A Study on Scaling Up Multilingual News Framing Analysis

Anonymous ACL submission

Abstract

Media framing is the study of strategically selecting and presenting specific aspects of political issues to shape public opinion. Despite its relevance to almost all societies around the world, research has been limited due to the lack of available datasets and other resources. This study explores the possibility of dataset creation through crowdsourcing, utilizing non-expert annotators to develop training corpora. We first extend framing analysis beyond English news to a multilingual context (12 typologically diverse languages) through automatic translation. We additionally present a novel benchmark in Bengali and Portuguese on the immigration and same-sex marriage domains. Last, we show that a system trained on our crowd-sourced dataset, combined with other existing ones, leads to an accuracy of 73.22%, which is a 5.32% increase from the baseline. Additionally, we find that models built with fewer data can significantly outperform systems that are trained on far more data in a multilingual evaluation setting.[1]

1 Introduction

News framing refers to the power of the news media to define and interpret events, issues, and policies by emphasizing certain aspects while downplaying or excluding others. According to Entman (1993), it can "make a piece of information more noticeable, meaningful, or memorable to audiences". It plays a crucial role in influencing how people interpret and react to information presented in news articles. The language used in news media can shape public opinion and reveal biases and agendas, which can ultimately shape the way people understand and react to current events.

Traditionally, framing analysis has relied on manual annotation by linguists, social studies experts, and trained annotators, lacking the potential of AI-driven systems leading to a rather limited explorations of automating framing analysis. Moreover, existing studies have been restricted primarily to English-only data, leaving a gap in research concerning multilingual and low-resource contexts.

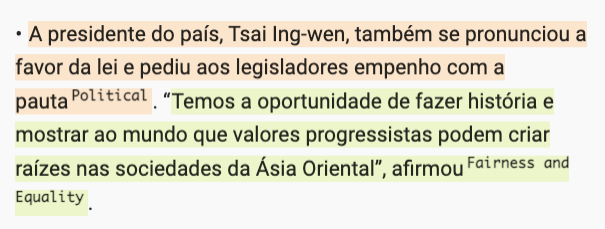

Figure 1: An example framing annotations from our new Portuguese test set.

Our work focuses on employing NLP techniques for the framing analysis task to automate the analysis process, extract insights from large datasets efficiently, and identify patterns in the language used in news media. To address these challenges, Boydstun et al. (2014) introduced a codebook, Policy Frames Codebook, based on which the Media Frames Corpus (MFC; Card et al., 2015) was created. This dataset is comprised broad categories of common policy frames and annotations of US news articles. However, the availability of such datasets in languages beyond English remains limited.

Getting a higher volume of higher quality data (such as, MFC) is time and resource intensive. Hence, we study the alternative of gathering a high volume of comparatively lower quality but easy-to-collect data. We achieve this through crowdsourcing and automatic translation techniques. We also examine the combination of lower and higher quality data.

In this study, we first **introduce a new crowdsourced dataset: Student-sourced Noisy Frames Corpus (SNFC)**. We have achieved time and cost efficiency by involving a large number of semi-trained annotators for the data collection and annotation process of the corpus. SNFC covers im-

[1] All data and code will be publicly released.

migration and same-sex marriage domains and includes **novel benchmark test sets in Bengali and Portuguese**, offering new perspectives in these languages. Additionally, we automatically expand multilinguality to the task by translating the MFC and SNFC to 12 more languages. We show that a neural classifier trained on the combination of both MFC and SNFC yields significant performance improvements, both in English as well as in a multilingual setting.

2 Related Work

Framing analysis provides valuable insights into different perspectives on news topics across various countries and languages. However, there is a notable lack of research and annotated corpora for framing analysis in languages other than English. This limitation hinders our understanding of media framing in different parts of the world and other societies' opinion regarding specific issues. To address this gap, a multilingual approach is essential in analyzing media framing across diverse linguistic and cultural contexts. Ali and Hassan (2022) provide a comprehensive survey of the framing analysis task, focusing specifically on studies conducted using English datasets exploring various approaches and techniques employed in framing analysis.

Two prominent datasets used for framing analysis are the Media Frames Corpus (MFC; Card et al., 2015) and the Gun Violence Frames Corpus (GVFC; Liu et al., 2019). The MFC, annotated according to the guidelines provided in the codebook of Boydstun et al. (2014), covers 6 different political issues including immigration, same-sex marriage, and gun violence, among others. It includes both article headlines and news texts, providing a broader and more comprehensive dataset. On the other hand, the GVFC focuses solely on the topic of gun violence, with 10 manually annotated frames defined in a different codebook, and it only includes article headlines.

Akyürek et al. (2020) extended the GVFC by curating headlines in German, Turkish, and Arabic following the same process as the original dataset from the respective news websites, specifically targeting keywords related to gun violence and mass shootings. The frames used in the multilingual datasets remained consistent with those in the GVFC, and is the one of the few multilingual sources for this task. Additionally, the Australian Parliamentary Speeches (APS) dataset (Khanehzar et al., 2019) offers another perspective on framing analysis, as it consists of transcripts speeches related to same-sex marriage bills presented in the Australian Parliament. Although the APS dataset focuses on data from a country other than the United States, it is still limited to English language texts, which narrows the scope of the framing analysis task.

The MFC has served as a valuable resource in various framing-related studies. For example, it was used to develop a semi-supervised model by extracting a Russian lexicon from their Russian test corpora which consists of news articles sourced from reputable Russian newspapers (Field et al., 2018). In a different vein, Naderi and Hirst (2017) used it to benchmark sentence-level classification tasks, employing LSTM, BiLSTM, and GRU-based systems. Considering the significant contributions of this corpus to the field, we have incorporated it into our system for training and evaluation purposes, alongside our SNFC dataset.

Several studies have employed various techniques such as topic modeling (DiMaggio et al., 2013; Roberts et al., 2014; Nguyen, 2015), cluster analysis (Burscher et al., 2016), and neural networks (Naderi and Hirst, 2017; Khanehzar et al., 2019; Mendelsohn et al., 2021; Kwak et al., 2020) to construct systems for framing analysis. These investigations have consistently demonstrated that leveraging state-of-the-art pre-trained models based on transformers (Devlin et al., 2019; Zhuang et al., 2021; Conneau et al., 2020) is a highly effective approach, yielding significantly improved results compared to other techniques. In our study, we follow the state of the art and build models similar to those employed by Liu et al. (2019) and Khanehzar et al. (2019).

3 Dataset Creation

In this section, we present our methodology for curating SNFC training dataset through crowdsourcing (§3) and outline the process of extending the dataset to incorporate multilinguality (§3). Lastly, we introduce our innovative Portuguese and Bengali benchmarks, highlighting their significance in the context of this study (§3).

SNFC Training Corpus To construct the crowdsourced training portion of the SNFC, we turned to students at ANONYMOUS University.[2] In particu-

[2]Anonymized for review.

Frames	Definitions
Economic	The financial consequences and economic implications of the matter on various levels (person, family, community or broader economy).
Capacity and Resources	The presence or absence of various resources(physical, geographic, human, and financial) and the ability of existing systems.
Morality	Perspectives, policy objectives, or actions driven by religious principles, duties, ethics, or social responsibilities.
Fairness and Equality	The balance or distribution of laws, rights, and resources among individuals or groups.
Legality, Constitutionality, Jurisdiction	Discusses rights, freedoms and authority of individuals, corporations, and government.
Policy Prescription and Evaluation	Specific policies proposed to address identified issues and the assessment of policy effectiveness.
Crime and Punishment	Effectiveness and implications of laws and their enforcement.
Security and Defense	Actions or calls to action aimed at protecting individuals, groups, or nations from potential threats to their well-being.
Health and Safety	Access to healthcare, health outcomes, disease, sanitation, mental health, violence prevention, infrastructure safety, and public health.
Quality of life	Threats and opportunities for the individual's wealth, happiness and well being.
Cultural Identity	Traditions, customs or values of a social group in relation to a policy issue.
Public Sentiment	References of attitudes and opinions of the general public, including polling and demographics.
Political	Political considerations, actions, efforts, stances, and partisan, bipartisan, or lobbying activities related to an issue.
External Regulation and Reputation	The external relations of nations or groups, trade agreements, policy outcomes, and external perceptions or consequences.
Other	Frames that don't fit into the categories above.

Table 1: Frames and their definitions as outlined by Policy Frames Codebook (PFC, Boydstun et al. (2014)). This codebook was given to the students as annotation schema.

lar, this was done as part of an in-class assignment for a graduate-level natural language processing class with about 80 students involved.[3]

The students were presented with the challenge of building a Media Frames Analysis system (effectively, a sentence-level neural classifier), without having access to significant amounts of data. In particular, the students were provided only with a description of the codebook of Boydstun et al. (2014) presented in Table 1, along with 250 sentence-level examples called the seed dataset from the MFC corpus sampled so that all 15 frame dimensions were present.

The codebook and the samples were meant to facilitate the annotators' understanding of the task. The only other information available to them was that their final systems would be evaluated on multiple languages (see §3) on the immigration and same-sex marriage domains.[4]

The students were first tasked with procuring 150 new sentences each, from any source and in any language, and label them, according to the codebook, to be used as their "first" training set. They then had to produce an additional 150 sentences which would then be annotated by two of their peers (so that we will be able to measure inter-annotator agreement). Any label disagreements were resolved by the students, by obtaining an ad-

[3]We are releasing these data with the students' consent.

[4]These evaluation sets were based on the MFC test sets.

ditional label for majority voting. All in all, each student produced a minimum of 300 annotated sentences. While the students had the option to collect data in any language, all of them, apart from two, collected and annotated the initial data in English. The two other students who collected data in different languages chose their native languages: Telugu, and Hindi.

To collect the data, the students were allowed to do anything they wanted. They ended up utilizing diverse techniques that range from targeted web scraping to generating sentences with the assistance of AI tools such as, ChatGPT (Radford et al., 2019). We can broadly categorize the sources of data into three categories: AI tools (such as ChatGPT and ChatSonic), online news platforms (including Online Articles, NBC, CNN, BBC, and NYTimes), and social media platforms (such as Twitter and Reddit). Students have used a combination of two or more categories to collect their data. Around 77% of students used AI tools, 14.8% relied on social media platforms, and 67.9% used online news platforms for data collection purposes.

In the end, we ended up with a total of 17,520 sentences from the combined student training corpus of 300 sentences each, eliminating the occasional duplicate instances. The dataset has a generally substantial inter-annotator agreement, with a Cohen's κ (Cohen, 1960) coefficient of 0.61.

To further contextualize this, we note that the inter-annotator agreement of the MFC (as detailed in the paper) is assessed using Krippendorff's α (Krippendorff, 2011), with respective values of 0.08 and 0.20 for the domains of same-sex marriage and immigration. SNFC (our dataset) combines sentences from both of these domains and the Krippendorff's α value for SNFC stands at 0.103 which is similar to the one of MFC. Given that this is a 15-way classification task, we believe the inter-annotator agreement for SNFC is not particularly low for such a nuanced task.

Multilinguality To benchmark media framing beyond English our first step is to simply translate the original MFC dataset into other languages. We use machine translation[5] to translate all sentences of the MFC corpus into 12 typologically diverse languages, namely Bengali, German, Greek, Italian, Turkish, Nepali, Hindi, Portuguese, Telugu, Russian, Swahili, and Mandarin Chinese.

While the primary reason for this process is the ability to benchmark the task on other languages (as well as the inability to collect annotated test sets in all of these languages – see also §3), this simple data augmentation technique is also a reasonable way to also obtain training data in other languages. Hence, we perform this translation both on the training and the dev/test portions of the dataset, and combine all languages to form the multilingual version of the dataset.

[5]Google Translate, specifically.

Language Pair	Rating (%)
English-Bengali	61.2
English-Greek	73.4
English-Hindi	77.4
English-Nepali	47.2
Comet Score (All languages)	76.05

Table 2: Average rating for Human Evaluation of the Automatic Translation Quality

Lastly, the same translation models were used to augment our crowd-sourced SNFC dataset to cover all of the above-mentioned languages.

We have studied the quality of the translation through human assessment. For each language, we took 100 translations from English and had them reviewed by bilingual speakers who scored the translations on a scale from 1 to 10 based on accuracy and clarity. For this evaluation, we used four languages: Bengali, Greek, Hindi, and Nepali. From the average rating for each language pair (See Table 2), we observe that the average rating is higher for higher resourced languages like Greek and Hindi. On the other hand, Nepali, being the only lower resourced language, has a lower rating of 4.72 out of 10, suggesting that perhaps Nepali results should be taken with a grain of salt, as the reason for general poor performance is likely to be the low quality of the translations.

We have also further performed quality estimation over all translations by calculating the CometKiwi score (Rei et al., 2023) of the translations. Note that we resort to automatic quality estimation since we do not have access to reference translations. The overall score of 76.05% is in line with our human evaluation over the sample, and suggests that automatic translations are largely reliable in our dataset. The higher scores for the high resource languages of the human-evaluation and CometKiwi (see Appendix B for a breakdown by language) indicate that automatic translations

can be a reasonable alternative to gathering large quantities of high quality multilingual data for the framing task.

Novel Test Set While the automatic translation of the MFC benchmark is a reasonable start for our multilingual exploration, it does not come without drawbacks: the provided text, regardless of the language, is only relevant to the USA cultural context.

To even better benchmark the quality of framing analysis systems on different language and cultural contexts, we create a pair of novel test sets in (Bangladesh) Bengali and (Brazilian) Portuguese. The news articles used in this test set were sourced from reputable newspapers in Bangladesh and Brazil, aligning with the chosen domains of immigration and same-sex marriage.

Each test set is comprised of of 10 news articles for each language. The annotators were native speakers of the languages and they adhered closely to the definitions provided by the authors (Table 1), ensuring consistency with the labels found in the MFC.

Figure 2 shows the label distribution for the MFC and the novel test set, listing the number of sentences per frame in each language. In the case of Bengali, the news articles predominantly focus on the immigration domain, reflecting the cultural disparities between Brazil and Bangladesh. Specifically, the test set emphasizes the economic and lifestyle aspects of immigration (Bengali), while also delving into the legal and policy-making dimensions of the domain (Portuguese).

It is of note that the two benchmarks, despite being rather small, still show interesting differences in terms of their label distribution. For example, the most common label on the Bengali set is "External Regulation and Reputation", which is the least common one in the Portuguese one. And the reverse is the case for the "Cultural Identity" label which is the most common in Portuguese and least common in Bengali. Another interesting observation is that the Bengali test set contains more data labeled as "Other" compared to the other two languages. Upon analyzing the data with the help of a native speaker, we found that most of the Bangladeshi articles emphasize a lot on reporting information in the form of dates and numbers, rather than offering opinions on the issues.

Tr. Data	#Sentences	Accuracy
Baselines		
MFC	9740	69.52
MFC10	1125	57.45
including crowd-sourced data		
SNFC	17520	54.37
MFC+SNFC	27260	72.07
MFC10+SNFC	18645	64.75
filtered crowd-sourced data		
MaSNFC	5182	48.77
MFC+MaSNFC	14922	**73.22**
MFC10+MaSNFC	6307	60.94

Table 3: Mean Accuracy Scores on the MFC evaluation set for RoBERTa models trained on English Datasets. # stands for number

4 Framing Analysis System and Results

Experimental Setup We approach the task as a multilabel classification problem (Tsoumakas and Katakis, 2007), leveraging the pretrained RoBERTa (Zhuang et al., 2021) language model, similar to the SOTA approach employed by Khanehzar et al. (2019). For all models we set the maximum sequence length to 256, with a batch size of 16,and train using a learning rate of 10^{-5}. To expand to more languages, we employ the multilingual XLM-RoBERTa model (Conneau et al., 2020). Throughout all experiments, we use the base model size.[6]

We first report results with models exclusively trained on MFC, and SNFC datasets, as well as their concatenation. To investigate a more data-scarce scenario, we also compiled a smaller sample consisting of about 10% of the original MFC, named MFC10, ensuring all 15 target labels are included. Beyond the single-dataset baselines, we combine the expert-annotated MFC and MFC10 with our crowd-sourced SNFC.

English Results and Discussion We first establish the usefulness of our crowdsourced data, by focusing on the performance on the original test set of the English MFC dataset (using the monolingual RoBERTa model). Results are presented in Table 3.

First, it is worth pointing out that relying solely on crowd-sourced data is not promising: the SNFC-only training underperforms both the MFC-only set-

[6]Appendix 7 and 8 also provides results with the BERT and mBERT (Devlin et al., 2019) models (but RoBERTa and XLM-R consistently outperformed BERT and mBERT.

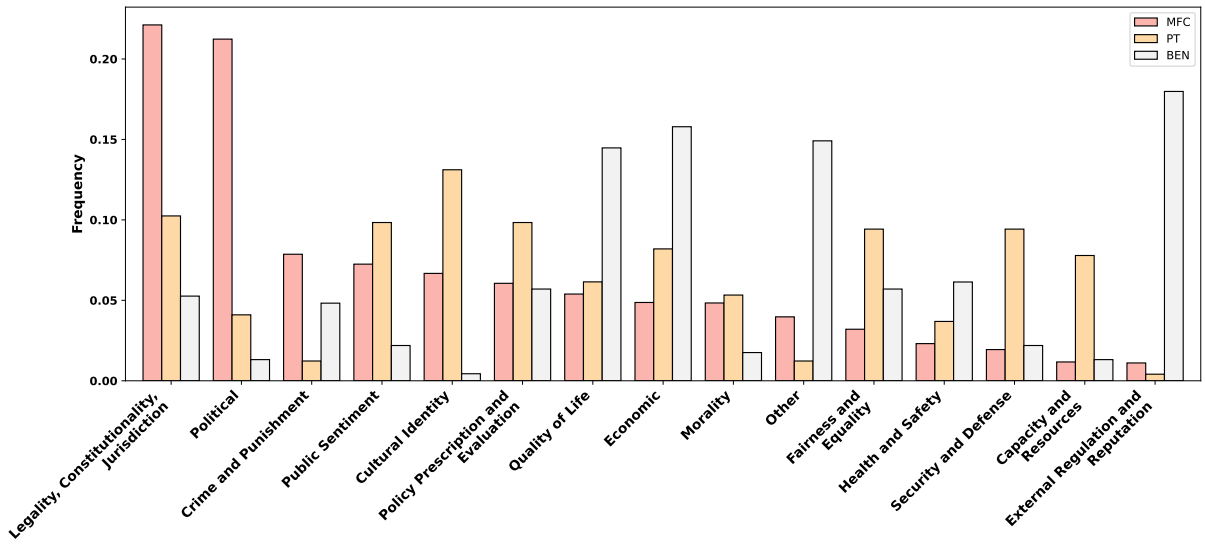

Figure 2: The label distributions of the MFC and our new Bengali and Portuguese test sets. Note that they differ significantly.

ting, as well as the MFC10-only setting, which has only around 10% of the training data size!

However, combining the expert-annotated data with the crowd-sourced ones yields significant improvements over the expert-only baselines, as MFC+SNFC yields an extra 2.5 accuracy points over MFC (72% vs 69.5%). The improvement is even larger (more than 7 accuracy points) in the resource-restricted MFC10 scenario.

Filtering of Crowdsourced Data Given the potential for noise in any crowd-sourced dataset, we explore a simple filtering technique to sample more high-quality crowd-sourced. In particular, we obtain sentence-level representations for each sentence, and select only the SNFC instances that exhibit more than 85% cosine similarity with any MFC instance. Effectively, we select SNFC sentences that are most similar to MFC ones. We refer to this sample as MFC-aligned SNFC (MaSNFC).

Results with this (almost 3x smaller) sample are more encouraging (Table 3): combining MaSNFC with MFC yields our best model with an accuracy of 73.22. In the data-scarce scenario of MFC10, adding MaSNFC is again beneficial, but including the whole unfiltered SNFC is even better.

These findings underline the promise of our crowd-sourced dataset, as we were able to achieve significant improvements beyond the baseline, even when evaluating on expert-annotated data.

Multilingual Results and Discussion For the first part of our multilingual experiments, we employ a translate-train and translate-test scenario. All of the dataset samples introduced above were translated to all 12 evaluation languages, and we now replicate the same experimental setups as above, the only difference being that we will use a multilingual LM (XLM-R instead of RoBERTa). All results are presented in Table 4 (which presents the average accuracy across the 12 languages for mMFC, as well as performance on our novel Bengali and Portuguese benchmark).

Tr. Data	mMFC	BENGALI	PORTUGUESE
Zero-shot (only English train)			
MFC	28.13	25.44	28.28
Baselines (translate-train)			
MFC	44.99	25.88	**33.61**
MFC10	28.64	23.68	27.87
+ crowd-sourced (translate-train)			
SNFC	28.04	25.44	23.77
MFC+SNFC	44.07	26.31	31.56
MFC10+SNFC	33.11	**32.02**	26.62
+ filtered crowd-sourced (translate-train)			
MaSNFC	27.55	16.67	15.98
MFC+MaSNFC	**45.73**	28.07	**33.61**
MFC10+MaSNFC	32.56	24.56	26.64

Table 4: Mean Accuracy Scores on the MFC evaluation set and Novel Multilingual Test Set for XLM-R models trained on Multilingual Datasets. The best scores have been highlighted.

First of all, we show that relying on zero-shot cross-lingual transfer, without employing the translate-train technique is not a competitive baseline. The translated MFC baseline is competitive on average, but as we discuss below it performs

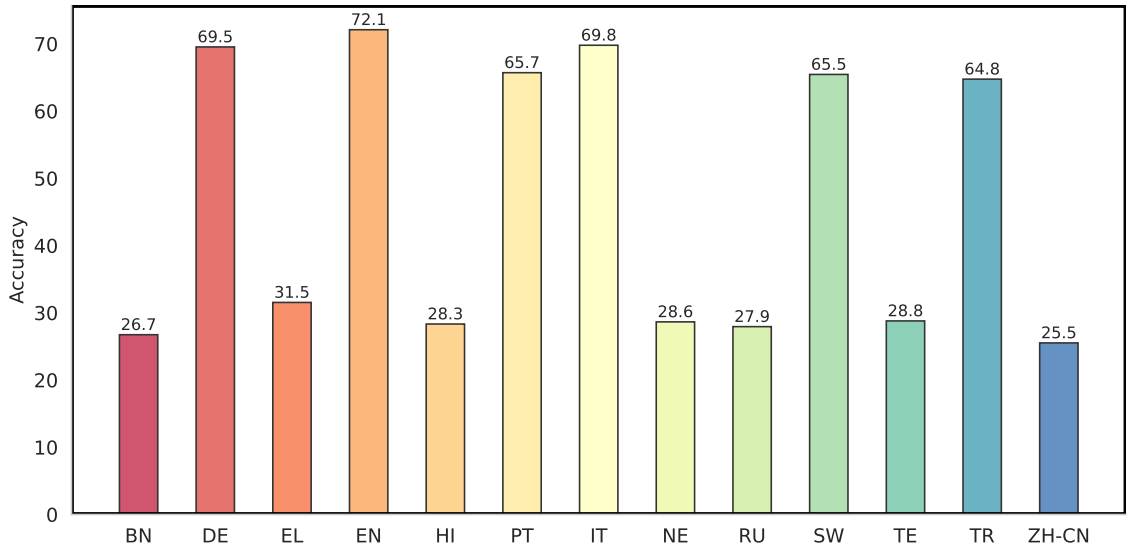

Figure 3: The best model performs very inequitably across languages on mMFC. The highest accuracy is in English (72.1%) followed by Italian and German, while other languages from non-western countries (e.g. Bengali, Hindi, Chinese, and others) have much lower performance (under 30%).

quite inequitably across languages. As before, combining expert annotated data with filtered crowd-sourced ones (MFC+MaSNFC) is best. Our findings from the monolingual experiments generally hold in the multilingual ones.

In the Bengali test set, the inclusion of all crowd-soured data improves upon the baseline by a small margin. The improvement from filtered crowd-sourced data is more modest. However, it is interesting that the best performance is obtained when using fewer expert annotations (MFC10+SNFC), improving by almost 6 percentage points over the baseline! We hypothesize that using the whole MFC dataset overfits the US context – but we leave this analysis for future work. In the Portuguese test set, we observe generally similar patterns as in the mMFC, with the exception that we do not observe any improvement from the crowd-sourced data. We leave a further investigation for future work.

We note that the accuracies for the Bengali and Portuguese test sets are significantly lower than those of the English MFC and the mMFC test sets. We suspect that the training data, being automatic translations, may not capture the nuances of the original news articles. Second, the domain shift due to cultural context differences between training and test may play a significant role. To improve the scores further, it may be necessary to obtain original news articles from diverse culturally distinct sources in different languages.

mMFC Breakdown per Language We further analyse the per-language performance of our best-performing model on mMFC (see Figure 3). English accuracy (72.1) is en par with the monolingual setting (73.2), and German, Italian, Swedish, and Turkish also yield accuracies higher than 64%. But for other languages the model performs much worse, including high-resource ones like Greek (31.5%), Russian (28%), and Chinese (25.5%). While translation errors may play a role here, we are confident that they are not enough to explain such a large discrepancy. For example, while Nepali has admittedly low-quality translations (see previous discussion), Hindi, Greek, and Chinese certainly have translations of fairly high quality and yet they fall in the same low performance ballpark. We suspect that this gap may only be bridged through data collection (either expert- or crowd-annotated) in the appropriate languages and cultural contexts.

Error Analysis We analyzed the errors using a confusion matrix for our best-performing model MFC+MaSNFC on the mMFC evaluation set, as shown in Figure 4. The heat-map reveals that out of 15 labels, 9 achieve the majority of instances correctly. Specifically, the labels 'Political' and 'Legality, Constitutionality, Jurisdiction' have the highest number of instances predicted correctly. However, when the model makes incorrect predictions, the errors are mainly categorized into the 'Political' and 'Legality, Constitutionality, Jurisdiction' labels. This led us to suspect a potential data imbalance in our training model. Further examination of the data confirmed that these two labels indeed have a

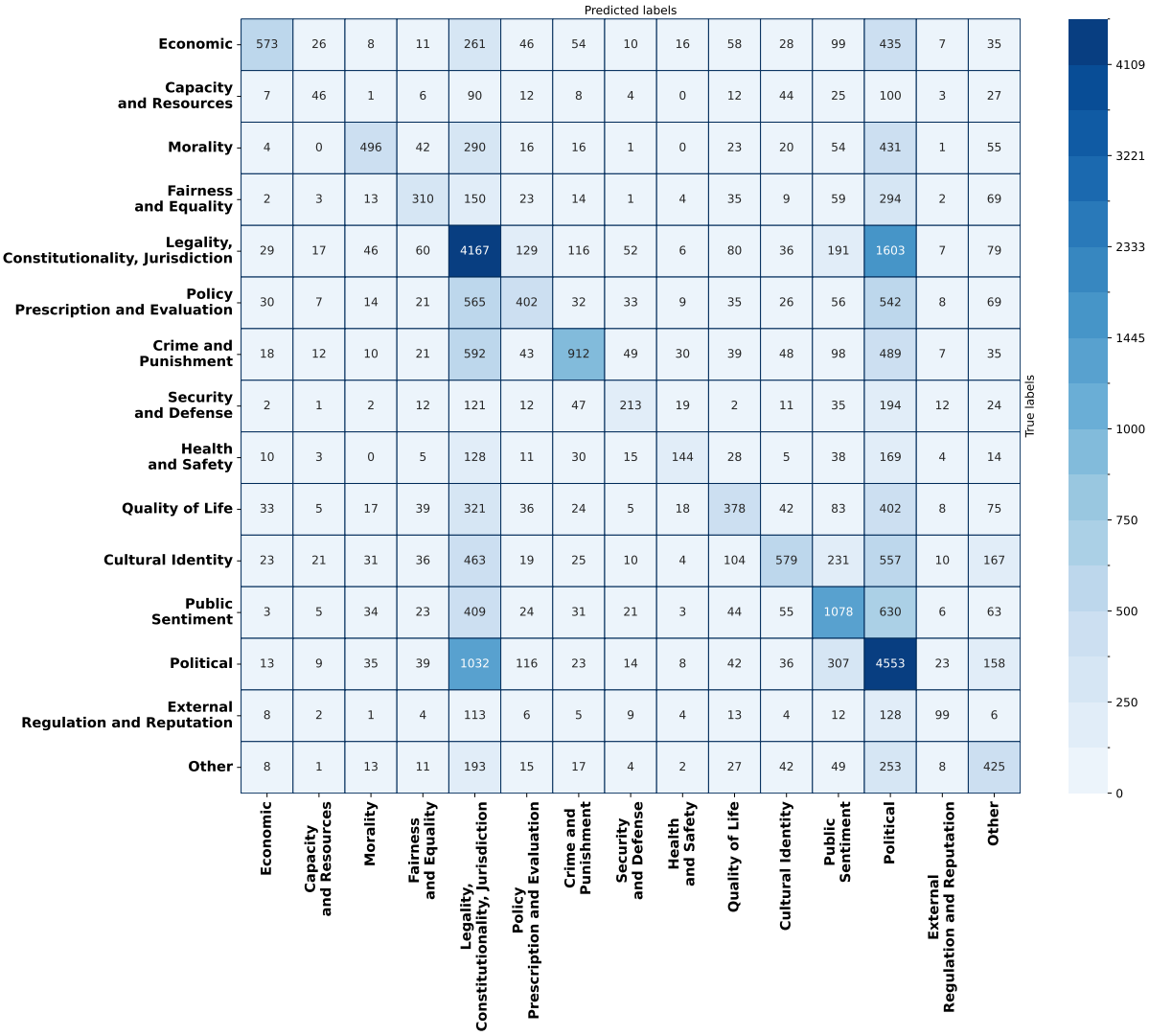

Figure 4: Confusion matrix for the best model's prediction for the mMFC Test set

majority of instances in the training set, leading to the tendency to predict these labels when uncertain.

One could also further argue that these two labels are quite close semantically and hence their confusion is perhaps expected. We have examined the original data from MFC for the immigration and same-sex issues, which were used to train our baseline model. This dataset indeed shows a skewed distribution with a disproportionate number of instances falling under these two labels. This suggests that US-based news articles covering these domains inherently tend to fall in these two categories. Given the domain, we deduce that such an imbalance in label distribution might be a common trend in news articles from other countries as well. This assumption can be further validated in our novel test sets derived from Bangladesh and Brazil, which also reveal a similar inclination towards certain labels, as discussed in the previous section.

5 Conclusion

In conclusion, our study emphasizes the importance of data quality and language diversity in multilingual framing analysis. Combining the Media Frames Corpus (MFC) with the Student-Sourced Noisy Frames Corpus (SNFC) yields significant improvements, highlighting the value of leveraging larger datasets. However, lower accuracies in multilingual experiments indicate the need for improved translations and culturally diverse training data to enhance the performance of multilingual framing analysis.

Limitations

The main limitation of this study is that it relies on automated translation via Google Translator to introduce multilinguality to the task. It is well

known that the translations conducted by Google Translator may not achieve the same level of quality as authentic translations. Moreover, for lower-resource languages such as Nepali and Swahili, the translations obtained from Google Translator may not fully capture the nuances and characteristics as well as it probably can if translated to higher-resource languages as German or Greek. Additionally, since the MFC dataset primarily consists of US news sources, the translations into different languages does not adequately reflect the biases and perspectives surrounding a specific political issue in different countries. We attempt to mitigate this limitation with our new Bengali and Portuguese test sets. Collecting more data from different countries in different languages will eventually address this limitation, but we leave this large-scale undertaking for the future.

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A Novel Bengali and Portuguese Test Set Statistic

Number of sentences	Bengali	Portuguese
Economic	36	20
Capacity and Resources	3	19
Morality	4	13
Fairness and Equality	13	23
Legality Constitutionality Jurisdiction	12	25
Policy Prescription and Evaluation	13	24
Crime and Punishment	11	3
Security and Defence	5	23
Health and Safety	14	9
Quality of Life	33	15
Cultural Identity	1	32
Public Sentiment	5	24
Political	3	10
External Regulation and Reputation	41	1
Other	34	3
Total	228	244

Table 5: Number of texts per frame per language

The distribution of labels in the Bengali and Portuguese test sets (see Table 5) reveals intriguing domain affinity. In the case of Bengali, the news articles predominantly focus on the immigration domain, reflecting the cultural disparities between Brazil and Bangladesh. Specifically, the test set emphasizes the economic and lifestyle aspects of immigration (Bengali), while also delving into the legal and policy-making dimensions of the domain (Portuguese).

B Assessing Translation Quality

Table 6 shows the breakdown of the comet score per language.

Language Pair	**Comet Score (%)**
English-Bengali	74.39
English-German	76.93
English-Greek	76.64
English-Hindi	67.87
English-Italian	79.04
English-Nepali	86.84
English-Russian	79.87
English-Swahili	73.71
English-Telugu	69.02
English-Bengali	78.79
English-Turkish	74.63
English-Chinese	74.63
English-Portuguese	74.89
System Score	76.05

Table 6: Average score from `CometWiki` of the Automatic Translation Quality without reference. The high resource languages (i.e., Italian, Greek etc) have higher scores than lower resource languages (i.e., Telugu)

C Complete Results for English and Multilingual Experiments

We observed the mean accuracy of the MFC evaluation set for models trained on English and Mulitlingual datasets. The key findings are summarized below:

1. The MFC alone achieved higher accuracy compared to other systems, with scores of 61.93% and 69.52% for BERT and RoBERTa-based models, respectively. However, when using the MFC10 dataset with limited high-quality data, the accuracy dropped significantly to 53.02% and 57.45% for BERT and RoBERTa models, respectively.

2. The SNFC and MaSNFC datasets exhibited lower accuracy when evaluated individually, compared to the MFC. However, the SNFC outperformed MFC10 in terms of accuracy for the BERT model. The SNFC has an accuracy of 60.57% while the MFC10 has gotten 53.02%. It is worth noting that the larger size of the SNFC contributed to its higher accuracy compared to MaSNFC, which is almost three times smaller.

3. Combining the MFC with our datasets led to substantial accuracy improvements. The models trained on MFC+SNFC (72.57%, 72.07%) and MFC+MaSNFC (72.85%, 73.22%) achieved higher accuracy than the MFC alone (61.93%, 69.52%), for both BERT and RoBERTa models.

4. Combining MFC10 with our datasets, we observed improved accuracy as well. The MFC10+SNFC combination yielded an accuracy improvement of 6.1 and 4.77 percentage points for BERT and RoBERTa models, respectively, compared to MFC10. Similarly, MFC10+MaSNFC demonstrated a similar improvement of 7.1 and 3.49 percentage points, respectively.

5. The overall accuracies of the MFC evaluation set for multilingual data (Table 3) are lower compared to the accuracies for English training (Table 2). This can be attributed to the fact that the training data in other languages were obtained through automatic translation, which may not be of the same quality as human translations or original news articles in those languages.

System Name	Number of Sentences	BERT	RoBERTa
MFC	9740	61.93	69.52
MFC10	1125	53.02	57.45
SNFC	17520	60.57	54.37
MaSNFC	5182	52.05	48.77
MFC+ SNFC	27260	72.57	72.07
MFC+ MaSNFC	14922	**72.85**	**73.22**
MFC10+ SNFC	18645	68.03	64.75
MFC10+ MaSNFC	6307	60.12	60.94

Table 7: Mean Accuracy Scores on the MFC evaluation set for models trained on English Datasets. The best scores have been highlighted.

6. Among the datasets, MFC+MaSNFC achieved the highest accuracy of 45.73 on the multilingual test set, outperforming both MFC and MFC10 datasets.

7. For the Bengali test set, the highest accuracy (32.02) was achieved by the MFC10+SNFC training dataset. As for the Portuguese test set, the highest accuracy of 33.61 was obtained by two systems: MFC and MFC+MaSNFC.

8. Overall, the accuracies for the Bengali and Portuguese test sets were lower than those for the MFC evaluation set. This can be attributed to two factors. First, the training data, being translations, may not capture the nuances of the original news articles. Second, the training data mainly consists of MFC, which is collected from US-based news media sources. The test sets, on the other hand, were collected from Brazil and Bangladesh, which have different cultural contexts in their news articles that cannot be fully replicated through translation. To improve the scores further, it would be necessary to obtain original news articles from diverse culturally distinct sources in different languages.

The study highlights challenges in multilingual framing analysis, with lower accuracies compared to English training. It emphasizes the need for high-quality translations and original news articles. Combining datasets like MFC+MaSNFC can enhance accuracy. Considering cultural and linguistic con-

System Name	MFC Evaluation Set		Bengali Test Set		Portuguese Test Set	
	mBERT	XLM-R	mBERT	XLM-R	mBERT	XLM-R
MFC (English)	27.70	28.13	16.67	25.44	26.23	28.28
MFC	44.87	44.99	21.93	25.88	30.33	**33.61**
MFC10	27.7	28.64	20.61	23.68	30.33	27.87
SNFC	28.05	28.04	22.37	25.44	27.05	23.77
MaSNFC	28.86	27.55	11.84	16.67	20.49	15.98
MFC+SNFC	**45.09**	44.07	**23.25**	26.31	29.92	31.56
MFC+MaSNFC	44.42	**45.73**	22.37	28.07	**31.97**	**33.61**
MFC10 + SNFC	30.01	33.11	25	**32.02**	29.51	26.62
MFC10+MaSNFC	33.33	32.56	22.81	24.56	22.13	26.64

Table 8: Mean Accuracy Scores on the MFC evaluation set and Novel Multilingual Test Set for models trained on Multilingual Datasets. The best scores have been highlighted.

texts and diverse training data is crucial for better understanding framing across languages and cultures.