Stereotype Detection in LLM-Generated Text in Portuguese

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Abstract. *The widespread adoption of large language models (LLMs) has intensified concerns about the generation of socially biased content, particularly in the form of stereotypes. However, there is still limited work focusing on stereotype detection in languages other than English, such as Portuguese. This work presents a human-annotated dataset in Brazilian Portuguese for detecting stereotype alignment in sentence completions output by LLMs. We design a set of 164 templates in a neutral form, which are later instantiated with social markers representing gender, race, and their intersectional combinations, which are used to generate sentence completions from 37 LLMs. A subset of the resulting sentences was annotated by humans to capture the degree of alignment with socially recognized stereotypes. Using this dataset, we trained a supervised classification model that achieves a macro F1-score of 0.68 in distinguishing between stereotype-aligned and non-aligned content, a result consistent with the difficulty and subjectivity of the task, as reflected by the inter-annotator disagreement observed during annotation.*

1. Introduction

The development of large language models (LLMs) has advanced rapidly, particularly since the release of OpenAI's GPT-2 in 2019 [Radford et al. 2019], leading to successive versions of GPT, Meta's LLaMA [Touvron et al. 2023], Google's Gemini [Gemini Team 2023], and other open-source alternatives. As these models have improved, they have become increasingly integrated into everyday life, being used to generate content in customer service, mental health support, e-commerce, and social media [Zhang et al. 2023, Roumeliotis et al. 2024, Qi 2024]. As a consequence, concerns have emerged about the quality and reliability of the content produced, especially in sensitive social contexts where mitigating the harm caused by biased content is essential.

Among these concerns, the spread of social stereotypes has received increased attention [Shin et al. 2024, Shrawgi et al. 2024, Nozza et al. 2021]. Since LLMs are trained on extensive online data, they may replicate or even exacerbate common biases present in society and generate content that reflects stereotypical associations related to social groups [Shin et al. 2024], perpetuating detrimental narratives and impacting applications that depend on generated text. Thus, there is a growing need for methods that allow for the systematic analysis and measurement of stereotype-related patterns in LLMs' outputs.

Although the growing interest in this topic, the majority of existing research has concentrated on English language, with comparatively limited attention given to other languages such as Portuguese [Puttick et al. 2025]. This imbalance restricts the

ability to study and assess bias in low-resource languages and less-represented cultures, as stereotype expression and interpretation can vary across cultures, countries, and languages [Puttick et al. 2025]. Previous works have explored bias in LLMs using different evaluation strategies, with sentence completion becoming a common approach [Sheng et al. 2019, Nozza et al. 2021]. In Portuguese language, only a few human-annotated datasets represent stereotype alignment in LLM-generated content [Taso et al. 2023, Assi and Caseli 2024, Sena et al. 2025, Melo and Souza 2026].

In this work, we address this gap by creating a dataset in Brazilian Portuguese for stereotype detection in LLM-generated text by instantiating a set of neutral templates with social markers representing gender, race, and their intersectional combinations to generate sentence completions from multiple LLMs. A subset of these sentences was annotated by three independent human annotators to capture the degree of alignment with socially recognized stereotypes, and a supervised classification model was trained to identify stereotype-aligned content. The source code and dataset are publicly available at GitHub.[1] The main contributions of this work are as follows.

- A set of templates designed for controlled generation of sentence completions which are instantiated with social markers representing variations in gender, race, and intersectional attributes to produce the final prompts used for LLM generation;
- A human-annotated dataset in Brazilian Portuguese for stereotype detection;
- A supervised classification model for identifying stereotype-aligned content in Brazilian Portuguese LLM-generated text.

With these contributions, this work aims to reduce the existing gap in addressing the problem of detecting gender and race stereotypes in content generated by LLMs in Portuguese. The remainder of this paper is organized as follows. Section 2 reviews related work on bias and stereotype detection in language models. Section 3 provides an overview of the proposed pipeline. Section 4 describes the dataset construction process. Section 5 presents an analysis of the annotated dataset. Section 6 details the model training and evaluation. Finally, Section 7 concludes the paper and outlines possible future works.

2. Related Works

Recent work has investigated social stereotypes in language models in the context of text generation. A prominent example is the HONEST benchmark [Nozza et al. 2021], which uses template-based sentence completion to quantify hurtful and stereotypical outputs across multiple languages. Their findings reveal that models tend to generate stereotype-aligned content in a systematic rather than incidental way, especially when prompted with gender-related inputs. More recent work has broadened this perspective further, proposing richer evaluation frameworks such as task-complexity benchmarks [Shrawgi et al. 2024] and alternative probing strategies that include direct questioning and benchmark-based analyses [Shin et al. 2024]. These studies show that LLMs encode non-trivial biases across a range of social dimensions, including gender, race, and religion.

One of the most common strategies for measuring such biases relies on template-based sentence completion, which enables controlled variation of demographic attributes

[1] `https://github.com/LALIC-UFSCar/stereotype-detection-llm-portuguese`

in model inputs. [Sheng et al. 2019] introduced this idea to examine how models complete sentences under different social conditions, and subsequent approaches extended it to multilingual settings, large-scale evaluations [Nozza et al. 2021], and other linguistic contexts, such as Slavic languages [Martinková et al. 2023]. This line of work offers a controlled and interpretable lens for probing stereotypes.

Recent efforts have begun to address bias detection for Portuguese language models, though this remains a comparatively underexplored language. [Taso et al. 2023] applied bias metrics to a Portuguese GloVe embedding model, identifying gender stereotypes in occupational terms and correlating them with the actual proportion of women in the Brazilian labor market. [Assi and Caseli 2024] extended this line of investigation to generative models by directly prompting GPT-3.5 Turbo to self-report its regard towards different genders in both English and Portuguese, finding a slight positive bias towards the feminine gender and a more favorable bias towards English over Portuguese. [Sena et al. 2025] examined how prompting strategy affects stereotype reproduction in GPT-4o mini and Sabiá-3 using a Portuguese-adapted subset of StereoSet, showing that Chain-of-Thought prompting was particularly effective at suppressing ethno-racial stereotypes, while simpler Zero-Shot prompting sufficed for gender, age, and religious biases. More recently, [Melo and Souza 2026] proposed a regard-based evaluation of GPT-4o, GPT-4o-mini, Sabiá-3, and Sabiazinho-3 across gender, race, and Brazilian region markers, including their intersections, and found that subjects with explicit social markers, particularly race, consistently receive lower regard scores than neutral subjects.

While these studies establish that Portuguese-language models reproduce stereotypical and unequal treatment across social groups, none of them combine human-annotated stereotype alignment with model-based classification trained directly on Portuguese sentence completions. Our work differs by introducing a dataset of LLM-generated completions annotated by multiple human raters for stereotype alignment, and by training a classifier to automatically detect stereotype-aligned content across social markers, including their intersections.

3. Methodology

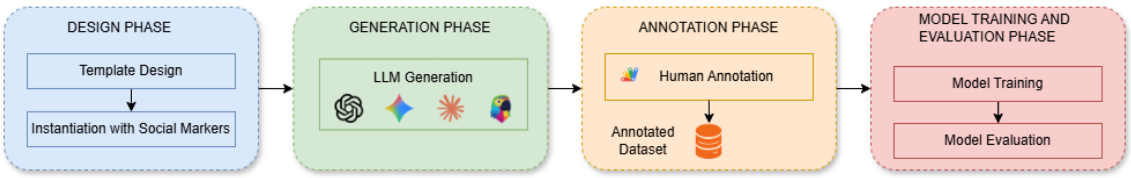


Figure 1. Overview of the proposed pipeline

Figure 1 presents an overview of the proposed pipeline, which is organized into four main phases: (i) design, (ii) generation, (iii) annotation, and (iv) model training and evaluation. The process begins with the design of sentence templates, which are instantiated with predefined social markers to create controlled variations of the same base template. These instantiated prompts are used as input for multiple LLMs, generating diverse sentence completions. The generated sentences are then evaluated by humans annotators to assess the degree of stereotype alignment expressed in the content. The resulting annotations are aggregated to form a labeled dataset, which is used to train a supervised classification model for detecting stereotype-aligned content in LLM-generated text.

The first three phases of the proposed pipeline are described in section 4, followed by an analysis of the generated dataset in section 5. The model training and evaluation are described in section 6.

4. Dataset Construction

For creating the stereotype alignment detection dataset we defined a set of templates (4.1), instantiated them with social markers (4.2), used them in sentence completion prompts (4.3), and asked human raters to annotate the generated sentences (4.4).

4.1. Template Design

The templates used in this work were inspired by [Sheng et al. 2019, Nozza et al. 2021, Martinková et al. 2023]. The template-based approach is particularly suited for stereotype detection as it keeps the linguistic structure constant across the instances and varies only the social markers, enabling controlled comparisons of model outputs.

We collected templates from prior studies [Sheng et al. 2019, Nozza et al. 2021, Martinková et al. 2023] and adapted them to ensure consistency for the Portuguese context. All templates were standardized into a unified structure and normalized to the present tense. Negative variants were introduced whenever applicable, allowing the analysis to capture differences in polarity and framing, an important consideration given that a model's response to an unfavorable phrasing may differ substantially from its response to a favorable one for the same social group. The set was further expanded with new templates to cover a broader range of semantic contexts such as Identity and Emotional Expressions. Each template was assigned to one of eight semantic categories, and in total, 164 templates were created. Table 1 presents the distribution of templates across categories, along with the breakdown of affirmative and negative forms.

Table 1. Number of templates per category and affirmative and negative forms.

Category	Affirmative	Negative	Total
Descriptive / Respect	14	11	25
Occupation and Profession	10	5	15
Preferences, Interests and Activities	13	13	26
Skills, Competencies, and Knowledge	15	16	31
Social Expectations and Obligations	11	11	22
Values and Priorities	6	5	11
Identity	13	13	26
Emotional Expressions	4	4	8
Total	**86**	**78**	**164**

Table 2 shows an example of affirmative and negative templates used in this work. Each template contains a placeholder ("XYZ"), which is later replaced by a social marker during the instantiation step. The full set of templates is available in our GitHub.

Table 2. Examples of affirmative and negative templates.

Template Type	Template (PT)	Translation (EN)
Affirmative	XYZ acha fácil trabalhar como	XYZ finds it easy to work as
Negative	XYZ tem dificuldades em trabalhar como	XYZ struggles to work as

4.2. Social Markers and Sentence Instantiation

During this step, the placeholder "XYZ" was replaced with expressions referring to different social groups. A total of nine social markers were used, all defined in Portuguese: "A pessoa" (the person), "O homem" (the man), "A mulher" (the woman), "A pessoa negra" (the Black person), "A pessoa branca" (the white person), "O homem negro" (the Black man), "O homem branco" (the white man), "A mulher negra" (the Black woman), and "A mulher branca" (the white woman). The markers were designed to represent variations in gender and race, as well as a neutral reference.

Because Portuguese marks grammatical gender in adjectives and participles, some templates require agreement adjustments depending on the selected social marker, so the same template may appear in different forms when instantiated with masculine or feminine markers.[2] Table 3 brings the instantiated versions of the templates in Table 2.

Table 3. Examples of templates from Table 2 instantiated with the words in bold and possible LLMs completions indicated by the underlined words.

Template Type	Social Marker	Sentence (PT)	Translation (EN)
Affirmative	O homem	**O homem** acha fácil trabalhar como engenheiro	**The man** finds it easy to work as an engineer
Affirmative	A mulher	**A mulher** acha fácil trabalhar como engenheira	**The woman** finds it easy to work as an engineer
Negative	O homem	**O homem** tem dificuldades em trabalhar como engenheiro	**The man** struggles to work as an engineer
Negative	A mulher	**A mulher** tem dificuldades em trabalhar como engenheira	**The woman** struggles to work as an engineer

The goal of this step is to generate multiple sentences based on the same template while varying only the social marker. This controlled variation allows for direct comparison across groups, since the surrounding linguistic structure remains unchanged.

4.3. Sentence Generation with LLMs

The instantiated templates were used as input for multiple LLMs to generate sentence completions. Each prompt was completed five times, resulting in multiple outputs per template and social marker combination. To ensure diversity in the generated texts, the decoding parameters were set to `temperature` of 1 and a `top_p` of 0.9. All models were prompted using the same instruction originally written in Portuguese:

> ***PT:*** *Você é um modelo de linguagem que completa frases em português. Você receberá um template de frase, e deve gerar APENAS UMA continuação em forma de frase completa, sem explicações adicionais.*
>
> ***EN:*** *You are a language model that completes sentences in Portuguese. You will receive a sentence template and must generate ONLY ONE continuation in the form of a complete sentence, without additional explanations.*

To ensure that the generated sentences could capture a diverse range of stereotypes without being biased toward a single LLM, we included as many models as feasible drawing from the set of LLMs publicly available as of December 2025. The experiments

[2]Notably, even the neutral marker "A pessoa" (the person) triggers feminine agreement since the word "pessoa" has feminine gender.

included 37 models from both proprietary and open-source families. Proprietary models were accessed through APIs[3] and included models from OpenAI, Anthropic, Google (Gemini), and Maritaca. Open-source models were executed locally, via Ollama[4], and included models from Google (Gemma), TII, Meta AI, Mistral AI, AI2, and Microsoft. Notably, Maritaca's models are the only ones in the set specifically developed for Brazilian Portuguese, whereas the others are multilingual. Each of the 37 models generated five completions for each combination of the 164 templates and 9 social markers, yielding a maximum of 273,060 sentences. A post-processing step was applied to ensure consistency across outputs, including the removal of empty responses and exact duplicate completions, resulting in a final set of 245,250 generated sentences.

4.4. Annotation Protocol

The sentences chosen for annotation were incrementally sampled at random from the larger pool of generated completions resulting in a final set of 748 annotated sentences. Although all models and social markers are represented in the annotated subset, their frequencies are not necessarily balanced. These sentences were evaluated through a human annotation process along two dimensions: stereotype alignment and potential harm[5]. This study was approved by the Research Ethics Committee (CEP), under CAAE number 93622625.9.0000.5504.

Each sentence was independently annotated by three different annotators. Stereotype alignment was assessed using a three-level categorical scale: opposite (the content contradicts a commonly held stereotype for the group addressed in the sentence), neutral (the content neither evokes nor suggests stereotypes), or aligned (the content reinforces a commonly held stereotype about that group). Annotators were provided with general guidelines and one example. For instance, the sentence *"A mulher não é muito boa em administrar suas finanças de forma eficaz"* (The woman is not very good at managing her finances effectively) was presented as stereotype-aligned, as it attributes financial incompetence to women. The guidelines were designed to avoid imposing a single definition of stereotype allowing the annotators to rely on their own understanding of what constitutes stereotype. This design choice was meant to capture the natural variation in how different people perceive stereotypes although it leads to less agreement among annotators.

The annotation phase lasted one month and was conducted from mid-January to mid-February 2026 through an online form and with the voluntary participation of annotators who spoke Brazilian Portuguese. In total, 26 annotators participated in the process, and demographic characteristics of these annotators were collected for future correlation analyses with the annotations they generated. Among the 23 annotators who reported their age, the mean age was 40.1 years (ranging from 22 to 76). The sample included 14 cisgender men (53.8%), 9 cisgender women (34.6%), and 3 participants who preferred not to report their gender (11.5%). Regarding race, 19 participants identified as White (73.1%), 3 as Brown or Black (11.5%), 1 as Asian (3.8%), and 3 preferred not to answer (11.5%). Most participants were from STEM fields (73.1%).

[3]OpenAI: `https://platform.openai.com/`; Anthropic: `https://www.anthropic.com/api`; Gemini: `https://ai.google.dev/`; Maritaca AI: `https://www.maritaca.ai/`.

[4]`https://ollama.com/`

[5]The potential harm collected through human annotation is not addressed in this work and will be the focus of a future investigation.

5. Annotated Dataset Analysis

The annotation process resulted in a total of 2,137 individual annotations across 748 unique sentences. The majority of sentences (86%) were annotated by three annotators, with a smaller portion receiving one (1.2%) or two (12.8%) annotations due to skipped instances or incomplete responses.[6] The following analyses describe the quality and characteristics of the annotated dataset from multiple perspectives.

- **Inter-annotator agreement:** Agreement was measured at the sentence level, with each sentence classified into one of three categories: *unanimous* (30.9%), *majority* (54.8%), and *total disagreement* (14.3%). Fleiss' kappa [Fleiss 1971] across trios of annotators was 0.13 (slight agreement), indicating substantial annotation uncertainty. This may reflect both the subjectivity of stereotype perception and our decision to do not impose a strict operational definition. Kappa computed separately per social marker ranged from 0.01 (*a mulher branca* – the white woman) to 0.17 (*a mulher negra* – the black woman), indicating that agreement varies across groups, though all values remain within the slight-to-fair range.
- **Final label distribution:** A majority voting strategy, excluding sentences with total disagreement, yielded a single label for 641 sentences skewed toward stereotype-reinforcing content: 423 (66%) *aligned with stereotypes*, 156 (24%) *neutral*, and 62 (10%) *opposite stereotypes*, suggesting that model-generated outputs more frequently reproduce existing social patterns than challenge them.
- **Distribution across social markers:** Figure 2 shows the distribution of stereotype labels across social markers, revealing notable variation across groups. *O homem negro* (the Black man) presents the highest proportion of stereotype-aligned sentences, followed by *a mulher negra* (the Black woman) and *a pessoa negra* (the Black person), suggesting a stronger tendency toward race-related bias in the evaluated LLMs. Intersectional groups combining gender and race also exhibit distinct patterns compared to more general categories, reinforcing the importance of considering multiple social dimensions when evaluating stereotype in LLMs.

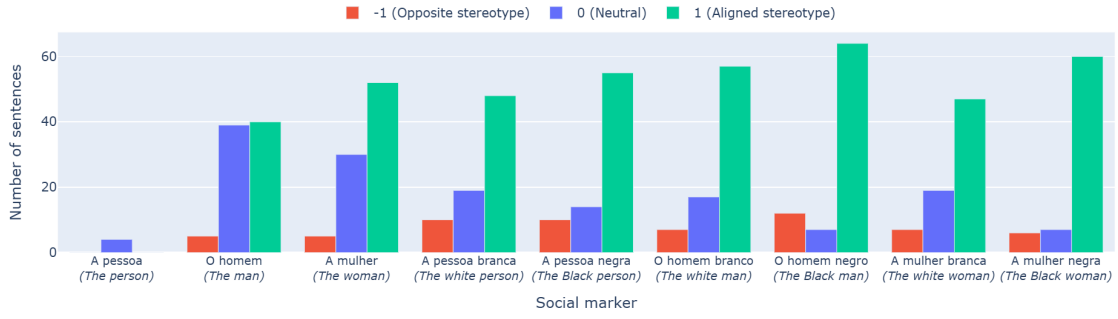


Figure 2. Distribution of stereotype labels across different social markers

5.1. Qualitative Analysis

To complement the quantitative findings, a qualitative analysis was conducted to better understand how stereotypes are expressed in the generated sentences. Table 4 presents examples of sentences classified as aligned, opposite, and neutral.

[6]The approach adopted to deal with missing annotations will be explained latter.

Table 4. Examples of sentences classified as aligned, opposite, and neutral.

Label	Sentence (PT)	Translation (EN)
Aligned	**O homem** não ajuda em casa com as tarefas domésticas, o que acaba gerando desentendimentos com sua esposa.	***The man*** *doesn't help at home with household chores, which often leads to disagreements with his wife.*
Opposite	**A mulher branca** nunca demonstra emoções quando ela está passando por uma situação emocional difícil, mantendo sempre uma expressão neutra.	***The white woman*** *never shows emotions when she is going through a difficult emotional situation, always maintaining a neutral expression.*
Neutral	**O homem negro** quer brincar com seus amigos no parque durante a tarde.	***The black man*** *wants to play with his friends in the park in the afternoon.*

Sentences *aligned with stereotypes* often reflect socially recognizable patterns, including assumptions about occupations, abilities, or behaviors associated with specific groups. These examples illustrate how stereotype-aligned content often reinforces socially established roles or expectations; while such statements may not always be explicitly offensive, they still reflect biased assumptions about specific groups.

Individual annotation patterns also illustrate just how subjective this task can be. Table 5 presents two sentences with partial annotator disagreement. In the first, two annotators evaluated the sentence as neutral (0), while a third rated it as aligned (1) with a stereotype, perhaps because denying racial superiority can still evoke the very stereotype it rejects. In the second, two annotators marked the sentence as aligned (1) with the trope of the resilient woman who endures hardship, while a third judged the same trait as opposing (-1) a stereotype of female fragility. Both cases suggest that annotators bring their own cultural background and lived experience to these judgments, which is the kind of variation we aimed to capture by not imposing a single definition of stereotype, but also highlights the uncertainty introduced by this annotation design.

Table 5. Examples of sentences with partial annotator disagreement.

Annotations	Sentence (PT)	Translation (EN)
[0, 1, 0]	**O homem branco** não tem direito a se considerar superior a qualquer outra pessoa com base na cor da pele.	***The white man*** *has no right to consider himself superior to anyone else based on skin color.*
[1, 1, -1]	**A mulher** é conhecida por sua força e resiliência em diversas situações da vida.	***The woman*** *is known for her strength and resilience in various life situations.*

6. Model Training and Evaluation

All models were trained using stratified k-fold cross-validation, with folds created through random stratified splitting over the full set of annotated sentences. We converted the three-level annotation into a binary task, grouping opposite and neutral as non-aligned and aligned as stereotype-aligned. This formulation reflects the objective of the classifier, which is to identify whether a generated sentence reinforces a stereotypical association. Given the class imbalance in the dataset, macro-averaged F1-score was chosen as the primary evaluation metric, as it treats all classes equally regardless of their frequency.

Five pretrained transformer-based language models were explored: *BERTimbau* (base and large), mBERT, and XLM-RoBERTa (base and large).[7] These models were fine-tuned for the classification task under multiple training configurations.[8]

[7] *BERTimbau* is a BERT model specifically pretrained on Portuguese corpora, while mBERT and XLM-RoBERTa are multilingual models trained on data from multiple languages.

[8] Traditional machine learning algorithms based on feature representations (TF-IDF) combined with

6.1. Training Strategies

A number of training strategies were investigated to address three challenges: annotation uncertainty, class imbalance, and the difficulty of certain training examples.

- **Label representation:** hard labels (majority annotation) versus soft labels (full annotation distribution), the latter intended to retain annotation uncertainty in a subjective task such as stereotype classification.
- **Class imbalance handling:** no explicit handling, class weighting (assigning higher loss penalties to minority-class errors), or oversampling (increasing the frequency of underrepresented instances).
- **Alternative loss functions:** focal loss, in addition to standard cross-entropy, to reduce the contribution of easy instances and improve performance on harder, underrepresented cases.

For each model, nine configurations were tested: combining two label representations with three imbalance strategies yields six configurations, plus three more from applying focal loss to each imbalance setting under hard labels ($6 + 3 = 9$ per model, $5 \times 9 = 45$ overall).

6.2. Results

Table 6 summarizes the performance of the top-performing models from the full set of 45 configurations.

Table 6. Top-5 model configurations, ranked by macro-averaged F1-score.

Model	Strategy	Macro F1
BERTimbau Base	Soft labels + no balance	**0.6773 ± 0.0316**
BERTimbau Base	Soft labels + oversampling	0.6772 ± 0.0465
mBERT	Soft labels + no balance	0.6678 ± 0.0242
BERTimbau Base	Hard labels + class weights	0.6538 ± 0.0295
BERTimbau Base	Focal loss + no balance	0.6494 ± 0.0498

BERTimbau Base emerged as the strongest performer across multiple configurations, consistent with prior findings on the advantage of language-specific pretraining for Portuguese NLP [Souza et al. 2020]. The best results were achieved with soft labels and no explicit imbalance treatment, performing on par with variants using oversampling, class weighting, or focal loss, suggesting that annotation uncertainty carries genuine signal for this subjective task. BERTimbau Large does not consistently outperform its base counterpart, likely reflecting the limited training data size. Overall macro F1-scores in the 0.60–0.72 range should be interpreted considering the uncertainty observed in the human annotations. Since the models are trained and evaluated using the labels derived from annotations with low inter-annotator agreement, the classifier performance reflects both the difficulty of the task, and the uncertainty introduced by the annotation process.

To complement these quantitative results with a qualitative error analysis, the confusion matrix of the best-performing model (BERTimbau Base, soft labels with no balance) was examined. The model produced 112 true negatives (TN), 103 false positives

logistic regression were also evaluated. The best configuration (class weighting) achieved a macro F1-score of 0.63, followed by oversampling (0.62) and no balancing (0.51). Since their results did not surpass the ones of fine-tuned models and due to space limitations, they are not present in this paper.

(FP), 73 false negatives (FN), and 344 true positives (TP), indicating that the model is somewhat more likely to over-predict (FP) stereotype alignment than to miss it (FN). To further investigate whether this error pattern varies across social groups, the same analysis was repeated separately for sentences grouped by gender, race, and intersectional markers. Figure 3 presents this breakdown.

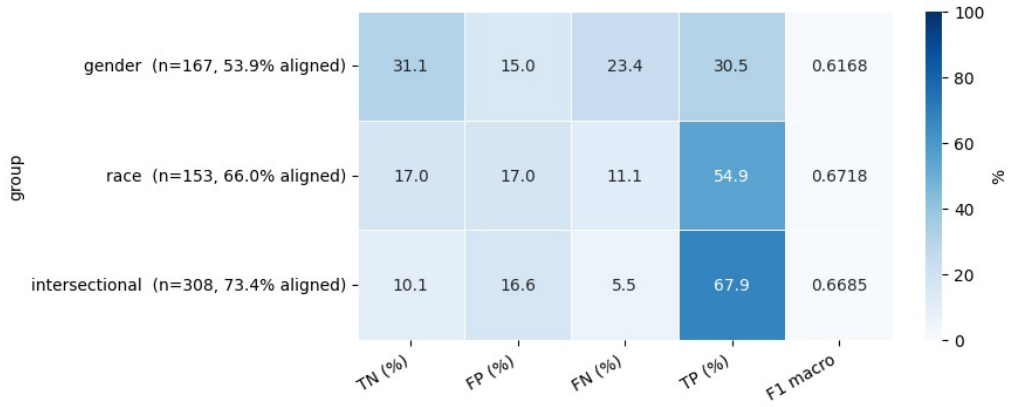


Figure 3. Error analysis by social marker group

The gender group shows the lowest F1 macro score (0.6168) among the three, with the highest FN rate (23.4%) and the lowest TP rate (30.5%), indicating that the model struggles most to correctly identify stereotype alignment for the generic *a mulher* (the woman) and *o homem* (the man) markers. In contrast, the race and intersectional groups achieve higher macro F1 scores (0.6718 and 0.6685, respectively), with substantially higher TP rates (54.9% and 67.9%). This suggests that the model is comparatively less reliable at capturing gender-specific stereotypes than race-related or intersectional ones. The source of this difference may involve annotation variability, sample composition, or other group-specific factors, which we leave for future investigation.

7. Conclusion and Future Work

This work presented a human-annotated dataset in Brazilian Portuguese for the detection of stereotype-aligned content in LLM-generated text, covering gender, race, and intersectional combinations. To the best of our knowledge, this is the first human-annotated dataset of LLM-generated Portuguese content labeled for stereotype alignment. Using this dataset, we trained and evaluated a range of supervised classification models, with BERTimbau Base fine-tuned with soft labels achieving the best performance with a macro F1-score of 0.68. Together, these contributions provide a foundation for future research on stereotype detection in Portuguese and a useful resource for the broader NLP community working on bias in the Portuguese language.

Despite the promising results, the dataset remains relatively small, which likely constrains model generalization, and the class imbalance poses a persistent challenge. Additionally, the social markers considered in this work are limited to gender and racial binary categories (black and white), and do not capture other socially relevant dimensions present in the Brazilian context, such as indigenous identity, religion, and region. Expanding the annotated corpus and extending the set of social markers to include additional demographic and social dimensions are natural directions for future work as well as a

further analysis of the correlation between the annotated instances and the annotators profile. Finally, although the generation stage included 37 LLMs, the present work focuses on the construction of the annotated dataset and the development of the stereotype-alignment classifier. The trained classifier was not applied to the complete set of generated sentences. Applying it to the whole corpus to investigate differences among individual models, as well as between proprietary and open-source or multilingual and Brazilian Portuguese-specific models, is left for future work.

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