

PlastiNews: An In-Depth Analysis of Media Coverage Regarding Plastic Pollution in India and the United States Using a Large Language Model (LLM)

Abstract

A 2023 United Nations Environment Programme report found that 3200 out of the 7000 substances associated with plastic have hazardous properties. Plastic pollution is clearly a global health crisis. The issue is also multi-faceted: the International Union for the Conservation of Nature calls it an issue that has “multiple sources and actors.” Despite this, media coverage of plastic pollution has largely focused on only a few of its forms. This can create a dangerous restriction in public perspective, which plays a major part in preventing the taking of action against underrepresented forms of plastic pollution. In this paper, we conduct a computational analysis of nearly 1600 newspaper articles from 10 of the most popular media sources in the United States and India. Our analysis shows that despite increasing media coverage of plastic pollution, certain forms remain dangerously underreported. Additionally, there is a discernible difference between coverage in the two countries, suggesting the need for consumers to aggregate information to get a comprehensive view of the issue. Our use of a large language model – as opposed to a manual approach – allows us to conduct our analysis on a larger dataset in the future, while still retaining high classification accuracy.

1 Introduction

Plastic pollution is a growing global problem that is having concerning effects on human and planetary health. Plastics have been linked to higher risks of myocardial infarctions, strokes, and death in humans (Marfella et al., 2024); tissue damage in fish, which serve as common vectors for microplastic transport into humans (Bhuyan, 2022; Alberghini et al., 2022); and limited crop output, leaching into the soil and negatively affecting

consumer health (United Nations Environment Programme [UNEP], 2022). With this, plastic pollution has been classified into numerous forms. Classifications based on the source of the pollution and the environment in which it occurs include marine plastic pollution, single-use plastic pollution, E-waste, biomedical plastic pollution, agricultural plastic pollution, urban plastic pollution, and industrial plastic pollution. Classifications of plastics based on size include nanoplastics, which are 1nm to 1µm long (Gigault et al., 2018); microplastics, which are <5mm long (National Oceanic and Atmospheric Administration [NOAA], 2023); and macroplastics, which are ≥5mm long (Lechthaler et al., 2020).

For plastic pollution, public perception often plays a key role in determining the success of proposed solutions and reducing the impact of the issue. Pahl et al. (2020) describe aquatic plastic pollution, for example, as an issue entirely due to humans, with humans making decisions at every step of the plastic production, consumption, and disposal process that ultimately result in plastic ending up in aquatic environments. Media coverage has been shown to strongly influence public perception of topics across various domains. Boomgaarden and de Vreese (2007) explained how exposure to media coverage after a dramatic real-world event, specifically an assassination in the Netherlands, led to increased threat perceptions among those who consumed more of it. Palau and Davesa (2013) showed that increases in media coverage of corruption in Spain resulted in greater amounts of citizen concern regarding the issue. Additionally, Sampei and Aoyagi-Usui (2009) demonstrated that Japanese media coverage of global warming had an immediate impact on public awareness of the issue. The analysis of media coverage related to plastic pollution is therefore an important task for understanding public perception of the issue. The understanding of this perception,

in turn, can be valuable information for regulatory agencies and activist organizations seeking to understand areas in which public awareness is lacking. This understanding could help create more effective campaigns and regulations in the fight against plastic pollution.

1.1 Previous Works: Plastic Pollution & Environment-Related Media Analysis

Despite its importance, there has been limited work done in analyzing media coverage regarding plastic pollution. Keller and Wyles (2021) analyzed 943 news articles from four of the UK's most popular newspapers, with a balance of left-wing/right-wing sources and tabloid/broadsheet-style papers. Using STM, a topic-modeling algorithm, the authors were able to identify four subthemes in the main theme of marine plastic pollution, with further division into specific topics (e.g., "ocean and river cleaning devices"). Males and Van Aelst (2020) evaluated the effects of the popular BBC documentary series, *The Blue Planet II*, on the U.K. public, media, and politics. The authors suggest that the documentary played a key role in increasing discourse about plastic pollution across the three mediums, with an increase in relative popularity by as much as 900% on days on which the broadcasted episode explicitly mentioned marine plastic pollution & its effects. McKinnon (2021) conducted a content analysis of 98 articles from French sources *Le Monde* and *Le Figaro* and American sources *The New York Times* and the *Los Angeles Times* to understand the differences in coverage of marine litter between the two countries. McKinnon found that both French and American sources used similar metaphors, such as the "Great Pacific garbage patch" and the "seventh continent" to misclassify the plastic debris in the Pacific Ocean. However, while French media frequently framed marine litter as a political issue, American media framed it most commonly as a "cultural dilemma."

More work has been done in the broader area of analyzing environment-related media. Reis (1999) analyzed 649 news items from two Brazilian newspapers, *Folha de S. Paulo* and *O Globo*, to understand differences in coverage of the 1992 United Nations Conference on Environment and Development (UNCED), commonly referred to as the Earth Summit. The author found that environmental issues made up

only 34% and approximately 51% of *Folha's* and *O Globo's* coverage, respectively. More focus was instead given to economic affairs, external international agreements, the conference's impact on the city and country, and the organization of the conference. Maria Jönsson (2011) conducted an analysis of 6,033 articles published by the popular Swedish newspaper *Dagens Nyheter* to understand media focus on environmental risks in the Baltic Sea and how it has changed over time. On the issue of climate change and global warming, Das (2020) analyzed 426 articles from three newspapers, namely *The Times of India*, *The Hindu*, and *The Indian Express* to discover how climate justice was portrayed in Indian media during COP21 and COP22 (United Nations Climate Change Conferences, held in December 2015 and November 2016, respectively). Das found that more than 80% of the analyzed articles covered climate justice, with a greater focus across the three sources on harm avoidance rather than burden sharing. Additionally, the "morality" frame was the most common for burden sharing, while the "impact" frame was the most common for harm avoidance. Keller et al. (2019) analyzed 18,000 climate change articles published from 1997 to 2016 in *The Times of India* and *The Hindu* to discover trends and prominent topics in Indian media's coverage of climate change. The authors discovered a significant increase in media coverage of climate change over the last 20 years. Furthermore, using LDA, another topic modeling algorithm, the authors were able to classify articles into four main themes: climate change and society, climate change impacts, climate politics, and climate science. According to the authors, these topics reveal "the myriad ways in which the Indian media expose and potentially educate the Indian public about climate change." Finally, Dotson et al. (2012) did a content analysis of 269 climate change-related articles from Chile's conservative newspaper *El Mercurio* and liberal newspaper *La Nación*. The analysis revealed a greater number of articles & graphics and a higher word count in *La Nación* than in *El Mercurio*, while there were a higher number of articles in *El Mercurio* that framed climate change as a binary (positive/negative) issue than one that could be a neutral balance.

1.2 Shortcomings in Previous Works

These studies fall short in various ways, however. First, all but one analyze data exclusive to one country. Conducting an international-level analysis could provide valuable data about how factors like development level, major industries, and cultural norms influence media coverage of plastic pollution. Secondly, all but two use a manual-based approach to analysis. This greatly restricts the amount of data that can be analyzed, as automated approaches based in fields like NLP (natural language processing) can have tremendous impacts on efficiency and enable a larger scale of analysis. Furthermore, even the two previous studies that use automated analysis methods fail to take advantage of recent developments in NLP, with the largest being the creation and popularization of the large language model (LLM). LLMs have been shown to be effective few-shot learners, meaning models like OpenAI’s GPT-3.5 only need a few training examples before being able to accurately complete a desired learning task. For analyzing media coverage where, for example, manually classifying numerous articles’ frames can be inconvenient, few-shot learning with LLMs is an effective method to automate analysis.

In response to these shortcomings, we present PlastiNews. Using a large language model, we analyze nearly 1600 news articles from India and the United States to understand how media coverage of plastic pollution differs between the two countries.

2 Materials and Methods

2.1 Data Collection

We began by collecting articles from five of the most popular American media sources and five of the most popular Indian news sources. For the American newspapers, we used the ProQuest US Major Dailies database, which provides an archive of the *Chicago Tribune*, the *Los Angeles Times*, *The New York Times*, the *Wall Street Journal*, and the *Washington Post*. For Indian newspapers, we used the NewsBank world newspaper database and selected *The Times of India*, the *Hindustan Times*, *The Hindu*, the *Indian Express*, and the *Economic Times*. For both databases, we used the search term “plastic pollution,” which meant that only articles containing the exact phrase “plastic pollution” were returned. From this, we collected 1595 articles – 358 from the United States and 1237

from India – to analyze. The breakdown of these articles is detailed in Tables 1 & 2 and Figures 1 & 2. American news articles ranged in publishing date from 2006 to 2023, while collected Indian news articles were more recent and ranged in publishing date from 2018 to 2023.

Source	No. of articles analyzed	% of total articles
Chicago Tribune	39	10.9%
Los Angeles Times	39	10.9%
The New York Times	96	26.8%
Wall Street Journal	109	30.4%
Washington Post	75	20.9%
TOTAL	358	100%

Table 1: Breakdown of American media sources analyzed.

Source	No. of articles analyzed	% of total articles
The Times of India	498	40.3%
Hindustan Times	292	23.6%
The Hindu	283	22.9%
Indian Express	110	8.9%
Economic Times	54	4.4%
TOTAL	1237	100%

Table 2: Breakdown of Indian media sources analyzed.

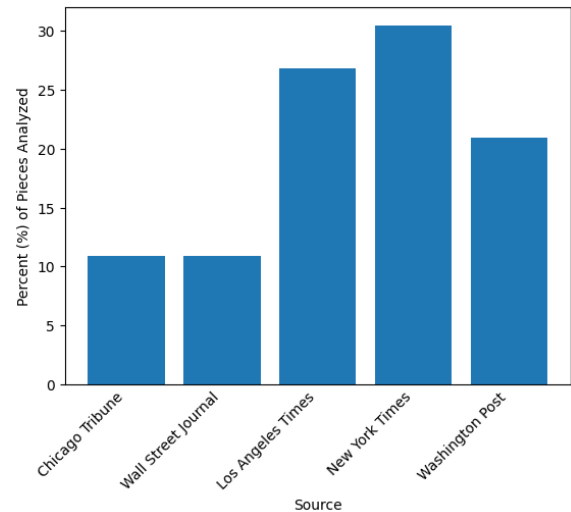


Figure 1: Breakdown of American media sources analyzed by percentage.

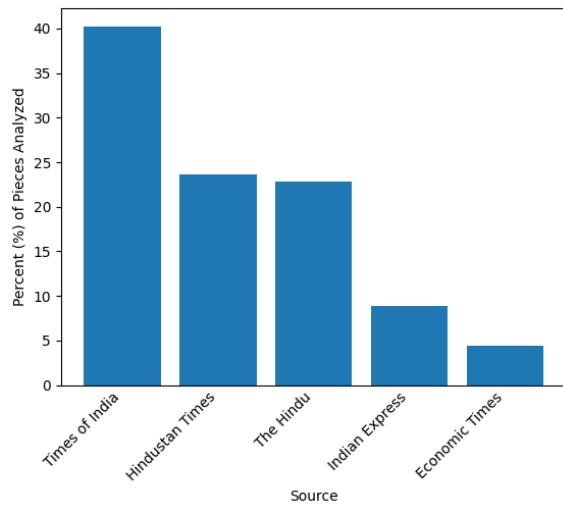


Figure 2: Breakdown of Indian media sources analyzed by percentage.

2.2 General Data Analysis

We first conducted a general, exploratory data analysis. This was done through sentiment and subjectivity analysis. The former provides information on the tone of media towards plastic pollution, while the latter ensures that there is no significant bias in collected data. Figures 3 and 4 are boxplots of the sentiment of American and Indian articles, respectively. The median sentiment for both is relatively close to 0, and outliers across the two boxplots do not fall below approximately -0.3 or above approximately 0.6. This demonstrates that there is a relatively neutral tone for both American and Indian media towards plastic pollution, which makes sense as most articles are not emotionally charged pieces. There was little change in the shape of the two boxplots between the two countries.

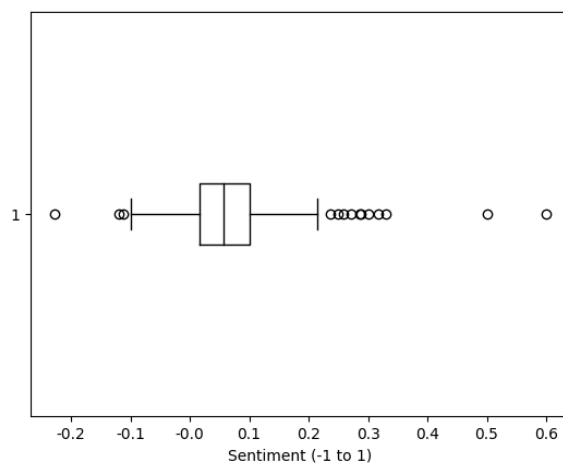


Figure 3: A boxplot of the sentiment of American media covering plastic pollution. A value of -1 reflects a purely negative sentiment, while a value of +1 reflects a purely positive sentiment.

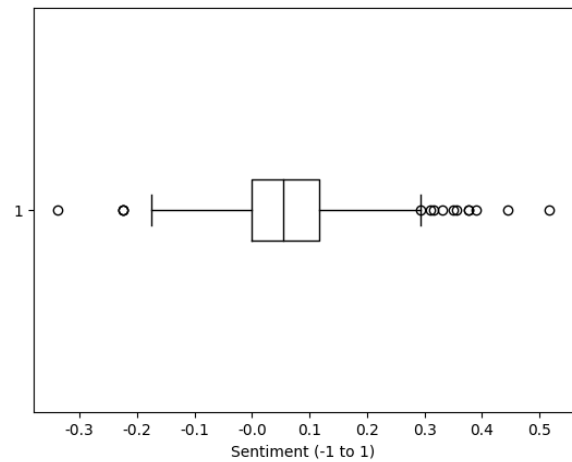


Figure 4: A boxplot of the sentiment of Indian media covering plastic pollution. A value of -1 reflects a purely negative sentiment, while a value of +1 reflects a purely positive sentiment.

Figures 5 and 6 are boxplots of the subjectivity of American and Indian articles, respectively. Both boxplots have medians of roughly 0.4, which reflects a slightly higher number of objective articles than subjective (e.g., opinion pieces) articles. Understandably, however, there was a wide range of outliers – across the two, outliers spanned from approximately 0 to 0.9 – as opinion pieces have subjectivities very close to 1, while purely informative pieces have subjectivities very close to 0. A mix of these article types therefore produces a wide range of values between 0 and 1. Unlike the sentiment boxplots, there was a difference in shape between the two subjectivity boxplots: the one for Indian media had a slightly higher spread and more clustered outliers.

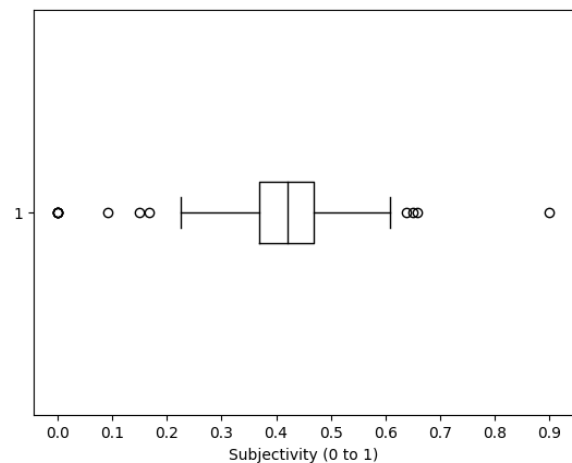


Figure 5: A boxplot of the subjectivity of American media covering plastic pollution. A value of 0 reflects a purely objective article, while a value of 1 reflects a purely subjective article.

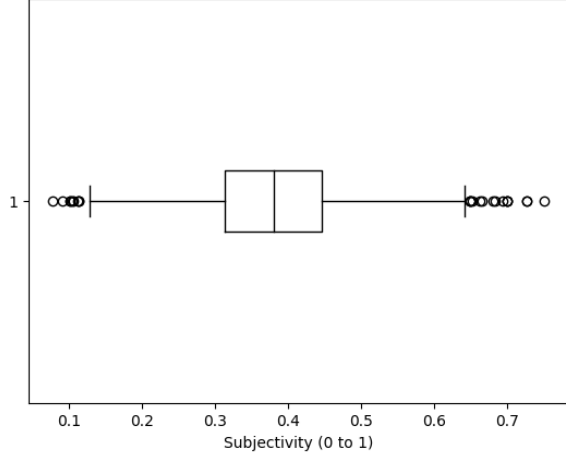


Figure 6: A boxplot of the subjectivity of Indian media covering plastic pollution. A value of 0 reflects a purely objective article, while a value of 1 reflects a purely subjective article.

Overall, this general data analysis illustrated that collected media had a relatively neutral tone towards plastic pollution and had a mix of objective and subjective pieces, with a slightly higher number falling into the former category.

2.3 LLM-Based Classification

An interesting point that has not been explored in previous studies is the form of plastic pollution covered in media sources. That is to say, whether a media source is primarily talking about single-use plastic pollution, marine plastic pollution, agricultural plastic pollution, biomedical plastic pollution, or WEEE plastic pollution (E-Waste). Conducting such classification on a dataset of our size or larger would be tedious and likely require reading through each article fully. Fortunately, this process can be automated with a large language model.

We first began by selecting to use the OpenAI GPT-3.5 Turbo model. At the time of our analysis, it was the most recent GPT model. The model has a context window of 16,385 tokens. Since the context window determines the maximum number of input tokens that can be fed into the model, a large context window enables few-shot learning and detailed prompt engineering. We used a temperature of 0 to decrease the randomness of the model outputs.

Zero-Shot Learning We began by testing zero-shot learning (i.e., no training examples were provided). The prompt provided was as follows:

“Your name is Dr. PlastiNews. You are an expert on plastic pollution and have spent your life studying the field. You have recently been tasked with a new job: categorize news articles given to you into one of five subject categories: 1. Single-

use 2. Agricultural 3. Marine 4. Biomedical 5. WEEE (electronic) Do this based on the article content. Note that there may be some overlap between categories. In the case of an overlap, please mention all categories covered. But an article must truly talk about a type of plastic pollution for you to put it into the corresponding category. It must be a core subject of the article. If the article does not fall into any of the categories, label it as a member of the ‘6. No Tag’ category.”

The OpenAI function calling feature was also used. The following function description was provided:

“Return the classification of the given article on plastic pollution as either single-use, agricultural, marine, biomedical, WEEE, or no tag.”

A list of the tags was provided as a part of the function call, restricting the model’s outputs to those given in the list ([“single-use”, “agricultural”, “marine”, “biomedical”, “WEEE”, “no tag”]).

A random sample of 310 documents was taken from the entire corpus and fed into the GPT 3.5-Turbo model with the prompt above. Each document was also manually classified by the first author into one or more of the six categories. The sample size was determined based on Cochran’s sample size formula for finite populations at the 95% confidence level, a margin of error of 0.05, $p = 0.5$, and $N = 1595$:

$$n = \frac{\frac{z^2 \times p(1-p)}{E^2}}{1 + \frac{z^2 \times p(1-p)}{E^2 N}} \quad (1)$$

252 out of 310 of the manually classified documents were placed into the same category by the first author and the GPT model. We therefore estimated the accuracy of this zero-shot learning approach to be 81.3%.

Other Approaches We also experimented with one-shot and few-shot learning (two-shot to five-shot), yet these resulted in minimal improvements in accuracy. The maximum change was with three-shot learning, which resulted in an accuracy of 81.6%. Four-shot and five-shot learning resulted in decreases in accuracy, in fact: 79% and 78.4%, respectively. We believe that these changes in accuracy were only marginal because GPT models already have extensive knowledge of plastic pollution and thus classification examples provide little help. For this reason, we decided to conduct our analysis with zero-shot learning, since the slight variations in accuracy were not enough for us to sacrifice the benefits in price and speed that came with a shorter prompt.

3 Findings

3.1 Time Series Analysis

We first did a time series analysis on our data to see how media coverage of plastic pollution has changed over time and its relationship with historical events. Figure 6 illustrates the number of articles on plastic pollution published per year from 2006 to 2023 in American media, while Figure 7 illustrates the number of articles on plastic pollution published per year from 2018 to 2023 in Indian media.

This analysis revealed several key points. First, the graphs show a general increase in media coverage of plastic pollution in both American and Indian media coverage. This supports the idea that the world is becoming increasingly knowledgeable about plastic pollution and related environmental issues. However, there was a significant decrease in media coverage regarding plastic pollution in India in 2020. A similar, but less sharp, trend was seen in the United States. This may have been because plastic pollution was overshadowed by other topics, such as the spread of the COVID-19 pandemic, in media coverage.

Additionally, the financial publications in the group – the *Wall Street Journal* in the United States and the *Economic Times* in India – understandably covered plastic pollution the least, as there is likely little finance-related coverage on the topic. Finally, there was a clear increase in media coverage of plastic pollution in 2022 in both countries. This is likely because of the groundbreaking UN resolution to end plastic pollution by 2024. This resolution was approved in 2022 and attracted significant media coverage. Notably, it created the Intergovernmental Negotiating Committee (INC), which will have its fifth session (INC-5) in November 2024.

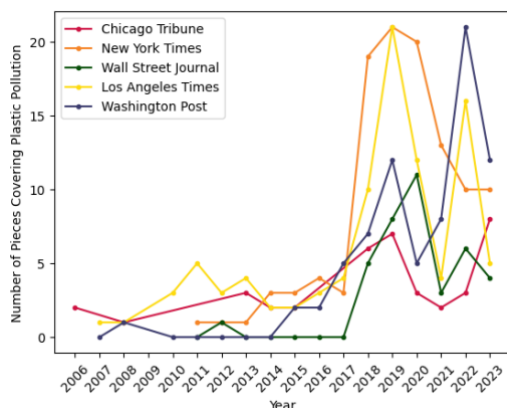


Figure 6: A graph of the number of pieces covering plastic pollution in American media from 2006 to 2023.

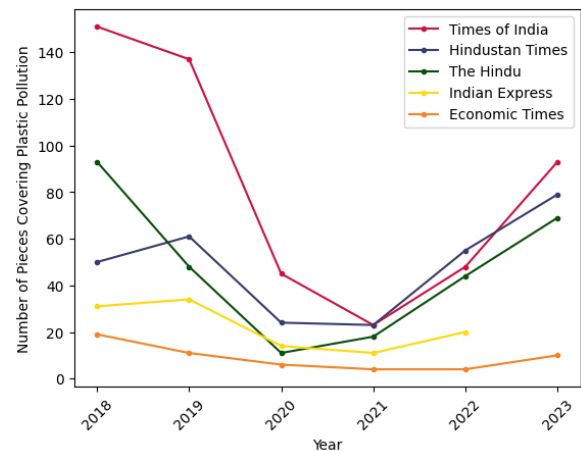


Figure 7: A graph of the number of pieces covering plastic pollution in Indian media from 2018 to 2023.

3.2 Classification Comparison

Figures 8 and 9 display a breakdown of American and Indian media coverage of plastic pollution by type. From the graph, we see that Indian media has a higher focus on agricultural plastic pollution than American media. This makes sense, considering the larger role agriculture plays in Indian society. For example, in 2021, while agriculture only made up 0.96% of U.S. GDP and 1.66% of total U.S. employment, it makes up 17.3% of India's GDP and employs 44.1% of the population (The World Bank, 2023). As a result, Indian media is more likely to report on agricultural plastic pollution than American media; it is more relevant in India than in the U.S.

Furthermore, in India, there is a much lower focus on marine plastic pollution than in the United States. We believe this may be because land plastic pollution is much more prevalent in India than in the United States. This is because of poor waste management systems that struggle to keep up with the rapidly increasing and urbanizing population (Kumar et al., 2017). As a result, media coverage in India focuses more on the common and visible land plastic pollution and less on the marine plastic pollution that is less prevalent in inland areas. Waste management systems in the U.S. are generally more advanced, owing in large part to the higher level of development (United Nations Development Programme [UNDP], 2024). Differences in media coverage are thus not static; as India continues to develop (Gutta and Kedia, 2024), media coverage of plastic pollution may become like that in the United States.

Finally, both countries focus on single-use plastic pollution, which makes sense as products

like plastic bags are ubiquitous (Parker, 2019) and largely not related to a country's level of development or economy. Concerningly, however, little focus is placed on biomedical and WEEE plastic pollution. These problems are not small. For example, India was producing more than 530 tons (480 metric tons) of biomedical waste per day according to data gathered in 2018 (Datta et al., 2018). Furthermore, over 70% of toxic waste in U.S. landfills is e-waste (United States Environmental Protection Agency [EPA], 2011). However, because these issues are not frequently covered in media, citizens may remain uninformed about the dangers of these issues and continue to contribute to the pollution problem.

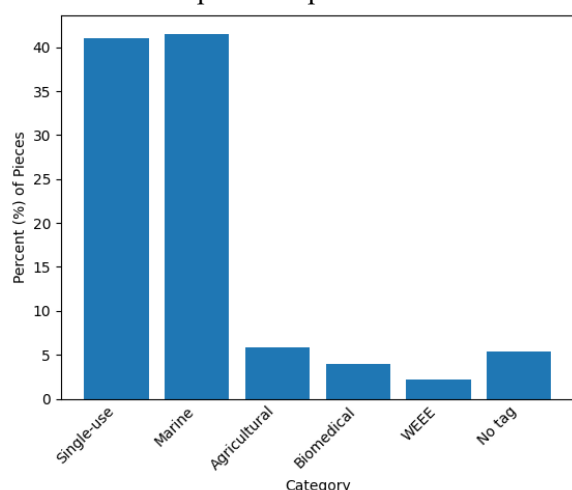


Figure 8: A graph of the percentage per category of all pieces covering plastic pollution in American media.

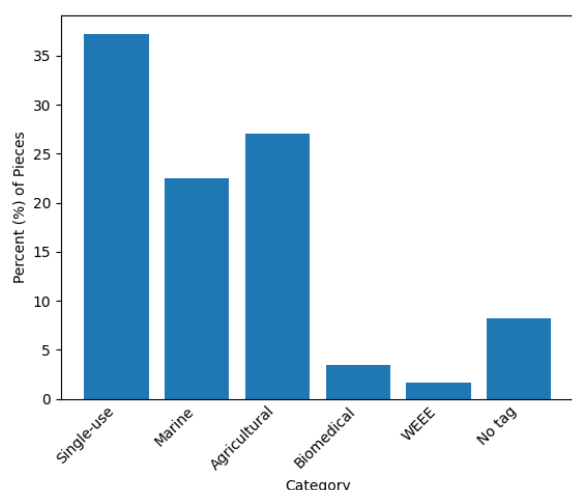


Figure 9: A graph of the percentage per category of all pieces covering plastic pollution in Indian media.

4 Conclusion

We presented PlastiNews, an analysis of nearly 1600 news articles from the United States and India

on plastic pollution. We conducted a time series analysis, showing a general uptick in plastic pollution media coverage over time in both countries and changes in coverage associated with historical events. Using a large language model, we also identified differences in media coverage between the two countries. These differences are aligned with other aspects of the countries, such as the level of development and the major economic contributors. Finally, we showed that coverage of both biomedical and WEEE plastic pollution remains low, despite the large impacts that both forms have. Our findings highlight the need for increased media coverage and awareness of these issues. Furthermore, our findings could be useful for government organizations and activists looking to create more effective targeted anti-plastic pollution campaigns.

5 Next Steps

We are expanding our research to include analysis of social media data, which could provide a more direct insight into public perspective on plastic pollution. Additionally, we are broadening our media coverage analysis to include countries that are at different development levels, have extensive government initiatives specifically targeted at reducing plastic pollution, and have different major industries. This expanded analysis could help us further explore the impact of these factors on media coverage of plastic pollution. This analysis would also utilize the newer GPT models and experiment with various other large language model families, such as Google's Gemini, Anthropic's Claude, or Meta's LLaMA.

6 References

Raffaele Marfella, Prattichizzo, F., Celestino Sardu, Fulgenzi, G., Graciotti, L., Spadoni, T., Nunzia D'Onofrio, Scisciola, L., Rosalba La Grotta, Chiara Frigé, Pellegrini, V., Maurizio Municinò, Siniscalchi, M., Spinetti, F., Vigliotti, G., Vecchione, C., Albino Carrizzo, Giulio Accarino, Squillante, A., & Spaziano, G. (2024). Microplastics and Nanoplastics in Atheromas and Cardiovascular Events. *The New England Journal of Medicine*, 390(10), 900–910. <https://doi.org/10.1056/nejmoa2309822>

Bhuyan, Md. S. (2022). Effects of Microplastics on Fish and in Human Health. *Frontiers in Environmental Science*, 10. <https://doi.org/10.3389/fenvs.2022.827289>

- Alberghini, L., Truant, A., Santonicola, S., Colavita, G., & Giaccone, V. (2022). Microplastics in Fish and Fishery Products and Risks for Human Health: A Review. *International Journal of Environmental Research and Public Health*, 20(1), 789. <https://doi.org/10.3390/ijerph20010789>
- Plastic leaching into farmer's fields at alarming rate: new report. (2022, October 17). UNEP. <https://www.unep.org/news-and-stories/story/plastic-leaching-farmers-fields-alarming-rate-new-report>
- Gigault, J., Halle, A. T., Baudrimont, M., Pascal, P. Y., Gauffre, F., Phi, T. L., El Hadri, H., Grassl, B., & Reynaud, S. (2018). Current opinion: What is a nanoplastic?. *Environmental pollution (Barking, Essex : 1987)*, 235, 1030–1034. <https://doi.org/10.1016/j.envpol.2018.01.024>
- National Oceanic and Atmospheric Administration. "What Are Microplastics?" NOAA.gov, National Oceanic and Atmospheric Administration, 14 Dec. 2023, <https://oceanservice.noaa.gov/facts/microplastics.html>.
- Lechthaler, S., Waldschläger, K., Stauch, G., & Schüttrumpf, H. (2020). The Way of Macroplastic through the Environment. *Environments*, 7(10), 73. <https://doi.org/10.3390/environments7100073>
- Pahl, S., Richter, I., & Wyles, K. (2020). Human Perceptions and Behaviour Determine Aquatic Plastic Pollution. *The Handbook of Environmental Chemistry*. https://doi.org/10.1007/698_2020_672
- Boomgaarden, H. G., & de Vreese, C. H. (2007). Dramatic Real-world Events and Public Opinion Dynamics: Media Coverage and its Impact on Public Reactions to an Assassination. *International Journal of Public Opinion Research*, 19(3), 354–366. <https://doi.org/10.1093/ijpor/edm012>
- Palau, A. M., & Davesa, F. (2013). El impacto de la cobertura mediática de la corrupción en la opinión pública española. *Reis. Revista Española de Investigaciones Sociológicas*, 144, 97–126. <http://www.redalyc.org/articulo.oa?id=99729556005>
- Sampei, Y., & Aoyagi-Usui, M. (2009). Mass-media coverage, its influence on public awareness of climate-change issues, and implications for Japan's national campaign to reduce greenhouse gas emissions. *Global Environmental Change*, 19(2), 203–212. <https://doi.org/10.1016/j.gloenvcha.2008.10.005>
- Keller, A., & Wyles, K. J. (2021). Straws, seals, and supermarkets: Topics in the newspaper coverage of marine plastic pollution. *Marine Pollution Bulletin*, 166, 112211. <https://doi.org/10.1016/j.marpolbul.2021.112211>
- Males, J., & Van Aelst, P. (2020). Did the Blue Planet set the Agenda for Plastic Pollution? An Explorative Study on the Influence of a Documentary on the Public, Media and Political Agendas. *Environmental Communication*, 15(1), 1–15. <https://doi.org/10.1080/17524032.2020.1780458>
- McKinnon, A. (2021). Journalism Needs to Get Political about Plastic Pollution: French vs US Approaches. *Critical Studies on Corporate Responsibility, Governance and Sustainability*, 191–204. <https://doi.org/10.1108/s2043-905920210000015011>
- Reis, R. (1999). Environmental News: Coverage of the Earth Summit by Brazilian Newspapers. *Science Communication*, 21(2), 137–155. <https://doi.org/10.1177/1075547099021002003>
- Jönsson, A.M. Framing Environmental Risks in the Baltic Sea: A News Media Analysis. *AMBIO* 40, 121–132 (2011). <https://doi.org/10.1007/s13280-010-0124-2>
- Das, J. (2020). The Struggle for Climate Justice: Three Indian News Media Coverage of Climate Change. *Environmental Communication*, 14(1), 126–140. <https://doi.org/10.1080/17524032.2019.1629976>
- Keller, T. R., Hase, V., Thaker, J., Mahl, D., & Schäfer, M. S. (2019). News Media Coverage of Climate Change in India 1997–2016: Using Automated Content Analysis to Assess Themes and Topics. *Environmental Communication*, 14(2), 219–235. <https://doi.org/10.1080/17524032.2019.1643383>
- Dotson, D. M., Jacobson, S. K., Kaid, L. L., & Carlton, J. S. (2012). Media Coverage of Climate Change in Chile: A Content Analysis of Conservative and Liberal Newspapers. *Environmental Communication*, 6(1), 64–81. <https://doi.org/10.1080/17524032.2011.642078>
- The World Bank. (2023). *World Development Indicators*. The World Bank. <https://databank.worldbank.org/source/world-development-indicators>
- Kumar, S., Smith, S. R., Fowler, G., Velis, C., Kumar, S. J., Arya, S., Kumar, R., & Cheeseman, C. (2017). Challenges and opportunities associated with waste management in India. *Royal Society Open Science*, 4(3), 160764. <https://doi.org/10.1098/rsos.160764>
- United Nations Development Programme. (2024). Specific country data. [Hdr.undp.org. https://hdr.undp.org/data-center/specific-country-data](https://hdr.undp.org/data-center/specific-country-data)

667 Gutta, S., Kedia, S., & World Economic Forum. (2024,
668 January 15). India could become the world's 3rd largest
669 economy in the next 5 years. Here's how. World
670 Economic Forum.
671 [https://www.weforum.org/agenda/2024/01/how-india-](https://www.weforum.org/agenda/2024/01/how-india-can-seize-its-moment-to-become-the-world-s-third-largest-economy/)
672 [can-seize-its-moment-to-become-the-world-s-third-](https://www.weforum.org/agenda/2024/01/how-india-can-seize-its-moment-to-become-the-world-s-third-largest-economy/)
673 [largest-economy/](https://www.weforum.org/agenda/2024/01/how-india-can-seize-its-moment-to-become-the-world-s-third-largest-economy/)
674
675 Parker, L. (2019, April 17). Plastic bag bans are
676 spreading. But are they truly effective? National
677 Geographic.
678 [https://www.nationalgeographic.com/environment/artic](https://www.nationalgeographic.com/environment/article/plastic-bag-bans-kenya-to-us-reduce-pollution)
679 [le/plastic-bag-bans-kenya-to-us-reduce-pollution](https://www.nationalgeographic.com/environment/article/plastic-bag-bans-kenya-to-us-reduce-pollution)
680
681 Datta, P., Mohi, G. K., & Chander, J. (2018). Biomedical
682 waste management in India: Critical appraisal. Journal
683 of laboratory physicians, 10(1), 6–14.
684 https://doi.org/10.4103/JLP.JLP_89_17
685
686 Environmental Protection Agency. (2011, March 15).
687 03/15/2011: EPA and Pelham Students Learn
688 Importance Of Recycling Electronics at Visit to
689 Recycling Plant in Mt. Vernon, NY. Wwww.epa.gov.
690 [https://www.epa.gov/archive/epapages/newsroom_arch](https://www.epa.gov/archive/epapages/newsroom_archive/newsreleases/2b721e26484eb12a85257855006acce)
691 [ive/newsreleases/2b721e26484eb12a85257855006acce](https://www.epa.gov/archive/epapages/newsroom_archive/newsreleases/2b721e26484eb12a85257855006acce)
692 [5.html](https://www.epa.gov/archive/epapages/newsroom_archive/newsreleases/2b721e26484eb12a85257855006acce)