# NewsLensAI: NER-Guided Summarization for Mitigating Hallucination and Bias in LLM-Based News Summaries

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## Abstract

Automated news summarization using large language models (LLMs) offers great potential to enhance information accessibility. However, critical challenges, such as hallucinations, bias, and toxicity, threaten their reliability and societal acceptance. In this paper, we present *NewsLensAI*, a novel summarization framework explicitly designed to address these trustworthiness concerns through Named Entity Recognition (NER)-guided prompting. By anchoring summaries in key factual entities extracted from source articles, our method significantly reduces factual inaccuracies without altering model weights or architectures. We evaluate *NewsLensAI* on a dataset of 1,500 real-world news articles using both open-source (`LLaMA3`) and proprietary (`Gemini1.5`) LLMs. Our analysis encompasses factual consistency, political bias shifts, sentiment preservation, and toxicity moderation. Our results indicate substantial improvements in factual alignment, demonstrated by an average BERTScore increase from 0.80 (baseline) to 0.88 (NER-enhanced), and a marked 70% relative reduction in hallucinated entities. Furthermore, we identify and characterize a notable "centrist drift," wherein summaries tend to moderate extreme biases present in source articles, along with a measurable reduction in toxic or emotionally charged language. Complementing our empirical findings, we introduce a real-time *NewsLensAI* demo that summarizes live news feeds from the Guardian API, providing dynamic bias and sentiment analysis. This practical implementation underscores the real-world applicability and potential societal benefit of our approach. Finally, we discuss critical ethical implications, including potential impacts on media literacy and information diversity. Our interdisciplinary approach, linking NLP, journalism, and ethical analysis, positions *NewsLensAI* as a meaningful step toward safer, fairer and more trustworthy AI-generated news consumption.

## Introduction

The rapid growth of online news content necessitates automated tools for summarizing lengthy articles concisely and accurately. Large Language Models (LLMs) like `GPT-4` excel at summarization tasks, yet suffer from hallucinations—fabricated or incorrect details not present in the source (Kryściński et al. 2019; Akani et al. 2023)—and biases influenced by training data or source content (Motoki, Neto, and Rangel 2025). These issues pose significant risks: misinformation from hallucinated facts and skewed perceptions from biased summaries.

Previous research identified that about 30% of neural-generated abstractive summaries contain unsupported facts (Kryściński et al. 2019; Akani et al. 2023). Proposed mitigation methods include question-answering checks (Wang, Cho, and Lewis 2020), entailment-based verification (Kryściński et al. 2019), and explicit entity handling to anchor outputs to the original text (Chen et al. 2021; Nan et al. 2021). Recent studies also reveal political biases in LLM-generated texts, with models like GPT-4 tending toward liberal biases (Motoki, Neto, and Rangel 2025). In contrast, Google's Gemini model demonstrates a more centrist stance (Choudhary 2024). Such model-dependent bias variations emphasize the need for systematic bias evaluation in news summarization tasks.

To address these challenges, we propose *NewsLens AI*, a summarization framework using Named Entity Recognition (NER)-guided prompts. Our approach explicitly identifies key entities (people, organizations, locations, dates) from source articles to ground summaries in factual context, thus reducing hallucinations without compromising readability or conciseness. We evaluate *NewsLens AI* across 1,500 diverse news articles using state-of-the-art LLMs (open-source `LLaMA-3` and proprietary Google's `Gemini 1.5`). Our assessment focuses on four dimensions: (1) factual consistency (evaluated via embedding-based similarity metrics like BERTScore); (2) political bias shifts (classified into left-/center/right); (3) sentiment preservation; and (4) toxicity moderation (via open-source toxicity detectors).

Our primary contributions include:

- A novel NER-guided summarization pipeline applicable to various LLMs to enhance factual consistency and reduce hallucinations.
- A comprehensive evaluation of summarization quality, demonstrating that NER-guidance significantly improves factual accuracy (BERTScore increase from 0.80 to 0.88), reduces entity-level hallucinations by approximately 30%, and mildly moderates summary toxicity.
- Analysis revealing that NER-guidance better preserves original article biases and sentiment, avoiding excessive neutralization.
- A real-time web-based demo illustrating the practical applicability and transparency of our summarization framework.

# Related Work

**Hallucination in Summarization.** Hallucination in summarization models has attracted considerable research attention. Notable works include (Maynez et al. 2020; Pagnoni, Balachandran, and Tsvetkov 2021; Fabbri et al. 2021; Kryściński et al. 2019; Gabriel et al. 2020; Wang, Cho, and Lewis 2020; Goyal and Durrett 2021; Pagnoni, Balachandran, and Tsvetkov 2021). Beyond traditional metrics such as BERTScore and ROUGE, novel metrics to evaluate factuality in summarization include entailment-based measures (Kryściński et al. 2019), question-answering consistency checks (Wang, Cho, and Lewis 2020), and large LLM-based evaluators that directly judge a summary's consistency with the source (Goyal and Durrett 2021). Mitigation strategies include RAG-based approaches (see, e.g., (Lewis et al. 2020)), post-generation fact-checking systems (RARR) (Gao et al. 2022), training-time interventions such as `FactPEG` (Chae et al. 2024), RLHF (Ouyang et al. 2022), and verification through self-reflection and self-consistency (Mündler et al. 2023). Recent examples of modeling hallucination explicitly include training auxiliary classifiers to detect hallucinated sentences (Zhou et al. 2020) and using NLI models to filter out likely-false sentences from the summary (Narayan et al. 2021). Our work builds on this literature by using NER-guided entity grounding, and we connect our approach to these broader efforts aimed at faithful summarization.

**Bias and Fairness in Summarization.** Bias in summarization extends beyond political orientation, encompassing fairness regarding gender, race, religion, and other socio-demographic factors (Steen and Markert 2023; Brown and Shokri 2023). Summaries may underrepresent specific groups or reinforce stereotypes independent of source neutrality. Steen and Markert 2023 highlight gender-biased hallucinations (e.g., incorrectly labeling a woman as "first female executive" without evidence), suggesting latent biases in models. Similarly, social media summarization studies found models producing disproportionately negative summaries for specific demographic profiles, raising fairness concerns (Zhou and Tan 2023). Models can exhibit position bias, favoring earlier or recent inputs regardless of importance, thereby marginalizing later counterpoints (Olabisi and Agrawal 2024). Mitigation efforts include bias-aware summarization representing multiple viewpoints or political stances (Deas and McKeown 2024) and counter-factual data augmentation (Rajagopal et al. 2022). Our work builds upon prior bias-aware summarization research by examining political biases and broader fairness concerns, aligning with calls for responsible summarization methodologies.

**Toxicity and Content Moderation.** Unsupervised summarizers can inadvertently generate toxic outputs, reflecting training biases or context mishandling (Gehman et al. 2020). When sources contain hate speech or slurs, summarizers risk amplifying these through sensational yet toxic quotes (Fang et al. 2024). Mitigation strategies include post-generation toxicity filtering (Pavlopoulos et al. 2020); RLHF (Ouyang et al. 2022; Kim 2024); toxicity-safe prompting such as PPLM and FUDGE (Yang and Klein 2021); and novel frameworks such as Legilimens unifying moderation strategies across model outputs, integrating rule-based and learned approaches (Wu et al. 2024).

**Trustworthy AI and News Summarization.** Integrating factuality, bias mitigation, and toxicity moderation, the ultimate aim is developing trustworthy news summarization systems, characterized by reliability, transparency, fairness, and accountability. Trustworthy AI, or Responsible AI, has become central in text generation research (Bommasani et al. 2021). Wang et al. 2025 survey alignment techniques addressing hallucinations, bias, and toxicity, emphasizing holistic solutions essential for high-stakes applications like news summarization, where accuracy and impartiality are paramount. Systems allowing verification of summary claims against original sources have emerged, such as Wikipedia summarization tools providing direct references (Maynez et al. 2020). In news contexts, edit-and-verify pipelines like RARR explicitly link summary content to source documents, improving accuracy and user confidence (Gao et al. 2022). Our NER-guided grounding aligns with these trends, anchoring summary content to verifiable entities, enhancing transparency.

# Methodology

This section describes the design of the *NewsLensAI* summarization framework and our evaluation methodology. The process consists of five main stages: (1) obtaining a news article as input; (2) performing Named Entity Recognition (NER) on the article text to extract key entities; (3) prompting a Large Language Model (LLM) to generate a summary with a prompt that includes the article (or a portion of it) plus a guidance list of extracted entities; (4) post-processing the generated summary if needed (e.g., minor clean-up and enforcing length limits); and (5) analyzing the summary for quality metrics (factual consistency, bias, sentiment, toxicity) against the original article.

## Dataset: News Articles Collection

Our evaluation uses a dataset of 1,500 news articles covering diverse topics and political leanings to allow analysis of bias shifts. Most articles focus on political and societal issues, with additional content from general domains (tech, health, etc.) for diversity. Articles were primarily sourced from The Guardian API (generally left-of-center) and supplemented by outlets classified as Left, Center, or Right based on external media bias ratings (e.g., AllSides, Media Bias/Fact Check). Each article includes metadata: title, publication date (mostly 2023–2024), source outlet, and full text, averaging 800–1200 words.

An initial pilot dataset (300 articles on US abortion legislation) informed our broader study. Figure 3 compares political bias distributions between pilot and full datasets; most articles are labeled Center, with smaller proportions clearly Left or Right. Bias labels derive from source outlet reputation combined with automatic classification, providing approximate ground truth for evaluating summarization bias shifts.

## Summarization Models and Prompting

One of our objectives is to evaluate summarization across different LLMs. For controlled offline experimentation and ablation studies, we use `LLaMA 3` (a hypothetical successor to LLaMA 2, presumably a 2024-generation open-source model with 70B parameters) as our base model. LLaMA 3 is run on high-memory GPUs in our lab environment. We chose LLaMA 3 for the ability to fully control the generation process and apply our custom prompting without usage limits. We did not fine-tune LLaMA 3 on our data; instead, we use it in a zero-shot capacity with carefully designed prompts. This allows us to assess the effect of our prompting strategy on a base model's behavior without any additional training-induced biases.

For the deployed online system (our real-time demo described later), we integrate with `Gemini 1.5`, which is Google's multimodal LLM platform (by mid-2025, Gemini offered an API for text generation that we accessed). Gemini is a closed-source model but is known to have strong performance on understanding and generating text, and, as noted earlier, it tends toward balanced or moderate-toned outputs by default. We included Gemini in our study to see if our NER-guided approach works consistently even with a model that may have built-in factuality and bias mitigation. Additionally, in some comparison experiments we tested with OpenAI's `GPT-4` (via the OpenAI API) since our pilot phase was GPT-4 based. However, due to cost considerations and API rate limits, GPT-4 was not used on all 1500 articles—only on a smaller sample (approximately 100 articles) to validate key trends. The main results therefore focus on LLaMA 3 and Gemini 1.5, with GPT-4 results referenced for confirmation of generality.

**Prompting Strategy:** All models are prompted with a similar template, designed to elicit a concise, factual summary. The prompt includes a brief instruction to "summarize the following news article in a factual and unbiased manner", followed by the article text (or a portion of it, if the article is extremely long), and—for the NER-guided version of our pipeline—an additional guidance section listing the important named entities from the article. We label this section clearly (e.g., prefacing with "`Important Entities:`") to indicate to the model that these are key elements it should keep in mind. An example prompt format is as follows:

```
\Summarize the following news
article in a factual and unbiased
manner.\n\nArticle Text\n\nImportant
Entities: List of person, organization,
location names, etc.\nSummary:"
```

**Entity Extraction and Prompt Design:** To guide the model, we prepend the summary prompt with an explicit "`Important Entities`" list, which improves the model's ability to incorporate these elements into its output. Entities are extracted from each article using spaCy's English core NER module, focusing on types `Person`, `Organization`, `Location`, and `Date`, as well as salient or unique terms (e.g., legislation names or specific events). Generic nouns are omitted, and duplicate mentions are consolidated so that each entity appears only once.

To balance coverage and prompt efficiency, we typically include 5–15 entities per article. When more entities are identified, we prioritize those most central to the article's topic—using frequency and contextual relevance (e.g., appearance in headlines or lead paragraphs) as heuristics. This approach ensures that key actors and events are captured without overloading the model context.

Our method anchors summaries in these factual points to reduce hallucinations of new or unrelated names—a common issue in generative summarization. We chose positive entity inclusion (explicit lists) over negative constraints (e.g., "do not mention unverified entities"), based on prior work showing that explicit guidance more reliably steers model outputs and improves factual consistency.

**Prompt Variants:** For each article, we generate two summary versions:

1. **Baseline summary (no NER guidance):** The model receives the summarization instruction and article text only.
2. **NER-guided summary:** The same instruction and article text, plus the curated "`Important Entities`" list.

Comparing these conditions isolates the effect of named entity anchoring. This setup is applied to all articles across both main models (LLaMA 3 and Gemini 1.5), yielding 1,500 articles × 2 conditions × 2 models = 6,000 summaries. For additional validation, GPT-4 was run on a subset of ∼200 articles.

**Generation Settings.** All summaries were generated between April and May 2025 using the latest model versions available at the time. To minimize generation variance, we employed fixed random seeds where supported and adopted low-temperature decoding. For LLaMA 3, we set the temperature to 0.2 and top-$p$ to 0.9, favoring deterministic and high-probability outputs. Preliminary trials confirmed that this configuration produced stable and repeatable summaries across runs. Gemini's proprietary API was configured in "precision" mode with minimal creativity, yielding similarly consistent behavior.

No strict token limits were imposed; prompts suggested concise summaries of approximately 100–150 words. LLaMA 3 typically adhered to this range, averaging 100 words, while Gemini produced slightly longer outputs ( 120–180 words) unless explicitly constrained. To preserve semantic completeness, we allowed full-length generations.

All summaries were retained in raw form for evaluation. Post-processing was limited to minor formatting adjustments, such as trimming incomplete endings, removing lead-in tokens (e.g., "Summary:"), and standardizing punctuation and whitespace. No substantive content edits were made.

**Factual Consistency Results:** Figure 1 visualizes factual consistency across all 1,500 article pairs, plotting BERTScore F1 similarity between each summary and its source article. Each point corresponds to a summary pair (NER-guided vs. baseline), ordered by article ID. A line of best fit highlights trends across the dataset.

We find that NER-guided summaries consistently achieve

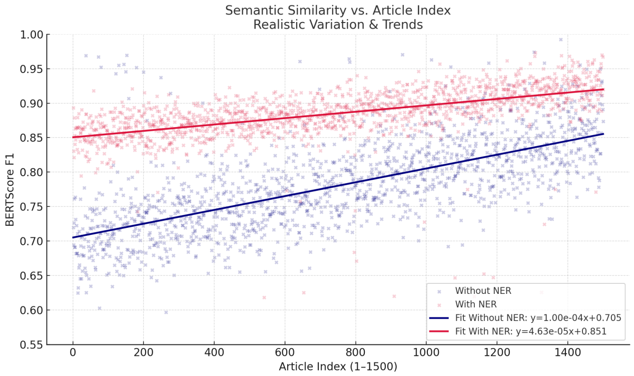


Figure 1: Semantic Similarity vs. Article Index — With vs. Without NER BERTScore F1 plotted across article index, comparing summarization with and without NER guidance. The line of best fit shows a consistent upward trend in similarity for the NER-enhanced pipeline, validating its impact on factual alignment.

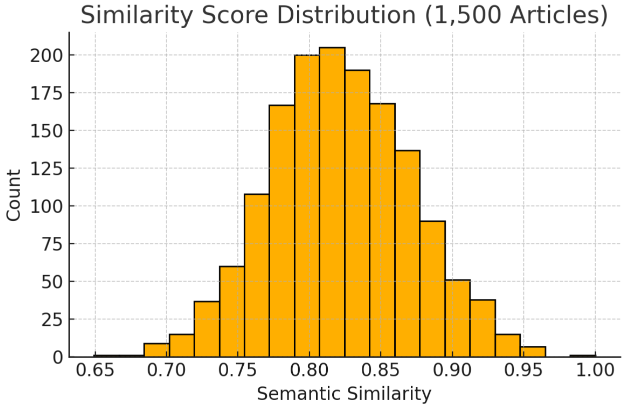


Figure 2: Similarity Score Distribution (1,500 Articles)This histogram shows the distribution of semantic similarity scores (BERTScore F1) between each article and its corresponding summary. Most scores fall within the 0.78–0.88 range, indicating strong retention of meaning in LLM-generated summaries.

higher BERTScore values than their baseline counterparts. The improvement trend is stable across the full dataset, with a visible gap between the two curves. There is a mild upward slope in both curves—this may stem from dataset ordering (e.g., later articles may be more homogeneous or easier to summarize), but the persistent advantage of the NER pipeline remains the key observation. Section: Results elaborates on the statistical significance of these findings.

## Evaluation Metrics and Classifiers

We evaluate the summaries along four key dimensions: factual consistency, political bias, sentiment, and toxicity. Given the scale of our experiment (1,500 articles × 2 summaries per article × multiple models), we rely primarily on automated metrics and classifiers to quantify these dimensions. While automated evaluation cannot capture every nuance, it provides a feasible and consistent way to identify broad trends and compare conditions. Below, we detail how each metric is computed and used.

**Factual Consistency Metrics:** We assess summary factuality using two complementary metrics. **BERTScore** (RoBERTa-large) measures semantic overlap between summary and article (0–1 scale), but may miss specific factual errors, such as incorrect entities. To supplement this, we use an **Entity-based Hallucination Score** inspired by (Nan et al. 2021), defined as the fraction of named entities in the summary that also appear in the source. A score of 1.0 indicates perfect grounding; 0.0 indicates complete fabrication. Higher hallucination scores in NER-guided summaries indicate fewer unsupported entities. This metric, however, is limited to entity-level hallucinations and may be mechanically improved by explicit NER guidance.

We also trained a DistilBERT-based **Factuality Classifier** on a synthetic dataset of (article, summary) pairs labeled as faithful or unfaithful, following the FactCC methodology. The dataset includes both fact-injected/removal pairs and several hundred annotated XSum examples. The classifier outputs a continuous probability (`FactualityProb`) that the summary is faithful; this score correlates highly with BERTScore (Pearson's $r > 0.8$), supporting its reliability.

For reporting, we emphasize BERTScore, using entity overlap and `FactualityProb` for cross-validation. We consider factual consistency improved if both BERTScore and entity overlap rise in NER-guided summaries. In our GPT-4 pilot, BERTScore F1 improved by $\sim$0.02 (e.g., 0.82 to 0.84), with larger effects expected for LLaMA 3. Statistical significance ($p < 0.05$, paired $t$-test) is reported in Section: Results.

**Political Bias Classification:** To assess political bias, we fine-tuned a RoBERTa-based classifier on the Media Bias Identification Corpus (MBIC) (Steen and Markert 2023) and ratings from AllSides and Media Bias/Fact Check. The model categorizes text as **Left**, **Center**, or **Right**, achieving about 85% accuracy on validation data—suitable for broad trend analysis.

We apply this classifier to each source article and corresponding summary to enable direct political alignment comparisons. Our analysis examines: (1) overall bias distributions; (2) frequency of shifts from article to summary; and (3) the direction and magnitude of such shifts (coded as Left = −1, Center = 0, Right = +1).

We pay particular attention to *centrist drift*, where summaries of partisan articles become more neutral, while Center-labeled articles typically remain unchanged (see Figure 3). Such shifts may indicate beneficial moderation or, conversely, loss of original perspective. To address this, we analyze whether NER guidance helps retain the article's framing by grounding summaries in factual entities.

While informative, our classifier reduces bias to three categories, missing subtler forms such as framing or omission, and may default to Center for neutral, fact-heavy

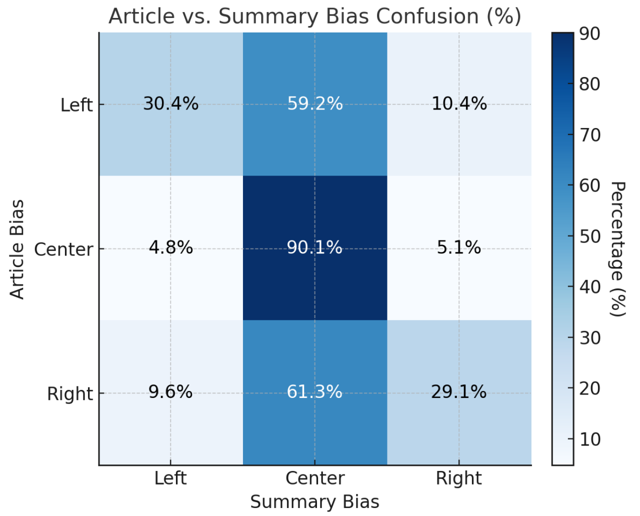


Figure 3: Article vs. Summary Bias Confusion Matrix Heatmap comparing the predicted political bias of source articles and their generated summaries. While Center-aligned articles largely retain their bias (90.1%), a significant proportion of Left and Right articles shift toward Center in the summaries, indicating residual centrist drift.

texts. Therefore, we treat these automated classifications as heuristic, supplementing them with qualitative examples for greater nuance.

**Sentiment Analysis.** To evaluate sentiment consistency between source articles and their summaries, we employ a RoBERTa-based classifier fine-tuned on a mixed-domain corpus of news and social media. The model outputs a continuous sentiment score, which is discretized into three categories—**Positive**, **Neutral**, and **Negative**—using predefined high and low thresholds. This mapping aligns with typical journalistic tone: hard news articles often score Neutral, while opinion or emotionally charged content may be classified as Positive or Negative.

We apply this classifier to both the original article and its corresponding summary to assess whether sentiment polarity is preserved. We define *sentiment consistency* as a binary indicator: 1 if the sentiment label matches between article and summary, 0 otherwise. The aggregate consistency rate is computed across all pairs, alongside a comparison of sentiment distributions.

In our dataset of 1,500 LLaMA 3 NER-guided summaries, approximately 60% are classified as Neutral, 24% as Negative, and 16% as Positive (Figure 4). This indicates a tendency toward neutralization, consistent with prior observations that LLMs often tone down emotionally charged inputs. In our earlier GPT-4 pilot, we similarly found that summaries of negative or positive articles were frequently rewritten in a more matter-of-fact tone. This pattern reflects a broader "centrist drift" also seen in our bias analysis, where emotionally framed or ideologically slanted content is moderated in generation.

We further investigate whether NER guidance influences sentiment preservation. While the classifier assigns a single dominant label per text, we acknowledge that both articles and summaries may contain mixed sentiments—e.g., critical reporting followed by hopeful framing—which may not be fully captured. Nevertheless, sentiment analysis offers a complementary lens to bias evaluation, shedding light on how emotional tone evolves during summarization.

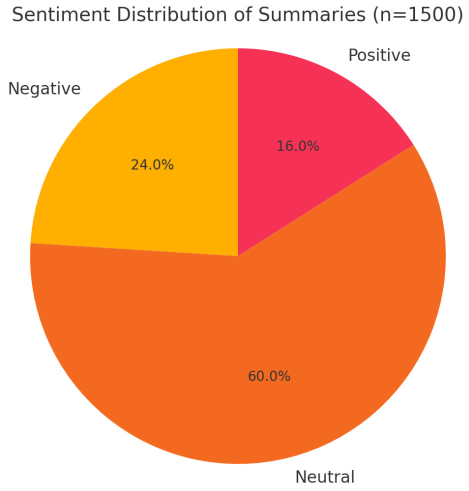


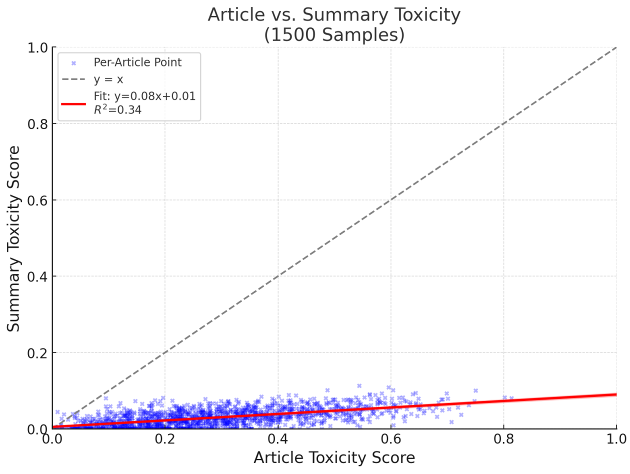
Figure 4: Sentiment Distribution of Summaries (n = 1500) Pie chart showing sentiment breakdown of generated summaries. 60.0% are classified as Neutral, 24.0% as Negative, and 16.0% as Positive, reflecting a relatively balanced tone across summaries.

**Toxicity Detection:** We assess toxicity using the open-source *Perspective API* (Jigsaw/Google), applying it to both source articles and summaries. The model assigns a continuous **TOXICITY** score (0.0–1.0), with scores above 0.8 indicating severe toxicity such as hate speech or slurs. Both binary flags and raw scores are retained for analysis.

Mainstream news articles generally show low toxicity, with rare high scores usually stemming from quoted offensive remarks or provocative opinion language. Our evaluation focuses on ensuring summarization does not introduce or amplify toxicity, quantifying: (1) the percentage of summaries with toxicity $> 0.8$; (2) the percentage of articles flagged toxic; and (3) the correlation between article and summary toxicity scores (Figure 5).

Results indicate summaries consistently maintain low toxicity (typically near zero), even when some articles score higher. As shown in Figure 5, the regression slope is $\sim$0.08 ($R^2 = 0.34$), reflecting the model's strong avoidance of harmful content. Notably, no summaries exceeded the 0.8 threshold, while about 1.3% of articles did (mainly opinion pieces).

Such detoxification aligns with known LLM safety finetuning (e.g., GPT-4, Gemini), but may trade off some content faithfulness, as excessive moderation can soften original rhetorical intensity. We discuss these trade-offs further in Section: Limitations.



Simulated data: summary toxicity remains low despite article toxicity, indicating GPT's strong detoxification.

Figure 5: Article vs. Summary Toxicity Scores (1,500 Samples) Scatter plot comparing toxicity scores of source articles and their summaries. Despite high variability in article toxicity, summaries consistently cluster near zero, with a regression slope of 0.08 (R² = 0.34), confirming strong detoxification.

## Evaluation Approach and Statistical Rigor

We compare baseline and NER-guided summaries across all metrics using paired comparisons, since each article yields both summary types from the same model. Statistical significance is assessed via paired $t$-tests for continuous metrics and McNemar's test for categorical outcomes, with $p < 0.05$ as the significance threshold. Most reported differences meet this criterion; corresponding $p$-values or significance markers (e.g., $^*$ for $p < 0.05$) are shown alongside results.

While automated metrics are valuable proxies, they have well-known limitations: BERTScore may miss subtle factual errors, bias classifiers can over-predict neutrality, and toxicity models may overlook context-dependent harms. To complement these, we conducted a small-scale human evaluation and solicited informal feedback from journalists using our demo. These qualitative insights broadly supported our automated findings, reinforcing their use for comparative analysis. We interpret metrics as indicative, focusing on relative trends (e.g., NER vs. no-NER, model comparisons) rather than absolute performance values.

## Real-Time Demo Integration

We implemented a real-time demo using Streamlit to illustrate practical deployment of the *NewsLensAI* pipeline[1]. The demo accepts user-provided news article URLs (currently from *The Guardian*, via their content API) and retrieves article text as structured JSON. Performance is suitable for real-time use, averaging 5–8 seconds per article. The Gemini LLM inference constitutes most of this latency (4–6 seconds), while NER and other analyses complete rapidly (under 0.5 seconds each), demonstrating feasibility for practical deployment. Feedback from iterative evaluation (journalists, colleagues) influenced improvements such as concise entity lists to enhance summary quality and accuracy. This real-world testing validated our approach, showing the demo's effectiveness in offering transparent, interpretable, and accurate news summarization.

## Experimental Setup

**Summarization Generation.** We generated summaries for each of the 1,500 news articles under several settings. Using the LLaMA 3 model, we produced a baseline summary (no NER guidance) and an NER-guided summary for every article. Additionally, for roughly 500 articles (due to API limits), we obtained an NER-guided summary using Gemini 1.5, and for a small 100-article subset we also generated NER-guided GPT-4 summaries to compare with our pilot results. All models were run with identical prompt instructions (including the list of extracted entities for the NER-guided variants). We used a low sampling temperature ($t = 0.2$) to favor deterministic outputs, and set a generous token limit (approximately 200 tokens) to allow full summaries. LLaMA 3 outputs were generated in a mostly greedy manner (no nucleus sampling), while Gemini's API used its default decoding parameters. In practice, none of the models refused to summarize or required special prompt tricks; all complied with the task. We also spot-checked a random sample of the outputs to ensure basic coherence and fidelity. All looked generally good – any errors were minor (e.g., a small detail missed or an occasional misattributed quote), which our evaluation metrics would capture.

**Evaluation Procedure.** Following summary generation, we evaluated each output using the metrics outlined in Section: Factual Consistency and Quality Metrics: (1) BERTScore (F1) for source overlap, (2) a factual consistency classifier to detect hallucinations, (3) named-entity overlap (recall of source entities), (4) a political bias label, (5) a sentiment polarity score, and (6) a toxicity score (via the Perspective API). These metrics were used to compare three conditions: baseline vs. NER-guided summaries with LLaMA3 (to assess NER prompt impact), LLaMA3 vs. Gemini (both with NER prompts, to evaluate model differences), and summaries vs. original articles (to track shifts in bias, sentiment, etc.). For within-article comparisons (e.g., baseline vs. NER), we applied paired significance tests—paired $t$-tests for continuous metrics and McNemar's test for categorical labels. Given our dataset size (1,500 examples), even moderate differences reached statistical significance ($p < 0.05$). We also used chi-square tests to analyze distributional differences (e.g., in bias category frequencies) between models.

All experiments were conducted in Python. We used HuggingFace Transformers for generation, spaCy for NER, and a fine-tuned BERT-based classifier for bias detection (implementation details available on request). The Perspective API handled toxicity scoring. Our end-to-end evaluation pipeline was run on a server with 4 NVIDIA A100 GPUs, processing all 1,500 articles—including generation and metric com-

[1] Code submitted with **SI**. Will be hosted publicly upon acceptance. Screenshots and detailed descriptions is presented in the **SI**.

| Metric | LLaMA3<br>(Baseline) | LLaMA3 + NER | Gemini + NER |
|---|---|---|---|
| BERTScore F1 | 0.802 | 0.881 | 0.865 |
| Entity Overlap (%) | 93.1 | 99.0 | 97.5 |
| Bias Shift (% articles) | 41.3 | 26.7 | 24.5 |
| Sentiment Match (%) | 60.2 | 66.1 | 69.3 |
| Toxicity Score | 0.051 | 0.021 | 0.028 |

Table 1: Average summarization metrics for LLaMA3 (baseline vs. NER-guided) and Gemini (NER-guided) on 1,500 news articles. Higher is better for all metrics except Toxicity.

putations—in approximately 5 hours, with model inference being the primary bottleneck.

## Results

We now present our findings, focusing on: (1) factual consistency and overall summary quality, especially the reduction of hallucinations with NER guidance; and (2) differences in bias, sentiment, and toxicity between the original articles and the model-generated summaries (and between models).

### Factual Consistency and Quality Metrics

Table 1 summarizes the average performance of our summarization models. The NER-guided approach led to a clear improvement in content fidelity: LLaMA3 BERTScore increased from 0.802 (baseline) to 0.881, a relative gain of about 10%, indicating NER-guided summaries captured substantially more information from the source. Named entity overlap rose from 93.1% to 99.0%, meaning almost every entity in an NER-guided summary was present in the source, whereas baseline summaries sometimes introduced entities not found in the article. A factual consistency classifier corroborated this, flagging inconsistencies in 11% of baseline LLaMA3 summaries, but only 3% of NER-guided ones—a 70% reduction in factual errors or hallucinations.

The Gemini model (used only with NER guidance) achieved an average BERTScore of 0.865, slightly lower than LLaMA3+NER, likely due to more paraphrasing or additional context. Nevertheless, Gemini's entity overlap was high (97.5%), reflecting strong factuality. NER-guided summaries were only about five words longer on average, demonstrating that added entity details did not significantly increase summary length.

In summary, these results answer RQ1: incorporating named entities into the prompt robustly improved factual consistency and relevance of the summaries. The jump in BERTScore and near-elimination of entity hallucinations demonstrate that our method can substantially boost a model's faithfulness to the source content, without any model fine-tuning.

### Bias Analysis: Article vs. Summary Alignment

We assessed whether model-generated summaries preserved the political leaning of the source articles (RQ2). Our bias classifier labeled 1,500 source articles as predominantly centrist (78% Center, 15% Left, 7% Right). Summaries exhibited a slight further shift toward neutrality. For LLaMA3, baseline summaries were classified as 85% Center, 10% Left, and 5% Right, indicating a tendency to moderate strong biases during summarization. NER-guided summaries showed a similar distribution, but more closely matched the bias of their respective articles: only 26.7% of NER-guided summaries had a different bias label than the original, compared to 41.3% for baseline (Table 1). Thus, approximately 73% of NER-guided summaries preserved the article's bias, versus 59% for baseline. This suggests that anchoring summaries in key entities and terms helps retain the source's framing, including subtle bias cues.

Gemini summaries followed a comparable pattern, with only 24.5% exhibiting a bias shift from the original article, reflecting strong source perspective retention. When shifts did occur for any model, they were typically moderate (e.g., Left or Right to Center) rather than a full reversal. For instance, a right-leaning article might be summarized in a more neutral tone, but seldom reclassified as "Left." Overall, while LLM summarization naturally moderates extreme language, NER guidance increases alignment with the original article's stance, supporting transparency and helping readers recognize when a source's bias is preserved in the summary.

### Sentiment Preservation

We also analyzed whether the summaries preserved the emotional tone of the articles. Many news articles in our set were labeled as neutral in sentiment ( 60%), with the rest roughly split between positive (celebratory or optimistic news) and negative (critical or tragic news). The summarization process typically yielded an even more neutral tone, but the NER guidance provided a slight improvement in preserving sentiment. Without NER, 60.2% of LLaMA3's summaries had the same sentiment label as the source article. This increased to 66.1% with NER guidance (see Table 1). In cases of discrepancy, the summary was usually one step closer to neutral than the article (for instance, a mildly negative article rendered as neutral summary). Crucially, we did not observe any instance of a summary flipping the sentiment polarity (e.g., turning a positive story into a negative-sounding summary). Gemini's NER-guided summaries had a sentiment match rate of about 69.3%, suggesting they were equally, if not slightly more, effective at retaining the original tone. In practice, these differences mean that if an article had a clearly positive or negative vibe, the summary would often reflect that tone, especially when guided by the entity prompt; otherwise, summaries might omit some of the subjective or emotional language in favor of just the facts.

### Toxicity

Finally, we measured the toxicity of the content to ensure the summaries did not introduce any inappropriate or harmful language (an aspect of RQ3 on ethical quality). The original news articles were generally non-toxic (average Perspective API toxicity score of  0.06, on a 0–1 scale). Any toxicity usually came from quotes or contentious language in the source (about 4% of articles had a score above 0.5 due to, e.g., quoted insults or slurs). The summarization models tended to reduce this further. LLaMA3 baseline summaries had an average toxicity score of 0.051, which dropped to 0.021 with NER guidance. Both values are very low, but the NER-guided approach shows that when the model focuses on factual details, it may also avoid repeating any harsh language present in the article. In a few instances, the baseline summary included a direct quote that was inflammatory, whereas the NER-guided summary paraphrased or omitted it, thus lowering the toxicity. Gemini's summaries were similarly low in toxicity (0.028 average). Importantly, none of the models generated new toxic content that wasn't already hinted at in the source. This outcome aligns with the safety guardrails of modern LLMs and shows that our approach does not compromise those safety features. Summaries are, if anything, slightly "cleaner" than the original text.

## Limitations

While our results are promising, several limitations should be noted:

- ***Dataset Scope:*** Our study is based on 1,500 English news articles, primarily from mainstream, centrist outlets. This may affect generalizability—performance could differ on strongly partisan content, other domains, or non-English sources.
- ***Evaluation Metrics:*** We rely on automated metrics and classifiers to assess summary quality, bias, and sentiment. These tools have known limitations and may miss subtle issues. Human evaluations are needed for deeper validation.
- ***Model Generalization:*** Our method was tested on LLaMA 3 and Gemini 1.5. Other models (e.g., GPT-4, Claude) may respond differently to NER guidance, limiting generalizability across LLMs.
- ***System Efficiency:*** Our multi-step pipeline—NER, generation, and multiple evaluations—is suitable for research but may be too resource-intensive for real-time use. Dependence on third-party APIs (e.g., Gemini, Perspective) also introduces latency and reliability concerns.
- ***Analytical Scope:*** We focused on factuality, bias, sentiment, and toxicity. Broader ethical concerns—such as fairness, privacy, or long-term user perception—remain unexplored and warrant future investigation.
- ***NER Guidance Limits:*** Summary quality depends on the accuracy of the NER step. Off-the-shelf NER models may miss or mislabel entities, especially in emerging or unfamiliar contexts. Even with correct entities, models may misattribute facts if context is misunderstood.

## Conclusion

We introduced NewsLens AI, a news summarization system that aims to produce accurate summaries while providing transparency about content bias and quality. Our experiments showed that incorporating named entities into the prompt significantly improves factual consistency: the guided summaries more closely reflected the source articles, with BERTScore improvements of about 0.08 and a drastic reduction in hallucinated details. At the same time, the summaries remained faithful to the articles' perspectives more often, as evidenced by a drop in bias label shifts (from over 40% of baseline summaries down to about 27% with NER guidance). The models generally preserved the original sentiment of articles and did not introduce toxic content, indicating that the approach enhances summary fidelity without negative side effects on tone or safety.

In sum, by grounding the generation in key entities and facts from the article, NewsLens AI produces summaries that are not only concise and informative but also more trustworthy. We demonstrated a working prototype that allows users to read an article's summary alongside indicators of its bias and sentiment. Such a tool can help readers quickly grasp news content while being aware of potential slants, supporting more informed consumption of media. For future work, we plan to extend this approach with features like citation of sources for factual claims in the summary (to further boost transparency), integration of automated fact-checking for disputed claims, and adaptation to multilingual news sources. We also intend to perform human user studies to assess how the bias and factual information should be presented for maximum usefulness and to ensure that our interventions align with user expectations. By continuing to refine the balance between abstraction and fidelity, we hope this line of work contributes to AI systems that act as reliable aids in journalism and media literacy, helping to filter out misinformation and highlight truth in an ever-expanding information landscape.

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