providing user-specific examples increases label variability but does not necessarily lead to greater alignment between the models' and annotators' label distributions.

PERSEVAL is implemented in a Python library (detail in Appendix F).

Limitations

In this paper, we primarily focus on presenting a comprehensive framework for evaluating perspectivist models. Our goal is not to test an extensive range of models; instead, we conducted experiments on just three baseline models. We believe that the framework and library introduced here will serve as a valuable resource for future research in evaluating real-world systems within similar contexts. While we considered multiple datasets, all are in English and most feature binary labels. In future work, we plan to expand this work by incorporating disaggregated datasets in various languages.

While PERSEVAL covers a framework of evaluation, it is supposed to be applied in those contexts where is not possible to assess a single ground truth. Thus, this framework does not cover tasks having a single possible correct answer.

The presented framework provides tools to study user- and trait-specific bias learned by classification models; however, guidelines for practically limiting the impact of such biases depend on the specific context under study and remain a responsibility of users leveraging the tool.

Ethical statement

The work presented in this paper is in the context of a broader initiative to consider the subjectivity of the annotators in NLP applications, encouraging reflection on the different perspectives encoded in annotated datasets to minimize the amplification of biases. The proposed benchmark can be used as a basis for evaluating a wide range of NLP models, including LLMs, according to their capability of representing the variability of human perspectives.

However, as discussed by Fortuna et al. (2022), working with grouped or individual annotators may represent a risk if it is not clearly defined which perspectives are warranted in the real-world usage of models and resources. For example, as the authors note, while understanding how white supremacists view hate speech could be informative, training models on their annotations would result in systems that would hurt marginalized communities.

Since perspectivist research is recently proposing annotator- and personalization-based approaches, analyzing models' biases becomes fundamental. PERSEVAL is conceived as a tool to systematically evaluate perspectivist classification—accounting for the risk of stereotype propagation in models that encode user metadata or treat annotators as isolated sources—while aiming to prevent harm to targeted groups and minorities. We believe this is a necessary step in the NLP community interested in considering annotators' subjectivity, especially for monitoring the possible drawbacks associated with using these approaches in tasks such as offensive and hate speech detection.

As regards the language resources included in the benchmark, they were built adopting measures to protect the privacy of annotators and data handling protocols designed to safeguard personal information. Some of the material could contain racist, sexist, stereotypical, violent, or generally disturbing content.

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A Datasets

We present all the datasets incorporated in PERSEVAL.

BREXIT is a dataset for abusive language detection, consisting of 1,120 English tweets. The dataset is annotated by 6 annotators from 2 groups: 3 Muslim immigrants in the UK (target group), and 3 researchers (control group). Each annotator annotated the entire corpus with binary label for multiple aspects: hate speech, aggressiveness, offensiveness, and stereotype. The only available user trait is the group each annotator belongs to i.e., target or control. In PERSEVAL the positive class is *hate speech*, however the dataset is highly unbalanced toward the negative class.

EPIC (English Perspectivist Irony Corpus) consists of 3,000 texts collected from Twitter and Reddit in 5 English-speaking countries and annotated by 74 crowd workers. Each annotator labeled around 200 texts, for a total of 14,172 annotations. The authors also released annotators' demographic information (Appendix B), balanced across gender and nationality. The target class is *irony*.

MHS (Measuring Hate Speech) contains 39,565 English comments extracted from YouTube, Twitter, and Reddit. It has been annotated by 7,912 people, resulting in 135,556 annotations with both a specific label and multiple hate-informative labels to capture the degree of hatefulness in a continuum. The annotators shared their demographics, reported in Appendix B.The positive class is *hate speech*.

MD-Agreement (Multidomain Agreement), recently used in LeWiDi (Leonardelli et al., 2023), comprises 10,753 English tweets from three domains associated with the hashtags #BlackLivesMatter, #Election2020 and #Covid-19. Each text has been annotated 5 times by 819 annotators, for a total of 53,765 annotations. No demographic trait is available. The positive class is *offensiveness*.

DICES (Diversity in Conversational AI Evaluation for Safety) focuses on AI safety. It is a multi-turn conversation corpus generated by humans interacting with an AI-chatbot, provoking it to respond with an undesirable or unsafe answer. For PERSEVAL we opted for DICES-350, designed to study in-depth cross-demographic differences within the US. Specifically, it consists of 350 multi-turn conversations (within a maximum of 5 turns), fully annotated by 123 people, having a total of 43,050 annotations. This is the only dataset with a non-binary label (with values harmful, not harmful and unsure). The author released annotators' traits, reported in Appendix B.

B User traits

Table 7 shows the traits in the BREXIT, DICES, EPIC and MHS datasets.

C Training parameters

Table 8 presents the training parameters for the Encoder model.

D Prompt example

In this section, we report the prompts used in each setting, taking as examples EPIC and BREXIT datasets, the first with both a context and a text, the second with text only.
Warning: Examples could contain racist, sexist, violent, and generally offensive content.

D.1 Base-zero

Base prompt with EPIC:

> *Instruction: You are provided in input (Input) a pair of sentences (post, reply) extracted from social media conversations. Your task is to determine if the reply is ironic in the context of the post. Please provide in output (Output) a single label among the following array ["irony", "not irony"].*
>
> *Input:*
>
> *- post: YouTube told me to.*
>
> *- reply: Lol*
>
> *Output:*

Base prompt with BREXIT:

> *Instruction: You are provided in input (Input) a sentence (tweet) extracted from Twitter. Your task is to determine if the tweet is hateful. Please provide in output (Output) a single label among the following array ["hate speech", "not hate speech"].*
>
> *Input: tweet: #brexit is going to effect other countries economically and they are most likely going to pass laws against the refugees that come in from*
>
> *Output:*

D.2 Perspective

Prompting in Perspective-setting with EPIC:

Instruction: You are Irish. You are provided in input (Input) a pair of sentences (post, reply) extracted from social media conversations. Your task is to determine if the reply is ironic in the context of the post. Please provide in output (Output) a single label among the following array ["irony", "not irony"].

Input:

- post: YouTube told me to.

- reply: Lol

Output:

Prompting in Perspective-setting with BREXIT:

Instruction: You are a researcher. You are provided in input (Input) a sentence (tweet) extracted from Twitter. Your task is to determine if the tweet is hateful. Please provide in output (Output) a single label among the following array ["hate speech", "not hate speech"].

Input:

tweet: #brexit is going to effect other countries economically and they are most likely going to pass laws against the refugees that come in from

Output:

D.3 IPA Named

Prompting in IPA Named setting with EPIC:

Instruction: You are Irish. You are provided in input (Input) a pair of sentences (post, reply) extracted from social media conversations. Your task is to determine if the reply is ironic in the context of the post. Please provide in output (Output) a single label among the following array ["irony", "not irony"].

{User-specific Example 1}

{User-specific Example 2}

{User-specific Example 3}

{User-specific Example 4}

{User-specific Example 5}

{Example to label}

Input:

- post: YouTube told me to.

- reply: Lol

Output:

Prompting in IPA Named setting with BREXIT:

Instruction: You are a researcher. You are provided in input (Input) a sentence (tweet) extracted from Twitter. Your task is to determine if the tweet is hateful. Please provide in output (Output) a single label among the following array ["hate speech", "not hate speech"].

{User-specific Example 1}

{User-specific Example 2}

{User-specific Example 3}

{User-specific Example 4}

{User-specific Example 5}

{Example to label}

Input:

tweet: #brexit is going to effect other countries economically and they are most likely going to pass laws against the refugees that come in from

Output:

D.4 IPA Unnamed

Prompting in IPA Unnamed setting with EPIC:

Instruction: You are provided in input (Input) a pair of sentences (post, reply) extracted from social media conversations. Your task is to determine if the reply is ironic in the context of the post. Please provide in output (Output) a single label among the following array ["irony", "not irony"].

{User-specific Example 1}

{User-specific Example 2}

{User-specific Example 3}

{User-specific Example 4}

{User-specific Example 5}

{Example to label}

Input:

- post: YouTube told me to.

- reply: Lol

Output:

Prompting in IPA Unnamed setting with BREXIT:

> *Instruction: You are provided in input (Input) a sentence (tweet) extracted from Twitter. Your task is to determine if the tweet is hateful. Please provide in output (Output) a single label among the following array ["hate speech", "not hate speech"].*
>
> *{User-specific Example 1}*
>
> *{User-specific Example 2}*
>
> *{User-specific Example 3}*
>
> *{User-specific Example 4}*
>
> *{User-specific Example 5}*
>
> *{Example to label}*
>
> *Input:*
>
> *tweet: #brexit is going to effect other countries economically and they are most likely going to pass laws against the refugees that come in from*
>
> *Output:*

E Error analysis

We present the complete results of the error analysis.

E.1 Q1: What is the contribution of each trait when ensembling the model's outputs?

Results from the ablation study are presented separately for each dataset in Table 9 (EPIC), Table 10 (MHS on *Perspective setting*), Table 11(MHS on *IPA setting*), and Table 12 (DICES).

E.2 Q2: Which demographic trait most significantly impacts the model's label predictions in the presence of varying annotator characteristics?

Table 13 illustrates the extent to which changing the value for each trait in the prompt influences the label assigned to the text.

E.3 Q3: How similar the distribution of models' predictions is to the distribution of the annotators' chosen labels?

This third question has been assessed by computing the Jensen-Shannon Divergence between models and annotators' label distributions. Scores are presented separately for each dataset in Table 14 (EPIC), 15 (MHS), Table 16 (DICES), and Table 17 (BREXIT).

F The PERSEVAL Python Library

PERSEVAL is implemented as a Python library to facilitate access to the data, the different splits related to task variants, and the evaluation metrics.[6] The main interaction starts by instantiating a dataset from the `data` submodule. The user can then request the training, test, and optionally adaptation data splits with the `get_splits()` method, indicating whether the adaptation data (`user_adaptation`) is absent (`False`), available at training time (`train`) or at inference time (`test`). Additionally, the user chooses whether to extend the training split including texts also in test instances (`extended=True`) or to exclude them (`extended=False`). The dataset object contains a series of metadata about the dataset, such as its name, label names, and a dictionary of the annotator traits. Moreover, it contains the three splits, instantiated as objects of the same `PerspectivistSplit` class. These objects, called `training_set`, `test_set`, and `adaptation_set`, contain the list of users, texts, and the annotations, for the respective split. The `User` objects contain a unique identifier and a dictionary of traits. The `Text` objects contain a dictionary with the textual content of an instance, depending on the structure of the dataset. The `annotation` property is a dictionary where the keys are a pair (*User id*, *Text id*), and the value is a dictionary containing a value for each annotated label.

Besides providing access to the datasets and appropriate splits of the data for each task variant, the PERSEVAL library facilitates the automatic evaluation of models. The library implements the class `Evaluator`, which can be instantiated by passing the path of a file containing the predictions, a test set, and a target label name. The `Evaluator` object implements the functions to calculate the evaluation metrics described in Section 5. The output of the global, annotator-, text-, and trait-level metrics can be visualized in their aggregated forms and can be accessed (also at the level of each individual annotator, text, and trait) programmatically for a deeper analysis.

[6] The code will be released upon acceptance.

Dataset	Traits	Values
BREXIT	Group	Target, Control
DICES	Gender	Male, Female
	Age	GenX+, GenY, GenZ
	Education	College degree or higher, High school or below
	Ethnicity	Asian, Black, Latinx, White
EPIC	Gender	Male, Female
	Age	19-64 y/o, grouped in Boomer, GenX, GenY and GenZ
	Nationality	Australia, India, Ireland, United Kingdom, United States
MHS	Gender	Male, Female
	Age	18-81 y/o, grouped in Boomer, GenX, GenY, GenZ
	Education	College degree or higher, High school or below
	Income	less than 50k annual income, more than 50k annual income

Table 7: The sets of user traits included in PersEval for the BREXIT, DICES, EPIC and MHS datasets.

Parameter	Value
eval_strategy	epoch
greater_is_better	False
learning_rate	$5e^{-6}$
load_best_model_at_end	True
metric_for_best_model	eval_loss
num_train_epochs	5
per_device_eval_batch_size	32
per_device_train_batch_size	16

Table 8: Model parameters for the Encoder-based model.

Traits combination	Model	Precision	Recall	F1
Gender	Perspective-Llama	.473	.489	.481
Generation		.473	.553	.510
Nationality		.463	.473	.468
Generation-Nationality		.473	.553	.510
Gender-Generation		.471	.513	.491
Gender-Nationality		.470	.481	.475
Gender-Generation-Nationality		.472	.498	.484
Gender	Perspective-Mixtral	.485	.525	.504
Generation		.495	.592	.539
Nationality		.497	.501	.499
Generation-Nationality		.501	.557	.528
Gender-Generation		.484	.551	.515
Gender-Nationality		.489	.512	.500
Gender-Generation-Nationality		.485	.530	.507
Gender	IPA-Llama	.404	.829	.544
Generation		.401	.857	.546
Nationality		.389	.880	.539
Generation-Nationality		.397	.865	.544
Gender-Generation		.402	.841	.544
Gender-Nationality		.397	.850	.541
Gender-Generation-Nationality		.402	.857	.547
Gender	IPA-Mixtral	.406	.696	.554
Generation		.456	.688	.548
Nationality		.453	.706	.552
Generation-Nationality		.451	.691	.546
Gender-Generation		.455	.693	.549
Gender-Nationality		.455	.699	.551
Gender-Generation-Nationality		.460	.696	.554

Table 9: Precision, Recall, and F1 scores of the positive class on each trait, and their ensembled combinations on EPIC.

Traits combination	Model	Precision	Recall	F1
Age	Perspective-Llama	.448	.580	.505
Education		.469	.799	.591
Income		.404	.270	.324
Gender		.474	.719	.571
Ideology		.460	.413	.435
Gender-Income		.452	.492	.471
Gender-Ideology		.468	.564	.512
Gender-Education		.472	.760	.582
Gender-Age		.458	.644	.536
Age-Education		.459	.689	.551
Age-Ideology		.450	.493	.471
Age-Income		.436	.426	.431
Education-Income		.451	.530	.487
Education-Ideology		.463	.602	.523
Income-Ideology		.443	.348	.389
Gender-Age-Education		.467	.717	.566
Gender-Age-Income		.454	.567	.504
Gender-Age-Ideology		.456	.590	.514
Gender-Education-Income		.470	.694	.561
Gender-Education-Ideology		.470	.702	.563
Gender-Income-Ideology		.446	.451	.448
Age-Education-Income		.448	.576	.504
Age-Education-Ideology		.452	.601	.516
Age-Income-Ideology		.443	.432	.437
Education-Income-Ideology		.445	.456	.450
Gender-Age-Education-Income		.459	.638	.534
Gender-Age-Education-Ideology		.461	.651	.540
Gender-Age-Income-Ideology		.445	.503	.473
Gender-Education-Income-Ideology		.456	.571	.507
Age-Education-Income-Ideology		.455	.588	.513
Gender-Age-Education-Income-Ideology		.455	.588	.513
Age	Perspective-Mixtral	.505	.875	.640
Education		.509	.872	.643
Income		.514	.866	.645
Gender		.506	.873	.641
Ideology		.525	.853	.650
Gender-Income		.511	.871	.644
Gender-Ideology		.516	.863	.646
Gender-Education		.508	.873	.642
Gender-Age		.506	.874	.641
Age-Education		.507	.875	.642
Age-Ideology		.515	.862	.645
Age-Income		.510	.871	.644
Education-Income		.512	.871	.645
Education-Ideology		.517	.862	.646
Income-Ideology		.520	.858	.648
Gender-Age-Education		.504	.876	.640
Gender-Age-Income		.505	.876	.641
Gender-Age-Ideology		.509	.875	.643
Gender-Education-Income		.506	.873	.641
Gender-Education-Ideology		.510	.871	.643
Gender-Income-Ideology		.515	.869	.647
Age-Education-Income		.508	.875	.643
Age-Education-Ideology		.510	.873	.644
Age-Income-Ideology		.514	.870	.646
Education-Income-Ideology		.514	.867	.645
Gender-Age-Education-Income		.505	.875	.641
Gender-Age-Education-Ideology		.508	.874	.642
Gender-Age-Income-Ideology		.510	.872	.643
Gender-Education-Income-Ideology		.511	.871	.644
Age-Education-Income-Ideology		.511	.873	.644
Gender-Age-Education-Income-Ideology		.508	.874	.643

Table 10: Precision, Recall, and F1 scores of the positive class on each trait, and their ensembled combinations on MHS in *Perspective* setting.

Traits combination	Model	Precision	Recall	F1
Age	IPA-Llama	.546	.763	.636
Education		.532	.779	.632
Income		.545	.756	.633
Gender		.540	.772	.635
Ideology		.532	.778	.633
Gender-Income		.542	.767	.635
Gender-Ideology		.537	.775	.634
Gender-Education		.535	.777	.634
Gender-Age		.543	.767	.636
Age-Education		.539	.771	.635
Age-Ideology		.539	.768	.634
Age-Income		.545	.760	.635
Education-Income		.538	.766	.633
Education-Ideology		.534	.779	.634
Income-Ideology		.540	.766	.633
Gender-Age-Education		.540	.774	.636
Gender-Age-Income		.544	.766	.636
Gender-Age-Ideology		.541	.775	.638
Gender-Education-Income		.540	.772	.635
Gender-Education-Ideology		.537	.780	.636
Gender-Income-Ideology		.542	.773	.637
Age-Education-Income		.542	.769	.636
Age-Education-Ideology		.540	.778	.637
Age-Income-Ideology		.542	.770	.636
Education-Income-Ideology		.539	.774	.636
Gender-Age-Education-Income		.540	.769	.635
Gender-Age-Education-Ideology		.539	.777	.637
Gender-Age-Income-Ideology		.542	.773	.637
Gender-Education-Income-Ideology		.540	.775	.637
Age-Education-Income-Ideology		.542	.773	.637
Gender-Age-Education-Income-Ideology		.542	.773	.637
Age	IPA-Mixtral	.579	.688	.629
Education		.587	.681	.631
Income		.579	.687	.628
Gender		.572	.708	.633
Ideology		.607	.645	.626
Gender-Income		.575	.697	.630
Gender-Ideology		.589	.676	.630
Gender-Education		.580	.693	.631
Gender-Age		.576	.700	.632
Age-Education		.582	.682	.629
Age-Ideology		.594	.668	.629
Age-Income		.578	.688	.628
Education-Income		.583	.684	.629
Education-Ideology		.597	.664	.629
Income-Ideology		.593	.668	.628
Gender-Age-Education		.581	.695	.633
Gender-Age-Income		.578	.698	.632
Gender-Age-Ideology		.586	.686	.632
Gender-Education-Income		.581	.695	.633
Gender-Education-Ideology		.592	.683	.634
Gender-Income-Ideology		.587	.688	.633
Age-Education-Income		.581	.688	.630
Age-Education-Ideology		.593	.677	.632
Age-Income-Ideology		.589	.681	.631
Education-Income-Ideology		.532	.677	.632
Gender-Age-Education-Income		.580	.695	.632
Gender-Age-Education-Ideology		.588	.687	.634
Gender-Age-Income-Ideology		.584	.688	.632
Gender-Education-Income-Ideology		.589	.687	.635
Age-Education-Income-Ideology		.590	.682	.633
Gender-Age-Education-Income-Ideology		.586	.689	.634

Table 11: Precision, Recall, and F1 scores of the positive class on each trait, and their ensembled combinations on MHS in *IPA* setting.

Traits combination	Model	Precision	Recall	F1
Gender	Perspective-Llama	.320	.310	.295
Generation		.318	.314	.267
Education		.330	.338	.312
Race		.311	.310	.292
Gender-Generation		.321	.317	.285
Gender-Education		.325	.321	.302
Gender-Race		.315	.305	.291
Generation-Education		.328	.330	.293
Generation-Race		.316	.313	.281
Education-Race		.321	.324	.302
Gender-Generation-Education		.324	.323	.297
Gender-Generation-Race		.317	.308	.289
Gender-Education-Race		.323	.327	.304
Generation-Education-Race		.321	.317	.294
Gender-Generation-Education-Race		.322	.320	.298
Gender	Perspective-Mixtral	.256	.249	.249
Generation		.262	.252	.251
Education		.279	.256	.257
Race		.246	.242	.241
Gender-Generation		.258	.254	.251
Gender-Education		.264	.248	.251
Gender-Race		.253	.244	.246
Generation-Education		.271	.256	.256
Generation-Race		.258	.253	.251
Education-Race		.267	.256	.255
Gender-Generation-Education		.260	.252	.252
Gender-Generation-Race		.260	.256	.254
Gender-Education-Race		.257	.248	.250
Generation-Education-Race		.262	.255	.254
Gender-Generation-Education-Race		.263	.257	.256
Gender	IPA-Llama	.379	.364	.365
Generation		.392	.385	.385
Education		.390	.370	.375
Race		.374	.359	.363
Gender-Generation		.383	.369	.370
Gender-Education		.386	.368	.372
Gender-Race		.378	.363	.365
Generation-Education		.411	.391	.398
Generation-Race		.396	.381	.385
Education-Race		.377	.361	.365
Gender-Generation-Education		.384	.371	.373
Gender-Generation-Race		.372	.362	.364
Gender-Education-Race		.384	.366	.370
Generation-Education-Race		.389	.370	.375
Gender-Generation-Education-Race		.375	.363	.365
Gender	IPA-Mixtral	.321	.332	.310
Generation		.293	.327	.298
Education		.299	.329	.299
Race		.294	.323	.300
Gender-Generation		.316	.331	.307
Gender-Education		.331	.334	.311
Gender-Race		.309	.329	.306
Generation-Education		.282	.326	.295
Generation-Race		.296	.326	.300
Education-Race		.300	.327	.301
Gender-Generation-Education		.311	.331	.302
Gender-Generation-Race		.302	.328	.302
Gender-Education-Race		.320	.332	.305
Generation-Education-Race		.305	.330	.301
Gender-Generation-Education-Race		.311	.331	.303

Table 12: Macro-averaged Precision, Recall, and F1 scores on each trait, and their ensembled combinations for the DICES dataset.

Dataset	Model	Trait	Label change
Epic	Perspective-Llama	Gender	0.011
		Generation	0.028
		Nationality	0.033
	Perspective-Mixtral	Gender	0.027
		Generation	0.037
		Nationality	0.042
	IPA-Llama	Gender	0.122
		Generation	0.117
		Nationality	0.082
	IPA-Mixtral	Gender	0.173
		Generation	0.163
		Nationality	0.161
MHS	Perspective-Llama	Gender	0.037
		Age	0.053
		Education	0.054
		Income	0.045
		Ideology	0.119
	Perspective-Mixtral	Gender	0.034
		Age	0.021
		Education	0.030
		Income	0.025
		Ideology	0.048
	IPA-Llama	Gender	0.086
		Age	0.085
		Education	0.095
		Income	0.100
		Ideology	0.094
	IPA-Mixtral	Gender	0.078
		Age	0.074
		Education	0.070
		Income	0.084
		Ideology	0.076
DICES	Perspective-Llama	Gender	0.001
		Generation	0.006
		Education	0.006
		Race	0.008
	Perspective-Mixtral	Gender	0.003
		Generation	0.008
		Education	0.006
		Race	0.008
	IPA-Llama	Gender	0.004
		Generation	0.005
		Education	0.007
		Race	0.008
	IPA-Mixtral	Gender	0.007
		Generation	0.007
		Education	0.006
		Race	0.010

Table 13: Normalized label change for each trait.

Model	Trait	Value	JSD
Perspective-Llama	Gender	Male	0.380
		Female	0.326
	Generation	GenX	0.352
		GenY	0.316
		GenZ	0.370
	Nationality	Ireland	0.362
		India	0.386
		UK	0.308
		Australia	0.341
		US	0.291
Perspective-Mixtral	Gender	Male	0.346
		Female	0.283
	Generation	GenX	0.290
		GenY	0.291
		GenZ	0.323
	Nationality	Ireland	0.264
		India	0.370
		UK	0.299
		Australia	0.293
		US	0.271
IPA-Llama	Gender	Male	0.489
		Female	0.466
	Generation	GenX	0.438
		GenY	0.462
		GenZ	0.433
	Nationality	Ireland	0.468
		India	0.508
		UK	0.564
		Australia	0.444
		US	0.441
IPA-Mixtral	Gender	Male	0.432
		Female	0.380
	Generation	GenX	0.358
		GenY	0.393
		GenZ	0.336
	Nationality	Ireland	0.323
		India	0.433
		UK	0.398
		Australia	0.318
		US	0.312

Table 14: Similarity of the distributions between models predictions and annotators' labels for each trait, computed through Jensen-Shannon Divergence (JSD) on EPIC.

Model	Trait	Value	JSD
Perspective-Llama	Gender	female	0.332
		male	0.310
		non-binary	0.387
	Generation	Boomer	0.340
		GenX	0.371
		GenY	0.366
		GenZ	0.384
	Education	high	0.318
		low	0.341
	Income	high	0.457
		low	0.471
	Ideology	liberal	0.354
		conservative	0.491
		neutral	0.436
Perspective-Mixtral	Gender	female	0.281
		male	0.295
		non-binary	0.282
	Generation	Boomer	0.251
		GenX	0.276
		GenY	0.269
		GenZ	0.276
	Education	high	0.283
		low	0.270
	Income	high	0.298
		low	0.276
	Ideology	liberal	0.281
		conservative	0.274
		neutral	0.268
IPA-Llama	Gender	female	0.234
		male	0.250
		non-binary	0.193
	Generation	Boomer	0.239
		GenX	0.238
		GenY	0.233
		GenZ	0.219
	Education	high	0.254
		low	0.249
	Income	high	0.246
		low	0.254
	Ideology	liberal	0.252
		conservative	0.250
		neutral	0.272
IPA-Mixtral	Gender	female	0.215
		male	0.222
		non-binary	0.238
	Generation	Boomer	0.208
		GenX	0.205
		GenY	0.220
		GenZ	0.184
	Education	high	0.228
		low	0.231
	Income	high	0.235
		low	0.227
	Ideology	liberal	0.227
		conservative	0.218
		neutral	0.242

Table 15: Similarity of the distributions between models predictions and annotators' labels for each trait, computed through Jensen-Shannon Divergence (JSD) on MHS.

Model	Trait	Value	JSD
Perspective-Llama	Gender	woman	0.460
		man	0.429
	Generation	Millenial	0.531
		GenX	0.506
		GenZ	0.502
	Education	college degree or higher	0.416
		high school or below	0.432
	Race	Black/African American	0.393
		LatinX, Latino, Hispanic or Spanish Origin	0.453
		Asian/Asian subcontinent	0.463
		White	0.413
		Multiracial	0.408
Perspective-Mixtral	Gender	woman	0.312
		man	0.302
	Generation	millenial	0.311
		GenX	0.271
		GenZ	0.323
	Education	college degree or higher	0.253
		high school or below	0.312
	Race	Black/African American	0.260
		LatinX, Latino, Hispanic or Spanish Origin	0.262
		Asian/Asian subcontinent	0.335
		White	0.294
		Multiracial	0.348
IPA-Llama	Gender	woman	0.166
		man	0.163
	Generation	millenial	0.207
		GenX	0.185
		GenZ	0.178
	Education	college degree or higher	0.193
		high school or below	0.187
	Race	Black/African American	0.202
		LatinX, Latino, Hispanic or Spanish Origin	0.220
		Asian/Asian subcontinent	0.210
		White	0.171
		Multiracial	0.174
IPA-Mixtral	Gender	woman	0.134
		man	0.113
	Generation	millenial	0.115
		GenX	0.120
		GenZ	0.121
	Education	college degree or higher	0.113
		high school or below	0.108
	Race	Black/African American	0.154
		LatinX, Latino, Hispanic or Spanish Origin	0.120
		Asian/Asian subcontinent	0.113
		White	0.116
		Multiracial	0.110

Table 16: Similarity of the distributions between models predictions and annotators' labels for each trait, computed through Jensen-Shannon Divergence (JSD) on DICES.

Model	Trait	Value	JSD
Perspective-Llama	Group	Control	0.151
		Target	0.138
Perspective-Mixtral	Group	Control	0.198
		Target	0.193
IPA-Llama	Group	Control	0.416
		Target	0.302
IPA-Mixtral	Group	Control	0.169
		Target	0.174

Table 17: Similarity of the distributions between models predictions and annotators' labels for each trait, computed through Jensen-Shannon Divergence (JSD) on BREXIT.