

Exploring Cross-Cultural Differences in English Hate Speech Annotations: From Dataset Construction to Analysis

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Abstract

Warning: this paper contains content that may be offensive or upsetting.

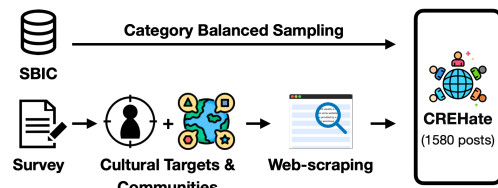
Most hate speech datasets neglect the cultural diversity within a single language, resulting in a critical shortcoming in hate speech detection. To address this, we introduce **CRE-Hate**, a **C**Ross-cultural **E**nglish **H**ate speech dataset. To construct CREHate, we follow a two-step procedure: 1) cultural post collection and 2) cross-cultural annotation. We sample posts from the SBIC dataset, which predominantly represents North America, and collect posts from four geographically diverse English-speaking countries (Australia, United Kingdom, Singapore, and South Africa) using culturally hateful keywords we retrieve from our survey. Annotations are collected from the four countries plus the United States to establish representative labels for each country. Our analysis highlights statistically significant disparities across countries in hate speech annotations. Only 56.2% of the posts in CREHate achieve consensus among all countries, with the highest pairwise label difference rate of 26%. Qualitative analysis shows that label disagreement occurs mostly due to different interpretations of sarcasm and the personal bias of annotators on divisive topics. Lastly, we evaluate large language models (LLMs) under a zero-shot setting and show that current LLMs tend to show higher accuracies on Anglosphere country labels in CREHate. Our dataset and codes are available at: <https://github.com/nlee0212/CREHate>

1 Introduction

Identifying hate speech is highly subjective and relies heavily on an annotator’s understanding and knowledge of the cultural context (Aroyo et al., 2019; Waseem, 2016). Unfortunately, existing English hate speech datasets often overlook the cultural diversity within the posts and the annotators.

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1. Cultural Post Collection



2. Cross-cultural Annotations

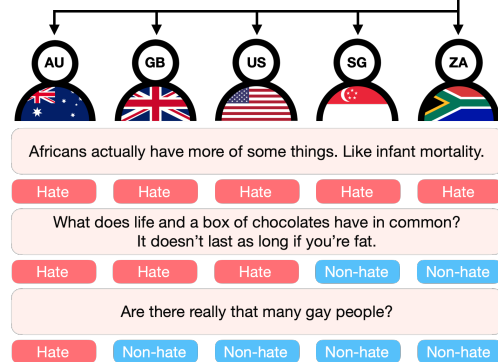


Figure 1: Illustration of the two-step procedure of CREHate construction: 1) cultural post collection and 2) cross-cultural annotation. The examples show how annotations on identical posts differ across countries.

They are predominantly collected from Twitter (Table 1), reflecting a disproportionate representation of certain countries, notably the United States¹. Furthermore, annotators’ geographic location is either neglected or limited to only one or two countries, despite English being spoken in over 50 countries². This limitation hinders the datasets’ ability to capture diverse viewpoints. Figure 1 illustrates how people from different countries show varying hate speech annotations on identical posts.

Our research aims to investigate the influence of cultural diversity on hate speech. To achieve this, we construct a dataset that reflects diversity and examine how cultural background affects the inter-

¹The US has the most Twitter users by country (<https://datareportal.com/essential-twitter-stats>).

²The World Factbook, Languages (<https://www.cia.gov/the-world-factbook/field/languages/>)

pretation of hate speech by annotators. Specifically, we align culture with nationality when exploring how cultural background influences annotators’ interpretations of hate speech. We acknowledge that focusing only on cross-country differences may not fully encompass the multifaceted cultural dynamics within each country. However, it offers a starting point to understand how annotators’ cultural background based on nationality affects language interpretation, particularly in sensitive areas like hate speech. This approach underlines the importance of further, more detailed studies into the complex interplay of cultural identities and their impact on language perception (Kramsch, 2014), especially for enhancing hate speech moderation on global platforms.

To this end, we construct **CREHate**—a **C**Ross-cultural **E**nglish **H**ate speech dataset—comprising 1,580 online posts annotated by individuals from five English-speaking countries: Australia (AU), United Kingdom (GB), Singapore (SG), the United States (US), and South Africa (ZA)³. Construction of CREHate is done in a 2-step procedure: 1) cultural post collection and 2) cross-cultural annotation (Figure 1). For cultural post collection, we collect 600 posts from YouTube and Reddit using keywords gathered from surveys from four countries: AU, GB, SG, and ZA. We also sample 980 posts from SBIC (Sap et al., 2020), a toxic language dataset of social media posts including diverse target groups, primarily reflecting a North American perspective (Table 1)⁴. For cross-cultural annotation, five annotators from each country annotate each post to establish representative labels for each country. Based on cross-cultural considerations, this dataset creation procedure makes CREHate more culturally comprehensive than datasets that ignore cultural differences within English-speaking countries.

We show that cross-cultural annotations of CREHate demonstrate significant differences across countries. Only 56.2% of the entire posts receive unanimous label agreement across all five countries, and the average pairwise agreement between countries is 78.8%, with a maximum label disagreement of 26.0%. The pairwise label agreement distribution among countries exhibits a notable deviation

³Two-letter ISO country codes (<https://www.iso.org/iso-3166-country-codes.html>).

⁴Reddit and Gab’s users are mainly from the US (<https://www.semrush.com/website/reddit.com/overview/>, <https://www.semrush.com/website/gab.com/overview/>), as well as Twitter.

⁵CA refers to Canada.

Datasets	Post Source	Source Country	Annotation Platform (Country)
MLMA (Ousidhoum et al., 2019)	Twitter	US*	MTurk (N/A)
ImplicitHateCorpus (ElSherief et al., 2021)	Twitter	US	MTurk (N/A)
SBIC (Sap et al., 2020)	Twitter, Reddit, Gab, Stormfront	US*	MTurk (US, CA ⁵)
HateXplain (Mathew et al., 2021)	Twitter, Gab	US*	CrowdFlower (N/A)
OLID (Zampieri et al., 2019)	Twitter	US*	CrowdFlower (N/A)
Davidson et al. (2017)	Twitter	US*	CrowdFlower (N/A)
Founta et al. (2018)	Twitter	US*	CrowdFlower (N/A)
CREHate (Ours)	Twitter, Reddit, Gab, Stormfront, YouTube	AU, GB, SG, US*, ZA	MTurk, Prolific, Tictag (AU, GB, SG, US, ZA)

Table 1: Datasets for toxic language detection annotated using crowdsourcing platforms. Existing datasets neglect or limit the cultural backgrounds of the annotators and posts. ‘US*’ means there is a high possibility that the post sources are biased towards US due to the platform’s skewed user demographics, even if not explicitly targeted during the data collection stage.

from that of randomly selected annotator groups, with its average being 2.58σ lower than the average pairwise label agreement of the random groups. Furthermore, by conducting a qualitative analysis of potential reasons for label disagreements, we show that the primary contributing factors are likely due to different understandings of sarcasm and the personal bias of annotators on divisive topics.

Finally, we show that current LLMs tend to show higher accuracy scores on core Anglosphere country labels in CREHate. We further identify the limitations of these models in culture-specific hate speech classification, in which they are asked to predict hate speech based on the target country.

Our main contributions are as follows:

- We build CREHate, a cross-cultural English hate speech dataset including posts and annotations from diverse cultural backgrounds.
- Through quantitative and qualitative analysis, we identify significant variations in hate speech annotations attributed to the cultural backgrounds of the posts and the annotators.
- We show LLMs’ higher accuracies on core Anglosphere country labels in hate speech classification and limitations in making culture-specific predictions.

2 Related Work

Impact of Annotator Demographics. Annotator demographics, such as gender, affect their annotations in NLP datasets (Biestler et al., 2022). Hate speech detection is particularly a subjective task where the demographics can affect the annotations, inter-annotator agreement (IAA), and classifier performance (Waseem, 2016; Sap et al., 2022; Goyal et al., 2022; Larimore et al., 2021; Binns et al., 2017).

Cultural Considerations in Hate Speech Detection. Recent research in offensive language examined cultural differences and built datasets in diverse languages (Lee et al., 2023; Jeong et al., 2022; Jin et al., 2023; Arango Monnar et al., 2022; Deng et al., 2022; Demus et al., 2022; Mubarak et al., 2022), but these papers assume that a single language reflects a single culture. However, languages such as English are spoken by a culturally diverse population, necessitating the consideration of cultural differences among language speakers. Arango Monnar et al. (2022) built the first hate speech dataset for Chilean Spanish to enrich the cultural diversity of Spanish datasets. They evaluated knowledge transfer performance on another Spanish dataset with a different cultural background, but the impact of cultural background on annotations was unexplored. We aim to conduct a thorough study of how hate speech and its annotations vary across English-speaking countries.

Multiple Cultures in English NLP. Frenda et al. (2023) developed a corpus for irony detection, focusing on which annotator demographic group’s perspectives are more represented by majority voting. They collected posts and gathered annotators from five English-speaking countries: Ireland, India, AU, GB, and US. Our study, focusing on hate speech detection, extends the scope by collecting posts as well as annotations from different cultures and investigating the annotation disparities stemming from cultural variations.

3 Dataset Construction

This section describes the construction process of CREHate, an English hate speech dataset with both posts and annotations collected from five different countries to analyze the country-level divergences when it comes to hate speech. We follow a 2-step procedure: 1) cultural post collection and 2) cross-cultural annotation. The dataset consists of 1,580 posts, each with five labels representing five countries, resulting in a total of 7,900 labels. Dataset

Data	Source	# Posts
CREHate	Reddit	568
	Twitter	273
	Gab	80
	Stormfront	59
	<i>subtotal</i>	<i>980</i>
CP	Reddit	311
	YouTube	289
	<i>subtotal</i>	<i>600</i>
total	1,580	

Table 2: Data statistics and sources of CREHate. CC-SBIC refers to cross-culturally re-annotated SBIC posts. CP refers to additionally collected cultural posts from four countries (AU, GB, SG, and ZA), which are also cross-culturally annotated.

statistics are shown in Table 2.

English-speaking Countries. We choose one country from each continent to ensure geographical diversity while also considering cultural differences within and outside the Anglo-American sphere of influence (Cox and O’Connor, 2020; Gamble, 2021). Specifically, we select three core Anglo-sphere countries—AU, GB, and US (Davies et al., 2013)—and two countries with English as official language but not necessarily the primary language—SG and ZA (Khokhlova, 2015; Tan, 1997).

3.1 CREHate Post Collection

3.1.1 Sampling from SBIC

To incorporate hate speech targeting diverse groups, we sample posts from the SBIC dataset (Sap et al., 2020), which contains annotations of offensive posts targeted towards different demographic groups and minorities. From SBIC, we sample 980 posts while balancing the target group categories. The details of SBIC and the sampling process are specified in Appendix A.1.1. This set of sampled posts is referred to as CC-SBIC (Cross-Cultural SBIC) throughout the paper, as it is cross-culturally re-annotated as mentioned in §3.2.

3.1.2 Collecting Cultural Samples

The sources of SBIC’s posts are culturally skewed towards the US, resulting in a bias towards prevalent target groups and the cultural context of the US. To address this issue, we collect and annotate 150 cultural online posts each (a total of 600 posts) from four English-speaking countries: AU, GB, SG, and ZA. The posts are collectively referred to as CP, and the country-specific posts are called CP_{AU} , CP_{GB} , CP_{SG} , and CP_{ZA} , respectively.

Data	Post	AU	GB	SG	US	ZA
CC-SBIC	Why did they plant trees in harlem? For free public transit.	○	○	○	○	×
CP _{AU}	The special treatment is for real abbos only..... equality.	○	○	×	×	○
CP _{GB}	@USER A pikey calling someone uneducated. The irony is painful.	×	○	○	○	○
CP _{SG}	The attitude of Malays being "holier than thou" is kinda sickening. Have experienced it many times, sadly it's not gonna stop.	○	○	×	×	○
CP _{ZA}	I wonder when people will recognize the EFF for what it really is. It's not a political party, it's a terrorist organization.	×	×	×	×	○

Table 3: Examples of annotated posts in CREHate. ○ refers to ‘hate’, and × refers to ‘non-hate’ label. The example posts require culture-specific knowledge on target minorities (abbos, Malays), locations (Harlem), public organizations (EFF), and slang (pikey). People from different countries provide different hate speech annotations for posts including culture-specific context.

Keyword Collection. To efficiently gather hate speech posts, we use words that refer to specific demographic groups that are often subjected to hate as queries. We recruit workers whose nationality and current residency match our target country and who have spent most of their lives in their respective countries to obtain the most appropriate and culturally relevant keywords. We ask them to provide commonly targeted groups and possible hateful keywords that may refer to them within their culture. We collect target groups in *race/ethnicity*, *gender/sexuality*, and *religion/culture* categories, the three main categories within the original SBIC dataset. We continue collecting until we gather at least 20 keywords per country.

Post Collection. We gather popular social media and news sites from the workers in their countries and select Reddit as our primary social media platform for collecting comments, as it is widely used across all countries. We also crawl comments from the YouTube channels of news sites in each country. To ensure that we have enough potentially hateful posts in our dataset, we go through a pre-annotation stage, gathering only two annotations from the country the post originated from. Based on the pre-annotation results, we finalize 150 posts to be annotated from each country, maintaining the ratio of posts labeled as hate between 39.8% and 48.5% for each country⁶. As a result, the posts from each culture contain some unique topics and keywords, such as ‘*abo*’ or ‘*lebs*’ in CP_{AU}, ‘*gypsy*’ or ‘*paki*’ in CP_{GB}, ‘*malay*’ or ‘*pinoy*’ in CP_{SG}, and ‘*boer*’ or ‘*EFF*’ in CP_{ZA}.

3.2 Cross-Cultural Annotation

Annotator Recruitment. We recruit annotators from five countries, applying the same annotator

⁶Specific post crawling and sampling process is provided in Appendix A.1.2.

qualifications as we used for keyword collection, from Prolific⁷ (AU, GB, ZA), Amazon Mechanical Turk⁸ (US), and Tictag⁹ (SG) depending on annotator recruitment availability of the desired country. As a result, we have 1,061 annotators, balancing their gender but not restricting others for a broader representation of demographics (Frenda et al., 2023). Table 11 shows a detailed demographic distribution of annotators.

Annotation Process. Before annotating, annotators are required to review the definitions¹⁰ and examples of hate and non-hate speech. Examples are selected among posts with identical labels across all countries from the pilot study. The task is to annotate posts as either *Hate* or *Non-hate*, with an additional option of *I don’t know*¹¹. We obtain five *Hate* or *Non-hate* labels for each post from each country. The specific annotation process and quality control methods are in Appendix A.3.

Label Finalization. After gathering all five annotations, we use majority voting to finalize the representative labels for each country. Examples of posts with labels from each country are presented in Table 3.

4 Analysis on the Annotations

In this section, we show that varying cultural backgrounds of annotators and posts lead to a significant disparity in hate speech annotation.

⁷<https://www.prolific.co/>

⁸<https://www.mturk.com/>

⁹<https://www.tictagkr.com/>

¹⁰<https://www.un.org/en/hate-speech/understanding-hate-speech/what-is-hate-speech>

¹¹The *I don’t know* labels took up about 3-7% of the raw annotations, and more analysis on these labels are mentioned in Appendix B.

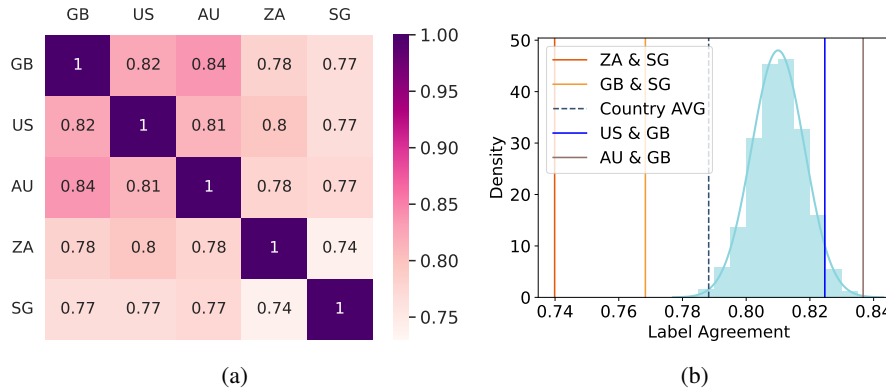


Figure 2: (a) Pairwise label agreements across countries ordered by the average agreement with others. Labels from Singapore tend to be the most different. (b) Comparison of the label agreements among country pairs and random ones. The histogram and its density function show the distribution of pairwise label agreements among randomly selected annotator groups. The solid lines indicate country pairs with top-2 and bottom-2 label agreement scores, and the dashed line indicates the average of label agreements of all country pairs. Countries that are closely related exhibit high label agreements compared to the random annotator groups, whereas culturally distant countries show significantly low label agreements compared to label agreements from random annotator groups.

4.1 Significance of Cultural Backgrounds

To analyze the role of an annotator’s cultural background in hate speech detection, we obtain labels representative of different demographic categories¹² using majority voting. We only collect labels from groups with at least three annotators per post on average. Labels from each group are subjected to chi-squared tests, and the results indicate significant disparities in annotations across country ($p = 0.000$), race ($p = 0.002$), gender ($p = 0.006$), and education level ($p = 0.000$), while there were no significant differences for other groups. Several studies have shown the importance of race or gender of annotators (Pei and Jurgens, 2023; Sachdeva et al., 2022), whereas the impact of annotators’ cultural background has been underexplored.

4.2 Label Agreement among Countries

Pairwise Country Label Agreement. Overall, only 56.2% of the posts achieve unanimous agreement across all countries, with 25.5% of the posts showing agreement across four countries. To further explore the label differences across cultures, we examine the label agreements between all pairs of countries, as shown in Figure 2a. It suggests pairwise label agreements among core Anglosphere countries are greater than those observed in other country pairs. Among all countries, AU and GB exhibit the highest label agreement at 83.7%, while SG and ZA show the lowest agreement at 74.0%.

We compare these results to the cultural distance

index (Kogut and Singh, 1988)¹³ between countries, which measures the degree to which cultural norms in two countries differ (Table 13). The cultural distance and the hate speech label agreements among the countries show a high negative Pearson correlation with $r = -0.658$ ($p = 0.039$). This implies that country pairs with more considerable cultural distances have lower label agreement. SG and ZA, the country pair with the lowest label agreement, show a higher cultural distance (2.178) than AU and GB (0.144), the country pair with the highest agreement.

Furthermore, to investigate the pairwise label differences on identical posts across different countries, we employ the McNemar Test (McNemar, 1947). The results indicate significant pairwise label disparity between 8 out of 10 country pairs.

Comparison with Random Annotator Groups.

To show that label disparities stem from the annotators’ cultural backgrounds rather than random variations among individuals, we compare the pairwise country label agreements with the distribution of label agreements between randomly organized annotator groups. For each post, we create two groups of five randomly selected annotations out of 25 (5 from each country) and construct representative labels from each group via majority voting. We calculate the label agreement of the two groups for the whole dataset and repeat this process 10^5 times. The outcomes of this comparison, illustrated in Figure 2b, include a histogram and an estimated normal distribution curve of the label agree-

¹²For more details on the demographic categories analyzed and their statistics, please refer to Table 11 in the Appendix.

¹³A value of 0 indicates identical cultural norms, while a value close to 1 indicates average distance among all countries.

	Agreement	H-F1	N-F1
CREHate	0.7882	0.7636	0.8077
CC-SBIC	0.8045	0.8034	0.8050
CP	0.7617	0.6762	0.8108
CP_{AU}	0.7293	0.6937	0.7565
CP_{GB}	0.7493	0.6851	0.7913
CP_{SG}	0.7827	0.6583	0.8390
CP_{ZA}	0.7853	0.6565	0.8433

Table 4: The average pairwise label agreement scores (Agreement), F1 scores for hate (H-F1), and non-hate (N-F1) labels among all country pairs. Our cultural posts (CP) show lower average pairwise country label agreement and lower F1 scores for hate labels.

ments among these random groups. Based on the D’Agostino-Pearson normality test (D’Agostino and Pearson, 1973), the label agreements among random annotators follow a normal distribution with $\mu = 0.81$ and $\sigma = 0.008$.

A critical observation from our analysis is the notable disparity in label agreements when comparing different countries. Specifically, the two highest label agreements, observed between core Anglosphere countries (US & GB, AU & GB), exceed the average agreement of the random groups by 1.77σ and 3.22σ , respectively. However, the two lowest agreements observed between culturally distant countries (GB & SG, ZA & SG) fall significantly below this average, at 5.01σ and 8.44σ . This pronounced disparity, along with the average pairwise label agreement between different countries being 2.62σ lower than the average for random groups, strongly indicates that variations in perceptions of hate speech are not merely random differences among individuals. Instead, they are significantly influenced by cultural factors, showing more consistency within Anglosphere countries but substantial variation among other countries. This underscores the critical role of cultural contexts in hate speech detection and annotation across different English-speaking countries.

Label Agreements on Subsets of CREHate. We also analyze label agreements among countries on different subsets of CREHate (Table 4). Firstly, we compare the label agreements on two disjoint subsets of CREHate, CC-SBIC and CP. Our findings reveal that CP has a lower average pairwise label agreement than CC-SBIC. Although the two divisions show similar average pairwise F1 scores for non-hate labels, the F1 score for hate labels on CP significantly lags behind CC-SBIC’s. This implies that CP derives more considerable label disparities for identifying one post as hate compared to

Categories	Subtypes
Sloppy Annotation	noise
Ambiguity	analogy, false assertion, rhetorical question, sarcasm, word play, reported speech
Missing Information	ungrammatical, no context, not complete
Subjectivity	personal bias, swearing, threatening

Table 5: Taxonomy of annotators’ disagreement in subjective tasks. We annotate the possible reasons behind label disagreements between countries, on top of culture-relevance labeling.

Data	Post	Reason Type
CP _{AU}	You’re Irish and you support your pals the Provisional IRA murderers of the innocent Australian civilians Stephen Melrose and Nick Spanos. You support terrorists.	personal bias
CP _{GB}	Gays have cards? are they sparkly?	sarcasm
CP _{SG}	So with the repeal of 377A, married men are going to church to have gay sex?	not complete

Table 6: Examples of disagreement reason annotation. For a sampled set of posts that countries disagree on, we annotate the possible reasons behind the disagreements following the disagreement reason taxonomy for subjective tasks by Sandri et al. (2023).

CC-SBIC. This trend is consistent across all sets of posts collected from different countries.

Annotator Agreement. Krippendorff’s α is used to calculate IAA in US ($\alpha = 0.462$), GB ($\alpha = 0.425$), AU ($\alpha = 0.408$), ZA ($\alpha = 0.351$), and SG ($\alpha = 0.344$). These are higher than or comparable to those achieved in previous work in toxic language detection (Ross et al., 2016; Sap et al., 2020).

4.3 Annotators’ Disagreement Analysis

We analyze the main factors behind label disagreements across countries using the taxonomy of reasons for annotators’ disagreement for subjective tasks proposed by Sandri et al. (2023). The categories and subtypes of the taxonomy are shown in Table 5. Appendix D shows detailed definitions and examples for each reason type. Some of the annotated examples are shown in Table 6.

Disagreement Reason Annotation. Among the 1,580 posts in CREHate, 692 posts exhibit label discrepancies across countries. To conduct a thorough analysis, we randomly sample 400 posts, including 200 posts from CC-SBIC and 50 posts from each of the four country’s CP posts. After a norming session, in which we clarify category definitions and apply them to our task, two authors annotate

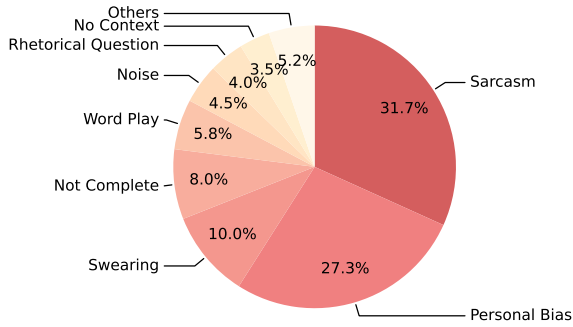


Figure 3: Ratio of disagreement reasons within posts. Differing interpretations of sarcasm and personal bias on divisive topics contribute to the main factors of disagreement.

all sampled posts. The initial Cohen’s Kappa score from the two authors is 0.556, which is comparable to that of the annotations in Sandri et al. (2023) (0.591), done by two linguists. After that, the authors go through a discussion stage to establish a consensus on all labels. As a result, the labels on the reasons for disagreement are finalized based on a unanimous agreement between the authors.

Possible Factors behind Disagreement. Overall, *ambiguity* and *subjectivity* of the posts contributed the most to the disagreements, taking up 44.3% and 37.5%, respectively. Among the lower-level subtype reasons, *sarcasm* was the most frequently observed, followed by *personal bias*, *swearing*, and *not complete* as shown in Figure 3. A detailed analysis comparing CC-SBIC and CP’s main disagreement reasons are shown in Appendix 4.3.

Sarcasm heightens challenges in intercultural agreement in hate speech annotation, as annotators’ sensitivity to sarcasm may vary depending on the topic and the annotators’ cultural backgrounds. Furthermore, sarcasm referring to a specific culture-specific context may be difficult for annotators from different backgrounds to accurately identify.

Personal bias also plays a significant role in label disagreements, as they may arise when annotators hold differing opinions about specific topics, especially divisive issues. For example, if the post is about divisive topics within the annotator’s culture, their personal bias would have a larger impact on the annotation.

Swearing is important in label disagreement since annotators’ perceived offensiveness of a swear word can vary depending on their backgrounds. Different cultures may have varying perceptions of swear words based on their usage and social context, resulting in label disagreements on

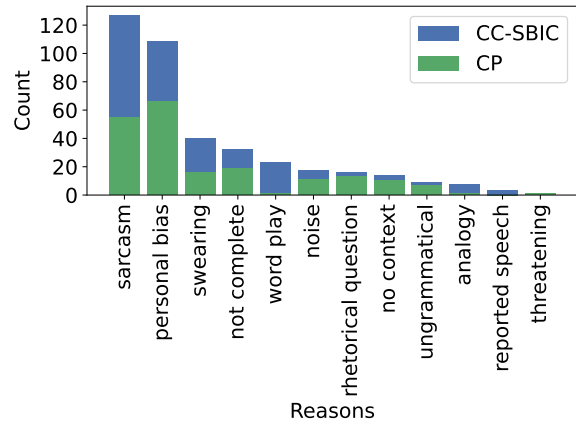


Figure 4: Disagreement reason count for CC-SBIC and CP posts.

the text containing them.

Not complete indicates insufficient information for annotators to fully comprehend the post. Annotators from diverse cultures may struggle to label posts involving cultural references or nuances from other cultures when crucial information is missing, requiring extra cultural background knowledge.

Comparison between CC-SBIC and CP. Figure 4 shows the counts of all disagreement reason subtypes within CC-SBIC and CP posts. In both CC-SBIC and CP, *sarcasm* and *personal bias* are the two most significantly contributing reasons for label disagreements. However, there are some differences in the reasons for disagreement between the two dataset divisions. First of all, CP has more posts that the label disagreement is due to the *personal bias* of annotators. This could be attributed to the comments on YouTube news videos included in CP, which primarily involve the authors’ opinions on social issues handled within the videos. In addition, since CP posts contain more culturally intense topics within different countries in contrast to SBIC, they contain more *not complete* posts, which require cultural knowledge for full comprehension. On the other hand, CC-SBIC has more posts containing *word play* and *swearing* compared to CP. One possible reason for this result is that people tend to be less constrained and write more freely on Twitter and hate sites, primary data collection sources not included in CP, compared to YouTube news comments.

5 Experiments

This section evaluates the performance of current LLMs in hate speech classification on CREHate, with a specific focus on analyzing their perfor-

mance with respect to country-specific annotations. **Experimental Settings.** We conduct zero-shot experiments using a multiple-choice question format. We use five variations of the question prompt, each presented with two answer options: ‘Hate’ and ‘Non-hate.’ We test both answer option orders for all prompts, resulting in 10 formats¹⁴. All 1,580 instances of the CREHate corpus are used in the experiments, and all the prompts are generated by the authors.

The experiments are divided into two parts. In §5.1, we ask the model to predict whether a given post is hate speech. In §5.2, we add a target country to the question prompt to examine the model’s ability to make culture-specific predictions in hate speech detection. For all results, we present the average values for all variations and perform a Wilcoxon rank-sum test to determine any statistically significant differences between each model’s highest and lowest accuracy scores across different countries.

The models evaluated include GPT-4 (gpt-4-1106-preview), GPT-3.5 (gpt-3.5-turbo-1106), Orca 2 (7B) (Mitra et al., 2023), Flan-T5-XXL (Chung et al., 2022), and OPT (Iyer et al., 2022)¹⁵.

5.1 Zero-shot Predictions and Country Labels

We obtain the predictions of LLMs using prompts such as:

Answer if this post is hate or not with a single alphabet letter among given answer choices a and b.

Table 7 shows that the accuracy scores of all models, except for GPT models, are below 73% when evaluated against all country labels on CREHate. We also assess whether LLM-based hate speech predictions are biased towards particular cultures by comparing the accuracy of model predictions against the labels from each country. Our analysis reveals that GPT models exhibit cultural bias, as their predictions display higher accuracy to the core Anglosphere cultures’ labels. While GPT-4 shows the highest overall accuracy across all country labels with an average value of 78.2%, it also exhibits a significant performance gap with a maximum value of 6.79%, most prominently between US labels (highest accuracy) and SG labels (low-

¹⁴The prompts we use are listed in Appendix E.1.

¹⁵For GPT models, we use the OpenAI API and set the temperature as 0 to use greedy decoding (<https://platform.openai.com/docs/models>). For other models, we use the Huggingface Transformers (Wolf et al., 2020) library (<https://github.com/huggingface/transformers>).

Model	Data	GB	US	AU	ZA	SG
GPT-4	CREHate	79.66	80.64*	78.02	78.03	<u>74.65</u>
	CC-SBIC	80.74	82.13*	79.28	80.63	<u>75.34</u>
	CP	77.91	78.21*	75.96	73.79	<u>73.54</u>
GPT-3.5	CREHate	72.47*	70.62	72.39	<u>69.28</u>	71.94
	CC-SBIC	75.73	75.00	75.75*	<u>73.20</u>	75.10
	CP	67.13*	63.47	66.90	<u>62.87</u>	66.77
Orca 2	CREHate	69.99	69.09	69.80	68.80	<u>68.61</u>
	CC-SBIC	72.19	72.58	72.13	72.15	<u>70.87</u>
	CP	66.38	63.38	65.98	<u>63.32</u>	64.92
Flan T5	CREHate	68.58	<u>67.49</u>	68.28	68.35	68.15
	CC-SBIC	72.49	72.86*	71.84	71.63	<u>70.35</u>
	CP	62.18	<u>58.72</u>	62.48	62.98	64.55*
OPT	CREHate	66.25	69.29	64.68	66.94	<u>64.11</u>
	CC-SBIC	65.22	68.75	64.27	67.68	<u>63.06</u>
	CP	67.93	70.18*	<u>65.36</u>	65.72	65.83

Table 7: Accuracy of the models in terms of each country’s labels in each dataset division. The highest score is highlighted in **bold**, while the lowest score is underlined. The asterisk (*) means the two values differ significantly ($p < 0.05$).

est accuracy). These findings suggest that high model accuracy does not necessarily equate to fairness, highlighting the need for more diverse training datasets and methods to mitigate cultural biases.

To determine if the IAA differences among countries (as shown in §4.2) are the primary cause of varying accuracies, we examine the model accuracy on posts with unanimous annotator agreement within each country¹⁶. Our analysis reveals that GPT-4 shows higher accuracy for US labels (95.25%) and lower accuracy for SG labels (87.11%), even on unanimously agreed posts. This suggests that the bias is inherent to the model’s processing rather than a reflection of annotation quality.

Furthermore, we observe that the overall accuracy for CP posts is lower than that of CC-SBIC across all countries. Even for posts with unanimous annotator agreement within each country for the two dataset divisions, accuracies for CC-SBIC are higher than those on CP for most models. This indicates difficulties in models classifying hate speech in CP posts explicitly sourced from countries other than the US.

5.2 Culture-Specific Hate Speech Classification

In this section, we explore the culture-specific hate speech classification capability of GPT-4, which is the model that performed better overall in our pre-

¹⁶Please refer to Table 14 for the results for all models in the Appendix.

Prompt	GB	US	AU	ZA	SG
Original	79.66	80.64*	78.02	78.03	<u>74.65</u>
+ in GB	79.66	80.28*	77.97	77.36	<u>73.52</u>
+ in US	79.27	80.26*	77.34	77.09	<u>73.32</u>
+ in AU	79.62*	79.59	77.95	77.40	<u>73.48</u>
+ in ZA	79.07	79.61*	77.38	77.44	<u>72.91</u>
+ in SG	79.70*	79.56	78.02	77.53	<u>73.27</u>

Table 8: Accuracy of GPT-4 in terms of each country labels when asked to predict whether a given post is hateful within specific countries (e.g., “Answer if this post is hate or not in Australia.”). The highest score is highlighted in **bold**, while the lowest score is underlined. The asterisk (*) means the two values differ significantly ($p < 0.05$).

vious experiment. We aim to evaluate the model’s ability to make culturally tailored predictions regarding hate speech classification using prompts that target specific countries:

Answer if this post is hate or not **in {country}** with a single alphabet letter among given answer choices a and b.

Our analysis indicates that GPT-4’s performance remains consistent, regardless of including specific country information in the prompts, as shown in Table 8. The inclusion of country names in the prompts led to only a marginal variation in predictions, with a 6.5-8% difference from the predictions obtained using the original, non-country-specific prompts. This finding implies that providing country context alone does not significantly enhance GPT-4’s ability to identify hate speech accurately across different cultural contexts. Consequently, this underscores a limitation in the model’s capability to adapt its hate speech detection to specific cultural nuances merely through the explicit mention of a country in the prompt. However, introducing cultural background information or other extra knowledge about the target country, or even using different prompts, may show different results. We leave the exploration of prompt engineering that could enhance culture-specific hate speech detection in LLMs for future work.

6 Conclusion

In this paper, we analyze how cultural differences across English-speaking countries affect hate speech annotations. To this end, we develop CREHate, a cross-cultural English hate speech dataset comprising 1,580 posts from five English-speaking countries—AU, GB, SG, US, and ZA. Our work shows that there are notable variations in hate speech interpretations between these countries

through various statistical methods. The overall agreement on hate speech identification across all countries is only 56.2%, with an average pairwise country disagreement of 21.2%. Qualitative analysis suggests these differences stem from varied understandings of sarcasm and annotators’ biases on divisive topics. We also discover that GPT models display higher accuracies with labels from Anglo-sphere cultures and fail to make culturally tailored predictions when the target country is given.

This research establishes a foundational framework for continuously evaluating and adapting hate speech models and datasets. We suggest expanding CREHate to include more countries and posts to create a comprehensive tool for assessing cultural biases in model predictions and enhancing culturally tailored hate speech detection. We urge collaborative efforts in constructing datasets with broad cultural references and contextual nuances. Annotators with relevant cultural knowledge should be employed to construct a more representative cultural dataset. Such a comprehensive approach is crucial for developing more effective, culturally sensitive hate speech classifiers and promoting safer and more inclusive online communication.

Current hate speech detection tools often struggle with cultural biases, particularly skewing toward US or Western perspectives. This results in inadequate representation and understanding of socio-cultural contexts from other English-speaking countries. For example, a phrase considered derogatory in one culture might be benign in another, leading to false positives or negatives in detection. Interpretations of posts can vary significantly between cultures, influenced by factors like local idioms, societal norms, and historical contexts. Therefore, a more nuanced and inclusive approach to dataset creation and algorithm development is needed to ensure broader cultural representation and sensitivity.

Limitations

CREHate consists of 1,580 posts, making it relatively small compared to other existing English hate speech datasets. Moreover, the collection of culture-specific posts was limited to Reddit and YouTube based on fixed hate-related keywords, which may introduce bias into the collected posts. Also, employing a single crowdsourcing platform for collecting each country’s annotation may lead to annotator bias, as different platforms possess varying user demographics. To enhance the repre-

sentativeness and generalizability of our findings, we anticipate future efforts to expand our dataset by using diverse platforms and post collection methods.

Considering that many countries are multi-cultural, it is also essential to examine within-country annotation differences. For instance, Singapore has a diverse population, including Chinese, Malaysians, and Indians. Exploring hate speech annotation differences across different ethnicities within a country presents another avenue for investigation. Moreover, although we recruit annotators from countries where English is one of their official language(s), this may not be enough to cover all English-speaking cultures. Further study is needed to include English as a Foreign Language (EFL) learners in cross-cultural hate speech detection. Moreover, the same approach could be extended to languages other than English (e.g., Spanish) spoken in various countries.

There are other subjective tasks that are affected by cultural context, such as common sense reasoning. Future research could extend the scope of our study to other tasks by constructing datasets tailored towards specific cultures, both within and across countries with diverse languages.

Ethics Statement

This research project was performed under approval from KAIST IRB (KH2023-068). The instructions that were given to the annotators, including the disclaimer, can be seen in Figure 5 in the Appendix. We made sure to inform the annotators from the crowdsourcing platforms that the contents they encounter during the annotation task may potentially be offensive or distressing. We also provided access to online therapy platforms and encouraged the annotators to seek help in case they experience any strong negative reactions or mental distress.

We conducted our crowd worker recruitment without any discrimination based on age, ethnicity, disability, or gender. Our workers are compensated at a rate higher than Prolific’s ethical standards. Our payment principles are based on the ethical standards of Prolific, and we ensure that our workers are compensated at a rate higher than the minimum wage of £9.00 per hour. It is worth noting that this amount exceeds the federal minimum wage in the United States and Singapore, where the annotation process was held on other crowdsourcing platforms.

We are aware of the potential risk involved in releasing a dataset containing hate speech or offensive language. We will explicitly state the terms of usage, emphasizing our unequivocal disapproval of any form of malicious exploitation. We urge researchers and practitioners to harness this dataset only for constructive purposes. We expect our dataset to contribute to developing more equitable and culturally sensitive automated content moderation systems. We emphasize our unequivocal disapproval of any form of malicious exploitation of our dataset, including any misuse of our dataset for generating hateful language. We demand that researchers and practitioners use this dataset solely for constructive purposes.

We used AI assistants — ChatGPT¹⁷, Google Translate¹⁸, and Grammarly¹⁹ — to assist with editing and translating sentences in our paper writing. The CREHate dataset is licensed under CC BY-SA 4.0.

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¹⁷<https://chat.openai.com>

¹⁸<https://translate.google.com>

¹⁹<https://app.grammarly.com>

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Appendix

A Dataset Construction Details

A.1 Post Collection

A.1.1 SBIC

Category	Original Test Set (%)	Sampled Dataset (%)
Race/Ethnicity	819 (17.5)	150 (15.3)
Gender/Sexuality	503 (10.7)	150 (15.3)
Religion/Culture	495 (10.6)	150 (15.3)
Victims	215 (4.6)	150 (15.3)
Disability	112 (2.4)	112 (11.4)
Social/Political	104 (2.2)	104 (10.6)
Body/Age	58 (1.2)	58 (5.9)
Non-hate	2765 (58.9)	327 (33.4)
Total	4691	980

Table 9: Category distribution within the original and the sampled SBIC test set. CC-SBIC posts are comprised of randomly sampled 980 posts from the original SBIC test set, maintaining balance among target group categories. Multi-labeled group categories are split into multiple individual categories when counting.

Source	Reddit	YouTube
AU	r/australia, r/Australian, r/melbourne, r/sydney, r/perth, r/brisbane, r/Adelaide	Sky News Australia
GB	r/unitedkingdom, r/CasualUK, r/england, r/Scotland, r/Wales, r/northernireland	SkyNews, GBNews
SG	r/singapore, r/SingaporeRaw, r/singaporehappenings, r/singapuraa	CNA, The Straits Times
ZA	r/southafrica, r/RSA, r/capetown, r/johannesburg, r/Durban, r/Pretoria	SABC News, eNCA

Table 10: Data sources for each country. We crawled comments from country-specific subreddits and news platforms’ YouTube channels.

Posts in SBIC originate from subReddits, microaggressions corpus (Breitfeller et al., 2019), Twitter (Founta et al., 2018; Davidson et al., 2017; Waseem and Hovy, 2016), and hate sites (Gab²⁰ and Stormfront (de Gibert et al., 2018)). The dataset contains offensive posts targeted towards diverse demographic group categories, including *race/ethnicity, gender/sexuality, religion/culture, victims, disability, social/political, and body/age*. We maintain a 2:1 ratio between hateful and non-hateful posts in our sampled SBIC data to prioritize our analysis on hate speech rather than non-hate speech. The sampled SBIC data statistics are shown in Table 9.

A.1.2 Cultural Posts

Specific subReddits and news sites used for post crawling are shown in Table 10. There is only one news site for Australia, as no other YouTube channels of news sites provided by the workers allow comments. On Reddit, we extract all comments on the posts that include the target group names or the keywords provided by workers. On YouTube, we search using the query, ‘<media name> + <target group name>’, to locate comments related to the target groups (e.g., ‘BBC news pakistani’). We only include comments and posts written in 2020 or later for an up-to-date dataset.

After crawling cultural posts from the four countries, we go through a pre-annotation stage in order to balance hate and non-hate speech in our dataset to the extent possible. The process begins by randomly selecting 300 comments from each country, balancing those from Reddit and YouTube. We then obtain two annotations per comment from the source country of the comments. Subsequently, we curate a collection of 150 comments by selecting 50 from each of the three hate annotation counts, ranging from 0 to 2. With this procedure, we get

²⁰https://files.pushshift.io/gab/GABPOSTS_CORPUS.xz

	AU	GB	US	SG	ZA
No. of Annotators	216	405	166	103	173
Gender (%)					
male	51.39	45.68	53.61	54.46	50.29
female	46.30	52.35	46.39	44.55	48.55
non-binary	2.31	1.98	-	0.99	1.16
Race (%)					
Asian	23.61	4.20	4.22	100.00	4.05
Black	0.46	2.72	6.63	-	77.46
Hispanic	-	0.25	0.60	-	-
Middle Eastern	1.85	0.25	0.60	-	0.58
White	67.59	89.14	86.75	-	11.56
Other	6.49	3.44	1.20	-	6.35
Level of Education (%)					
Below High School	1.39	0.74	-	-	-
High School	11.11	14.07	16.87	15.84	16.76
College	20.83	23.70	36.14	15.84	28.90
Bachelor	46.30	43.95	40.96	62.38	48.55
Master’s Degree	17.59	15.80	4.82	5.94	5.78
Doctorate	2.78	1.73	1.20	-	-
Age (%)					
18-19	2.31	1.73	-	1.98	0.58
20-29	52.31	27.90	3.01	60.40	73.41
30-39	22.22	27.90	41.57	27.72	18.50
40-49	15.28	21.73	25.90	2.97	2.89
50-59	4.63	13.58	18.07	1.98	2.89
60-69	2.31	5.43	9.04	4.95	1.73
70-79	0.46	1.73	2.41	-	-
80-89	0.46	-	-	-	-
Political Orientation (%)					
Liberal/Progressive	42.59	29.88	39.76	15.84	21.97
Moderate Liberal	27.78	29.38	22.89	19.80	19.08
Independent	18.52	17.53	11.45	37.62	35.26
Moderate Conservative	6.02	14.07	16.27	14.85	14.45
Conservative	3.70	5.68	9.04	9.90	9.25
Other	1.39	3.46	0.60	1.99	-
Religion (%)					
None	64.81	62.47	50.60	38.61	16.19
Christian	20.83	28.89	37.95	26.73	75.72
Buddhism	2.78	0.74	-	24.75	-
Islam	0.93	3.21	0.60	4.95	3.47
Judaism	-	0.49	1.81	1.98	-
Hinduism	0.46	0.25	-	-	-
Irreligion	5.56	1.23	3.61	-	0.58
Other	4.63	2.72	5.42	2.98	4.04

Table 11: Annotator demographic statistics from each country.

600 cultural posts from four countries.

A.1.3 Post-processing of Posts

SBIC posts and crawled Reddit and YouTube comments contained usernames and URLs that were not masked. To anonymize all posts, we mask the usernames as @USER, and URLs as URL.

A.1.4 Terms of Use

Our research is performed in the public interest under GDPR, as we meet the substantial public interest conditions as academic research. The SBIC dataset is licensed under CC BY 4.0. We use Reddit’s official data API, following the terms of

use mentioned in ‘Data API Terms’²¹. We use YouTube API from Google for Developers site, following the terms of use mentioned in Complying with YouTube’s Developer Policies page²². The CREHate dataset is licensed under CC BY-SA 4.0.

A.2 Annotator Demographics

Table 11 shows the total number of annotators and the proportion of all demographic groups among annotators from each country. The first three demographic categories—gender, ethnicity, and level of education—are shown to be factors that significantly affect hateful post annotations.

A.3 Annotation Process

Disclaimer and instruction are first shown to the annotators, as shown in Figure 5. Each annotator is then asked to answer a demographic survey. If the annotator matches our target group mentioned in Section §3.1.2, annotators proceed to the guideline page shown in Figure 6. After reading the guideline for a minimum of 30 seconds, annotators are asked to annotate 15 posts (Figure 7) that are randomly assigned among the remaining ones.

We include two explicit and two implicit attention check questions among the annotation questions to ensure the dataset’s quality. The implicit attention check questions are selected from the samples on which all annotators from all countries agree in previously completed annotations. For the first round of the actual survey, we choose samples with total agreement from the pilot study. As the study progresses, we update them with the new samples the annotators agreed on. The two explicit attention checks instruct the annotators to choose a specific label. Only annotations from annotators that pass all attention checks are included in the dataset. To avoid a single annotator significantly affecting the annotation, each annotator can only contribute to a maximum of 5% of the total annotation.

B Analysis on *I Don’t Know* Labels

Table 12 reveals that the annotations in CREHate dataset contain only a few *I don’t know* labels. Across all countries, the ratio of *I don’t know* labels per post is only around 5% within CREHate. Notably, annotations from the US exhibit a lower

²¹<https://www.redditinc.com/policies/data-api-terms>

²²<https://developers.google.com/youtube/terms/developer-policies-guide?hl=en>

	AU	GB	SG	US	ZA
CREHate	0.0630	0.0678	0.0628	0.0273	0.0582
CC-SBIC	0.0504	0.0552	0.0712	0.0281	0.0532
CP	0.0835	0.0885	0.0491	0.0260	0.0663
CP _{AU}	0.0482	0.0749	0.0502	0.0265	0.0838
CP _{GB}	0.0578	0.0498	0.0362	0.0086	0.0675
CP _{ZA}	0.1397	0.1252	0.0762	0.0337	0.0425
CP _{SG}	0.0883	0.1042	0.0338	0.0355	0.0713

Table 12: The average ratio of *I don’t know* labels per post within each dataset division.

Country Pairs	Cultural Distance Index
AU-SG	3.842
SG-US	3.653
GB-SG	3.484
SG-ZA	2.178
GB-ZA	0.458
GB-US	0.446
ZA-US	0.344
AU-ZA	0.344
AU-GB	0.144
AU-US	0.015

Table 13: Cultural distance index values between country pairs (Kogut and Singh, 1988; Hofstede, 1984).

average *I don’t know* count compared to other countries. We collect annotations from the US using the Amazon MTurk, limiting participation to Masters. As highly experienced annotators, Masters may have refrained from selecting *I don’t know* labels. Additionally, for CP posts, there is a moderate tendency among annotators to select fewer *I don’t know* labels within posts originating from their own country.

We also analyze the correlation between the existence of *I don’t know* label and the ratio of *hate* labels within posts. Posts with disagreement among annotators from the same country, those with *hate* label ratios ranging from 0.2 to 0.8, tend to have a higher percentage of posts containing *I don’t know* labels. On the other hand, strongly hateful posts, where all annotators agreed that the post is hateful, tend to have fewer *I don’t know* labels, even compared to posts with annotators’ unanimous agreement on annotating them as non-hate. This suggests that people tend to be more confident in labeling posts as hate, while they feel less confident about non-hateful posts.

C Analysis on Pairwise Country Labels

Table 13 shows the cultural distance index values between all country pairs. Cultural distance index values tend to be higher in country pairs with Singapore, whereas those between core Anglosphere

Thank you for participating in our task!

In this task, we are trying to collect **hate speech annotations** from people with different cultural backgrounds.

You will be asked to classify **15 posts** from the **unfiltered internet**, and the estimated time of completion is **6 minutes (£0.90/\$1.12)**.

If you are new to our task, we would also ask your **demographic information**. This is to find out whether you match the target for our study. You will be asked to return your submission if you don't match our conditions.

NOTE: We may **reject** your submission if you **do not participate faithfully** (i.e. by repeatedly giving "I don't know" as the answer), or give wrong answers for the quality control task.

If you are ready to proceed, please enter your **Worker ID** below. Please ensure you provide your precise ID as we compare it with the participant list from the previous task.

Worker ID

⚠ Contents Warning

We use some posts from public datasets that the authors of the respective papers built with posts discovered from the unfiltered internet. Although it's essential for us to annotate them, we do not support any stereotypes or inappropriate/offensive material. Some of the content may be distressing, so if you have any concerns, questions, or strong negative reactions, please contact us via email or seek help via online therapy chatbot (Woebot ([iOS](#), [Android](#))).

Figure 5: Disclaimer and instruction shown to the annotators.

Hate Speech Annotation

ⓘ Please Read the Following Instruction Carefully

You will be allowed to proceed only after 30 seconds.

Main Task

Please judge whether a provided post sourced from social media is **hate speech or non-hate speech**. If you cannot judge it, please select 'I Don't Know.' However, we encourage you to choose one of hate or non-hate speech as far as possible.

Please **label them based on your cultural perspectives**. Try to think how the people from your nationality would think about the sentences.

Definition of Hate Speech

Hate speech refers to offensive discourse targeting a group or an individual based on *inherent characteristics* such as race, religion, sexual orientation, gender, or any other factors that may threaten social peace.

The difference of hate speech and offensive speech is that *offensive speech* may also target an individual, but *not* by their inherent characteristics.

Therefore, "**non-hate**" can include **both offensive and non-offensive**, where "**offensive non-hate**" refers to **posts targeting individuals, not target minorities**.

Note that we are looking for **hate speech**, **NOT** offensive speech.

✓ **Hate and Offensive:** "all the liberals who are saying to get rid of guns are talking about liberals who are using guns maybe get rid of liberals instead of guns"

✗ **Non-hate but Offensive:** "@USER HE IS CLUELESS!!! DAMN THIS FUCKING GUY!!!"

Figure 6: Guideline page of the hate speech annotation task shown to the annotators.

Hate Speech Annotation (1/15)

Definition of Hate Speech

Hate speech refers to offensive discourse targeting a group or an individual based on *inherent characteristics* such as race, religion, sexual orientation, gender, or any other factors that may threaten social peace.

Please keep the above definition in mind, and **label the following post based on your cultural perspectives.**

Post:

Morals? Blowing children up in Arena's....throwing gays off rooftops, beheading soldiers in the street. If that's your idea of "Morals", then god help us.

Is the above post a **hate speech**? *

- Hate
- Non-hate
- I Don't Know

Figure 7: Hate speech annotation page shown to the annotators.

countries tend to be lower.

D Disagreement Reason Taxonomy

As mentioned in Section §4.3, we leverage the taxonomy of annotation disagreement in subjective tasks from Sandri et al. (2023). The categories and subtypes of the taxonomy are shown in Table 5.

D.1 Category Definitions

The definitions (taken from Sandri et al. (2023)) and examples of each category are as follows.

D.1.1 Sloppy Annotation

Noise corresponds to posts that are clearly labeled incorrectly, such as by annotating the following as hate speech: *Blue Bell ice cream has one showing five kids one black playing in the fields and barn.*

D.1.2 Ambiguity

Analogy encompasses comparison mechanisms like simile and metaphor. An analogy can cause ambiguity, especially for posts from different countries, as certain comparisons may only be used and understood in specific cultural groups. (e.g., *Black people are like mitochondria They're the powerhouse of the cell.*)

False Assertion refers to instances where users convey opinions opposite to their actual beliefs or express falsehoods and exaggerations in relation to the context. (e.g., *Another attempt backfired on them, George Floyd cured Covid-19 and opened up the economy!*).

Rhetorical Question includes posing a question not with the intention of receiving an answer but rather to rhetorically highlight a concept (e.g., *I read recently in cold black and white print that there was around 10,000 nigerians in Ireland ... Now you say close to 300,000 ?????!*).

Sarcasm is defined by the use of words to convey meanings opposite to their literal definitions, primarily employed for the purpose of mocking a particular topic or an individual (e.g., *I joined a suicide cult today It's known as the American Public School System.*)

Word Play is a figure of speech that utilizes literary elements to modify words, serving as a demonstration of someone's wit and cleverness. (e.g., *I hate jokes about 9/11 victims they always fall flat.*)

Reported Speech is defined as the presentation of text that claims to be from a previous occasion and may have originated from another author. (e.g., *Now on Britains pressing issues: can occasion cards be too offensive? Find out after we bubble wrap this child.*)

D.1.3 Missing Information

Ungrammatical posts lead to disagreement because of noticeable language use, such as non-standard varieties, slang, code-switching, or simple typing errors. This includes posts containing the colloquial forms of English used in different countries, such as Singaporean English or South African English. (e.g., *@USER chibai you eat babi at hawker centre, they got put headcover anot.*)

No Context encompasses a linguistic phenomena that require context for unequivocal interpretation, such as anaphora and deixis. Posts including URLs also fall into this category. (e.g., *What’s she got that stick for if she can read [that book]?*).

Not Complete includes all instances that fail to convey complete information and do not fit into any other subcategory. This subcategory also includes posts that require additional cultural common-sense knowledge to understand. (e.g., *You think the ANC would have sympathy with not wanting to be caledon a terrorist organisation*).

D.1.4 Subjectivity

Personal Bias includes post that belong to divisive topics like politics, COVID-19, social movements, etc. Although it is challenging to precisely identify disagreements stemming from personal bias when annotators are unknown, posts within these contentious topics are likely to be inferred as containing personal bias due to the heightened probability. (e.g., *You’re Irish and you support your pals the Provisional IRA murderers of the innocent Australian civilians Stephen Melrose and Nick Spanos. You support terrorists.*).

Swearing can be perceived as offensive and hurtful by certain annotators, while for others, they seem to be desemanticized. (e.g., *when ya name gain weight ya ex hoes can’t let go*).

Threatening involves linguistically violent expressions or threats and relies on annotators’ sensitivity to verbal aggression and intimidation. (e.g., *Go to hell, Abbo knees*).

E Zero-shot LLM Experiment Settings

E.1 Prompts for Zero-shot Experiments

We use five different prompts formatted as multiple-choice questions for the zero-shot LLM experiments. For each prompt, we add the exact definition of hate speech that we provided the human annotators. As we evaluate the model with and without specifically targeted countries, all five prompts have the corresponding versions. For culturally specific hate speech classification experiments, we fill in the {country} slots with each country name. For the general zero-shot experiments, we exclude the phrases within the parentheses.

Definition of Hate Speech:

Hate speech refers to offensive discourse targeting a group or an individual based on inherent characteristics such as race, religion, sexual orientation, gender, or any other factors that may threaten social

peace.

{PROMPT #1 - #5}

POST: {POST}

a: {Hate or Non-hate}

b: {Non-hate or Hate}

answer:

PROMPT #1:

Answer if this post is hate or not (in {country}) with a single alphabet letter among given answer choices a and b.

PROMPT #2:

Given a POST from online, answer if it is ‘Hate Speech’ or ‘Non-Hate Speech’ (in {country}). Answer with only one single alphabet between ‘a’ and ‘b’, with no other description.

PROMPT #3:

(As a person raised up in {country},) would you consider this post as a hate speech? Give an answer in a single alphabet only.

PROMPT #4:

(You are from {country},) Do you think this is a hate speech? Answer with only one single alphabet between ‘a’ and ‘b’, with no other description.

PROMPT #5:

(Consider yourself as a very typical person in {country},) Would you consider this post as a hate speech? Give an answer in a single alphabet only.

E.2 Experimental Settings

4 Quadro RTX A6000 48GB were used with CUDA version 11.4 for all experiments. For GPT models, we set the temperature as 0 to use greedy decoding. Inference on all models took less than 1 hour for each prompt variant. We use the PyTorch library²³ for all experiments.

E.3 Unanimously Agreed Posts

Table 14 shows the accuracy scores on each country label only on posts that are unanimously agreed on within each of the countries.

E.4 Out-of-choice (OOC) Rates

The generative models sometimes fail to output the answers in the specified format (such as ‘a’, ‘b’, ‘hate’, or ‘non-hate’). We refer to those outputs as *out-of-choice* (OOC). Table 15 shows the OOC rates for all models for the experiment shown in §5.1. All models except for OPT show less than 0.1% of OOC answers, illustrating the high instruction following capabilities of the models. It is important to note that even though the models tend to follow the instructions well, some models show biased prediction similarities, while some show poor performances on hate speech classification overall.

²³<https://pytorch.org/>

Model	Data	GB	US	AU	ZA	SG
GPT-4	CREHate	94.29	95.25*	93.54	92.82	<u>87.11</u>
	CC-SBIC	94.65	96.19*	94.85	93.73	<u>87.16</u>
	CP	93.55*	93.40	90.82	90.49	<u>87.02</u>
GPT-3.5	CREHate	85.22	<u>82.60</u>	85.41	83.68	85.09
	CC-SBIC	88.85	<u>86.78</u>	88.60	86.82	89.41
	CP	77.70	<u>74.27</u>	78.79	75.65	77.45
Orca 2	CREHate	82.56	81.89	82.35	82.76*	<u>80.02</u>
	CC-SBIC	85.06	85.32	83.63	85.00	<u>82.59</u>
	CP	77.37	<u>75.06</u>	79.71*	77.02	75.47
Flan T5	CREHate	82.22	<u>80.58</u>	80.91	81.03	81.20
	CC-SBIC	85.79	86.11*	83.79	<u>83.76</u>	83.97
	CP	74.79	<u>69.57</u>	74.93	74.04	76.30*
OPT	CREHate	77.76	80.99	76.44	77.62	<u>74.95</u>
	CC-SBIC	76.59	79.84	76.30	76.55	<u>74.59</u>
	CP	80.21	83.27*	76.71	80.35	<u>75.58</u>

Table 14: Label similarities of the models’ predictions with different country labels in each dataset division only on unanimously agreed-upon posts within each country. The highest score is highlighted in **bold**, while the lowest score is underlined. The asterisk (*) means the two values differ significantly ($p < 0.05$).

Model	OOO (%)
GPT-4	0.09
GPT-3.5	0.01
Orca 2-7B	0.00
Flan-T5-XXL	0.00
OPT	0.11

Table 15: OOC rates for all models for §5.1.

Model	Prompt	OOO (%)
GPT-4	+ in GB	0.42
	+ in US	0.41
	+ in AU	0.27
	+ in ZA	0.22
	+ in SG	0.30

Table 16: OOC rates for GPT-4 for §5.2.

Table 16 shows the OOC rates for GPT-4 for the experiment shown in §5.2. The model still shows less than 0.5% of OOC answers, but the values are higher than compared to the OOC rates when a target country was not specified. The model sometimes avoids making predictions for specific countries, emphasizing that they are only an AI language model (e.g., “*I am an AI developed by OpenAI, and I do not have a geographical location or personal opinions*”).

F Culturally-adapted Model Training

This section shows that models trained solely on labels from one country yield different predictions for identical posts, underscoring the importance of including diverse cultural perspectives to ensure their efficacy across various communities. Lastly, we use several methodologies to train models ca-

	AU	GB	SG	US	ZA
BERTweet	67.59	67.32	69.60	64.89	71.64
+ ML	72.48	71.91	71.72	72.04	73.04
+ MTL	73.09	72.60	72.06	72.63	72.52
+ TAG	73.97	72.64	70.37	73.12	70.65
HateBERT	74.14	71.11	63.72	69.71	70.47
+ ML	73.46	75.54	70.64	74.05	72.87
+ MTL	73.43	74.91	69.98	74.66	73.06
+ TAG	73.54	77.88	71.93	72.83	71.92
TwHIN-BERT	65.79	66.67	66.67	67.38	71.70
+ ML	70.51	71.27	69.75	72.44	71.70
+ MTL	70.23	70.69	68.95	72.24	71.30
+ TAG	69.72	71.09	67.91	71.20	69.27
Twitter-RoBERTa	75.63	74.34	67.53	71.66	68.52
+ ML	75.19	76.51	71.84	76.52	72.48
+ MTL	75.59	76.95	72.31	76.80	72.57
+ TAG	78.45	79.45	73.45	76.14	70.65
ToxDect-RoBERTa	69.96	71.02	67.73	65.64	66.39
+ ML	72.68	73.27	70.54	72.44	70.01
+ MTL	73.03	73.47	70.91	72.89	69.86
+ TAG	72.97	71.03	71.56	70.41	68.27
BERT	69.53	70.48	62.56	67.78	67.31
+ ML	69.48	71.21	67.02	72.10	71.22
+ MTL	69.74	72.21	67.85	72.40	71.97
+ TAG	70.39	68.97	69.64	63.23	68.97
RoBERTa	72.50	69.52	66.37	75.71	72.73
+ ML	73.22	74.36	70.84	75.57	73.62
+ MTL	73.38	74.56	71.23	75.13	73.37
+ TAG	73.06	73.68	69.16	73.68	72.28

Table 17: Macro-F1 scores of the models’ predictions on each country’s labels. LLM results are calculated based on the comparison of the predictions with each country label. For BERT-variants, we show monocultural and cross-cultural model results. Multi-labeling (ML), multi-task learning (MTL), and culture tagging (TAG) outperform monoculturally trained models.

pable of making culturally tailored predictions in a unified model. We leverage multi-labeling and multi-task learning that are known to be effective on learning disagreements (Mostafazadeh Davani et al., 2022). We also introduce culture tagging, which shows comparative results in our experiment.

F.1 Experimental Settings

To develop culturally aware classifiers, we use a ratio of 7:1.5:1.5 for train, validation, and test. We experiment with all possible country permutations when training with multi-labeling and multi-task learning. We randomly shuffle the entire culture-tagged dataset to prevent the models from learning from the order of the country tags. The final value we present is an average of all these iterations.

Models used are as follows: BERTweet-base (Nguyen et al., 2020), HateBERT (Caselli et al., 2021), TwHIN-BERT (Zhang et al., 2023), Twitter-RoBERTa (Barbieri et al., 2020), ToxDect-RoBERTa (Zhou et al., 2021), BERT-

Source	Post	M_{AU}	M_{GB}	M_{SG}	M_{US}	M_{ZA}
SBIC	MeToo Movement Femoid Likens Being Hit on in Public to Being Mugged.	○	○*	×	×	○*
CP _{GB}	Out of all the immigrants how many are gonna go back home?	○*	○*	○	×	○
CP _{ZA}	Reading this thread has turned me into a communist, the morality and values of rich Boers is some real upside-down twisted shit lmao	×	○*	○	○*	○*
CP _{ZA}	Wow. Rainbow turned completely black	×	×	×	×	○*

Table 18: Examples of predictions from models that are monoculturally trained. M_{AU} refers to model predictions trained on Australian labels and the same for all other countries. ○ refers to ‘hate’, and × refers to ‘non-hate’ label. * means the prediction and the actual label are the same. This table shows that models trained on different perspectives show different labeling tendencies even for an identical post.

base-cased (Devlin et al., 2019), and RoBERTa-base (Liu et al., 2019). We use the Transformers library from Huggingface²⁴ for all models except for HateBERT, which we download the model from its repository²⁵.

4 Quadro RTX A6000 48GB were used with CUDA version 11.4 for all experiments. For GPT-3.5, we set the temperature as 0 to use greedy decoding. For training BERT-variants, we use AdamW (Loshchilov and Hutter, 2019) as the optimizer with a learning rate $2e-5$ and use linear scheduling for training with six epochs. We set the maximum sequence length of texts to 128 and batch size to 32 for training and evaluation steps. We use the PyTorch library²⁶ for all experiments. We calculate the Macro-F1 scores using the scikit-learn library²⁷.

F.2 Monoculturally Trained Models

This section analyzes to what extent monoculturally trained models exhibit different label predictions. In Table 17, the first row for each BERT-variant model showcases its performance when trained on a particular country label. The models trained on respective country labels show an average of 82.1% of average pairwise label agreements within the test set, with a range of 78.6% to 84.4%. Notably, these models showed higher average label agreements within the CC-SBIC posts (85.7%), compared to CP posts (76.4%), showing a similar trend with the entire CREHate dataset, as mentioned in Table 4. Then, we utilize Twitter-RoBERTa, achieving the best average performance for monocultural training, to present specific examples of how each model shows distinct predictions on identical posts, as displayed in Table 18. Despite sharing the same baseline model, the models show different predic-

tions on identical posts.

F.3 Cross-cultural Training

Culture Tagging Similarly to BERT’s [CLS] token, a token representing each culture is added to the beginning of every post and utilized as a single data sample. Posts with labels corresponding to those from each country are prepended with a [country_code] token (e.g., [AU]). This approach enables the model to predict the label for each culture using the culture token. Its efficiency lies in the fact that not all labels from each country need to be collected for the model to be trained. Unlike multi-labeling or multi-task learning, culture tagging’s strength is in the separate learning of all data points by the model, thereby not requiring all five labels to exist.

Cross-cultural Model Results As shown in Table 17, our study goes parallel with the work of Mostafazadeh Davani et al. (2022) that multi-labeling and multi-task learning benefits from sharing layers to learn each country’s perspectives. Multi-task learning slightly outperforms multi-labeling for most of the models in our experiment, as it trains separate classifier layers for each country. The model performance increased up to 8.2% when utilizing culture tokens for learning each country’s perceptions compared to monocultural models. Compared to multi-labeling and multi-task learning, the results suggest that culture tagging shows a comparable performance.

²⁴<https://github.com/huggingface/transformers>

²⁵<https://osf.io/tbd58/>

²⁶<https://pytorch.org/>

²⁷<https://scikit-learn.org/stable/>