

# The FIGNEWS Shared Task on News Media Narratives

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## Abstract

We present an overview of the FIGNEWS shared task, organized as part of the Arabic-NLP 2024 conference co-located with ACL 2024. The shared task addresses bias and propaganda annotation in multilingual news posts. We focus on the early days of the Israel War on Gaza as a case study.<sup>1</sup> The task aims to foster collaboration in developing annotation guidelines for subjective tasks by creating frameworks for analyzing diverse narratives highlighting potential bias and propaganda. In a spirit of fostering and encouraging diversity, we address the problem from a multilingual perspective, namely within five languages: English, French, Arabic, Hebrew, and Hindi. A total of 17 teams participated in two annotation subtasks: bias (16 teams) and propaganda (6 teams). The teams competed in four evaluation tracks: guidelines development, annotation quality, annotation quantity, and consistency. Collectively, the teams produced 129,800 data points. Key findings and implications for the field are discussed.

## 1 Introduction

The FIGNEWS 2024 shared task,<sup>2,3</sup> henceforth FIGNEWS, addresses the critical need for analyzing bias and propaganda in multilingual news discourse surrounding the Israel War on Gaza. This task aligns with the NLP community’s growing efforts to create datasets and guidelines for complex opinion analysis through collaborative shared tasks and datathons. Such a meta-task allows for the exploration of various annotation frameworks in particular for complex and challenging subjective tasks. FIGNEWS focuses on a diverse multilingual corpus, emphasizing the development of guidelines

with rich examples, while fostering a research-oriented collaborative environment. By simultaneously examining multiple languages, comparing and contrasting various narratives, FIGNEWS aims to unravel the layers of possible bias and propaganda within news articles with alternative media narratives. This is especially critical at times of any war or conflict. The media’s portrayal of events during such events has significant implications on public perception, policy-making, and international relations. By addressing bias and propaganda, we hope to illuminate the varied ways in which news can shape, and sometimes distort, public understanding of complex geopolitical events. This initiative seeks to explore diverse perspectives, cultures, and languages, thereby fostering a comprehensive understanding of events through the lens of major news outlets across the globe.

Developing guidelines for complex data is a challenging task. The problem is exacerbated when the data is contemporaneous hence the annotators and the task organizers might have a stance on the subject matter. FIGNEWS is our attempt at addressing the creation of annotation guidelines, addressing what relevant best practices should be. We use the Israel War on Gaza as a use case to highlight some of these aspects. To that end, we curate a shared corpus for comprehensive annotation across various layers, crafting annotation guidelines shaped by the diverse range of conflicting discourses around this sensitive topic. This endeavor facilitates the development of robust methodologies and metrics for detecting and analyzing bias and propaganda, which are crucial for ensuring fair and accurate media reporting. The curated corpus, along with meticulously developed guidelines and annotations, will serve as a valuable resource for future research in NLP and related fields.

This initiative also seeks to bring to light both challenges and commendable aspects within the data, fostering a collaborative community that can

<sup>1</sup>FIGNEWS: *Framing the Israel War on Gaza News*.

<sup>2</sup>Website: <https://sites.google.com/view/fignews>

<sup>3</sup>Code and Data: <https://github.com/CAMEL-Lab/FIGNEWS-2024> & <https://huggingface.co/datasets/CAMEL-Lab/FIGNEWS-2024>

learn from each other’s approaches and findings. We believe that a collaborative, research-oriented environment is essential for tackling the intricate task of bias and propaganda detection.

The FIGNEWS shared task thus represents a significant step forward in the field of data annotation, media analysis and NLP. A step towards an annotation science. It not only provides a platform for examining critical issues of bias and propaganda but also promotes the development of best practices in data annotation and analysis. Through this shared task, we aim to contribute to the broader goal of improving media literacy and fostering a more informed and critically engaged public.

## 2 Related Work

Propaganda and bias can have far-reaching implications depending on the context and medium in which they are propagated. Polarization, conflict and injustice are but some of the side effects they can create in any context. In the context of politics, they can alter the outcomes of elections and change the face of nations (Gorenc, 2020; Maweu, 2019; Solopova et al., 2024). News media framing and narratives around wars and socio-political events have been extensively studied, with a focus on identifying bias, propaganda, offensive language detection, and diverse perspectives (Entman, 2007; Baumer et al., 2015; Fan et al., 2019; Morstatter et al., 2018; Park et al., 2009; Martino et al., 2020b; Aksenov et al., 2021; Yenikar et al., 2022; Kameswari et al., 2020; Hong et al., 2023; Kim et al., 2023; Sharma et al., 2023; Maab et al., 2023; Rodrigo-Ginés et al., 2024; Hamad et al., 2023; Darwish et al., 2021). Several works have proposed computational approaches to detect media bias through analysis of word choice, labeling, and factual reporting (Hamborg et al., 2019; Budak et al., 2016; Vaagan et al., 2010; Varacheva and Gherghina, 2018).

Entman (2007) defines *framing* as the process of selecting certain aspects of perceived reality and constructing a narrative that emphasizes their connections to promote a specific interpretation. This foundational work highlights how news framing can influence public perception by emphasizing particular elements over others. Entman (1993) further elaborates on this concept, providing a comprehensive framework for understanding how media frames can shape political and social realities.

Several studies have developed methods and

datasets to detect news bias. Budak et al. (2016) used crowdsourced content analysis to quantify media bias, while Baumer et al. (2015) compared computational approaches for detecting framing in political news. Tools like Biasly (2017) help users gauge news bias, quantifying liberal or conservative leanings.

In the context of multilingual and multi-label news framing analysis, Akyürek et al. (2020) explored the complexities of news framing across different languages. Their work is crucial for understanding how bias and framing manifest in multilingual contexts, aligning closely with the objectives of the FIGNEWS shared task. Similarly, the study by (Heppell et al., 2023) offers a valuable dataset and linguistic insights from two multilingual disinformation websites, providing a foundation for further exploration of language-specific disinformation techniques and their impact on news framing.

Recent advances in bias detection have also emphasized the importance of detailed and well-annotated datasets. Spinde et al. (2021a) introduced the MBIC dataset, which includes detailed information about annotator characteristics and provides labels for bias identification at both the word and sentence levels. This dataset represents a significant step forward in creating reliable ground-truth data for bias detection. Additionally, Spinde et al. (2021b) developed TASSY, a text annotation survey system that enhances the quality control of annotation processes in NLP tasks.

Annotation of biased language and framing in news articles has been explored using techniques like expert annotation (Al-Sarraj and Lubbad, 2018) and crowdsourcing (Lim et al., 2020, 2018). Quality control and guidelines for annotation processes in NLP tasks have also been investigated (Grosman et al., 2020; Spinde et al., 2021b). Grosman et al. (2020) developed ERAS, a system designed to enhance quality control in NLP tasks, which is particularly relevant for ensuring the reliability of annotations in bias and propaganda detection.

Further contributions to the detection of bias and propaganda include the work of Rashkin et al. (2017), who analyzed language in fake news and political fact-checking, and Barrón-Cedeno et al. (2019), who organized news based on their propaganda-prone content. These studies provide foundational techniques for the identification and analysis of biased and propaganda language in news media.

The shared task on propaganda detection at SemEval-2020, organized by Martino et al. (2020a), is directly relevant to the FIGNEWS task. This task focused on detecting propaganda techniques in news articles, providing valuable benchmarks and methodologies that can be applied to the detection of bias and propaganda in social media posts.

In the context of the Israel-related wars and conflicts, Al-Sarraj and Lubbad (2018) conducted a sentiment analysis study to detect bias in Western media coverage. This work highlights the specific challenges of detecting bias in a highly polarized and sensitive geopolitical context. Additionally, Hamad et al. (2023) introduced a new dataset designed for detecting and classifying various forms of offensive language in Hebrew on social media. Furthermore, the WojoodNER Shared Task 2024 offered a new NER dataset related to the Israeli War on Gaza called *Wojood<sup>Gaza</sup>* (Jarrar et al., 2024).

Research on detecting political bias in social media includes Zhou et al. (2020), who identified bias in user-generated content, and Li et al. (2019), who surveyed sentiment analysis techniques. The Propitter corpus (Casavantes et al., 2024) was developed using distant supervision with refined annotations. Hamborg et al. (2019) advanced media bias detection by focusing on automated identification through word choice and labeling. Fan et al. (2019) analyzed factual reporting to reduce bias, stressing the need for objectivity.

Among the studies forming a strong basis for understanding bias and propaganda detection in media are the following. Baly et al. (2020) examined news media profiling using text and social media analysis, showing how news context affects bias perception. Allcott and Gentzkow (2017), Vosoughi et al. (2018), and Grinberg et al. (2019) studied fake news spread during the 2016 US election, highlighting the need for reliable information. Lazer et al. (2018) detailed fake news detection methods, while Horne and Adali (2017) emphasized high-quality data for combating misinformation. Sharma et al. (2019) surveyed fake news identification techniques. Zhou and Zafarani (2020) reviewed fake news detection theories and methods, pointing to future research opportunities.

While prior work has made notable contributions, our shared task focuses on comprehensive annotation of media narratives and framing around a specific war to uncover new insights. We build upon existing annotation frameworks (Zaghouani et al., 2016; Zaghouani and Charfi, 2018) to de-

velop improved guidelines and foster a collaborative exploration of media discourses through a multilingual, multicultural lens.

### 3 Data Collection and Selection

We used the CrowdTangle<sup>4</sup> platform to collect Facebook posts related to the Israel War on Gaza in five languages: English, French, Arabic, Hebrew, and Hindi. Specifically, we retrieved public posts containing the keyword “Gaza”<sup>5</sup> from verified blue-check accounts, publicly posted between October 7, 2023, and January 31, 2024.

For each language, we collected approximately 300,000 posts. To narrow this down to 3,000 posts per language and have a balanced distribution, we focused on ten key moments in the first few months of the war: starting with the events of October 7, 2023 and the declaration of war, and including the bombings in Jabalia refugee camp, Al-Shifa hospital, and St. Porphyrius Church, as well as the ceasefire and hostage release, Gaza mass arrests, and the coverage of the International Court of Justice case till the end of January 2024.

For each of the ten moments, we selected the top 200 posts per language, ranked by total interaction count (likes, shares, comments, etc.). As a result, we selected 15,000 posts with the highest interactions, covering different key moments of the War, in five languages.

We divided the 15,000 posts into 15 batches ( $\{B01, B02, \dots, B015\}$ ) with 1,000 posts in each batch. Each batch contains 200 posts per language. Additionally, each batch included 20 posts for each of the 10 key moments during the War.

Since the annotators may not speak all five languages, we provided machine translations (Google Translate) into English and Arabic to facilitate annotation across the multilingual corpus. While machine translation inevitably introduces some noise, we considered this to be reflective of the real-world reliance on such technologies.

To compare the Inter-Annotator Agreement (IAA) among all participating teams in a fair manner, we randomly selected 20 posts from each language (i.e., 100 posts, which is 10%) from each batch, totaling 1,500 posts. All participants received the dataset in a Google Sheet file with two sheets: “Main” and “IAA”. The “Main” sheet con-

<sup>4</sup><https://crowdtangle.com>

<sup>5</sup> غزة, גאזה, गाजा, and Gaza.

tains 13,500 posts, while the “IAA” sheet contains 1,500 posts. See Appendix B for a screenshot of the interface.

It is important to note that participants were provided only with the original posts and their translations. Information such as account owner, date, and total interactions were not given to any participating team (See the ethical consideration section).

## 4 Subtasks and Evaluation Tracks

This section presents the shared task subtasks, evaluation tracks and minimal requirement for teams to qualify. Further details are in Appendix A.

### 4.1 Minimal Requirements to Qualify

To qualify, each participating team **must provide full annotation guidelines** for each subtask they choose to work on; and they **must annotate at minimum Batch 1 and Batch 2**, i.e. (1,800 posts) and their designated Inter-annotator agreement subset (200 posts) for a total of 2,000 posts.

### 4.2 Annotation Subtasks

The shared task consists of two subtasks: Bias Annotation and Propaganda Annotation.

#### 4.2.1 Bias Annotation Subtask

The Bias Annotation subtask involves assigning one of the following seven labels to each post: (1) **Unbiased**, (2) **Biased against Palestine**, (3) **Biased against Israel**, (4) **Biased against both Palestine and Israel**, (5) **Biased against others**, (6) **Unclear**, and (7) **Not Applicable**. Examples illustrating each label are provided in the shared task description in Appendix A.

#### 4.2.2 Propaganda Annotation Subtask

The Propaganda Annotation subtask requires participants to classify each post into one of the following four categories: (1) **Propaganda**, (2) **Not Propaganda**, (3) **Unclear**, and (4) **Not Applicable**. Examples showcasing each category are included in the shared task description in Appendix A.

### 4.3 Evaluation Tracks

For each subtask, there are four evaluation tracks.

#### 4.3.1 Guidelines Track

Participants have the freedom to design their own annotation guidelines and apply them to the shared data. The organizers will evaluate the guidelines based on an 8-point checklist, which includes items

such as defining objectives, describing the task, establishing categories, providing detailed guidelines with examples, outlining the annotation process, setting quality standards, handling ambiguities, ensuring consistency, and considering ethical aspects.

The **Guidelines Score** used to determine the winners of this track is the average normalized Document Score and normalized IAA Kappa score. The Document Score is equal to the number of satisfied document checklist items, a range from 0 to 8. The IAA Kappa score of a team is the average of all pairwise IAA Kappas over team annotators per batch (same as IAA Quality Score discussed next). For both sub-scores, normalization is accomplished by dividing by the maximum value attained by any qualified team. Further details are in Appendix A.

#### 4.3.2 IAA Quality Track

In the IAA Quality Track, teams compete based on their internal (within team) IAA Kappa scores (Cohen, 1960). In addition to the Kappa score (our primary metric), we report on a number of other useful metrics.

- **IAA Kappa** (Primary Metric) A team’s IAA Kappa score is calculated as the average of all pairwise Kappa scores between team annotators for each relevant IAA batch and subtask.
- **Accuracy (Acc)** The percentage of agreed upon data points (Bias and Propaganda)
- **Macro F1 Average** The average F1 score over all the Bias or Propaganda subtask labels over all pairs of annotators and relevant IAA batches, i.e. batches which the pairs of annotators annotated.
- **F1 Bias\*** The value of the average F1 score of all Bias labels collapsed as Bias vs other.
- **F1 Prop\*** The value of the average F1 score of *Propaganda* label alone.

#### 4.3.3 Quantity Track

In the Quantity Track, teams compete based on the number of annotated data points. They must complete the batches in order and finish one batch before moving to the next.

#### 4.3.4 Consistency Track

In the Consistency Track, teams compete based on the centrality of their annotation choices compared to all other teams. Centrality reflects the consistency of a team’s annotations with those of other teams. We define a team’s centrality as **Macro F1**

Team Name	System Description	Bias	Propaganda
<b>Bias Bluff Busters</b>	Pareti et al. (2024)	X	X
<b>BiasGanda</b>	Al Wardi et al. (2024)	X	
<b>BSC-LANGTECH</b>	Ruiz-Fernández et al. (2024)	X	
<b>Ceasefire</b>	Sadiah et al. (2024)	X	
<b>DRAGON</b>	Jafari et al. (2024)	X	
<b>Eagles</b>	Ean et al. (2024)	X	
<b>Groningen Annotates Gaza</b>	Khatib et al. (2024)	X	
<b>JusticeLeague</b>	Saleh et al. (2024)	X	
<b>Narrative Navigators</b>	Al Emadi et al. (2024)	X	X
<b>NLPColab</b>	Rauf et al. (2024)	X	X
<b>Sahara Pioneers</b>	Solla et al. (2024)		X
<b>Sina</b>	Duaibes et al. (2024)	X	X
<b>SQUad</b>	Al-Mamari and Al-Farsi (2024)	X	
<b>The CyberEquity Lab</b>	Helal et al. (2024)	X	X
<b>The Guideline Specialists</b>	Bourahouat and Amer (2024)	X	
<b>The Lexicon Ladies</b>	El-Ghawi et al. (2024)	X	
<b>UoT1</b>	Nwesri et al. (2024)	X	
<i>Totals</i>		16	6

Table 1: The participating teams: names, papers, and subtasks.

**Average** of its Bias or Propaganda annotations (as relevant) against other teams’ annotations. A more central team, with higher consistency, is one that other teams agree with more on average. We report on all the metrics mentioned in Section 4.3.2 except that we consider the annotations in Main Batch 1 and Batch 2 for this track, and only compare annotators in different teams (across teams).

## 5 Results

### 5.1 Teams

Out of the 23 teams that registered, only 17 technically qualified per the rules of the shared task, i.e., minimally provided batches 1 and 2 in Main and IAA fully. Table 1 lists the qualifying teams and the subtasks they participated in. All of the qualifying teams submitted system description papers which are included in the proceedings.

### 5.2 Annotators

In total, 85 annotators from 16 teams participated in the Bias subtask, and 51 annotators from 6 teams participated in the Propaganda subtask. Table 10 in Appendix C highlights the diversity among the annotators based on the information they provided voluntarily. Only half of the annotators are native Arabic speakers and close to one-third are Urdu speakers. Half are between the ages 18-24 and close to one-third 25-34. Over three-quarters identify as female. They claim many regions of origin (South Asia 33%, Levant 27%, North Africa 13%, Western Europe 11%, among others). Almost all are highly educate with close to half with Master’s

degree. Two thirds of the annotators come from Engineering and Technology areas of expertise.

### 5.3 Bias Subtask

In total, there were 85 annotators across 16 teams and they annotated together 72 Main sets and 237 IAA sets, for a total of 88,500 data points. Table 2 and Table 3 present the results on the Bias Subtask. The winners are presented in Table 5.

**Guidelines Track** The winners of the Bias Guidelines Track are NLPColab (1st), Eagles (2nd) and Narrative Navigators (3rd). Details on their scores and ranking are in Table 2.

**IAA Quality Track** The winners of the Bias IAA Quality Track are NLPColab (1st), JusticeLeague (2nd) and Sina (3rd). Details on their scores are in Table 3.

**Quantity Track** The winners of the Bias Quantity Track are DRAGON (1st), NLPColab (2nd) and Sina (3rd). The sum of their annotations equal to 56% of all Bias subtask annotations. Details on their scores are in Table 3.

**Consistency Track** The winners of the Bias Consistency Track are The Lexicon Ladies (1st), NLPColab (2nd) and Narrative Navigators (3rd). Details on their scores are in Table 3.

**Observations** As anticipated, within-team IAA scores significantly surpass across-team IAA, with an average absolute increase of 22.6% (**Kappa**) and 19.4% (**Macro F1 Average**). The **F1 Bias\*** scores, indicating binary bias determination, show

	Team	Define Objectives	Establish Categories	Provide Examples	Outline Process	Quality Standards	Handle Ambiguities	Ensure Consistency	Training & Support	Guidelines Document Score	IAA Kappa	Guidelines Score	Final Rank
Bias	Bias Bluff Busters	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	7	43.3	0.7120	4
	BiasGanda	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8	31.0	0.6964	6
	BSC-LANGTECH	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	Unclear	6	51.0	0.6982	5
	Ceasefire	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8	26.6	0.6685	8
	DRAGON	No	No	No	Yes	Yes	No	Yes	No	3	35.7	0.4140	16
	Eagles	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8	55.5	0.8519	2
	Groningen Annotates Gaza	Yes	Yes	Yes	No	No	No	No	No	3	43.5	0.4634	15
	JusticeLeague	Yes	Yes	Yes	Unclear	Yes	Unclear	No	No	4	64.4	0.6585	10
	Narrative Navigators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8	39.4	0.7497	3
	NLPColab	Yes	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	7	78.8	0.9375	1
	Sina	Yes	Yes	No	No	No	No	No	Yes	3	61.4	0.5771	14
	SQUad	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8	23.4	0.6483	11
	The CyberEquity Lab	Yes	Yes	No	Yes	No	No	Yes	Yes	5	48.1	0.6175	13
	The Guideline Specialists	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	7	28.6	0.6192	12
The Lexicon Ladies	Unclear	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7	37.2	0.6732	7	
UoTI	Yes	Yes	Yes	Yes	Yes	No	Yes	Unclear	6	44.9	0.6598	9	
Propaganda	Bias Bluff Busters	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	7	31.5	0.6632	2
	Narrative Navigators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	8	12.8	0.5913	5
	NLPColab	Yes	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	7	69.9	0.9375	1
	Sahara Pioneers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	7	27.9	0.6373	4
	Sina	Yes	Yes	No	No	No	No	No	Yes	3	65.3	0.6551	3
The CyberEquity Lab	Yes	Yes	No	Yes	No	No	Yes	Yes	5	33.5	0.5521	6	

Table 2: Results of the guidelines evaluation track

a wide range of disagreements within teams (average 71.3%, stdev 10.9%) and across teams (average 60.2%, stdev 6.5%). This variability reflects the inherent subjectivity and complexity of bias labeling in general.

The bias labeling task is challenging, with high IAA difficult to achieve both within and across teams. However, the high scores of top-performing teams highlight the need for meticulous attention to detail and comprehensive training.

#### 5.4 Propaganda Subtask

In total, there were 51 annotators across 6 teams and they annotated together 36 Main sets and 89 IAA sets, for a total of 41,300 data points. Table 2 and Table 4 present the results on the Propaganda Subtask. The winners are presented in Table 5.

**Guidelines Track** The winners of the Propaganda Guidelines Track are NLPColab (1st), Bias Bluff Busters (2nd) and Sina (3rd). Details on their scores and ranking are in Table 2.

**IAA Quality Track** The winners of the Propaganda IAA Quality Track are NLPColab (1st), Sina (2nd) and The CyberEquity Lab (3rd). Details on their scores are in Table 4.

**Quantity Track** The winners of the Propaganda Quantity Track are NLPColab (1st), Sina (2nd) and The CyberEquity Lab (3rd). The sum of their annotations equal to 82.1% of all Propaganda subtask annotations. Details on their scores are in Table 4.

**Consistency Track** The winners of the Propaganda Consistency Track are NLPColab (1st), Bias Bluff Busters (2nd) and Sahara Pioneers and The CyberEquity Lab (tied 3rd). Details on their scores are in Table 4.

**Observations** As anticipated, within-team IAA scores significantly surpass across-team IAA, with an average absolute increase of over 21.1% (**Kappa**) and 18.9% (**Macro F1 Average**). The **F1 Prop\*** scores show a wide range of disagreements within teams (average 66.5%, stdev 15.4%) and across teams (average 55.5%, stdev 6.1%). This variability reflects the inherent subjectivity and complexity of this task.

Like Bias labeling, the Propaganda labeling task is quite demanding. Although it has a smaller number of labels, we see comparable patterns in terms of performance across a number of metrics.

Team	Quantity				Quality				Centrality			
	Anno #	Batches		Total	IAA Within Team				Main B1+B2 Across Teams			
		Main	IAA	Data Points	Kappa	Acc	Macro F1 Avg	F1 Bias*	Kappa	Acc	Macro F1 Avg	F1 Bias*
Bias Bluff Busters	4	2	8	2,600	43.3	56.3	48.5	69.3	14.4	28.7	21.0	61.7
BiasGanda	4	2	4	2,200	31.0	51.5	31.5	66.4	26.0	43.6	29.5	64.2
BSC-LANGTECH	2	2	4	2,200	51.0	65.5	39.8	81.5	26.5	46.6	29.2	60.2
Ceasefire	3	2	6	2,400	26.6	46.3	29.3	61.2	24.2	42.0	27.2	66.0
DRAGON	4	15	60	<b>19,500</b>	35.7	75.5	41.0	43.2	19.7	41.1	21.9	59.7
Eagles	4	2	8	2,600	55.5	75.4	48.4	68.5	25.6	46.0	25.4	55.3
Groningen Annotates Gaza	7	2	14	3,200	43.5	56.8	39.8	69.9	25.3	28.9	25.7	56.4
JusticeLeague	3	2	6	2,400	<b>64.4</b>	83.7	63.8	73.6	19.9	43.3	19.6	46.5
Narrative Navigators	7	2	4	2,200	39.4	56.5	45.5	70.5	28.0	44.5	<b>30.5</b>	66.6
NLPColab	21	15	30	<b>16,500</b>	<b>78.8</b>	85.3	76.1	94.3	27.7	42.4	<b>30.8</b>	67.3
Sina	10	12	24	<b>13,200</b>	<b>61.4</b>	81.4	55.4	75.1	11.8	38.7	17.2	48.1
SQUad	2	4	8	4,400	23.4	40.8	27.2	66.8	-0.2	8.5	5.8	56.2
The CyberEquity Lab	5	3	15	4,200	48.1	71.6	39.5	70.5	25.0	46.5	24.1	58.0
The Guideline Specialists	2	2	30	4,800	28.6	51.3	34.9	84.4	21.0	36.8	24.5	66.2
The Lexicon Ladies	3	2	4	2,200	37.2	53.0	35.4	73.4	29.1	44.1	<b>33.1</b>	66.3
UoT1	4	3	12	3,900	44.9	58.2	48.7	71.5	26.8	42.5	29.0	64.6
Average	5.3	4.5	14.8	5,531	44.5	63.1	44.1	71.3	21.9	39.0	24.7	60.2
Total	85	72	237	88,500								

Table 3: Results of the Bias subtask.

Team	Quantity				Quality				Centrality			
	Annot #	Batches		Total	IAA Within Team				Main B1+B2 Across Teams			
		Main	IAA	Data Points	Kappa	Acc	Macro F1 Avg	F1 Prop*	Kappa	Acc	Macro F1 Avg	F1 Prop*
Bias Bluff Busters	4	2	8	2,600	31.5	54.3	47.3	62.6	20.2	51.1	<b>37.6</b>	54.2
Narrative Navigators	7	2	4	2,200	12.8	54.5	54.6	63.1	19.4	52.7	37.1	60.7
NLPColab	21	15	30	<b>16,500</b>	<b>69.9</b>	87.3	73.1	92.1	21.5	53.3	<b>39.9</b>	61.6
Sahara Pioneers	4	2	8	2,600	27.9	49.1	46.3	50.5	18.7	48.7	<b>37.4</b>	56.3
Sina	10	12	24	<b>13,200</b>	<b>65.3</b>	85.7	67.9	76.7	12.5	48.1	27.7	44.5
The CyberEquity Lab	5	3	15	<b>4,200</b>	<b>33.5</b>	65.3	41.1	54.2	22.1	55.0	<b>37.4</b>	55.7
Average	8.5	6.0	14.8	6,883	40.1	66.0	55.0	66.5	19.1	51.5	36.2	55.5
Total	51	36	89	41,300								

Table 4: Results of the Propaganda subtask.

## 6 Discussion

We now consider the label distribution patterns for Bias and Propaganda, independently and together.

### 6.1 Bias Label Distributions

Table 6 summarizes the Bias label distributions overall and for different source languages: Arabic (Ar), English (En), French (Fr), Hebrew (He), and Hindi (Hi). The reported results here include all annotated data points (from Main and IAA). Naturally, data points from Batches 1 and 2 are over-represented since they were annotated by all teams. **Unbiased** was the highest overall label claiming over two-fifths of all data points. This is followed by **Biased against Palestine** (29.2%), then **Biased against Israel**; with **Biased against**

**Palestine** almost three times that of **Biased against Israel**. **Biased against others** appeared in about 1/16th of the cases. All labels seem to be generally equally distributed across source languages with the exception of **Biased against Palestine** and **Biased against Israel** standing out in Hebrew-sourced texts: **Biased against Palestine** is twice the average of other languages; and **Biased against Israel** is one-fifth the average of other languages. While this seems consistent with what would be expected of the news media of a country at war, it is possible that there is an additional priming bias from knowing the source language of the text. Perhaps in future editions, we could compare with a setting where all source language information is hidden and only translations are provided.

Subtask	Track	1st Place	2nd Place	3rd Place
Bias	Guidelines	NLPColab	Eagles	Narrative Navigators
Bias	IAA Quality	NLPColab	JusticeLeague	Sina
Bias	Quantity	DRAGON	NLPColab	Sina
Bias	Consistency	The Lexicon Ladies	NLPColab	Narrative Navigators
Propaganda	Guidelines	NLPColab	Bias Bluff Busters	Sina
Propaganda	IAA Quality	NLPColab	Sina	The CyberEquity Lab
Propaganda	Quantity	NLPColab	Sina	The CyberEquity Lab
Propaganda	Consistency	NLPColab	Bias Bluff Busters	Sahara Pioneers/The CyberEquity Lab

Table 5: Shared task winners for each subtask and track.

Label	Source Language					Total
	Arabic	English	French	Hebrew	Hindi	
Unbiased	9.5%	9.7%	8.6%	6.0%	9.0%	<b>42.8%</b>
Biased against Palestine	5.3%	4.6%	4.1%	<b>10.4%</b>	4.7%	<b>29.2%</b>
Biased against Israel	2.7%	2.2%	3.5%	<b>0.5%</b>	2.0%	<b>10.9%</b>
Biased against others	1.1%	1.4%	1.3%	1.1%	1.4%	6.4%
Unclear	1.0%	1.0%	1.4%	1.3%	1.7%	6.4%
Not Applicable	0.3%	0.7%	0.7%	0.6%	0.6%	2.8%
Biased against both Palestine and Israel	0.2%	0.4%	0.3%	0.1%	0.6%	1.6%
<b>Total</b>	20.0%	20.0%	20.0%	20.0%	20.0%	100.0%

Table 6: Bias Label Distributions in total and over source language.

Label	Source Language					Total
	Arabic	English	French	Hebrew	Hindi	
Propaganda	9.2%	8.3%	8.5%	<b>11.7%</b>	8.4%	<b>46.1%</b>
Not Propaganda	9.6%	10.1%	9.2%	<b>6.6%</b>	9.8%	<b>45.2%</b>
Unclear	0.9%	0.9%	1.6%	1.1%	1.4%	6.0%
Not Applicable	0.3%	0.7%	0.7%	0.5%	0.4%	2.7%
<b>Total</b>	20.0%	20.0%	20.0%	20.0%	20.0%	100.0%

Table 7: Propaganda Label Distributions in total and over source language.

Bias Labels	Propaganda Labels			
	Propaganda	Not Propaganda	Not Applicable	Unclear
Biased against Palestine	<b>74.3%</b>	-61.2%	-20.1%	-21.7%
Biased against Israel	-7.2%	<b>15.2%</b>	-12.5%	-6.4%
Biased against both Palestine and Israel	-9.0%	<b>13.7%</b>	-7.2%	-3.2%
Biased against others	<b>23.1%</b>	-20.0%	-7.0%	-4.0%
Unbiased	-69.8%	<b>78.7%</b>	-10.4%	-2.3%
Not Applicable	-27.9%	-14.7%	<b>85.9%</b>	25.5%
Unclear	-25.9%	-9.7%	31.2%	<b>57.6%</b>

Table 8: Pearson correlation coefficient for all Bias vs Propaganda label pairs.

## 6.2 Propaganda Label Distributions

Table 7 summarizes the Propaganda label distributions overall and for different source languages. The reported results here include all annotated data points (from Main and IAA). **Propaganda** and **Not Propaganda** split the distribution almost equally with **Propaganda** being slightly higher. All labels

seem to be generally equally distributed with the exception of of Hebrew-sourced texts where propaganda spikes: the ratio of **Propaganda** to **Not Propaganda** is 1.8 as opposed to less than 0.9 for the other source languages. The same observation made in the previous section applies here.



Lang	Text	English	Unbiased	Biased > Palestine	Biased > Israel	Propaganda	Not Propaganda
Hi	इसराइल-हमास के बीच अस्थाई युद्धविराम, वापस लौट रहे लोगों ने क्या कहा	Temporary ceasefire between Israel and Hamas, what the returning people said	94%				100%
En	Pro-Palestinian protesters marched in New York City on Sunday to call for a ceasefire between Israel and Hamas amid New Year's Eve celebrations.		94%				100%
Ar	فرحة كبيرة بالقدس والضفة الغربية بعد الإفراج عن أسرى المرحلة الأولى من صفقة التبادل بين حماس وإسرائيل.	Great joy in Jerusalem and the West Bank after the release of prisoners from the first phase of the exchange deal between Hamas and Israel.	88%				100%
He	נזכור ולא נשכח את הנרצחים והנופלים על הגנת המולדת. נלחם עד שהנאצים של חמאס יושמדו. עם ישראל חי! 🇮🇱💙🇮🇱	We will remember and not forget those who were murdered and who fell in defense of the homeland. Fight until the Hamas Nazis are destroyed. Israel Lives! 🇮🇱💙🇮🇱		88%			100%
Fr	Le Hamas se cache délibérément parmi les civils, faisant ainsi payer aux Gazaouis les conséquences des atrocités commises par le Hamas. Notre guerre est contre le Hamas, et non contre la population de Gaza. Nous prenons des mesures importantes pour minimiser les dommages causés aux civils, alors que le Hamas les utilise comme boucliers humains.	Hamas deliberately hides among civilians, making Gazans pay for the consequences of Hamas's atrocities. Our war is against Hamas, not against the people of Gaza. We are taking important steps to minimize harm to civilians while Hamas uses them as human shields.		88%			100%
Ar	حماس فتحت أبواب الجحيم على قطاع غزة #السيف_الحديدية	Hamas opened the gates of hell on the Gaza Strip #Iron_Swords		88%			100%
Fr	Cette nuit à Gaza...le massacre des civils se poursuit #GazaUnderAttack #Palestine	Tonight in Gaza...the massacre of civilians continues #GazaUnderAttack #Palestine	31%	13%	56%	83%	17%
En	Hamas has invited Elon Musk to witness in person the scope of the violence and devastation heaped upon the Gaza Strip by Israel		31%		63%	50%	50%
Hi	इसराइल के हमलों से अस्पताल भी अछूते नहीं... युद्ध-विराम खत्म होने के बाद से इसराइल और हमास के बीच एक बार फिर युद्ध छिड़ चुका है. इसराइल अब दक्षिणी गज़ा को भी निशाना बना रहा है, जिससे अस्पताल भी अछूते नहीं हैं.	Even hospitals are not untouched by Israeli attacks... Since the end of the ceasefire, war has once again broken out between Israel and Hamas. Israel is now targeting Southern Gaza as well, from which even hospitals are not untouched.	25%	13%	56%	50%	50%

Table 9: Examples of different texts and their most relevant annotation distributions.

### 6.3 Bias vs Propaganda Label Correlations

Finally, Table 8 presents a cross-comparison of Bias and Propaganda labels using Main Batches 1 and 2 (1,800 data points). For each text in this data subset, we calculate for each label in Bias and Propaganda subtasks the number of teams that selected that label. We then report the Pearson product-moment correlation coefficient of the 1,800 counts for every pair of Bias-Propaganda labels. Unsurprisingly, Bias **Not Applicable** and Propaganda **Not Applicable** relate closely ( $r=85.9\%$ ). Similarly  $r=78.7\%$  for **Unbiased** is **Not Propaganda**. The **Biased against Palestine** label correlates positively highly (74.3%) with **Propaganda**, and negatively strongly (-61.2%) with **Not Propaganda**. The patterns are reversed and much weaker for **Biased against Israel**. These are only high level initial observations that open exciting possibilities for further study.

### 6.4 Selected Examples

Table 9 presents a number of texts with their associated most prominent label averages across the participating teams. The examples are from Main Batches 1 and 2. There are nine examples; the first three were marked by the vast majority of teams as

**Unbiased** and **Not Propaganda**. The second set of three examples were marked by the vast majority again as **Biased against Palestine** and **Propaganda**. The last set shows examples with majority **Biased against Israel**.

## 7 Conclusion and Future Work

The FIGNEWS shared task successfully brought together a diverse community to annotate bias and propaganda in multilingual news posts. This initiative brought together 17 teams producing 129,800 data points. The shared task highlighted the crucial role of clear guidelines, examples, and collaboration in advancing NLP research on complex, subjective, and sensitive, opinion analysis tasks. The resulting dataset and insights contribute valuable resources and direction for future work in this important area. All data and code are publicly available.<sup>3</sup>

Future work should focus on expanding the annotation efforts to include more diverse languages and topics, and refining annotation guidelines based on participant feedback. The created data should be leveraged to advance NLP automatic bias and propaganda detection techniques, as well as foster interdisciplinary studies to deepen our understanding of bias and propaganda in news media.

## Limitations

We acknowledge the following limitations in the FIGNEWS shared task design and implementation.

- **Annotation Subjectivity** The task involves subjective judgments on bias and propaganda, which vary among annotators and teams, impacting annotation consistency and reliability. Teams' self-selection based on preconceived notions about the topic may further influence this variability.
- **Label Selection** We acknowledge that the set of labels we specified limit the space of possibilities and may oversimplify complex issues imposing a binary perspective that does not fully capture nuanced viewpoints and biases within the dataset.
- **Scope of Topics and Text Selection** The focus on the early days of the Israel War on Gaza may limit the applicability of findings to other types of news events or broader media contexts. The size of the corpus is relatively small, and may include some sampling bias.
- **Limited Diversity** while we observed a range of backgrounds among the annotators, we acknowledge that some groups were highly over-represented, which potentially biases the overall conclusions.

## Ethical Considerations

The FIGNEWS shared task deals with sensitive topics and media narratives related to the Israel War on Gaza. The organizers and participants have taken several measures to ensure ethical considerations are addressed:

- **Anonymization** All posts have been anonymized, with no identifying information about the account owners or users provided to the participants.
- **Public Posts** Only publicly available posts from verified accounts were included in the dataset, ensuring that the content was intended for public dissemination.
- **Balanced Representation** To ensure fair representation, the dataset includes a balanced number of posts from various viewpoints and narratives during the war.
- **Responsible Use** Participants were required to agree to use the dataset solely for research purposes and not for any unethical or illegal activities.

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## A Shared Task Details

We provide below an updated version of the shared task details reflecting the final decisions made in the effort, e.g., we added a fourth evaluation track (IAA Quality) that was not mentioned in the original call to participate.

### A.1 Shared Task Objectives

The shared task aims to serve as a collaborative platform where participants propose guidelines and diverse methods for annotating and analyzing the dataset.

**Provided Data** The organizers will provide 15 batches of social media posts, 1,000 post per batch. Each 1,000-post batch will contain 200 posts from 5 languages: Arabic, English, French, Hebrew, and Hindi, together with their machine translated versions into Arabic and English (as needed). Participants must specify whether they annotated the original language or its machine translated version. So a monolingual Arabic team can annotate the full batch in Arabic (original or translated). The batches will be provided to the annotation teams with clear instruction on how to submit the results.

**Minimal Annotations to Qualify** To qualify, each participating team **must provide full annotation guidelines** for each subtask they choose to work on; and they **must annotate a minimum of two batches**, i.e. (1,800 posts) and their designated Inter-annotator agreement subset (200 posts) for a total of 2,000 posts (specifically Batch 1 and Batch 2). The IAA subset must be done by every annotator on the team; but the rest can be divided among them.

### A.2 Shared Task Subtasks and Tracks

There will be two **subtasks** of focus. For each subtask, there will be four **evaluation tracks** for which winners will be crowned.

#### A.2.1 Subtask on Bias Annotation

The subtask is restricted to seven possible Labels, presented below with illustrative examples.

##### 1. Unbiased

Example: "In the ongoing Israel-Palestine conflict, recent events have escalated tensions. Yesterday, Israeli forces conducted operations in response to rocket attacks from Gaza. Both sides have reported casualties. International leaders are calling for restraint and a return to peace talks."

##### 2. Biased against Palestine

Example: "Once again, Palestinian aggression has disrupted peace in the region. Palestinian extremists, ignoring efforts for peace, launched unprovoked attacks on innocent Israeli civilians. Israel's response, though portrayed as harsh by some, is a justified measure to protect its citizens."

##### 3. Biased against Israel

Example: "In a typical display of excessive force, Israeli troops have yet again targeted Palestinian areas, causing numerous civilian casualties. This aggression, under the guise of self-defense, highlights the ongoing oppressive tactics Israel employs against Palestinians."

##### 4. Biased against both Palestine and Israel

Example: "In the latest chapter of their endless and futile conflict, Israeli and Palestinian forces have once again engaged in senseless violence. Both sides continue to commit atrocities, showing a complete disregard for peace or human life."

##### 5. Biased against others

Example: "In the shadow of the Israel-Palestine conflict, external actors, particularly Iran, are exacerbating tensions. Iran's covert support for extremist groups shows its intent to destabilize the region, disregarding the catastrophic impact on both Israeli and Palestinian civilians."

##### 6. Unclear

Example: "Recent developments in the Middle East have seen an increase in hostilities. The situation in the region is complex, with various factors contributing to the current state of affairs. The international community remains divided on the issue."

## 7. **Not Applicable**

Example: "In other news, the annual technology conference in Tel Aviv has unveiled groundbreaking advancements in cybersecurity. Industry leaders from around the globe gathered to showcase innovations that promise to shape the future of digital security."

### A.2.2 **Subtask on Propaganda Annotation**

The subtask is restricted to four possible Labels, presented below with illustrative examples.

#### 1. **Propaganda**

Example: "In a display of unmatched heroism, our troops have once again safeguarded our nation from the brink of destruction, heroically neutralizing the threat from Gaza, which aims to undermine our very existence."

#### 2. **Not Propaganda**

Example: "Yesterday, an escalation occurred along the Israel-Gaza border, resulting in casualties on both sides. Israeli and Palestinian officials provided conflicting accounts of the events that led to the confrontation."

#### 3. **Unclear**

Example: "The situation in Gaza remains tense, with reports of civilian distress and military movements. While some sources claim the military actions are defensive, others argue they are provocative, leaving the true nature of the situation open to interpretation."

#### 4. **Not Applicable**

Example: "A feature on Gaza's cultural scene highlights the resilience of its art community, showcasing how local artists use their craft to express hope and endurance amid challenging circumstances, without delving into the political context."

### A.2.3 **Guidelines Evaluation Track**

The teams have the freedom to design their own guidelines and apply them to the shared data. The following is the checklist of all items that will be evaluated by the organizers.

**Annotation Guidelines** Detailed annotation guidelines including examples for all main and corner cases. Consider the following components which will be used in the evaluation of the guidelines.

#### 1. **Define the Objective and Describe the Task**

Outline the purpose and specific NLP task. Provide a detailed task description with correct examples.

#### 2. **Establish Categories**

List and define all annotation labels/categories/tags.

#### 3. **Include Detailed Category Guidelines with Examples**

Explain application criteria for each category/tag, with examples. Offer examples for correct application and common mistakes.

#### 4. **Outline the Process**

Describe the step-by-step annotation process and tools used.

#### 5. **Set Quality Standards**

Define expectations for accuracy and consistency, along with quality check procedures.

#### 6. **Handle Ambiguities and Difficult Cases**

Provide guidance on ambiguous cases and a protocol for seeking clarification.

#### 7. **Ensure Consistency**

Implement measures for annotator consistency and recommend calibration sessions.

#### 8. **Training and Support**

Detail training procedures and support resources for annotators. Highlight unbiased annotation practices and handling of sensitive data. Schedule guideline reviews for updates based on feedback and new insights. Include a system for annotator feedback to refine guidelines and processes.

The teams must provide well-documented annotation guidelines including examples, and must provide inter-annotator agreement (IAA) numbers for at least 200 posts (40 from each language) from Batch 1 and Batch 2. We expect the IAA to be competitive (e.g. Cohen Kappa of 0.6+) in the target space.

The Guidelines Score used to determine the winners of this track is the average normalized Document Score and IAA Kappa score.

$$\text{GuidelinesScore}_i = \text{Average} \left( \frac{\text{DocumentScore}_i}{\text{DocumentScore}_{max}}, \frac{\text{IAAKappa}_i}{\text{IAAKappa}_{max}} \right)$$

The Document Score is equal to the number of satisfied document components mentioned above, a range from 0 to 8. The IAA Kappa score of a team is the average of all pairwise IAA Kappas over team annotators per batch.

#### **A.2.4 IAA Quality Evaluation Track**

We will also report the IAA Kappa scores per team and use them to determine the best performers, independent of the guidelines track.

#### **A.2.5 Quantity Evaluation Track**

The teams can compete in the number of annotated data batches. They must finish them in order and complete a batch before moving to the next. The teams with the highest number of completed batches will be crowned the Quantity track winners for the subtask of choice.

#### **A.2.6 Consistency Evaluation Track**

The various teams in the same subtask and shared completed batches will be compared for correlation against each other. The teams that have the highest correlation against other teams (centroidal choices) will be crowned winner. This needs a minimum of three teams per subtask.

### **A.3 Publication**

All teams participating in the shared task are invited to submit short paper (4 pages) descriptions of their efforts. These papers will be evaluated by multiple reviewers to be selected for publication in the ArabicNLP 2024 Conference Proceedings and indexed by the ACL Anthology.

### **A.4 Collaborative Commitment**

Participants are encouraged to join the shared task with a commitment to collaboration. Whether working independently or within teams, every effort and insight contributed should be shared openly. This collaborative ethos extends beyond individual tasks and includes sharing methodologies, findings, and results.

### **A.5 Optional Demographic Details**

We would like to invite participants to provide some demographic details voluntarily. This information includes aspects such as age range, native language, educational background, area of study or expertise, gender, and region of origin. Please note that providing this demographic information is entirely optional and will not influence the evaluation of your participation in any way. We respect your privacy and understand if you choose not to share these details.



## B Annotation Interface

	A	B	C	D	E	F	G	H	I	J	K
1	Batch	Source Language	ID	Type	Text	English MT	Arabic MT	Annotator ID	Bias	Propaganda	Comments
2	B01	English	1	MAIN	Yemen's Houthis have wad	Yemen's Houthis have wad	خاض الحوثيون في اليمن الحرب بين				
3	B01	Arabic	1	MAIN	الارهابية الداعشية تجلب العار للعرب	Hamas, the ISIS terrorist ori	حماس الارهابية الداعشية تجلب العار				
4	B01	French	1	MAIN	De la nourriture pour anima	Animal food transformed in	تحويل الغذاء الحيواني إلى دقيق ومن				
5	B01	Hebrew	1	MAIN	the whole world can see it	On the one hand, what hap	من ناحية، ماذا يحدث عندما يلتقي جنود				
6	B01	Hindi	1	MAIN	LIVE- अमेरिका-इजरायल मिलकर	LIVE- America-Israel will to	बैठ मिश्र- अमेरिका और इजरायल से				
7	B01	English	2	MAIN	Israel - Hamas Conflict   Fa	Israel - Hamas Conflict   Fa	إسرائيل - حماس   وجهها				
8	B01	Arabic	2	MAIN	رئيس المكتب السياسي لحركة "حماس" إسم	Head of the Hamas Politic	رئيس المكتب السياسي لحركة "حماس"				
9	B01	French	2	MAIN	Samedi 7 octobre, il était a	On Saturday October 7, it	في يوم السبت 7 أكتوبر، كانت الساعة ٧				
10	B01	Hebrew	2	MAIN	world would react to this!!!	On the morning of a Jewish	في صباح يوم عطلة يهودية في إسرائيل				
11	B01	Hindi	2	MAIN	LIVE   हमस पर 180 डिग्री वाले	LIVE   180 degree attacks	مباشرة   تبدأ الهجمات 180 درجة على				
12	B01	Arabic	3	MAIN	بصفحة الإعلام الغربي بأنه "مرعب إيرا	The Western media descri	بصفحة الإعلام الغربي بأنه "مرعب إيرا				
13	B01	French	3	MAIN	39 Gazaouis blessés, dont	39 injured Gazans, includin	تم علاج 39 مصابًا من سكان غزة، ب				
14	B01	Hebrew	3	MAIN	Gaza. My interview on RT.	I will not allow any present	إن أسمح لأي منتج يجري مقبلي في				
15	B01	English	4	MAIN	Videos show how armed m	Videos show how armed m	أظهرت مقطع فيديو كيف القحم مسلح				
16	B01	Arabic	4	MAIN	أطلقنا #السيف الحديدي ضد حماس و	We fired #iron_swords agai	أطلقنا #السيف الحديدي ضد حماس و				
17	B01	Hebrew	4	MAIN	זאת סבתא שלי! א	This is my grandmother! Yo	هذه جدتي! لقد تم اختطافك دون ع				
18	B01	Hindi	4	MAIN	अगर इजरायल और ईरान में हु	If there is a war between Is	إذا اندلعت حرب بين إسرائيل وإيران				
19	B01	French	5	MAIN	Gaza était la plus grande p	Gaza was the largest open	كانت غزة أكبر سجون مفتوح في العالم.				
20	B01	Hebrew	5	MAIN	ation must be made extinct.	Hamas leader Ismail Haniya	زعيم حماس إسماعيل هنية يختل من				
21	B01	Hindi	5	MAIN	हमस और इजरायल के युद्ध के क	Many days have passed sira	لقد مرت أيام عديدة على الحرب بين				
22	B01	French	6	MAIN	Un carnage humanitaire	Humanitarian carnage is	المنذبة الإنسانية مستمرة في غزة.				
23	B01	Hindi	6	MAIN	इजरायल की सेना से हमस के आ	What did the Hamas terror	ماذا فعل إرهابي حماس للجيش الإسرائيلي				
24	B01	English	7	MAIN	Protest in Aligarh Muslim U	Protest in Aligarh Muslim U	وقف احتجاجية في جامعة عليكرة الإسلام				
25	B01	Arabic	7	MAIN	مقابلة خاصة لـ #الحديث مع المتحدث باسم الجيش	A special interview for the	مقابلة خاصة لـ #الحديث مع المتحدث باسم الجيش				
26	B01	French	7	MAIN	Vous en pensez quoi des tv	What do you think of Benz	ما رأيكم بتفريعات بنزيما يا أحباب؟				
27	B01	Hindi	7	MAIN	हमस की हिमाकत..मोसाद की	Hamas' audacity..Mossa	جرأة حماس.. فشل الموساد!				
28	B01	English	8	MAIN	IDF releases audio recordir	IDF releases audio recordir	الجيش الإسرائيلي ينشر تسجيلًا صوتيًا				
29	B01	Arabic	8	MAIN	العدو لم يحقق أي إنجاز ميداني على الأرض سوى	The enemy did not achiev	"العدو لم يحقق أي إنجاز ميداني على				
30	B01	Hebrew	8	MAIN	לוחמיו היקרים ערכו אמש את	Our dear soldiers last night	جنودنا الأحرار أقفوا ليلة أمس صلاة				
31	B01	Hindi	8	MAIN	इजरायल-हमस युद्ध के बहाने द्वि	There is a flood of fake new	هناك طوفان من الأخبار الكاذبة على				
32	B01	French	9	MAIN	Malgré la trêve entrée en v	Despite the truce that came	رغم الهدنة التي دخلت حيز التنفيذ يوم				
33	B01	Hebrew	9	MAIN	Hello Hamas, I am so happ	Hello Hamas, I am so happ	مرحباً حماس، أنا سعيد جدًا بعودة				
34	B01	Hindi	9	MAIN	#LIVE : सुरंगों में छिपे हमस के	#LIVE: Hamas fighters hidi	#مباشرة: مقاتلو حماس يختبئون في				
35	B01	English	10	MAIN	CNN's Dana Bash pressed	CNN's Dana Bash pressed	حت دانا باش، مراسل سي إن إن، رفيع				
36	B01	French	10	MAIN	Tom Sisley, franco-israélien	Tom Sisley, Franco-Israeli	توم سيسلي، الفرنسي الإسرائيلي، "بيكر"				
37	B01	Hindi	10	MAIN	पाकिस्तानी टीम क्रिकेट खेलने आई	Pakistani team came to pla	المنتخب الباكستاني جاء لعب الكريكيت				
38	B01	Arabic	11	MAIN	أسيرة إسرائيلية مُرَج عنها: ممدت و	A released Israeli prisoner:	أسيرة إسرائيلية مُرَج عنها: ممدت و				
39	B01	French	11	MAIN	« Vous voulez qu'on se bat	"You want us to fight all our	"هل تريد منا أن نقاتل طوال حياتنا؟				
40	B01	Hebrew	11	MAIN	is launched a war on Israel!	Hamas has declared war on	حماس أعلنت الحرب على إسرائيل!				
41	B01	Hindi	11	MAIN	#IsraelPalestineWar: इजराय	#IsraelPalestineWar: How	#الحرب الإسرائيلية الفلسطينية: إلى				

Figure 1: A screenshot of the Google Sheet annotation setup for the Main data subset.

## C Annotator Demographics

Native Language	Bias	Propaganda	Total	Total (%)
Arabic	43	24	67	49.3%
Urdu	21	21	42	30.9%
Italian	4	2	6	4.4%
Persian	4	0	4	2.9%
Dutch	3	0	3	2.2%
English	2	1	3	2.2%
German	1	1	2	1.5%
Hindi/Urdu	2	0	2	1.5%
Russian	1	1	2	1.5%
Spanish	2	0	2	1.5%
Bengali	1	0	1	0.7%
Prefer not to say	1	1	2	1.5%
<b>Total</b>	85	51	136	100.0%

Age Range	Bias	Propaganda	Total	Total (%)
18-24	48	17	65	47.8%
25-34	20	19	39	28.7%
35-44	14	9	23	16.9%
45-54	1	1	2	1.5%
55-64	1	0	1	0.7%
Prefer not to say	1	5	6	4.4%
<b>Total</b>	85	51	136	100.0%

Gender	Bias	Propaganda	Total	Total (%)
Female	67	38	105	77.2%
Male	16	8	24	17.6%
Non-binary	1	0	1	0.7%
Prefer not to say	1	5	6	4.4%
<b>Total</b>	85	51	136	100.0%

Region of Origin	Bias	Propaganda	Total	Total (%)
South Asia	24	21	45	33.1%
Levant	19	17	36	26.5%
North Africa	16	2	18	13.2%
Western Europe	11	4	15	11.0%
GCC Countries	7	0	7	5.1%
Other Middle Eastern Countries	4	0	4	2.9%
Southeast Asia	1	0	1	0.7%
Prefer not to say	3	7	10	7.4%
<b>Total</b>	85	51	136	100.0%

Education Level	Bias	Propaganda	Total	Total (%)
Master's degree	36	27	63	46.3%
Bachelor's degree	38	12	50	36.8%
Doctoral degree	8	6	14	10.3%
Post-doctoral training	1	0	1	0.7%
Prefer not to say	2	6	8	5.9%
<b>Total</b>	85	51	136	100.0%

Area of Expertise	Bias	Propaganda	Total	Total (%)
Engineering & Technology	51	35	86	63.2%
Arts and Humanities	18	4	22	16.2%
Social Sciences & Law	10	10	20	14.7%
Education	3	0	3	2.2%
Business & Economics	1	1	2	1.5%
Natural Sciences	1	0	1	0.7%
Prefer not to say	1	1	2	1.5%
<b>Total</b>	85	51	136	100.0%

Table 10: Annotator demographics.