Narrative Media Framing in Political Discourse

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Abstract

Narrative frames are a powerful way of conceptualizing and communicating complex, controversial ideas, however automated frame analysis to date has mostly overlooked this framing device. In this paper, we connect elements of narrativity with fundamental aspects of framing, and present a framework which formalizes and operationalizes such aspects. We annotate and release a data set of news articles in the climate change domain, analyze the dominance of narrative frame components across political leanings, and test LLMs in their ability to predict narrative frames and their components. Finally, we apply our framework in an unsupervised way to elicit components of narrative framing in a second domain, the COVID-19 crisis, where our predictions are congruent with prior theoretical work showing the generalizability of our approach.[1]

1 Introduction

Narrative framing is a type of media framing that uses elements of narrativity to highlight some aspects of a complex issue and condense it into a simplified "story" that promotes a particular interpretation (Crow and Lawlor, 2016). These elements of storytelling, such as representing an issue through the lens of stakeholders and conflicts rather than direct description of the facts, make narrative frames a highly effective device, particularly in the context of contested issues such as climate change (Daniels and Endfield, 2009; Rodrigo-Alsina, 2019).

Narrative framing can draw the reader's attention to specific, nuanced aspects of an issue and instill a very precise interpretation that differs from the "default" reading inferrable from its generic or issue-specific frame. To give an example, the text in Figure 1 frames the topic of climate change through a "Polar Bear" issue-specific frame (Bushell et al., 2017) which describes the negative effects of climate change on animals (*rising temperatures have certainly put a strain on species*). However, this is not the actual message of the text: it depicts climate scientists as incorrect, while presenting pseudo-scientists from a hero-like angle. It uses devices of narrative framing to replace the default interpretation arising from a topic-like frame ("animals are victims of climate change and humans are villains") with an opposing idea that animals are doing fine and scientists who claim otherwise mislead the general public.

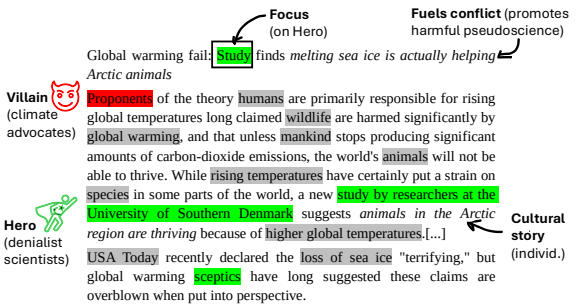

Figure 1: An except from a news article, with `hero` marked in green and `villain` in red. Entities that are not main characters are grayed out. The box shows the focal character (here, `hero`). The phrases in italic are cues which show that the article has an *individualistic* cultural story ("the nature can fix itself") and that it *fuels conflict* by actively promoting bad science.

While the importance of framing narratives for the communication and perception of news has been widely recognized in the social sciences (Shanahan et al., 2011), automatic framing analysis still mostly conceptualizes frames in a topic-like fashion (Ali and Hassan, 2022; Otmakhova et al., 2024). Recent work in NLP has studied elements of narratives such as characters or events in news reporting (Stammbach et al., 2022; Frermann et al., 2023; Gehring and Grigoletto, 2023; Zhao et al., 2024; Das et al., 2024). However,

[1]We release our code, data and annotations at https://github.com/julia-nixie/narratives.

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these studies are either topic-specific, or lose the link to the core mechanism of framing: For framing to occur, an **ambivalent** issue must be present (Sniderman and Theriault, 2004) and described in a way that **evokes a larger interpretative context** (schema) which goes beyond information directly inferrable from the text (Scheufele and Scheufele, 2010). As such, beyond the issue itself (aka Entman (1993)'s "problem statement"), there are other important mechanisms that turn a message into a frame, such as alluding to the **conflict** that led to the problem (=its cause), making a **moral evaluation**, or suggesting a **resolution** to it. We present a general formalization of narrative framing that comprises all these aspects.

We do so by integrating elements of narratology with social and media studies on narrative framing, to establish a framework which allows to identify and structurally represent narrative frames and to distinguish superficially similar frames from one another. First, our framework distinguishes character roles, and we show how issue **ambivalence** arises when actors in an article are assigned an archetypical role (Hero, Villain, Victim) and one of the roles is drawn into focus. This emphasis in turn evokes a **moral evaluation** of the personas in the article. As a second component, we position each character in terms of exacerbating or resolving the core **conflict** of the article. Finally, to link the presentation in the article to the **wider set of associations and beliefs** already existing in the receiver's perception (Nelson et al., 1997), we link our narrative frames to established "cultural stories" that define the attitude towards external control and the sense of unity with the group (Thompson, 2018). Figure 1 illustrates the three components with an example.

We apply our framework to analyze media framing of two distinct public issues – climate change and COVID-19. In particular, we make the following contributions:

1. We define elements of narrativity that are essential for narrative framing and are aligned with the definition of a media frame and show that our framework applies across topics (climate change and COVID-19) and domains (news articles and political speeches).

2. We show that framework enables reliable and effective annotation of narrative frames in the news, and improves the automatic detection of narratives.

3. We release a corpus of articles about climate change annotated with narrative frames, and use it to analyze the distribution of different narrative frames across political leanings.

4. We test a range of LLMs on their ability to automatically predict the components of our framework, leaving room for improvements.

2 Background

Narratives in political communication Following Fisher (1984)'s seminal paper coining the term "homo narrans" to illustrate the importance of storytelling for society, narratives in political communication have attracted substantial research attention (see also Bennett and Edelman (1985); Patterson and Monroe (1998)), exposing its effects from a critical vehicle in deliberative democracy (Boswell, 2013) to its use persuasive device (Skrynnikova et al., 2017). Similar to the concept of framing in general, a principled and empirically testable definition of "narrative framing" has long been lacking. However, recent work has progressed in developing frameworks that are testable and amenable to computational modeling (Shenhav, 2005; Robert and Shenhav, 2014), most prominently the Narrative Policy Framework (NPF; Jones et al. (2023)), which we build on in this work. The NPF defines a set of generalizable structural elements in political/policy narratives, including characters, settings, plot and moral evaluation which it uses to characterise the operation of narratives on the individual, group and cultural level. The NPF has been particularly instrumental in studying climate change narratives (Fløttum and Gjerstad, 2017), and identifying dominant narratives in the discourse (Bushell et al., 2017; Bevan, 2020). This paper adapts the elements of the NPF into a structured framework designed to support automated prediction.

Narrative framing and NLP Narrative framing intersects the concepts of storytelling and framing, i.e., the presentation of information in a way to evoke a specific association in the audience. Automatic narrative understanding has attracted substantial attention in NLP (Piper et al., 2021); however, it has focused mostly on fictional narratives (Bamman et al., 2014; Iyyer et al., 2016), personal narratives in social media (Lukin et al., 2016; Shen et al., 2023), or specific elements such as event chains (Chambers and Jurafsky, 2009). Few works have considered the intersection of stories

and framing (Levi et al., 2022), or used elements of narrativity such as events to improve on topic-focussed framing analysis (Das et al., 2024; Zhao et al., 2024).

While narrative framing research in the social sciences is strongly grounded in the NPF, this framework is yet to gain recognition in NLP approaches. Closest to our work are Stammbach et al. (2022) and Frermann et al. (2023) who study some narrative elements of framing devices (such as entities framed as heroes or victims), but do not model full narrative frames. In addition to entities Gehring and Grigoletto (2023) model relationships between them such as "harm" or "protect"; however, their approach does not map the identified elements back to more high-level (narrative) frames.

3 Components of narrative framing

We motivate our three core components which define a narrative frame. Each component contributes to the framing mechanism, by resolving the ambivalence through assigning moral evaluation to stakeholders (Characters), capturing the conflict and resolution aspect of a frame (Conflict and resolution), and evoking a wider set of cognitive schemata and cultural associations (Cultural stories).

3.1 Characters

Characters and their prototypical roles have been studied extensively in narratology (starting from formalist and structuralist approaches such as Propp (1968) and Greimas (1987)), and were adopted as a simplified `hero`, `villain`, and `victim` (HVV) triad by social sciences as part of Narrative Policy Framework (NPF) (Shanahan et al., 2018)[2]. In particular, the NPF prescribes that a narrative frame should include **at least one prototypical character**, i.e. one or more HVV roles should be filled by a prominent entity. By assigning an entity to a particular role, we resolve the issue ambivalence by conveying our moral judgment of that entity, as required by Entman's definition of a frame (Entman, 1993). Essentially, the reader's interpretation of the article depends on whether a particular entity (say, *climate advocates* as in Figure 1) is framed as a `hero` (their actions are evaluated as beneficial), a `villain` (as in Figure 1), or `victim` (of criticism or attacks by denialists).

Often there are multiple candidate entities for each HVV role in a text. We follow narratology approaches in distinguishing between main characters and other entities (Jahan and Finlayson, 2019), and use the *single most central character* fulfilling the respective role to represent a narrative frame. Figure 1 illustrates this, where the main characters are highlighted in color, while less central entities are grayed out. Moreover, to be able to compare instances of a particular narrative frame across texts with different people and events, we abstract away from specific characters to the stakeholder categories (common people, elites, etc.) they represent. The taxonomy of such stakeholders can either be inherited from the literature (as we do in Section 4) or derived from a corpus in a data-driven way (as demonstrated in Section 5).

To fully differentiate narratives, in addition to assigning characters to roles, it is necessary to identify the **focus** on either `hero`, `villain`, or `victim`, which results in "heroic", "blaming", and "victimizing" narrative frames, respectively. For example, two distinct narrative frames can both frame *climate activists* as a `hero` and *government* as a `villain`, but focus either on criticizing the government ("blaming") or praising the efforts of activists in opposing it ("heroic") – resulting in very different messaging.[3]

3.2 Conflict and resolution

Conflict/resolution[4] is a central element of a narrative frame. It encapsulates the "plot" element of the NPF, and links into Entman's (Entman, 1993) criteria of framing which state that, among its other functions, a frame can point to the cause of the issue and its underlying conflict, or prescribe a resolution. Accordingly, we conceptualize conflict and resolution as a four-way distinction: the characters assigned `hero` and `victim` roles in a narrative frame can either *fuel conflict* (perform actions that cause or exacerbate the issue), *fuel resolution* (perform actions that help to resolve the issue), *prevent conflict* (oppose actions that cause or exacerbate the issue), or *prevent resolution* (oppose actions that help to resolve the issue).

In NLP, relations between characters have a long

[2] In NLP, character (or agent) identification has attracted substantial attention, both from the narratology side (see (Piper et al., 2021)) and, less extensively, from the NPF angle (Frermann et al., 2023).

[3] Examples from Bevan (2020), see narrative frames "The collapse is imminent" vs "You're destroying our future" in Appendix E.

[4] Here we define it conflict as an underlying cause of an issue which characters strive to either escalate or resolve, rather than a driving force of a plot (Prince, 2003) or breaking point in its canonicity (Bruner, 1991), as understood in narratology.

history of research (Agarwal and Rambow, 2010; Shahsavari et al., 2020), including studies which specifically looks at conflicts (Han et al., 2019; Olsson et al., 2020). In comparison, our framework abstracts away from specific (and often sparse) entity relations and combines the attitude towards the issue (pro-conflict vs pro-resolution) with the level of intentionality and direct expression of that attitude (i.e. actively perform actions that support one's side, or oppose the actions of the other side). This definition of conflict/resolution based on abstract categories rather than on specific actions or events renders our approach generalizable across topics, as we show in Sections 4 and 5.

3.3 Cultural stories

Frames are distinguished from "unframed" types of communication by their ability to evoke a wider set of concepts, associations and judgments which already exist in the audience's perception (Scheufele and Scheufele, 2010). Narrative frames do this by mapping a particular combination of characters and conflict/resolution to one of four larger schemata of interpretation, which in social studies are referred to as **cultural value stories** (Thompson, 2018).[5] Cultural stories define to what degree our actions are controlled by external factors and by the sense of belonging to a group (Douglas, 2007). Depending on the combination of these two factors, a narrative frame can be *fatalist* (where people are at the mercy of forces outside their control, such as natural disasters or fate), *hierarchical* (where people are bound by social prescriptions and external control, such as government), *individualistic* (where social ties are loose and people reject the necessity of external control), or *egalitarian* (where people take collective action, opposing external control) (Figure 2). Cultural stories have been shown to directly affect public behavior: as an example, individualist and egalitarian stories have been linked to worse survival rates than a hierarchical story during the COVID-19 onset (Güss and Tuason, 2021).

To the best of our knowledge, cultural stories, or more generally cognitive and cultural schemata aiding interpretation, have not been explored in NLP. However, many NLP studies (Finlayson, 2012; Tangherlini et al., 2020) draw upon related concepts

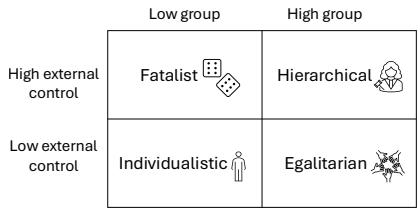

Figure 2: Cultural stories across dimensions of **external control** (grid) and belonging to a **group**

of narrative archetypes as overarching, culturally repetitive plots or narrative elements (Frye, 1957; Propp, 1968). In contrast, we focus on framing and its link to a well-defined space of cultural values which have been shown to affect perception and behavior.

4 Narrative Framing of Climate Change

In the remainder of this paper we apply our framework to perform narrative framing analysis on two topics: climate change and COVID-19. First, in this section, we use it to manually annotate the three components of narrative frames in news articles, and then map them to established narrative frames in the climate change domain. We use this corpus to evaluate the ability of multiple LLMs to predict narrative frame components and the frames themselves. Then, in Section 5 we show how the framework can be generalized to a domain without an established repertoire of narrative frames (politician's speeches on COVID-19), where the goal is to *discover* frames rather than classify them.

4.1 Data selection and annotation

Article selection. We manually annotate 100 articles randomly selected from an existing dataset of news stories on the topic of climate change (Frermann et al., 2023), originating from a range of US media outlets from different political leanings published between 2017 and 2019.[6] The articles are fairly evenly distributed across political leanings to ensure that the dataset contains a variety of narratives coming from different political groups. Detailed statistics are in Appendix A.

Annotation process. We use the example in Figure 1 to explain the steps of the annotation pro-

[5]Thus, all narrative frames are stories, i.e. contain elements of narrativity such as characters and plot (reduced to conflict and resolution). However, not all stories can be used as narrative frames: in order to so, they need to map to a broader, pre-existing context dictated by a cultural story.

[6]Due to space constraints, this paper covers only our US centric analysis. However, we also release an annotated dataset of 100 Australian climate-focused articles from 2024, which surfaced new narratives with different combinations of elements to previously recorded ones. The dataset together with its analysis is available at https://github.com/julia-nixie/narratives.

cess. First, we identify candidate entities for the `hero`, `villain`, and `victim` roles, and select at most one main character per role (as described in Appendix B). In our example, since `hero`, `villain`, and `victim` should align with the article's perspective, we remove potential victims like *animals* since the author believes they actually benefit from higher temperatures. Then, using an established taxonomy of stakeholder categories for the climate change domain (Frermann et al. (2023); details in Appendix C), we map the text spans that represent characters to labels indicating general classes of actors. Thus, we arrive at *science experts* (from the skeptics side) as `hero` and *environmental activists* as `villain`. To determine the focus, we rely on discourse structure of newspaper articles, namely the inverted pyramid where the most important content is presented first, and the relative proportion of text devoted to the different roles. Since the title highlights the research of climate skeptics and much of the article's content is devoted to describing it, we determine that the `focus` is on the `hero`. Next, since the article explicitly promotes dubious science harmful to the climate (rather than only criticizing actions of climate activists), it fuels `conflict`. Finally, as the article implies that nature is resilient and no actions are necessary, it corresponds to an *individualistic* cultural story. Appendix D provides more details on the annotation process, instructions, and quality assurance.

We apply this process to annotate the structure of the narrative frames in our corpus of 100 climate change articles, and use the same framework to determine the components of known narrative frames from the climate change literature (Bushell et al., 2017; Bevan, 2020; Lamb et al., 2020). Then, we map the article structures to the structures of known narrative frames to arrive at the final narrative frame label for the article. For example, the structure of the article in Figure 1 points to a denialist narrative frame "No need to act". Overall, this element-wise mapping between the articles and the theoretical literature resulted in defining 16 structurally distinct narrative frames, which are described in detail in Appendix E.

Annotation quality. Based on the component-wise annotation process described above we achieve reliable (in terms of Krippendorf α among all annotators) and very strong (in terms of agreement with an expert) inter-annotator agreement on all elements of the framework. In particular, we achieve a Krippendorf α agreement of 0.76 for `hero`, 0.67 for `villain`, and 0.81 for `victim` between four annotators, and Krippendorf α of 0.78 for `focus`, 0.82 for `conflict`, and 0.80 for Cultural Story between two annotators.

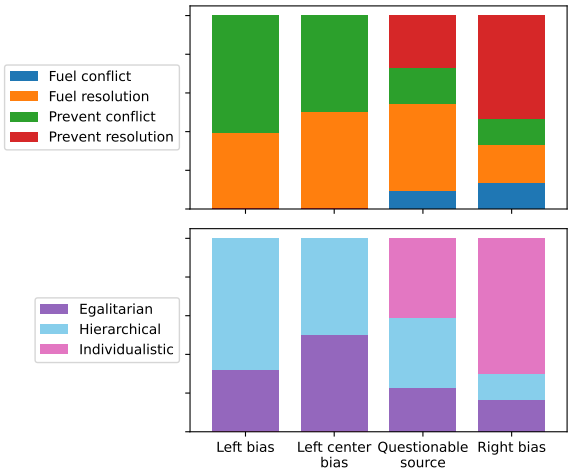

Figure 3: Distribution of `conflict` and `cultural story` values across political leanings

Since each narrative frame is derived from a unique combination of its elements, the reliable annotation of narrative frame components also ensures a more reliable annotation of resulting narratives than choosing them based on their description only. To demonstrate that, we compare the agreement between narrative labels derived from their components against agreement in a setting where annotators chose one out of 16 narratives directly based on their descriptions (Appendix D.2). The former leads to substantially higher agreement (63% vs 37%). Furthermore, the component-wise annotation was significantly faster than direct labeling due to the reduced cognitive load of annotators.

Final dataset. The final dataset contains 16 climate change narrative frames, as well as their components, and covers the majority of narrative frames mentioned in social studies literature. It includes frames that are similar on the surface, but differ in structure and thus can be used as a challenging test set for narrative frame detection in this domain. Full dataset statistics regarding the distribution of narrative frames and their components are provided in Appendix G.

4.2 Dataset Analysis

We analyze how the annotated narrative frames and their components vary across articles from different political leanings, and their alignment with more commonly used generic frames.

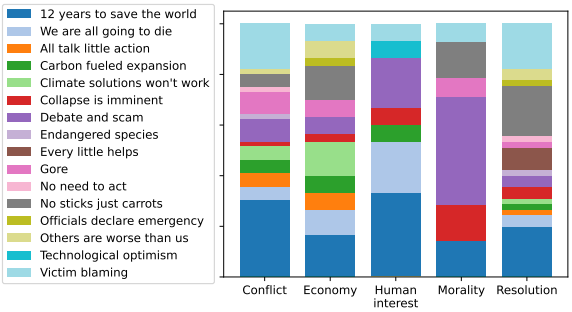

Figure 4: Narrative frames vs generic frames

Narrative frames across political leanings. Individual narrative components strongly associate with specific political leanings of news outlets: The overwhelming majority of right-bias articles are framed as *preventing resolution* (of the climate crisis) and exemplify the *individualistic* cultural story (Figure 3), while these values do not appear at all for left-bias and left-center outlets. Moreover, right-bias outlets frame scientists as heroes much more often than other sources (Appendix Figure 14): they often quote ''fake experts" in support of their anti-climate statements (as in Figure 1). The overall narrative labels are more distributed across political leanings (see Figure 13). Taken together, this shows that dissecting narrative frames into meaningful components affords more nuanced insights in relation to external metadata.

Narrative frames vs generic frames. The 100 articles in our narrative framing corpus were previously annotated with five generic frames originally defined by Semetko and Valkenburg (2000) (Conflict, Economic, Human Interest, Morality and Resolution). We intersect our labels with those generic frames to study the correlation of generic frames and narrative frames. Figure 4 shows little systematic correlation between generic and narrative frames: an article with a particular generic frame can have a variety of different narratives, and vice versa. For example, an "Economy"-framed article can emphasize the importance of fossil fuels ("Carbon fueled expansion" narrative), or focus on the economical effects of climate change ("12 years to save the world"). These observations align with theoretical works which showed that the same generic frame can have different intents (cf. Bushell et al. (2017); Shanahan (2007) for "Economy" frame), and highlights the added insights afforded by a narrative-focused frame analysis on top of generic emphasis frames.

4.3 Automatic Prediction of Narrative Frames and Components

We use our dataset to test narrative frame prediction capabilities of LLMs. We define the following predictive tasks, given the full article text as input:

• Choosing the stakeholder category for `hero`, `villain`, and `victim` (separately for each character type) as one of 10 classes (*government*, *climate activists*, etc.; see Section 3.1). To choose a stakeholder correctly, a model needs to perform several steps: determining if an entity is framed as a `hero`, `villain`, or `victim`, aggregating mentions of entities across the text to determine which of potential candidates is a main `hero`, `villain`, or `victim`; and finally determining to which stakeholder category this character belongs.

• Predicting the `focus` entity out of 3 classes (`hero`, `villain`, or `victim`). This task tests if a model can determine if the narrative frame is "heroic", "blaming", or victim-centered (see Section 3.1).

• Predicting `conflict` out of 4 classes (*fuel conflict, fuel resolution, prevent conflict, prevent resolution*, see Section 3.2). A model needs to identify the general intent of the narrative frame (if it pushes towards resolution of the crisis, or exacerbates it), and the article's strategy to do so (by supporting one side or by criticizing the opposite side).

• Predicting a `cultural story` out of 3 classes (*individualistic, egalitarian, or hierarchical*, see Section 3.3)[7]. To do so, the model needs to identify if the text implies collective vs individualistic action, and approval or disapproval of external control (such as from the government).

• Directly predicting one of 16 `narrative frames` given an article, based on their short descriptions sourced from the social studies literature (full list in Appendix E).

4.3.1 Models and prompts

We use our tasks to test narrative frame prediction of 5 base LLMs of different size (GPT4o, Mixtral, Llama, Gemini and Claude Sonnet), and one reasoning LLM (o1).[8] We set temperature=0 (except

[7]Though Section 3.3 introduces 4 cultural stories (Jones, 2014), the fatalist story is not present in our data set so we exclude it from experiments for fair evaluation.

[8]Versions used: gpt-4o-2024-11-20, o1-preview-2024-09-12, Mixtral-8x7B-Instruct-v0.1, Llama-3.1-8B-Instruct,

	Hero (10)	Villain (10)	Victim (10)	Focus (3)	Conflict (4)	Story (4)	Narrative (16)
Baseline	0.079	0.08	0.135	0.231	0.135	0.19	0.021
GPT4o	0.325	0.454	0.266	0.656	0.332	0.574	0.258
o1	0.363**	0.527*	0.455*	0.718**	**0.549**	**0.595**	0.330*
Mixtral	0.237	0.073	0.257	0.402	0.353	0.431	0.171
Llama	0.271	0.156	0.336	0.568	0.379	0.449	0.181
Gemini	0.326	0.292	0.230	0.635	0.361	0.482	0.319
Sonnet	**0.353**	**0.530**	**0.469**	**0.688**	0.399	0.561	**0.339**

Table 1: Zero-shot performance of 6 models across 7 narrative understanding tasks (macro-averaged F1). The number in brackets after the task's name indicates the number of classes in it. The baseline is calculated by using the most frequent label for the task as a predicted class. Results that had high (over 0.02) or very high (over 0.05) standard deviation across 5 runs are marked with * and ** respectively. The best performing models (considering variance) are in bold.

for o1 which does not allow to control generation) to ensure deterministic outputs. We perform each experiment 5 times to ensure there is no substantial variance in the results. With the exception of o1, which shows high variance on most tasks, models have zero or near-zero variance across runs, which allows to compare averaged results.[9]

The prompts used for each of the tasks are listed in Appendix K.1. The text of the prompts is based on descriptions of particular classes (stakeholders, culture stories, narrative frames etc.) in the social science literature. Prompts for HVV characters are domain-specific, i.e. they are based on a list of entities important for the climate change domain (we show how to generalize this approach by creating such list automatically in Section 5). Conversely, prompts for Focus, Conflict, and Cultural story tasks are domain-agnostic and describe the classes in general terms (e.g., *INDIVIDUALISTIC: this story assumes that the situation cannot be controlled externally, and no group actions are necessary*). We use the most abstract prompts possible to ensure the approach is generalizable, but we also found that abstract prompts lead to better performance compared to prompts specifically describing how a particular conflict or cultural story is manifested in the climate change debate.

4.3.2 Results

Results in Table 1 show that no single model consistently performed best (or worst) across all tasks. Mixtral and Llama are the weakest, especially in stakeholder prediction for for `hero` and `villain` where both models overpredict entities that are stereotypical heroes and villains for this topic. For instance, they select "environmental activists" as heroes and "pollution" as villain, despite the fact that they rarely occur in these roles in our articles. In a similar way, they overpredict rare narrative frames as "Carbon fuelled expansion" which claims that fossil fuels are necessary for the economy, presumably due to an over-reliance on surface cues (e.g., terms like "fossil fuels").

The strongest models, Sonnet and o1, tie in terms of results, though o1 does better in tasks which require a notion of the overall "gist" of the text, such as predicting Cultural story and Conflict. Still, o1 (as well as the other models) does not reliably detect narrative frames based on their description (Narrative task) and tends to excessively predict one class. Thus, despite the fact that human annotators had a high agreement on narrative components, none of the models reaches comparably high performance. Models are also unable to reliably differentiate narrative frames based only on their description, consistent with human performance. In section Section 4.3.3 we examine if the narrative structure helps the models to predict narrative frames better (as it does for human annotators).

We perform experiments to optimize the prompt and help models learn from examples (see Appendix I), but they do not lead to performance gains, which shows the difficulty of the tasks.

Effect of the number of classes. The difficulty of the Narrative frame prediction task is confounded by the number of classes that need to be distinguished (16). To test whether the performance would increase if the model is asked to choose between a smaller number of classes, we select a sample of three frequent, but similar narratives – "12 Years to save the planet", "We are all

gemini-1.5-flash, Sonnet 3.5. Model sizes are provided in Appendix F.

[9]When comparing with o1-preview-2024-09-12, we used the worst results rather than average to account for large variance.

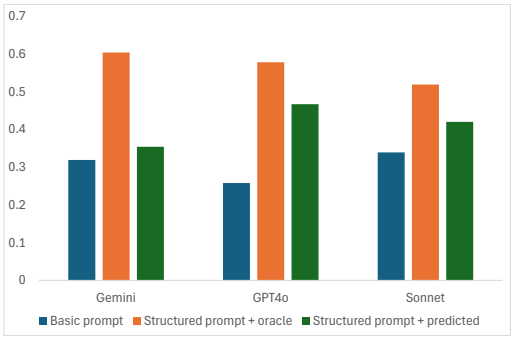

Figure 5: Predicting narrative frames using oracle (human-annotated) and noisy (predicted) labels for their `hero`, `villain`, `victim`, and `focus`; the results are macro-averaged F1.

going to die", and "Gore" (see Appendix E), and modify the Narrative prompt to include descriptions only of these three classes. However, this increases performance only minimally (from F1 of 0.258 to 0.270 for GPT-4o) and nowhere near the level for tasks with a comparable number of classes such as Focus and Conflict. Moreover, even for this simplified task there is a tendency to predict one class, and one of the classes is never chosen correctly (Figure 20 in Appendix).

4.3.3 Predicting narrative frames with component labels

In this section, we explore if using our narrative components (such as specifying `hero`, `villain`, `victim`, and `focus`) can improve narrative frame classification. For these experiments we use three models (the strongest Sonnet and middle-grade GPT-4o and Gemini[10]) in zero-shot mode. For each of the narrative frame definitions we add an informal description of typical stakeholders for `hero`, `villain`, `victim` (as listed in Appendix E for each of the narrative frames) and the `focus` role (see examples of modified prompts in Appendix K.2).

Next, for each input article we add labels that denote `hero`, `villain`, and `victim` stakeholder categories, as well as `focus`, to explicitly represent the structure of the narrative frame. As shown in Figure 5 (orange), with *oracle* (manually-annotated) labels the performance improves substantially across models (most notably in GPT4o). We repeat this experiment with noisy labels predicted by the model, and again observe gains compared to the prompt without structure (green in Figure 5). The models' behavior, however, is quite different: For Gemini we observe minimal improvement, while Sonnet benefits least from the structure labels overall, but does accommodate for the noisiness. GPT4o, despite being the weakest on this task, benefits most from structure and noisy labels, achieving substantially higher performance than the best-performing model (Sonnet) in this condition. Taken together, this shows that explicit structure – if of reasonably high quality[11] – is a more reliable cue for predicting the narrative than its description.

To examine how introduction of structure affects the narrative frame prediction, and analyze which narrative frames are hard for models to predict even when they are given correct labels for their characters, we compare confusion matrices for Narrative classification with a basic prompt (Figure 21 in the appendix), and with a structured prompt and oracle character labels (Figure 22). We observe that before the introduction of structure the predictions are scattered across the matrix; i.e. both the predictions and errors are not systematic. With the structure, however, we see clear patterns of consolidation: first, narrative frames that have a unique structure (such as "Officials declare emergency" which uniquely frames government as a `hero`) are now predicted (near) perfectly. Second, errors are now due to confusion of a handful of structurally similar narrative frames, most prevalently two frames that both focus on criticizing the government (`villain`), but have different cultural stories: "12 years to save the Earth" calls for even more governmental control (*hierarchical*), while "All talk no action" opposes government actions (*egalitarian*). This example highlights how cultural stories complement the character role component in our framework, and the importance of each component for effectively differentiating between narrative frames. Future work should explore incorporating all components (and not only characters and focus) in structured prompts.

5 Narrative Framing of COVID-19

In this section we apply our narrative frame structures taxonomy to texts with a different topic and style – politicians' speeches around the onset of COVID-19 – to demonstrate its generalizability to other domains. We show how models and prompts

[10]We exclude o1 due to its high costs and high variability of results between runs.

[11]These gains occur only when the labels are accurate enough: we observed only minimal gains or drops in performance when using predictions from less strong models.

developed within the supervised approach (Section 4) can be applied to analyze narrative frame components in an unsupervised way.

5.1 Dataset and model

We collect transcripts of head-of-state addresses regarding the onset of COVID-19 dating from February to end of July 2020, for three countries: Germany (Angela Merkel; N=12), UK (Boris Johnston; N=24) and Australia (Scott Morrisson; N=6).[12] We examine all addresses published during that period and select those that were dedicated to COVID-19.

We use the most reliable model identified in Section 4 (Claude Sonnet 3.5) in a zero-shot setting. Since the prompts for `focus`, `conflict`, and `cultural story` developed in Section 4 are domain agnostic, we apply them without changes, only substituting the topic name for "COVID-19". However, since the set of stakeholders is likely to be different for this topic, we modify the HVV prompts by replacing the classes with a list of topic-specific stakeholders. We compile this list automatically by generating them from the speeches: first we ask the LLM to extract and merge entities which are likely to represent `hero`, `villain`, and `victim`, then combine the extracted candidates from all speeches and cluster them into groups (prompts in Appendix L).

We arrive at a set of 8 stakeholders, some of which are generic and shared with the climate change domain (*government, general public*), while the majority are unique and topic-specific (*vulnerable population, healthcare*, etc). The final set of stakeholders corresponds to prominent stakeholders previously identified as `hero`, `villain`, `victim` in studies on narrative framing in these speeches (Bernard et al., 2021; Mintrom et al., 2021).

5.2 Results

We apply our approach to discover differences and commonalities in framing of politicians speeches regarding COVID-19.

First, all speeches across all three politicians were identified as *hero-focused* and *promoting resolution*, which is not surprising given the fact that they are all mobilizing narratives that suggest specific actions to solve the crisis and praise the role of heroes. Similarly, the `villain` is consistently detected as "pandemics", and `victim` is "general public", especially "vulnerable populations", and, later in the period, "economy".

However, the stakeholders that are pinpointed as `hero` differ across politicians: while all of them recognize the role of "healthcare workers", Merkel's speeches also highlight the role of "general public", and, later in the pandemic, of "global efforts". On the other hand, Morrison's speeches heavily revolve around the role of "government" as a hero, as well as "science experts". This divergence is in line with prior theoretical analyses of these speeches, which assert that chancellor Merkel recognized the value of combined efforts of the German public and countries around the globe (Mintrom et al., 2021), while prime minister Morrison often used reassuring framing relying on the role of science in pandemic management and the imagery of Australia as a "lucky country" (Bernard et al., 2021).

Similarly, the analysis of predicted cultural stories reveals that Morrison predominantly used *hierarchical* cultural stories (*'Government and following social prescriptions plays the biggest role in managing the crisis'*), Merkel had a larger proportion of *egalitarian* narrative frames than others (*'We must act as one to combat the crisis'*), while Johnson was the only one who alluded to *individualistic* cultural story (*'Take care of yourself and your family'*). Again, these insights align with previous theoretical analyses (Mintrom et al., 2021).

6 Conclusion

We presented a rigorous formalization and taxonomy of components of narrative framing, synthesizing the NPF and Entman (1993)'s components of a frame. Our method allows to inductively detect narratives from political texts in terms of their character roles, focus, conflict, and underlying cultural story. A high-quality data set of 100 manually labeled articles serves as a benchmark and basis for future annotation bootstrapping. We showed that our framework results in promising improvement of automatic narrative prediction with LLMs, laying a foundation for the important research agenda of large-scale studies of the manifestation and effects of narrative frames. Moreover, we showed that our framework is generalizable to other topics and can assist in exploratory framing analysis without requiring a labeled dataset.

[12] Sources: https://www.bundesregierung.de/breg-en/service/archive/ (official translation into English), https://www.gov.uk/government/speeches/, https://www.pm.gov.au/media.

7 Limitations

We acknowledge the small size of our data set relative to NLP benchmarks, but emphasize the difficulty of annotating news articles at this level. We prioritize depth over breadth, and our data set can serve both as a benchmark and a high-quality starting point for bootstrapping other story annotations.

Because our approach is inductive / bottom-up we cannot guarantee that the narratives we found cover all possible active narratives or reflect the true narrative distribution. However, since our inductive narratives overlapped with a large part of narratives described in the literature, we are confident that they are representative and comprehensive.

Additional LLM experiments, with larger example pools or advanced reasoning techniques may lead to further improvements but are outside the scope of this work. We showed that incorporating narrative structure into prompts improves performance more substantially than models with advanced reasoning abilities. Future work, however, may want to combine it with such models and techniques.

Ethics statement

This study was approved by the University of Melbourne ethics board (Human Ethics Committee LNR 3B), Reference Number 2023-22109-37029-4, and data acquisition and analysis has been taken out to the according ethical standards. The annotators were compensated at a rate of 35 USD per hour which is well above minimum hourly payment in Australia.

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A Statistics for the US Climate articles dataset

Figures 6 to 8 show the distribution of articles in the US climate narratives dataset according to their publication year (Figure 6), outlet (Figure 7), and the political leaning of the latter (Figure 8), as identified by the Media Bias Fact Check (MBFC) website[13].

[13] https://mediabiasfactcheck.com/

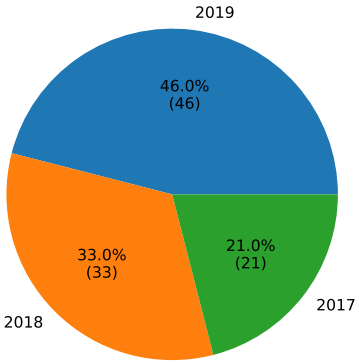

Figure 6: Distribution of articles across years

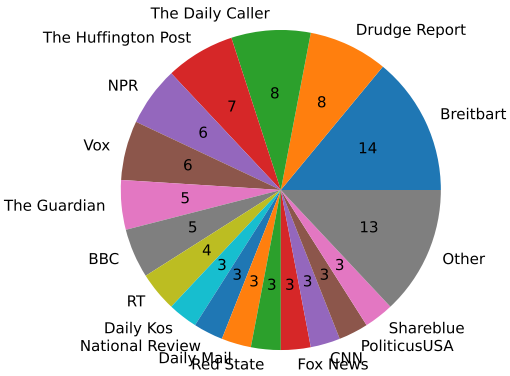

Figure 7: Distribution of articles across media outlets

B Identifying the main characters

As we explain in Section 3.1, not all entities in an article represent its main `hero`, `villain`, or `victim`. To be able to reliably and consistently identify the main characters, we adhere to the following process:

(1) We consider only the entities which are consistent with the overall stance of the article. In particular, journalists often cite the opposing view, and thus can mention a set of characters which is different from the one aligned with stance. For example, in the article in Figure 1, melting ice is a `victim` of rising temperatures, according to the viewpoint of climate activists. However, while the author cites this viewpoint, it does not reflect the main message of the article, so the corresponding entities are not considered as potential `hero`, `villain`, and `victim`. To summarize, the main characters are the ones framed so by the author/narrator.

(2) We discard characters that either form the backdrop of the story or are used to illustrate a minor (often competing) idea within the main narrative.[14] For example, in the narrative in Figure 1 melting ice or Arctic animals are only included as a point of tension between the climate activists and denialists but don't themselves play a major role in the narrative. The main characters are the parties expressing their opinion regarding them.

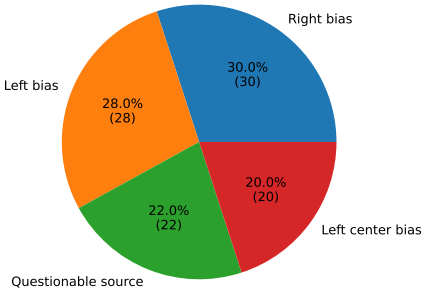

Figure 8: Distribution of articles across political leanings of the outlets

(3) The same character can be referred to several times and be represented with several stakeholders. For example, it is common for news stories to mention both climate change regulations/policies and the politicians that propose them. In such cases, instead of adding multiple stakeholders for a character, we choose the one that was most prominent in the context or can be used to infer the other (for example, we would choose policies over politicians if the article focuses on them).

(4) We only consider characters that are active in the plot, rather than references to potential or past heroes, villains, and victims. For example, a news story that paints Republicans as a `villain` for not implementing climate change measures[15] concludes with the following sentence:

> For 2020 and beyond, climate justice will have to become the most animating issue for Democrats.

Since the positive impact of Democrats is only hoped for or predicted to happen in the future, Democrats are not an active `hero`, and, overall, the `hero` in this news story is absent. It is important not to assign extraneous entities to the character slots, even if they are otherwise empty, as it will

[14] We are well aware that news stories are complex in terms of interplay of narratives within them and most of them contain what Fløttum and Gjerstad (2017) refers to as narrative polyphony. We intentionally restrict the task to identification of the main narrative only as the first step in disentangling narrative complexity.

[15] Article 512 in our dataset.

later help to differentiate between narratives. For example, here it allows us to distinguish a narrative criticizing the `villain` from alternative narratives which depict an active conflict between `hero` and `villain`.

(5) For the same reasons, we do not add stakeholders that are only implied but not directly referred to in the text. For example, we do not add "environment" as a `victim` unless it is specifically mentioned, though it can be inferred from the majority of pro-climate action news stories. Similarly, though the stories warning about the dangers of climate inaction are usually inspired by scientific evidence, scientists or scientific reports are not a `hero` in them unless they have an active role, as in here[16]

> Climate report warns of extreme weather, displacement of millions without action

This allows to differentiate between a narrative which appeals to authority of scientists (so called "Gore" narrative) from a similar but often more emotionally charged and less "objective" alarmist narrative ("12 Years to save the world") (see Appendix E for detailed description).

C Stakeholder categories

We use the following 10 stakeholder categories from (Frermann et al., 2023):
GOVERNMENTS_POLITICIANS: governments and political organizations
INDUSTRY_EMISSIONS: industries, businesses, and the pollution created by them
LEGISLATION_POLICIES: policies and legislation responses
GENERAL_PUBLIC: general public, individuals, and society, including their wellbeing, status quo and economy
ANIMALS_NATURE_ENVIRONMENT: nature and environment in general or specific species
ENV.ORGS_ACTIVISTS: climate activists and organizations
SCIENCE_EXPERTS_SCI.REPORTS: scientists and scientific reports/research
CLIMATE_CHANGE: climate change as a process or consequence
GREEN_TECHNOLOGY_INNOVATION: innovative and green technologies
MEDIA_JOURNALISTS: media and journalists

[16] Article 537 in our dataset.

D Annotation process

The annotation was performed in two stages:

D.1 Stage 1: Annotating `hero`, `villain`, and `victim`

During stage 1, we employed three external annotators, all with an academic background in the social sciences and familiar with the Narrative Policy Framework, and one of the authors of the article, who is considered an expert annotator with knowledge of media discourse and framing. For each article, each annotator had to (1) read it beginning to end and (2) identify the main `hero`, `villain` and `victim` (if any) and record them in free form based on the procedure described in Appendix B. They were also asked to record their reasoning in plain text (see an example and annotation interface in Figure 9).

Each of the 100 articles in the dataset was annotated at least by two external annotators, and all of them were in addition annotated by the internal expert annotator. Since the annotators were asked to specify entities for `hero`, `villain`, and `victim` in free form, their annotations were not directly comparable (e.g. "Biden" vs "Joe Biden" vs "Democrats"). Thus, to evaluate the annotation agreement, as well as to convert the data to a more abstract and useful structure (see Section 3.1), the expert annotator mapped the specific characters mentioned by each of the annotators to their stakeholder classes (Appendix C).

We evaluate the agreement between all four annotators using Krippendorf's α, and report the averaged agreement of each of the three external annotators with the expert. For the latter, we use the standard metrics of agreement rate (=accuracy), Cohen's κ, and the less commonly used Gwet's AC1, which compensates for the high imbalance in data distribution. The resulting inter-annotator agreement statistics can be found in Table 2. Overall, we observe acceptable to strong levels of agreement between all four annotators, as well as very high average agreement of each of the annotators with the expert (as judged based on Gwet's AC1). A relatively lower agreement for `hero` and `villain` in comparison to `victim` is explained by the fact that the annotators sometimes chose entities belonging to different stakeholder types to represent the same event. For example, a particular climate initiative can be represented both by a parliamentary bill such as New Green Deal (LEGIS-

Which entity did you identify as the HERO of the article (if any)?	Which entity did you identify as the VILLAIN of the article (if any)	Which entity did you identify as the VICTIM of the article (if any)?	Explanation (1-3 sentences)
None	Political Inaction, Italian apathy / lack of concern for climate change	People and City of Venice	public and a politician as essentially blaming a lack of serious climate change action for the floods. It's not clear the prime minister, Conte is being potrayed as HERO, as per the annotated article, maybe it is even portraying him as a villian for not taking sufficient action. Climate change, global warming, and the extreme floods are not
Climate Action, Those taking climate change seriously	Trump	Society/Nature	Article is criticizing politics, specifically the US president Donald Trump for his climate denial or at the very least climate inaction and prioritization of other political agendas. Article quotes leading scientists who warn about the devestating effects of climate change and there call for decisive action.
Other National leaders taking climate change seriously, UN Secretary	Trump	nature/society	Article heavily criticizes Trump for pretending to take climate change/action seriously, while actually not doing very much about it because he is actually a climate sceptic. Article also indicates other world leaders take climate change more seriously and implies Trump should follow suit

Figure 9: Example of stage 1 annotations (`hero`, `villain`, `victim`)

	Hero	Villain	Victim
Krippendorff's α	0.757	0.673	0.812
Agreement rate	0.852	0.855	0.927
Cohen's κ	0.783	0.745	0.876
Gwet't AC1	0.837	0.843	0.914

Table 2: Inter-annotator agreement for `hero`, `villain`, and `victim` annotation

	Focus	Conflict	Cultural story
Krippendorf's α	0.780	0.820	0.801
Agreement rate	0.867	0.867	0.867
Cohen's κ	0.776	0.817	0.800
Gwet't AC1	0.810	0.824	0.801

Table 3: Inter-annotator agreement for `focus`, `conflict`, and `cultural story` annotation

LATION_POLICIES), and by the group of people behind it (GOVERNMENTS_POLITICIANS). In case of disagreement the final label was chosen based on majority vote.

D.2 Stage 2: Annotating `focus`, `conflict`, and `cultural story`

In the second stage, the expert annotator annotated all 100 articles in terms of their `focus`, `conflict`, and `cultural story`. Next, a random sample of 30 articles was annotated by another internal annotator who is also an expert in Narrative Policy Framework and framing analysis. The instructions for the annotation and an example of an annotated article are shown in Figures 10 and 11 respectively. To ensure a high quality of the resulting dataset, all disagreements were discussed and adjudicated, and then the corresponding changes were reflected in the samples beyond this calibration study, if necessary.

Table 3 shows the agreement statistics between the two annotators in Stage 2, using the same metrics as for Stage 1. We observe high agreement rates for all three classes, with other scores varying slightly due to number of classes and class distribution, but all being within the strong or very strong agreement range. Disagreement analysis revealed that there were disagreements on `focus` (between `villain` and `victim`), when both were discussed at similar length and depth in the article. For `conflict` and Cultural story, the disagreements were more systematic (such as confusion between Fuel Resolution and Prevent Conflict, or between Hierarchical and Egalitarian stories); the insights arising from the discussion were reflected in the final labels and allowed us to refine the definitions of these concepts for the prompts used in LLM experiments.

Annotation with vs without narrative frame structure

We empirically tested if structural components help to differentiate between narratives in human annotation. Specifically, we compare agreement in narrative detection when using a structure-based annotation approach (bottom-up; as described above) vs using a more traditional approach where the annotators are asked to classify narratives top-down based on their descriptions.

For the structure-based approach, we estimate the agreement based on the sample of 30 articles we used for Stage 2 annotation (see Appendix D). In particular, we assume that both annotators agree on a particular narrative if they choose exactly the same values for all its components. For the traditional approach, we ask two annotators who took part in Stage 1 of annotation (and thus did not classify any elements of the narrative except for its characters) to choose a narrative frame for each article based on its description only (as listed in Appendix E).

We find that annotation using our narrative structures resulted in 63% agreement, while top-down annotation based on the narrative frame descriptions resulted in a substantially lower 37%. Thus, we can tentatively conclude that structure-based

Annotation Instructions

You will be given a full text of an article about climate change and asked to identify some elements of its narrative structure according to Narrative Policy Framework (NFP).

In NFP, a narrative contains at least one of the following characters: **Villain**, who is creating some conflict/problem; **Hero**, who is trying to resolve a conflict or problem; or a **Victim**, who is negatively affected by a conflict or problem. Not all of these characters need to be present in a narrative at the same time.

Each article can contain a mixture of narratives and thus have multiple villain-hero-victim sets. However, we can derive the overarching narrative of the article by determining its main hero, villain, or victim. For each of the articles you will see, we have already annotated the main hero, villain, and victim, so that you can focus on the main narrative characters when you do your annotation.

You will be asked three questions:

1. **Focus**: narratives can have the same characters (hero, villain, victim) but focus on different ones of them. For example, a narrative about negative effects of pollution on environment can focus either on the villain (criticise policies, governments, industries that cause pollution while mentioning its negative effects), or on the victim (describe negative effects on people or nature in detail while also mentioning the culprit).
   Which of the characters (Hero, Villain, or Victim) is the focus of the narrative?

2. **Conflict and Resolution**: apart from their characters, narratives in NFP are defined by the conflict/problem or its resolution described in them. In our case, the conflict/problem is climate change, and resolution is measures against climate change. Thus, a particular narrative can:

   FUEL RESOLUTION: propose or describe specific measures, policies, or events that would contribute to the resolution of the climate crisis.
   FUEL CONFLICT: propose or describe specific measures, policies, or events that would exacerbate the climate crisis.
   PREVENT RESOLUTION: criticise measures, policies, or events that contribute to the resolution of the climate crisis; or deny the climate crisis
   PREVENT CONFLICT: criticise measures, policies, or events that exacerbate the climate crisis; or provides the evidence of climate crisis.

   Please be mindful that the perspective of the author/narrator and the characters in the story regarding the conflict and its resolution can be different; identify and annotate the main perspective which corresponds to the author's/narrator's intention.

   Does this narrative fuel conflict, fuel resolution, prevent conflict, or prevent resolution?

3. **Cultural story**: narratives of climate change are aligned with the following cultural stories, which capture the ideas of the necessity of top-down control vs self-regulation, and the idea of group responsibility vs individual responsibility.

   HIERARCHICAL: this story assumes that the nature can be controlled but we need to be bound by tight social prescriptions. The villain is mismanaged society which led to excessive growth, and heroes are impartial scientists or government intervention.
   INDIVIDUALISTIC: this story assumes that the nature is resilient and will return to equilibrium. Villains here are people who try to control climate change or seek policy changes, and the heroes allow markets to move naturally as individuals compete to create innovative technologies.
   EGALITARIAN: this story assumes that the nature is fragile and there is little opportunity to correct mistakes. The cause of climate change is overconsumption; villains are profit-driven corporations and anyone who supports status quo, and heroes are groups who seek fundamental changes.
   FATALIST: the story assumes that the nature cannot be controlled, and climate change is inevitable whatever efforts we make.

   Which of the cultural stories (Hierarchical, Individualistic, Egalitarian, or Fatalist) does the narrative align with?

Figure 10: Instructions for Stage 2 annotation (`focus`, `conflict`, `cultural story`)

ID: 225

Article:

E.P.A. Plans to Get Thousands of Deaths Off the Books by Changing Its Math Want climate news in your inbox ? Sign up here for Climate Fwd :, our email newsletter. WASHINGTON — The Environmental Protection Agency plans to change the way it calculates the health risks of air pollution, a shift that would make it easier to roll back a key climate change rule because it would result in far fewer predicted deaths from pollution, according to five people with knowledge of the agency 's plans. The E.P.A. had originally forecast that eliminating the Obama - era rule, the Clean Power Plan, and replacing it with a new measure would have resulted in an additional 1,400 premature deaths per year. The new analytical model would significantly reduce that number and would most likely be used by the Trump administration to defend further rollbacks of air pollution rules if it is formally adopted. The proposed shift is the latest example of the Trump administration downgrading the estimates of environmental harm from pollution in regulations. In this case, the proposed methodology would assume there is little or no health benefit to making the air any cleaner than what the law requires. Many experts said that approach was not scientifically sound and that, in the real world, there are no safe levels of the fine particulate pollution associated with the burning of fossil fuels. Fine particulate matter — the tiny, deadly particles that can penetrate deep into the lungs and enter the bloodstream — is linked to heart attacks, strokes and respiratory disease."

Questions:

Considering that in this article the **Villain** is politicians, and the **Victim** is general public, answer the following:

1) Which of the characters (Hero, Villain, or Victim) is the focus of the narrative?

Hero **Villain** Victim

2) Does this narrative fuel conflict, fuel resolution, prevent conflict, or prevent resolution?

Fuels conflict Fuels resolution
Prevents conflict Prevents resolution

3) Which of the cultural stories (Hierarchical, Individualistic, or Egalitarian) does the narrative align with?

Hierarchical Individualistic Egalitarian Fatalist

Figure 11: An example of Stage 2 annotation (`focus`, `conflict`, `cultural story`)

analysis improves narrative detection and understanding. We also observed a reduction in time required for annotation (15 minutes per article based on descriptions of narrative frames vs 7 minutes per article based on its structure, on average).

E US Climate Narratives: Structures and description

In this section we list the 16 discovered narratives in the US climate change study, their structures, references to the literature where they have been discussed, and exact definitions taken from that source.

E.1 Narratives focusing on `hero`

E.1.1 You're destroying our future

Hero: ENV.ORGS_ACTIVISTS
Villain: GOVERNMENTS_POLITICIANS
Victim: <optional>
Conflict: FUEL RESOLUTION
Cultural story: EGALITARIAN
Description: The political stasis around climate change means that we cannot rely on politicians to create the change necessary. With collective action, even the politically weak can make a difference and secure a future for generations to come. This can manifest as anything from protests (school strikes) to non-violent civil disobedience.
Source: Bevan (2020)

E.1.2 Technological optimism

Hero: GREEN_TECHNOLOGY_INNOVATION
Villain: INDUSTRY_EMISSIONS, CLIMATE_CHANGE
Victim: <optional>
Conflict: FUEL RESOLUTION
Cultural story: EGALITARIAN
Description: We should focus our efforts on current and future technologies, which will unlock great possibilities for addressing climate change.
Source: Lamb et al. (2020)

E.1.3 Officials declare emergency

Hero: GOVERNMENTS_POLITICIANS
Villain: INDUSTRY_EMISSIONS, CLIMATE_CHANGE, GOVERNMENTS_POLITICIANS
Victim: <optional>
Conflict: FUEL RESOLUTION
Cultural story: HIERARCHICAL
Description: The climate crisis is sufficiently severe that it warrants declaring a climate emergency. This should occur at different levels of government as climate requires action at all levels, from the hyper-local to the global.
Source: Bevan (2020)

E.1.4 Every little helps

Hero: GENERAL_PUBLIC
Villain: GENERAL_PUBLIC
Victim: <optional>
Conflict: FUEL RESOLUTION
Cultural story: INDIVIDUALISTIC
Description: This narrative presents a society which has transitioned to a sustainable "green" way of life. Could be expressed by portraying individuals as the protagonists of stories that propose solutions to climate change.
Source: Bushell et al. (2017)

E.2 Narratives focusing on `villain`

E.2.1 12 years to save the world

Hero: <optional>
Villain: GOVERNMENTS_POLITICIANS
Victim: ANIMALS_NATURE_ENVIRONMENT, GENERAL_PUBLIC, CLIMATE_CHANGE
Conflict: PREVENT CONFLICT
Cultural story: HIERARCHICAL
Description: Past and present human action (or inaction) risks a catastrophic future climatic event unless people change their behaviour to mitigate climate change.
Source: Bevan (2020)

E.2.2 Gore

Hero: SCIENCE_EXPERTS_SCI.REPORTS
Villain: GOVERNMENTS_POLITICIANS, GENERAL_PUBLIC, INDUSTRY_EMISSIONS
Victim: ANIMALS_NATURE_ENVIRONMENT, CLIMATE_CHANGE
Conflict: FUEL RESOLUTION
Cultural story: HIERARCHICAL
Description: This is a narrative of scientific discovery which climaxes on the certainty that climate change is unequivocally caused by humans.
Source: Bushell et al. (2017)

E.2.3 The collapse is imminent

Hero: ENV.ORGS_ACTIVISTS
Villain: GOVERNMENTS_POLITICIANS
Victim: <optional>
Conflict: FUEL RESOLUTION
Cultural story: EGALITARIAN
Description: The climate crisis is such that some kind of societal collapse is near inevitable. Due to the inaction of the negligent or complacent politicians the social contract has broken down and it is incumbent upon individuals to engage in non-violent civil disobedience to shock society into urgent action.
Source: Bevan (2020)

E.2.4 Climate solutions won't work

Hero: <optional>
Villain: LEGISLATION_POLICIES, GREEN_TECHNOLOGY_INNOVATION
Victim: GENERAL_PUBLIC, ANIMALS_NATURE_ENVIRONMENT
Conflict: PREVENT RESOLUTION
Cultural story: INDIVIDUALISTIC
Description: Climate policies are harmful and a threat to society and the economy. Climate policies are ineffective and too difficult to implement.
Source: Lamb et al. (2020)

E.2.5 No sticks just carrots

Hero: LEGISLATION_POLICIES
Villain: LEGISLATION_POLICIES
Victim: GENERAL_PUBLIC
Conflict: PREVENT RESOLUTION
Cultural story: INDIVIDUALISTIC
Description: Society will only respond to supportive and voluntary policies, restrictive measures will fail and should be abandoned.
Source: Lamb et al. (2020)

E.2.6 All talk little action

Hero: <optional>
Villain: GOVERNMENTS_POLITICIANS
Victim: <optional>
Conflict: PREVENT RESOLUTION
Cultural story: EGALITARIAN
Description: This narrative emphasises inconsistency between ambitious climate action targets and actual actions.
Source: Lamb et al. (2020)

E.2.7 Victim blaming

Hero: <optional>
Villain: GENERAL_PUBLIC
Victim: GENERAL_PUBLIC
Conflict: PREVENT RESOLUTION
Cultural story: INDIVIDUALISTIC
Description: Individuals and consumers are ultimately responsible for taking actions to address climate change.
Source: Lamb et al. (2020)

E.2.8 Debate and scam

Hero: <optional>
Villain: GOVERNMENTS_POLITICIANS, LEGISLATION_POLICIES, ENV.ORGS_ACTIVISTS, MEDIA_JOURNALISTS
Victim: <optional>
Conflict: PREVENT RESOLUTION
Cultural story: INDIVIDUALISTIC
Description: The heroes of this narrative are sceptical individuals who dare to challenge the false consensus on climate change which is propagated by those with vested interests.
Source: Lamb et al. (2020)

E.2.9 Others are worse than us

Hero: GOVERNMENTS_POLITICIANS
Villain: GOVERNMENTS_POLITICIANS
Victim: <optional>
Conflict: PREVENT RESOLUTION
Cultural story: INDIVIDUALISTIC
Description: Other countries, cities or industries are worse than ourselves. There is no point for us to implement climate policies, because we only cause a small fraction of the emissions. As long as others emit even more than us, actions won't be effective.
Source: Lamb et al. (2020)

E.3 Narratives focusing on `victim`

E.3.1 Endangered species

Hero: <optional>
Villain: GOVERNMENTS_POLITICIANS, LEGISLATION_POLICIES, INDUSTRY_EMISSIONS
Victim: ANIMALS_NATURE_ENVIRONMENT
Conflict: PREVENT CONFLICT
Cultural story:HIERARCHICAL
Description: Endangered species (like polar bears) are the helpless victims of this narrative, who are seeing their habitat destroyed by the actions of villainous humans.
Source: Bushell et al. (2017)

E.3.2 We are all going to die

Hero: <optional>
Villain: CLIMATE_CHANGE, INDUSTRY_EMISSIONS
Victim: GENERAL_PUBLIC
Conflict: PREVENT CONFLICT
Cultural story: EGALITARIAN
Description: This narrative shows the current or potential catastrophic impact of climate change on people.
Source: Shanahan (2007)

E.3.3 Carbon fueled expansion

Hero: <optional>
Villain: LEGISLATION_POLICIES, GREEN_TECHNOLOGY_INNOVATION
Victim: GENERAL_PUBLIC, INDUSTRY_EMISSIONS
Conflict: PREVENT RESOLUTION
Cultural story: INDIVIDUALISTIC
Description:The free market is at the centre of this narrative which presents action on climate change as an obstacle to the freedom and well-being of citizens. The narrative can stress social justice or well-being of individual citizens.
Source: Bushell et al. (2017)

F Model sizes, costs and parameters

Model Parameters	
Mixtral-8x7B-Instruct-v0.1	46.7B params
Gemini-1.5-Pro	1.5T params
Llama-3.1-8B-Instruct	8B params
Experiment Costs	
Approximate costs	600 USD
Hyperparameters for Llama LoRA Fine-tuning	
Max sequence length	4000
r (LoRA rank)	16
LoRA alpha	16
LoRA dropout	0
Learning rate	2×10^{-4}
Optimizer	adamw8bit
Weight decay	0.01

G Annotated dataset statistics

In Figure 12 we show the distribution of all components of our framework (Hero, Villain, Victim stakeholders; Focus; Conflict; Cultural Story), as well as final narratives across the 100 articles.

H Distribution of narrative frame components across political leanings

We explore how different narrative frames and their components are used across political leanings. In particular, we show the distribution of high-level frames (Figure 13), narrative frames entities representing `hero` (Figure 14), `villain` (Figure 15), and `victim` (Figure 16); the choice of `focus` entity (Figure 17); the distribution of

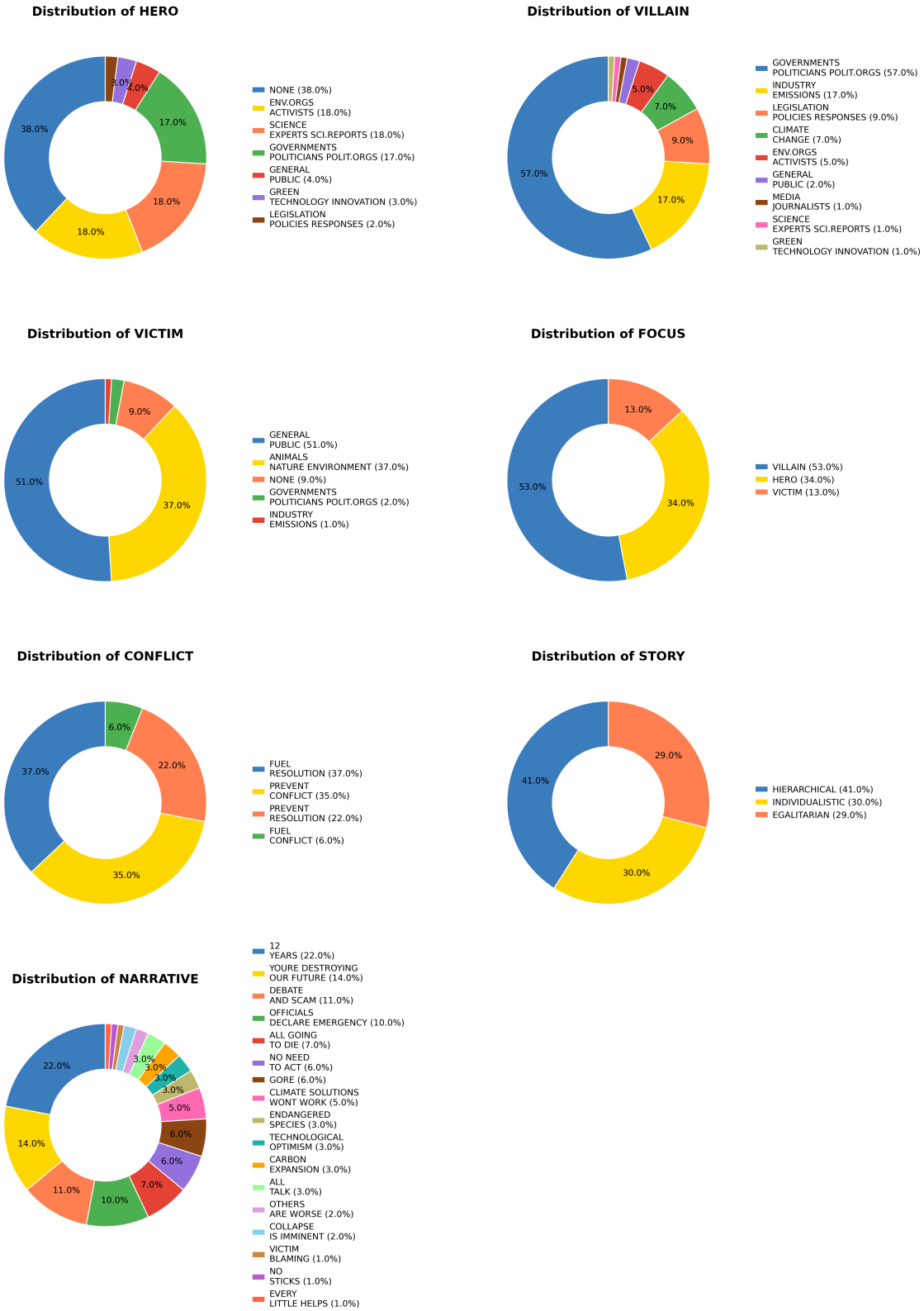

Figure 12: Label distributions for narrative frames and their components in our labelled dataset of 100 US climate change news articles.

`conflict` values (Figure 18) and that of cultural stories (Figure 19). Selected analyses are discussed in more detail in the main paper Section 4.2.

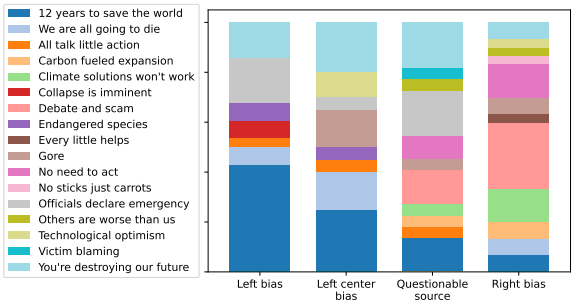

Figure 13: Distribution of narrative frames across political leanings

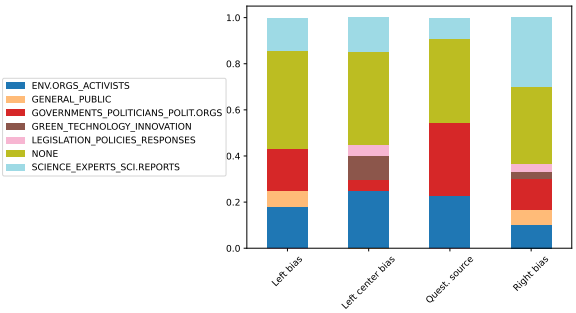

Figure 14: Distribution of entities representing HERO across political leanings

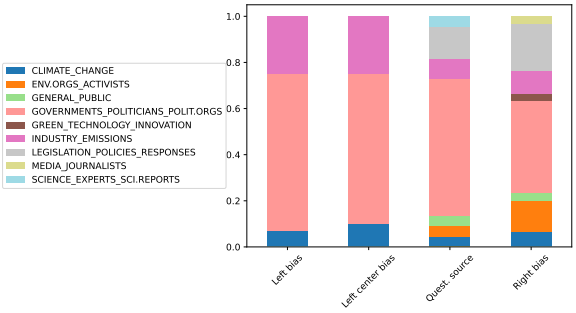

Figure 15: Distribution of entities representing VILLAIN across political leanings

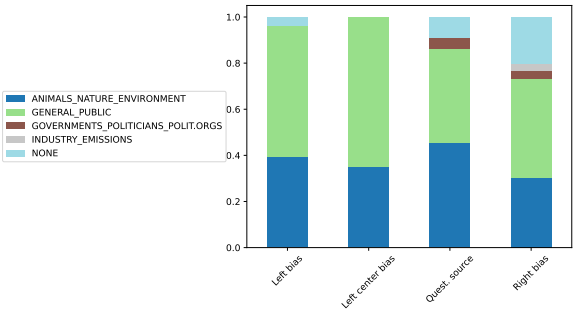

Figure 16: Distribution of entities representing VICTIM across political leanings

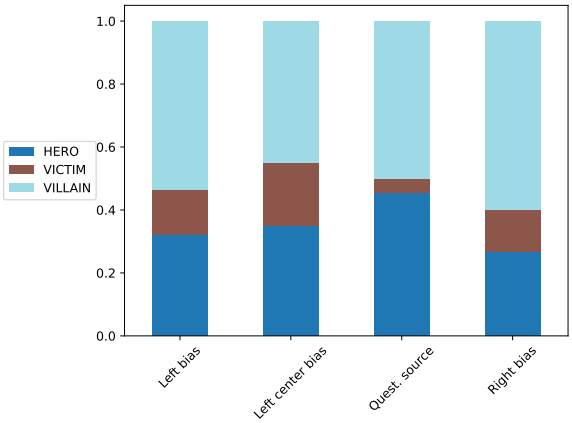

Figure 17: Distribution of FOCUS values across political leanings

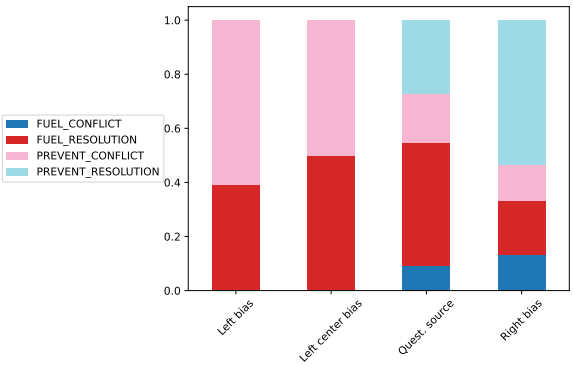

Figure 18: Distribution of CONFLICT values across political leanings

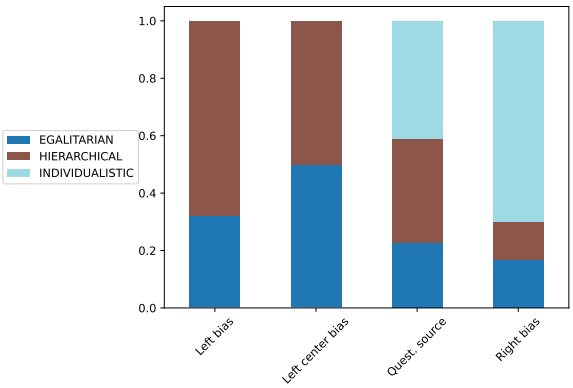

Figure 19: Distribution of CULTURAL STORY values across political leanings

I Additional experiment details

We examine if the performance can be improved by exposing models to annotated examples and optimizing the prompts by adding Chain-of-Thought steps. First, we use 5 randomly selected samples from our dataset for 5-shot learning with GPT4o model. However, except for Hero stakeholder identification, where it leads to some gains, it causes overgeneralization to seen labels and thus drop in performance (see Table 4). We observe similar effects when we perform Low-Rank Adaption (LoRA) fine-tuning (Hu et al., 2021) of Llama.[17] Similarly, we notice that the fine-tuned model tends to overpredict the most prominent labels, discarding minor classes. We also use the 5 random samples for a DSPy program (Khattab et al., 2023) to automatically generate and optimize reasoning steps for Chain-of-Thought (CoT) prompting. The gains (compared to non-optimized 5-shot prompting) are also minimal (see Table 4). In addition, we tried implementing Chain-of-Thought (CoT) manually for HVV identification tasks, where we guide the model through the steps of identifying candidate entities, choosing most prominent among them, and finally classifying their stakeholder type, but this lead to worse performance.
Overall, these additional experiments show that the tasks are difficult to meaningfully learn from examples or even through reasoning steps.

J Narrative frame prediction with and without structure

Below we show confusion matrices for GPT4o with a basic prompt (Figure 21) vs with a structured prompt and oracle (human-annotated) (Figure 22) labels.

K Prompts

K.1 Basic prompts

In the tables below we show the basic prompts used for the classification: Table 6 for Hero, Villain, Victim and Focus classes, Table 7 for Conflict and resolution classification, Table 8 for Story classes, and Table 9 for Narrative frame classification.

[17]We choose Llama as a stronger model among open-source ones, and perform 5-fold fine-tuning with 20% holdout set, ensuring balanced class representation (hyperparameters and details in Appendix F): despite improved classification of Hero, the overall performance drops (Table 5).

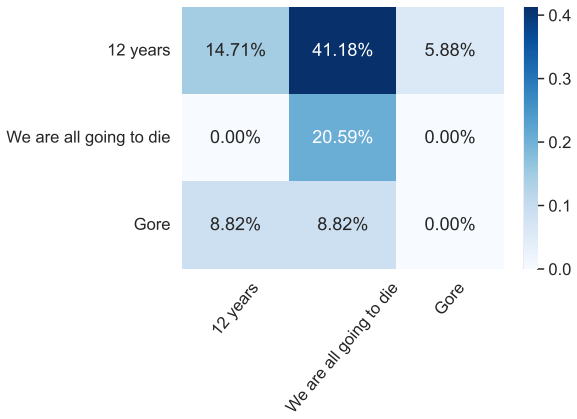

Figure 20: Confusion matrix for zeroshot prediction of only 3 narratives with GPT-4.

K.2 Modified prompts with structure descriptions

In Table 10 below we show the modified prompts used for Narrative prediction.

	Hero	Villain	Victim	Focus	Conflict	Story	Narrative
GPT4o zero-shot	0.325	0.454	0.266	0.656	0.332	0.574	0.258
GPT4o 5-shot	0.414	0.357	0.319	0.613	0.272	0.390	0.190
GPT4o 5-shot with CoT	0.417	0.412	0.330	0.627	0.332	0.430	0.178

Table 4: Macro-averaged F1 performance of GPT4o with 5 shot prompting and Dspy optimization for 7 narrative frame understanding tasks

	Hero	Villain	Victim	Focus	Action	Story	Narrative
Without LoRA	0.271	**0.156**	**0.336**	**0.568**	**0.379**	**0.449**	**0.181**
With LoRA	**0.338**	0.118	0.221	0.351	0.231	0.393	0.077

Table 5: Macro-averaged F1 performance of Llama 3.1 with vs without LoRA fine-tuning for 7 narrative understanding tasks

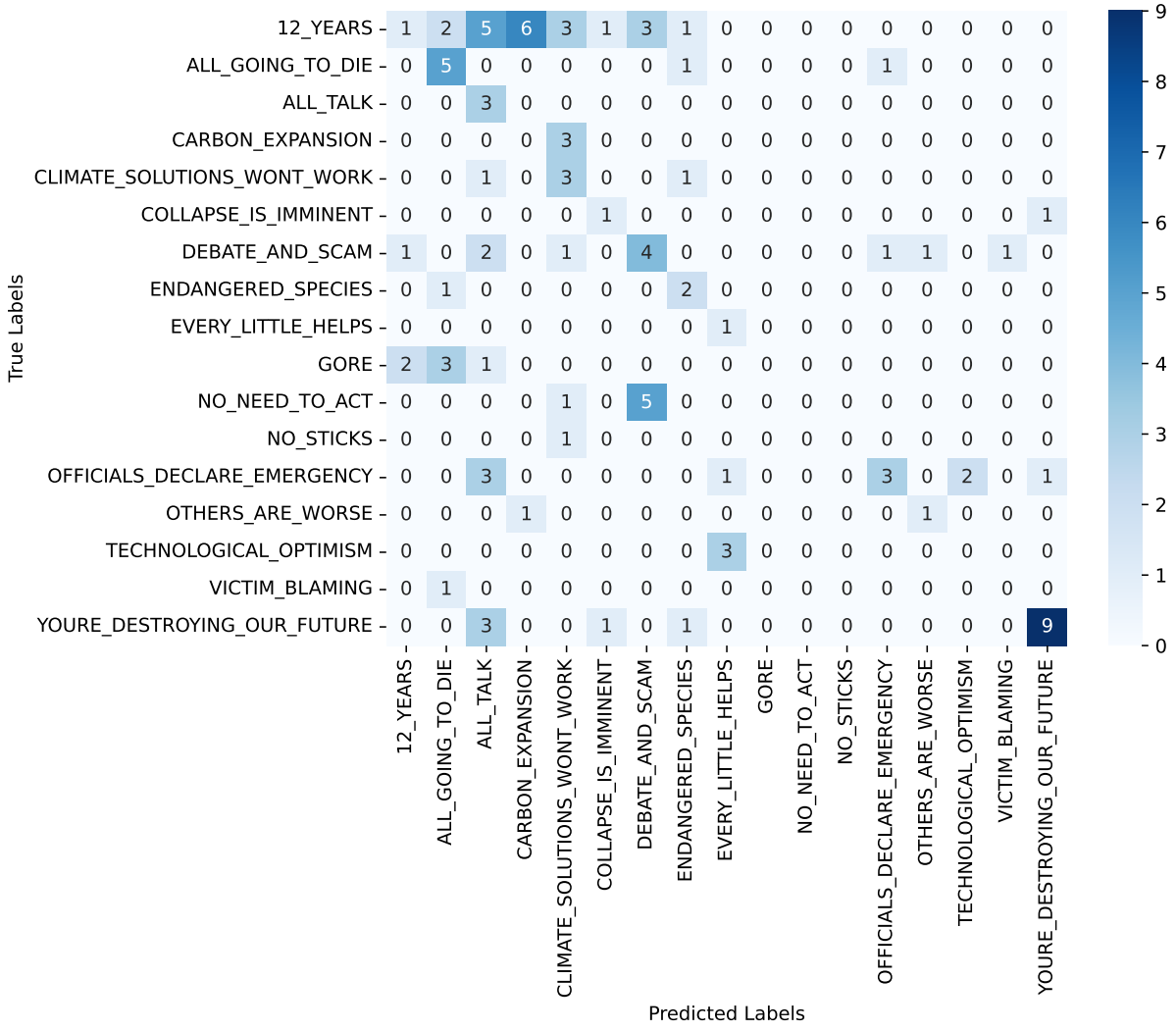

Figure 21: Confusion matrix for Narrative frames prediction using the basic prompt

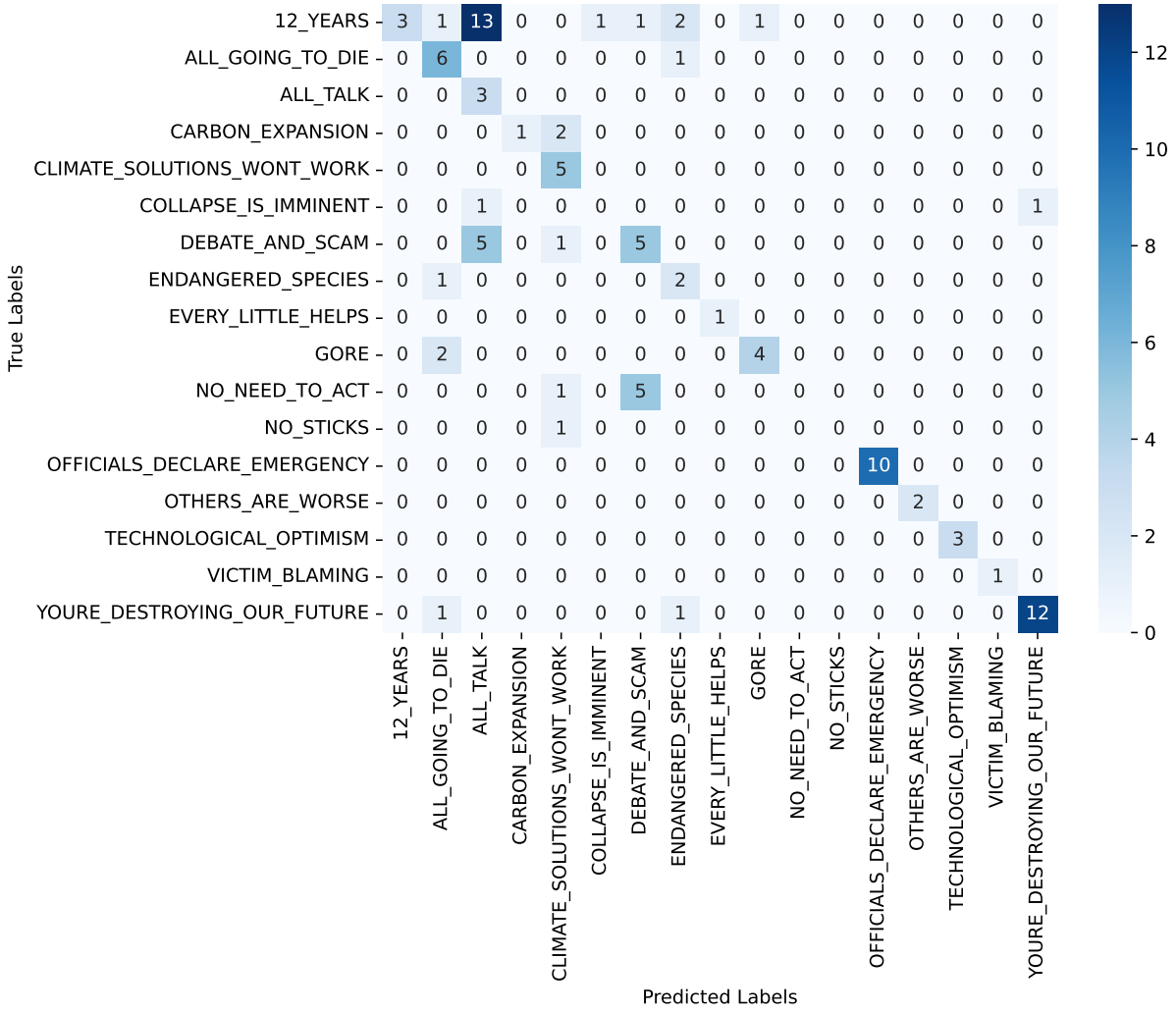

Figure 22: Confusion matrix for Narrative frames prediction using the structured prompt with oracle labels

You are a social scientist specializing in climate change. You will be given a newspaper article and asked who is framed as a hero, villain or a victim in it. For each of these categories, you will be also asked to specify the corresponding word or phrase, and to classify it into the following classes: GOVERNMENTS_POLITICIANS: governments and political organizations; INDUSTRY_EMISSIONS: industries, businesses, and the pollution created by them; LEGISLATION_POLICIES: policies and legislation responses; GENERAL_PUBLIC: general public, individuals, and society, including their wellbeing, status quo and economy; ANIMALS_NATURE_ENVIRONMENT: nature and environment in general or specific species; ENV.ORGS_ACTIVISTS: climate activists and organizations SCIENCE_EXPERTS_SCI.REPORTS: scientists and scientific reports/research CLIMATE_CHANGE: climate change as a process or consequence GREEN_TECHNOLOGY_INNOVATION: innovative and green technologies MEDIA_JOURNALISTS: media and journalists Finally, you need to detect which of the characters (hero, villain, or victim) the news story is focusing on. Please return a json object which consists of the following fields: hero_class: a label for the hero from the list above, or 'None' if the hero cannot be identified. villain_class: a label for the villain from the list above, or 'None' if the villain cannot be identified. victim_class: a label for the victim from the list above, or 'None' if the victim cannot be identified. focus: one of the following - HERO, VILLAIN, VICTIM

Table 6: Basic prompt for Hero, Villain, Victim, and Focus classification

L COVID-19: HVV stakeholder extraction

In this sections we provide prompts we used for multi-step clustering and extraction of stakeholder classes, and well as the list of the resulting classes to be used in HVV classification prompts.

L.1 Prompts

We provide prompts for identifying candidate entities in each speech Table 11, and then clustering them into stakeholder types Table 12.

L.2 Resulting classes

- HEALTHCARE: frontline workers, medical professionals, and institutions directly involved in providing care and combatting the pandemic;
- VULNERABLE_POPULATION: individuals at higher risk of severe illness or death from COVID-19;
- GENERAL_PUBLIC: general public, individuals, communities, and society;
- GOVERNMENT_POLITICIANS: national and regional governments and policymakers;
- BUSINESS_ECONOMY: businesses, workers, and the broader economy;
- SCIENCE_EXPERTS: scientists, researchers, and research institutions;
- FAITH_GROUPS: faith-based organizations;
- PANDEMIC: the virus itself and the pandemic;
- GLOBAL_EFFORTS: international organizations, global collaborations, and efforts to address the pandemic on a worldwide scale.

You are a social scientist specializing in climate change. You will be given a newspaper article and asked to identify how it relates to climate crisis. Assign one of the following classes: FUEL_RESOLUTION: the article proposes or describes specific measures, policies, or events that would contribute to the resolution of the climate crisis. FUEL_CONFLICT: the article proposes or describes specific measures, policies, or events that would exacerbate the climate crisis. PREVENT_RESOLUTION: the article criticises measures, policies, or events that contribute to the resolution of the climate crisis; or it denies the climate crisis. PREVENT_CONFLICT: the article criticises measures, policies, or events that exacerbate the climate crisis; or it provides the evidence for the climate crisis. Please return a json object which consists of the following field: conflict: one of the following labels: FUEL_RESOLUTION, FUEL_CONFLICT, PREVENT_RESOLUTION, PREVENT_CONFLICT.

Table 7: Basic prompt for Conflict classification

You are a social scientist specializing in climate change. You will be given a newspaper article and asked what is the cultural story reflected in it. You should choose one of the following classes: HIERARCHICAL: this story assumes that the situation can be controlled externally, but we need to be bound by tight social prescriptions and group actions. INDIVIDUALISTIC: this story assumes that the situation cannot be controlled externally, and no group actions are necessary. EGALITARIAN: this story assumes that the situation requires combined efforts and group actions of all members of society. Please return a json object which consists of the following field: story: a label from the classes above.

Table 8: Basic prompt for Cultural story classification

You are a social scientist specializing in climate change.
You will be given a newspaper article and asked what is the main narrative in it.
You should choose one of the following classes:
12_YEARS: 12 Years to save the world - Past and present human action (or inaction) risks a catastrophic future climatic event unless people change their behaviour to mitigate climate change.
ALL_GOING_TO_DIE: We are all going to die - This narrative shows the current or potential catastrophic impact of climate change on people
ALL_TALK: All talk little action - This narrative emphasises inconcistency between ambitious climate action targets and actual actions.
CARBON_EXPANSION: Carbon-fuelled expansion - The free market is at the centre of this narrative which presents action on climate change as an obstacle to the freedom and well-being of citizens.
CLIMATE_SOLUTIONS_WONT_WORK: Climate solutions won't work. Climate policies are harmful and a threat to society and the economy. Climate policies are ineffective and too difficult to implement.
COLLAPSE_IS_IMMINENT: The climate crisis is due to the inaction of the negligent or complacent politicians, and it is incumbent upon individuals to shock society into urgent action
DEBATE_AND_SCAM: The heroes of this narrative are sceptical individuals who dare to challenge the false consensus on climate change which is propagated by those with vested interests.
ENDANGERED_SPECIES: Endangered species (like polar bears) are the helpless victims of this narrative, who are seeing their habitat destroyed by the actions of villainous humans.
EVERY_LITTLE_HELPS: This narrative presents a society which has transitioned to a sustainable 'green' way of life. Could be by portraying individuals as the protagonists of stories that propose solutions to climate change.
GORE: This is a narrative of scientific discovery which climaxes on the certainty that climate change is unequivocally caused by humans.
NO_STICKS: No sticks just carrots - Society will only respond to supportive and voluntary policies, restrictive measures will fail and should be abandoned.
OFFICIALS_DECLARE_EMERGENCY: Officials declare a climate emergency - The climate crisis is sufficiently severe that it warrants declaring a climate emergency. This should occur at different levels of government as climate requires action at all levels, from the hyper-local to the global.
OTHERS_ARE_WORSE: Others are worse than us - Other countries, cities or industries are worse than ourselves. There is no point for us to implement climate policies, because we only cause a small fraction of the emissions. As long as others emit even more than us, actions won't be effective.
TECHNOLOGICAL_OPTIMISM: We should focus our efforts on current and future technologies, which will unlock great possibilities for addressing climate change.
VICTIM_BLAMING: Individuals and consumers are ultimately responsible for taking actions to address climate change.
YOURE_DESTROYING_OUR_FUTURE: The political stasis around climate change means that we cannot rely on politicians to create the change necessary. With collective action, even the politically weak can make a difference and secure a future for generations to come.
Please return a json object which consists of the following field:
narrative: a label from the classes above.

Table 9: Basic prompt for Narrative classification

You are a social scientist specializing in climate change.
You will be given a newspaper article and asked what is the main narrative in it. You should choose one of the following classes:

12_YEARS: 12 Years to save the world - Past and present human action (or inaction) risks a catastrophic future climatic event unless people change their behaviour to mitigate climate change. The villain here is government or industry pollution, and the victim is environment, people, or climate change. The narratives focuses on villain and shows how they deny climate change or abandon climate policies.
ALL_GOING_TO_DIE: We are all going to die - This narrative shows the current or potential catastrophic impact of climate change on people. The villain here is climate change or industry emissions, and the victim is general public. The narrative focuses on victim and raises the alarm.
ALL_TALK: All talk little action - This narrative emphasises inconcistency between ambitious climate action targets and actual actions. The villain here is government and politicians, and the victim is often climate change. The narrative focuses on villain who reneged on their promise to support climate policies.
CARBON_EXPANSION: Carbon-fuelled expansion - The free market is at the centre of this narrative which presents action on climate change as an obstacle to the freedom and well-being of citizens. The villain here is climate policies or green technologies, and the victim is general public or old industries. The narrative focuses on victim and advocates for abandoning climate policies.
CLIMATE_SOLUTIONS_WONT_WORK: Climate solutions won't work. Climate policies are harmful and a threat to society and the economy. Climate policies are ineffective and too difficult to implement. The villain is here climate policies or green technologies, and the victim is usually general public. The narrative focuses on villain and criticizes them.
COLLAPSE_IS_IMMINENT: The climate crisis is due to the inaction of the negligent or complacent politicians, and it is incumbent upon individuals to shock society into urgent action. The heroes here are environmental activists, and the villain is government. The narrative focuses on villain and advocated for taking action such as protests or disobedience.
DEBATE_AND_SCAM: The heroes of this narrative are sceptical individuals who dare to challenge the false consensus on climate change which is propagated by those with vested interests. The villains are governments, activists, journalist and policies that support climate measures. The narrative focuses on villains and exposes them.
ENDANGERED_SPECIES: Endangered species (like polar bears) are the helpless victims of this narrative, who are seeing their habitat destroyed by the actions of villainous humans. The villain here can be government, legislation, industry, and the victim is environment and nature. The narrative focuses on victims and shows how they are endangered.
EVERY_LITTLE_HELPS: This narrative presents a society which has transitioned to a sustainable 'green' way of life. Could be by portraying individuals as the protagonists of stories that propose solutions to climate change. The heroes here are individuals and common people, and it is implied that they are also a villain. The narrative focuses on hero and shows how they change their consumption.
GORE: This is a narrative of scientific discovery which climaxes on the certainty that climate change is unequivocally caused by humans. The heroes here are scientists, the villain is government, general public, or industry pollution, and the victim is environment or climate change. The narrative focuses on villain and raises alarm.
...
Please return a json object which consists of the following field:
narrative: a label from the classes above.

Table 10: Prompt for Narrative classification with Hero, Villain, Victim, and Focus specified (abbreviated)

You are a social scientist specializing in media analysis. You will be given a politician's address and asked asked who or what is framed as a hero, villain or a victim in it. List the entities corresponding to these character roles, and cluster them according to their type (i.e. what kind of entity they represent). Please return a json object which consists of the following fields: heroes: a list of entity types that you identified as heroes, villains: a list of entity types that you identified as villains, victims: a list of entity types that you identified as victims. Do not include anything apart from these fields.

Table 11: Basic prompt for candidate characters extraction

You are a social scientist specializing in media analysis. You will be given a list of entities that appear in politicians speeches regarding Covid 19. Many of these entities are similar or overlapping. Cluster them to derive the main actors or stakeholders groups.

Table 12: Basic prompt for grouping entities into stakeholder types