Media Coverage of Donald Trump: An Analysis of North American News Outlets Through Typology

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Abstract

This project examines how North American news outlets cover Donald Trump, with a particular focus on what topics are emphasized and whether coverage is positive or negative. We construct a stratified dataset of 500 Trump-related news articles collected via TheNewsAPI between November 2023 and November 2025 from ten U.S. and Canadian outlets spanning left, centre, and right positions. To avoid obvious sampling biases, we fix the number of articles per outlet and then draw a proportional subsample of 200 articles for topic development and analysis, ensuring that no single source, country, or period within the two-year window dominates the corpus. Using open coding on this 200-article subset, we iteratively develop a six-topic typology of Trump coverage (legal proceedings, elections and party politics, governance and policy, personal and business coverage, societal and media responses, and Trump-adjacent actors) and refine a detailed codebook so that each article is assigned to exactly one category. The remaining articles in the full dataset are then single-coded using this scheme, and all articles are further annotated as positive, negative, or neutral toward Trump based on explicit valence guidelines. To characterize the topics, we compute TF–IDF over categories to identify the ten most distinctive words for each topic and use a large language model to generate representative summaries of each category. Preliminary results suggest that outlets differ systematically in which topics they emphasize and in the balance of positive and negative coverage within those topics, with notable contrasts between U.S. and Canadian media and shifts over time across the two-year period. These patterns provide a structured baseline for interpreting how Trump is framed across North American news ecosystems.

Introduction

Donald Trump remains one of the most prominent and polarizing figures in North American politics. His ongoing electoral campaigns, multiple legal proceedings, and continued influence within the Republican Party ensure that he is a frequent subject of news coverage in both the United States and Canada. For a media company, understanding how Trump is covered, in terms of what kinds of stories dominate, whether that coverage tends to be positive, negative, or neutral, and how these patterns evolve over time, is essential for interpreting audience perceptions and for situating its own reporting within a broader media landscape.

This project responds to that need by asking three main questions. First, what are the main topics that structure Trump-related news coverage across North American outlets? Second, how does the tone of that coverage (positive, negative, or neutral) vary across topics, outlets, and countries? Third, how do topic prevalence and tone change over the two-year period we study? Rather than relying on black-box models, we focus on transparent, interpretable methods that make both our topic definitions and our sentiment labels easy to understand and critique.

Our analysis proceeds in three stages. We first construct a dataset of 500 Trump-related news articles collected from ten U.S. and Canadian outlets using TheNewsAPI over a fixed two-year window (November 20, 2023 to November 19, 2025). The outlets are selected to provide a mix of left, centre, and right-leaning sources in each country, and we enforce a fixed number of articles per outlet to avoid over-representing any single source. From this corpus, we draw a stratified sample of 200 articles and use open coding on titles and openings to develop a six-topic typology that captures the main ways Trump appears in the news. We then convert this typology into a detailed codebook and use it to annotate all articles in the dataset, assigning each article to exactly one topic and to a ternary sentiment label toward Trump. Finally, we characterize each topic by computing TF–IDF scores over categories to identify distinctive words, and we use a large language model to generate concise summaries of the content associated with each topic. Because the data are time-stamped and tagged by country and outlet ideology, this framework allows us to compare topic emphasis and sentiment across time, countries, and political leanings. The remainder of the paper describes the dataset and sampling strategy, details our coding and analysis methods, presents the resulting topic and sentiment distributions, and discusses what these patterns reveal about how Trump is framed in U.S. and Canadian news.

Data

Initial Collection and Observed Problems

Our data come from TheNewsAPI, which aggregates online news articles and allows keyword search over titles and full text. In our first attempt, we used a simple search query of the form Trump or "Donald Trump" for English-language articles from a small, ad hoc mix of U.S. and Canadian outlets. We did not constrain the time period, and we did not control how many articles we collected from each source.

This initial strategy produced two major problems. First, there were many “false positives”: when we inspected the titles, descriptions, and snippets used for coding, Trump often did not appear at all or was mentioned only in passing. In these cases, the keyword match seemed to be driven by content deeper in the article or by noisy indexing, which made the article a poor candidate for inclusion in a Trump-focused study. Second, because we did not stratify by outlet, a few sources that interacted well with the API were massively over-represented, while others appeared only rarely. We only fully appreciated these issues after drawing a 200-article subset from this initial corpus and using it for an open-coding exercise to draft a preliminary typology. That experience highlighted that our topic design was effectively being driven by a convenience sample.

Revised Collection and Filtering

We therefore redesigned the data collection pipeline before committing to a final dataset. In the revised approach, we restricted the time window to two years (20 November 2023 to 19 November 2025) and defined a set of ten mainstream outlets that TheNewsAPI covers reliably: five U.S. outlets (The Washington Post, ABC News, Associated Press, Fox News, New York Post) and five Canadian outlets (CBC News, Global News, CTV News, National Post, Financial Post). These outlets were chosen to span left, centre, and right positions within each country, based not on our personal impressions but on external media-bias ratings from AllSides and MediaBiasFactCheck. Using these independent ratings to guide selection does not remove all subjectivity, but it is more defensible than informally labelling outlets and helps us interpret differences across ideological clusters in a systematic way.

For each of the ten outlets, we queried TheNewsAPI’s “all news” endpoint for articles mentioning “Donald Trump” in the specified time window, limited to English. Because the API charges by request and paginated results can be large, we capped each outlet at at most 150 pages of results, which typically corresponded to well over 1,000 raw articles per source in the two-year window. From this pool, we applied stricter filtering than in the initial attempt. We concatenated the title, description, and snippet for each candidate article, and used a case-sensitive regular expression to require that the token “Trump” appear as a standalone word in at least one of these fields. Articles that did not meet this condition were discarded. This step ensures that Trump is explicitly mentioned in the part of the text we actually code (title and opening) and reduces the number of articles where he is only mentioned in passing or in unrelated context.

After filtering and deduplication, we randomly sampled a fixed number of articles per outlet: 70 from each of the five U.S. outlets and 30 from each of the five Canadian outlets, for a total of 500 articles (350 U.S., 150 Canadian). This per-outlet quota prevents any single source from dominating the dataset and gives us a stratified corpus that is balanced across outlets while still reflecting the greater volume of U.S. Trump coverage overall. From this 500-article corpus we first verified the absence of duplicates by UUID, then drew a stratified subset of 200 articles (preserving outlet proportions) for a second open-coding pass, used to validate and refine the six-topic typology that had been drafted from the initial, imperfect corpus. The detailed coding process is described in the methods section.

Final Corpus Characteristics and Limitations

The final dataset consists of 500 English-language articles about Trump, drawn from ten outlets across two countries, evenly distributed by source within country, and spanning a fixed two-year period. Each article record includes the outlet name and domain, country (U.S. or Canada), an ideological label (left, centre, or right based on external ratings), and a timestamp. These baseline characteristics allow us to compare coverage across time, country, and political leaning without being dominated by a single outlet or by a narrow moment in the news cycle.

At the same time, the corpus has clear limitations. It is constrained to outlets that TheNewsAPI indexes reliably; several prominent newspapers (for example, the New York Times, USA Today, the Toronto Star, and the Globe and Mail) either returned very few Trump-related articles in this window or were not consistently available through the API, and so could not be included under our per-outlet quotas. The dataset is also limited to English-language coverage, and, due to time and cost constraints, we rely on single rather than double annotation. We are explicit about these constraints because they shape how far our findings can be generalized.

Overall, however, the dataset is prepared in a way that avoids the most obvious convenience biases from our initial attempt. By enforcing fixed quotas per outlet, requiring that “Trump” actually appear in the text we read, grounding outlet ideology in external ratings, and fixing a clear time window, the final corpus has the baseline properties needed to support meaningful analyses of how Trump is covered across time, countries, and ideological positions.

Methods

Topic Design and Typology Development

We followed the open-coding protocol to start from representative data, propose topics, sanity-check them, and revise until system stability. The process spanned two iterations.

First, using the initial convenience-sampled corpus of 500 articles, we performed open coding on a 200-article subset, reading only titles and openings as instructed. We grouped articles into tentative categories, merged overlapping labels, and removed categories that were too narrow. This produced a six-topic typology capturing: legal and criminal proceedings, elections and party politics, governance and policy actions, personal and business coverage, societal and media responses, and news centered on a Trump-adjacent actor (family, close associates, or Trump-branded entities).

When the remaining 300 articles from this initial corpus were being annotated, the limitations of the underlying data became clear, among them false positives and heavily unbalanced outlets, which led us to redesign the dataset as described above. After collecting the new data, we drew a fresh, balanced sample of 200 articles and repeated the open-coding sanity check. The goal this time was not to invent new topics but to test whether the existing six were still sufficient or whether the boundaries needed sharpening. We paid particular attention to overlap between legal and electoral stories, and to when a piece should be treated as Trump-adjacent rather than directly about Trump. Only minor refinements were needed, so the same six topics were retained but given more precise definitions and explicit inclusion/exclusion rules. These rules were written into a new codebook ensuring each articles receives exactly one label.

Topic and Sentiment Annotation

Using the finalized codebook, we manually annotated all 500 articles in the stratified corpus. Each article was assigned exactly one of the six topic labels based on its title and opening. When an article appeared to fit more than one topic (for example, a legal decision with clear electoral implications), we applied a "primary focus" rule: if the story foregrounded the legal process, it was coded as legal; if it foregrounded campaign strategy, it was coded as elections and party politics. Edge cases that were hard to categorize prompted small tweaks to the codebook, with the aim of reducing subjectivity and keeping the typology compact.

Sentiment coding was conducted with articles labeled as positive, negative, or neutral toward Trump, again based only on the title and opening. "Positive" was used when the framing clearly portrayed Trump or outcomes for him in a favorable or sympathetic way, such as wins, gains, positive evaluations of his actions, or narratives in which he is treated as a victim. "Negative" was used when the framing was primarily critical or damaging, whether it be legal trouble framed as deserved, harm or risk linked to his actions, strong negative adjectives, or comparisons where Trump is clearly the worse side. Articles that did not clearly lean either way were labeled "neutral"; this included pure news write-ups, pieces that simply reported poll numbers, and mixed stories where praise and criticism were both present but neither dominated. In ambiguous cases we defaulted to neutral to avoid over-interpreting tone. During this sentiment pass the topic label for each article was visible, which provided an informal sanity check: if a topic assignment had seemed obviously inconsistent with the text, it could have been flagged and corrected, though this did not prove necessary.

Topic Characterization: TF–IDF and LLMs

To characterize the language that distinguishes each topic, we computed TF–IDF scores over topics rather than individual articles, following the definition used in class. For each article we concatenated the title, description, and opening and tokenized the text. We removed standard English stopwords and additionally excluded "Donald", "Trump", and "president", which would otherwise dominate the counts without telling us anything substantiative. Within each article we decided a word could contribute at most one count: if a term appeared multiple times in the same article, it still counted as one occurrence. This prevents a single repetitive article from artificially inflating a word's importance and makes term frequency effectively mean: "number of articles in this topic that use this word."

For each topic c and term t, the term frequency $TF_{c,t}$ was the number of articles in topic c that contained t at least once. The inverse document frequency was defined as $IDF_t = \log(N/n_t)$, where N is the number of topics and n_t is the number of topics in which t appears at least once. The TF–IDF score for term t in topic c was $TF_{c,t} \times IDF_t$. We then ranked the terms within each topic and kept the top ten as the most distinctive words. This implementation directly follows the intuition from class: words that are frequent in one category but rare in others receive high scores, while very common words across all topics are heavily penalized.

In addition, we used a large language model, ChatGPT, to generate qualitative summaries of each topic. For each category we supplied the complete set of titles and openings and asked the model to produce a neutral, informative summary of the topics covered in the articles. Both the TF–IDF word lists and the LLM summaries were used purely as interpretive aids: they did not influence how topics were defined, how articles were labeled, or how sentiment was coded. Instead, they provide a compact view of the language associated with each topic that would be difficult to obtain by manually scanning hundreds of articles, and they help us check whether our intuitive understanding of the categories matches the aggregate patterns in the data.

Results

Finalized Topics and Typology Validity

The analysis is organized around a six-topic typology that is intended to capture the major ways Donald Trump appears in news coverage while avoiding vague “other” categories. The typology is to be applied through a simple decision process. The first step is to determine whether Trump himself is the main subject of the article’s title and opening. If the story is primarily about a family member, close ally, or Trump-branded organization, it is assigned to the Trump-adjacent category and does not pass through the remaining topic decisions. If Trump is the main subject, the article is assigned to one of five domains based on what is foregrounded in the title and opening. The types are as follows:

1. **Legal and Criminal Proceedings:** includes articles whose core focus is legal or judicial process involving Trump. This covers investigations, indictments, trials, rulings, appeals, motions and disputes over presidential immunity or civil liability. Political or public reactions can appear in the background, but they are not what the story is “about.”
2. **Elections and Political Dynamics:** covers articles about electoral politics and party strategy centred on Trump: primary and general election campaigns, polling, endorsements, internal party conflicts, and strategic positioning by candidates and officials in response to Trump’s role in the race.
3. **Personal, Lifestyle and Business:** contains stories focused on Trump’s personal behaviour, lifestyle, interpersonal conflicts, branding, and non-governmental business ventures. These articles typically discuss his appearances at events, his social and media presence, or the performance of Trump-branded companies, provided that the framing is not primarily legal or about official policy.
4. **Governance, Policy and Official Actions:** is reserved for coverage of Trump’s use of governmental or quasi-governmental power, including executive orders, regulatory changes, policy proposals, diplomatic moves, military actions and institutional restructuring.
5. **Societal and Media Responses:** is used when the main subject is how non-political actors respond to Trump or to Trump-era politics. This includes public opinion polling, protests and civic mobilization, statements by corporations, universities and religious organizations, and media or commentator framing of Trump and his actions. Here, reactions and interpretations are central, rather than Trump’s own actions.
6. **Trump-Adjacent Focus:** is an override category for articles whose main subject is a family member, close associate, or Trump-linked organization. Stories about Melania Trump, Donald Trump Jr., or the Trump Organization are assigned to this type even when their content involves legal proceedings, campaigns or policy, because the narrative is framed around the adjacent figure rather than Trump himself.

This typology separates various facets surrounding Trump into distinct analytic units. Each of these plausibly carries different patterns of tone and framing, which allows sentiment to be compared across domains rather than across a single undifferentiated pool of Trump stories. The topics are defined in terms of subject matter rather than evaluation, so that sentiment labels can be applied independently.

Several design choices reduce subjectivity in applying the topics. The decision tree imposes a fixed order of questions, so coders are not free to choose a category purely by intuition, and the document provides definitions, inclusion criteria, and edge cases. The categories correspond to real, recurring clusters, and there is no open-ended “miscellaneous” topic; instead, societal and media responses and Trump-adjacent coverage are each defined with explicit inclusion rules. When articles appeared to fall between two categories, the written definitions were refined to clarify boundaries—for example, specifying whether a legal decision with electoral implications should be treated as legal or electoral—rather than adding new, idiosyncratic labels. Requiring each article to receive exactly one of the six types, under these clarified rules, helps to keep the typology both comprehensive and as objective as possible.

Topic Distribution and Engagement

Across the full corpus, governance and policy are the dominant way Trump appears in the news. Governance stories account for 38.2 per cent of all articles. Societal and media responses and elections/party dynamics follow at 20.8 per cent and 19.0 per cent, respectively. Legal proceedings make up 8.0 per cent, while personal and Trump-adjacent coverage each account for 7.0 per cent. Overall sentiment is 47.2 per cent neutral, 35.0 per cent negative and 17.8 per cent positive, so neutral hard-news style coverage is most common, and negative news is twice as frequent as positive.

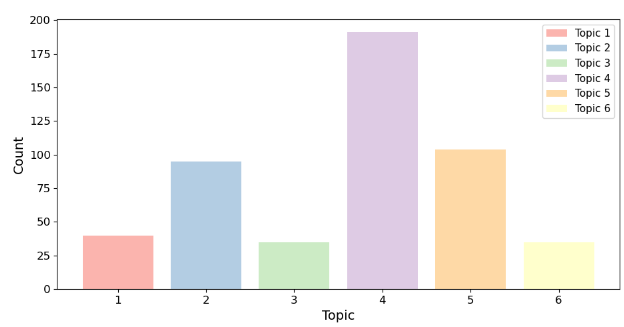

Figure 1: Overall Abundances Highlights Frequent Topics

Variation over time

Splitting the two-year window into eight quarters reveals a clear shift in attention. In the first half of the period, elections and party dynamics are central, accounting for around 40 per cent or more of Trump coverage in a given quarter, while governance stories are sparce. In the second half, this shifts. Governance stories rise to roughly half of all coverage in each quarter, while election stories drop to single-digit shares. The topic mix tracks the political timeline in an intuitive way and coincides with Trump's campaign period and ultimate reelection.

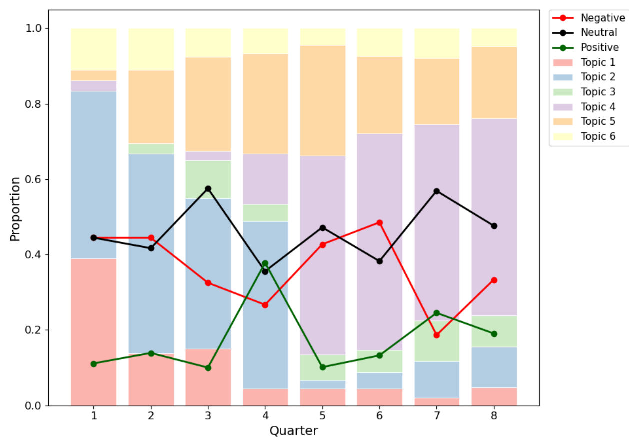

Figure 2: Time Series Shows Stark Shift in Coverage

Sentiment also varies. In Q1–Q3, neutral and negative coverage are fairly balanced and positive stories are rare at around 10%. Q4 and Q7 stand out as unusually favourable, with positive stories outnumbering negative ones.

Differences between Canadian and U.S. outlets

By topic, Canadian and U.S. outlets look strikingly similar. In both countries, governance is the largest category at around 40% followed by media responses and electoral dynamics at around 20% each. Legal, personal and Trump-adjacent stories fill out the remaining small shares in similar proportions. The sentiment profiles diverge more clearly. In Canada, coverage is roughly half neutral and half negative, with only 11 per cent positive. In the U.S., neutral coverage is similarly high, but positive stories are more common, and negative stories less so. The similar topic mix suggests that the main cross-national difference in this sample is not what Trump is covered for but how the coverage evaluates him.

Differences across political stances and outlets

Topic distributions change more noticeably when outlets are grouped by ideological stance. Left-leaning outlets devote nearly half of their Trump coverage to governance and policy, with elections/party dynamics and societal/media responses in second and third place. Centrist outlets follow almost the same pattern. Right-leaning outlets still cover governance extensively, but it drops to a little over a quarter of their Trump stories. Societal and media responses become their single largest category (about 30 per cent), and elections/party dynamics remain close behind. This indicates that left and centrist outlets are more likely to frame Trump as a policy and governing actor, while right-leaning outlets devote relatively more space to conflicts with media, institutions and publics.

Outlet-level patterns fit this stance-level picture. The left-leaning sources all have governance as their top topic, with elections second. Two right-leaning outlets, New York Post and Financial Post, also lead with governance, but Fox News and National Post lead with responses. Among centrist outlets, CTV in Canada has its largest share of Trump stories in electoral dynamics, whereas Associated Press in the U.S. focuses most heavily on governance.

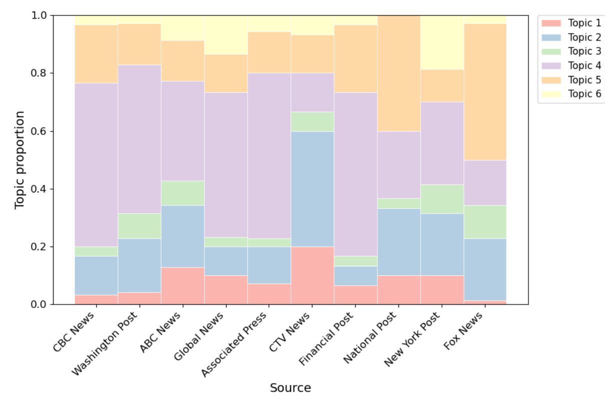

Figure 3: Divergence in Topics Covered Between Sources

Sentiment varies with stance in a way that aligns with expectations. Left-leaning outlets are almost evenly split between neutral and negative coverage, with only about 10 per cent positive. Centrist outlets are similar: just over half neutral, about 40 per cent negative and under 10 per cent positive. Right-leaning outlets, in contrast, have nearly 30 per cent positive coverage and only 25 per cent negative, with the remainder neutral. Thus, in left and centrist outlets, negative coverage is more common than positive, whereas in right-leaning outlets positive coverage is more frequent than negative, even though neutral stories remain the single largest category everywhere.

Topic characterization

TF–IDF and the LLM together show that the six topics are not only formally distinct but also have clearly different vocabularies and story worlds. The three more institutional topics, being legal proceedings, elections, and governance, are especially clean. In the legal category, TF–IDF surfaces a tight cluster of courtroom language ("appeals," "defamation," "civil," "filing," "immunity," "jury") and case-specific markers like "Fulton" and "probe." The LLM, working over the same articles, describes a world of criminal and civil prosecutions, fraud and defamation suits, bond postings and arguments about presidential immunity and "lawfare." Elections are framed very differently: their top words centre on campaigning and competition ("voters," "caucuses," "wins," "endorse," "running," and proper nouns like "Harris," "Robert," and "Hampshire"), and the LLM emphasizes primaries, debates, VP speculation and party factionalism. For governance, TF–IDF pivots again, now toward geopolitics and trade—"Canada," "Ukraine," "trade," "tariffs," "NATO," "China," "Iran," "war," "meeting"—and the LLM description focuses on executive orders, agency shake-ups, policing and crime, and an outward-facing foreign policy toward Ukraine, the Middle East and NATO allies. Together, these three categories look like three different "professional worlds" around Trump: the courtroom, the campaign trail and the state.

The more social and personal topics have looser, more scene-based vocabularies, but are still distinct from one another. In the personal category, TF–IDF surfaces words like "appearance," "NFL," "room," "surprise," "stroll" and "briefing," which point to specific events and settings rather than institutions. The LLM picks up that texture: Trump at sporting events and memorials, comments after an assassination attempt, podcast appearances, disputes over portraits and team names, and the fortunes of Trump-branded companies. Societal and media responses are marked by reaction words: "protests," "problem," "MSNBC," "rhetoric," "attempt," "anti," "Canadian" and "ice." Here the LLM describes polling, protests and counter-protests, commentary on his rhetoric and policing, reactions to January 6 pardons and assassination attempts, and meta-coverage of how different outlets and platforms frame Trump. This category is therefore not just a residual "everything else," but a coherent space where the main actors are publics, media and institutions responding to him.

The Trump-adjacent category has its own distinctive orbit. TF–IDF is dominated by relationship and family words such as lady," "Melania," "wife," "father," "photos," alongside "Las" and "Vegas" rather than by courts, campaigns or countries. The LLM's description mirrors this: stories about Melania Trump, Donald Trump Jr., JD Vance, Hope Hicks and other confidants, along with Trump-branded ventures and the personal and security fallout of Trump-era politics for those around him. In other words, when the decision rule sends a story into the Trump-adjacent bucket, the vocabulary really does shift away from Trump as an institutional actor and toward the network of people and businesses in his shadow.

Discussion

How Trump is Covered

Taken together, the topic patterns suggest that in this two-year period Trump is covered above all as a governing actor rather than only as a legal defendant, culture-war figure or celebrity. Governance and policy account for just under 40 per cent of all stories, with elections and societal/media responses each around one fifth, and legal, personal and Trump-adjacent coverage forming comparatively small minorities. At first glance this dominance of governance coverage could be read as a symptom of an overly broad category. However, the TF–IDF and LLM characterizations point to a coherent and quite specific domain: executive orders, agency restructuring, domestic law-and-order initiatives, trade and tariffs, and high-stakes foreign policy toward Ukraine, NATO and the Middle East. In other words, the category is large not because it is vague, but because Trump's second term in this corpus generates a steady stream of "article-worthy" policy moves and institutional clashes.

The contrast with the other major topics helps sharpen this picture. Elections and political dynamics are clearly delimited around primaries, caucuses, voter behaviour and partisan realignment, while societal and media responses are anchored in protests, public opinion, commentary and institutional reactions. Early in the period (roughly Q1–Q4), election coverage is central and governance coverage rare; after Trump's 2024 victory, this flips and policy stories become the main way he appears in the news. This shift is exactly what one would expect when coverage moves from a campaign phase into a governing phase. The relatively small size of the personal and Trump-adjacent categories also matters. It implies that, despite Trump's reputation as a celebrity figure, most coverage in this sample is not primarily about his private life or family drama, but about decisions taken in office and the institutional and societal fallout of those decisions.

Cross-national comparisons show that Canadian and U.S. outlets devote their Trump coverage to broadly similar topics but frame him somewhat differently. In both countries, governance dominates, with societal responses and elections in second and third place and the remaining topics playing minor roles. This suggests that, at the level of what Trump is covered for, Canadian and American newsrooms are responding to the same set of political and legal events.

How Trump is Evaluated

The sentiment distributions diverge more clearly across countries and stances. Canadian outlets are almost evenly split between neutral and negative tone, with very little positive coverage. U.S. outlets also have a strong neutral baseline but carry a noticeably larger share of positive stories and a smaller share of negative ones. Given the similar topic mix, this suggests that the main cross-national difference in this sample is not what Trump is covered for but how that coverage evaluates him. This pattern is sharpened by the source-level outliers: CBC and National Post, which sit on opposite sides of the Canadian ideological spectrum, are among the most negative in their Trump coverage, whereas the consistently positive skew is concentrated in the two U.S. right-leaning outlets.

Differences by ideological stance and outlet suggest that media polarization appears more in how Trump is situated than in whether he is covered at all. Left-leaning outlets, in both countries, put a large share of their Trump stories into governance and policy, with elections and societal responses following behind. Centrist outlets show almost the same pattern. Right-leaning outlets still cover governance heavily, but comparatively less than the other two groups, and devote a much larger share of their Trump coverage to societal and media responses. Fox News is especially notable here, with a strong emphasis on institutions, celebrities and publics reacting to Trump. One plausible interpretation is that left and centrist outlets tend to frame Trump as a governing and institutional actor whose policy choices have consequences, whereas right-leaning outlets spend relatively more space on a struggle between Trump and hostile elites, institutions and critics. The stance-level sentiment patterns are consistent with this reading: left and centrist outlets are dominated by neutral and negative coverage, while right-leaning outlets are the only group where positive stories outnumber negative ones, even though neutral coverage remains substantial.

The source-level exceptions are informative. National Post and CBC stand out as the two outlets where negative coverage clearly outweighs neutral coverage, despite their opposing ideological labels. This suggests that Canadian newsrooms, regardless of domestic orientation, tend to view Trump's presidency as a problem or risk, even while reporting many stories in a neutral tone. Conversely, Fox News and New York Post are the only outlets that frequently frame Trump positively, and they are also the only sources in the sample that are both American and clearly right-leaning. Right-leaning Canadian outlets in this dataset do not show a similar level of positive tone, which indicates that ideological affinity alone does not guarantee supportive coverage; the national context also matters.

Several findings run counter to common expectations about "liberal media" and are likely driven in part by the project's constraints. None of the left-leaning outlets in this corpus show overwhelming negative tone toward Trump; most of their coverage is coded as neutral based on the title and opening, with negative headlines and leads forming a large but not dominant minority. It is possible that some of these stories turn more evaluative or critical later in the article, but this is not visible under the coding rule, which was limited to the headline and opening paragraph. Similarly, some of the quarter-to-quarter spikes in positive or negative coverage, most notably the unusually positive Q4, almost certainly reflect specific news events such as the immediate aftermath of the 2024 election or key policy announcements that are not examined in detail here.

Conclusions and Future Directions

Overall, the results point to three broad conclusions. First, in this period Trump is covered primarily as a governing and institutional actor, and only secondarily as a defendant, celebrity or family figure. Second, while Canadian and U.S. outlets allocate attention to similar aspects of Trump's activity, Canadian outlets across the spectrum tend to frame him more negatively and less positively than their U.S. counterparts. Third, ideological differences shape both what parts of Trump's world are foregrounded, be it policy, elections or societal reactions, and how those stories are evaluated, with sustained positive framing largely confined to right-leaning U.S. sources. These patterns suggest that any assessment of bias in Trump coverage needs to distinguish between topic selection, national context and evaluative tone rather than treating them as a single dimension.

At the same time, several features of the design point toward future work. Coding was based only on titles and openings; a follow-up study could sample full-text articles to see whether tone shifts later in the piece. The analysis also relies on a limited set of outlets, with only one centrist source per country; expanding the outlet list would allow stronger claims about national media systems rather than particular brands. Finally, the descriptive patterns in specific quarters and around specific topics could be linked more directly to identifiable events (court decisions, policy announcements, campaign milestones) to test more fine-grained hypotheses about when and why coverage becomes especially positive or negative.

Group Member Contributions

- Omar Alshehabi: Second data collection, TF-IDF and LLM analyses, type annotation, data interpretation, report formatting and consolidation, figures
- David Marji: Sentiment coding, discussion and interpretation, figures and visualizations
- Anqi Peng: Initial data collection, typology design, primary coding, report writing

All group members contributed to the writing of the report as it pertains to their respective works. Oftentimes, group members assisted each other in the realization of each other's contribution, and the report as a whole therefore represents the efforts of the entire group.