NewsSlant: Analyzing Political News and Its Influence Through a Moral Lens

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***Abstract*—Political news is often slanted toward its publisher's ideology and seeks to influence readers by focusing on selected aspects of contentious social and political issues. We investigate political slants in news and their influence on readers by analyzing election-related news and readers' reactions to the news on Twitter. To this end, we collected election-related news from six major US news publishers who covered the 2020 US presidential election. We computed each publisher's political slant based on the favorability of its news toward the two major parties' presidential candidates. We find that the election-related news coverage shows signs of political slant both in news headlines and on Twitter. The difference in news coverage of the two candidates between the left-leaning (LEFT) and right-leaning (RIGHT) news publishers is statistically significant. The effect size is larger for the news on Twitter than for headlines. And, news on Twitter expresses stronger sentiments than the headlines. We identify moral foundations in readers' reactions to the news on Twitter based on the Moral Foundation Theory. Moral foundations in readers' reactions to LEFT and RIGHT differ statistically significantly, though the effects are small. Further, these shifts in moral foundations differ across social and political issues. User engagement on Twitter is higher for RIGHT than for LEFT. We posit that an improved understanding of slant and influence can enable better ways to combat online political polarization.**

I. Introduction

One of the most common ways people, particularly young adults, get political news is via social media [1]. While social media helps in the quick, large-scale dissemination of news, it also witnesses trolling and hate speech. The polarizing effects of political news can be observed on social media platforms [2]. Further, anger is the most common emotion in response to news on social media about politics in a crisis situation across cultures [3, 4], highlighting the need for more effective ways of disseminating political news.

People show partisan preference in online news consumption and more often subscribe to news that confirms their existing beliefs [5]. Previous studies suggest that exposure to belief-conforming political information correlates with polarizing people's opinions to align with the political party's values they support [6, 7, 8, 9]. News coverage in recent times has exhibited a noticeable increase in the use of polarizing language, especially when mentioning political figures [10], raising concerns about the potential aggravation of existing divisions on contentious social and political issues.

To understand political slants in news and their influence on readers, we analyze the 2020 US presidential election-related news and readers' reactions to political news on Twitter. We identify political slants based on the favorability of news toward the two major parties' presidential candidates. Favorability is computed as the ratio of the mean positive to the mean negative sentiment toward each candidate. We further identify the news topic to infer the relevant social and political issues being reported. Combining news topics and sentiment content provides useful insights into how public opinion varies [11]. Additionally, we identify moral foundations in readers' reactions to the news on Twitter using Moral Foundation Theory (MFT) [12].

We pick six US news publishers and group them based on political ratings from AllSides [13] into LEFT (left-leaning), RIGHT (right-leaning), and BALANCED (nonpartisan) news publishers. To ensure a fair comparison, we pick two LEFT, two RIGHT, and two BALANCED news publishers.

We investigate if election-related news shows signs of political slant and if the slants are similar in headlines and on social media (Twitter). We find that LEFT favors Biden (presidential candidate for the left-leaning party), and RIGHT favors Trump (presidential candidate for the right-leaning party). News from BALANCED is less slanted than LEFT or RIGHT. However, BALANCED is more favorable to Biden than either LEFT or RIGHT for some topics. The difference in sentiments (towards Biden and Trump) between LEFT and RIGHT is significant. The effects are higher in tweets than in headlines, suggesting more variance in political slants in news on Twitter. Further, news tweets are more sentimental than news headlines. The increase in the political slant in news tweets (versus headlines) is better aligned with the political leaning for RIGHT than LEFT.

We compare readers' reactions to the news on Twitter between LEFT and RIGHT. Moral foundations in readers' reactions to LEFT and RIGHT differ. The differences are statistically significant; however, the effects are very small. Further, the shift in moral foundations (from the mean) differs between LEFT and RIGHT across social and political issues. User engagement (number of reader reactions per tweet) is highest in reactions to the RIGHT and lowest in reactions to BALANCED.

To the best of our knowledge, this is the first work that analyzes how moral foundations differ between readers' reactions to the news from LEFT and RIGHT across social and political issues on Twitter. Analyzing political slants in news and readers' reactions to such news can aid us in understanding the influence of news in shaping public opinion and help us discern more proficient strategies for news propagation.

Organization. Section II describes the related works, Section III describes the dataset, Section IV explains the methodology, Section V details the results of our analysis, Section VI includes a discussion and underlines the limitations and threats to validity. The paper ends with a conclusion in Section VII.

II. Related Work

A. Slanted News and Influence on Readers

Bias exists in the selection and sharing of information, especially news [14, 15]. Online news consumption shows a partisan preference, with readers spending substantially longer on news sources that align with their political leaning [16]. Online news consumers visit a few favorite mainstream news publishers more often than others [5].

Exposure to attitude-conforming political information correlates with polarizing people's opinions to align with the values of the political party they support [6, 7, 8, 9]. Exposure to like-minded partisan news significantly increases political campaign activity, whereas exposure to conflicting news has the opposite effect [17]. Effects of counter-attitudinal news do not differ from those of balanced news [18]. The longer individuals spend on attitude-consistent from slanted sources, the more immediate attitude reinforcement occurs [9].

News publishers often have different ideological preferences [19]. Some news publishers align their content to the preference of their readers to ensure better subscription revenue [20, 21], some align their content to attract the audience that their advertisers want [22]. The newsroom's ideology also influences the news content and the political slant in the news [23, 24]. News organizations often express their ideological bias not by directly advocating for a preferred political party but by disproportionately criticizing one side [25].

Cicchini et al. [26] study news sharing behavior of Argentinian news media outlets on Twitter and find that media is biased towards the two major national parties and reader groups can be identified based on their news consumption. In the context of the US, prior studies suggest mixed findings. While some suggest strong liberal bias [27], others indicate a centrist stance [25, 28]. Garz et al. [29] find that headlines reported by LEFT are relatively favorable to Democrats, and headlines reported by RIGHT are relatively favorable to Republicans. Interestingly, news framing is not only consequential [30, 31] but also differs based on the publishers' ideology [32].

Many prior works have presented methods to identify political slants in news reporting. Groseclose and Milyo [27] measure the political slant of news publishers by monitoring the relative citation frequency of various policy groups by news publishers and members of Congress. Ho et al. [28] use positions taken on Supreme Court cases to identify publishers' ideological positions. Gentzkow and Shapiro [20] measure news media slant based on the similarity of a news publisher's language to that of a congressional Republican or Democrat. Le et al. [33] measure the slant of news by observing their sharing patterns on Twitter. Budak et al. [25] measure news media slant based on how positive, negative, or neutral news reports are toward members of different political parties.

Our definition of political slant in the news is inspired by Kahn and Kenney [34]. Kahn and Kenney [34] identify news slant based on the tone (i.e., positive, neutral, or negative) of news coverage toward incumbent senators. We identify political slants in the news based on news coverage of presidential candidates. Perception of candidates' traits among voters is important to analyze as it impacts voters' choices [35, 36].

Unlike previous approaches that rely on human annotations, our approach is unsupervised. Getting human annotations for large datasets can be expensive. Further, human annotations for political bias in news reports are sensitive to prior knowledge about the news event [37] and the differences in sensitivity to bias among annotators [38]. To overcome these challenges, we use a Target-dependent Sentiment Classification (TSC) approach to identify sentiments toward a political entity. We use the sentiments toward the two major parties' presidential candidates to infer political slant in news reporting. Our approach does not require human annotations and is scalable.

B. News and Social Media

Social media is one of the most common ways to get political news [1, 39], and influences the level of participation in traditional politics [40]. Social media platforms can potentially contribute to partisan polarization [2]. Politicians use social media for self-promotion, to disseminate information among their followers, and to set the agenda that favors their political interests [41]. Manifestations of politics can be identified in social media architecture (network structure) and dynamics (information flow) [42]. Mainstream news sources and the readers on social media are identifiably partisan [43].

Cross-cutting exposure in social networks fosters political tolerance and makes individuals aware of legitimate rationales for oppositional viewpoints [44]. Exposure to counter-attitudinal political information slows down polarization in a social network but also leads to lower user satisfaction [45]. However, algorithmic content filtering, an approach often employed by social media platforms to personalize content recommendations, is unlikely to expose its users to counter-attitudinal news [46].

Marozzo and Bessi [47] analyze how Twitter readers express their voting intentions about a referendum. They use a set of hashtags to categorize each tweet as supporting, neutral, or opposing the referendum. Hashtags are useful in identifying trends on social media; however, hashtags are prone to manipulation [48]. In contrast, we use target-based sentiments to determine favorability toward presidential candidates in news tweets and analyze reader reactions based on moral foundations.

Moral Foundation Theory (MFT) [12] is a social psychological theory that seeks to explain the origins of and variations in human moral reasoning. According to MFT, there are five dimensions of morality, each with two sides—virtue and vice. These five moral foundations are care/harm, fairness/cheating, loyalty/betrayal, authority/subversion, and purity/degradation. Liberals and conservatives rely on different sets of moral foundations; liberals more strongly endorse care/harm and fairness/cheating (i.e., the "individualizing" foundations), whereas conservatives more strongly endorse loyalty/betrayal, authority/subversion, and sanctity/degradation (i.e., the "binding" foundations) [49]. Further, the usage of moral foundations differs across politicians from different political parties [50].

Roy and Goldwasser [50] use MFT to identify stance and partisan sentiments of tweets by US parliamentarians and find a strong correlation between moral foundation usage and a politician's nuanced stances. Mokhberian et al. [51] use MFT to identify framing and ideological bias in the news and find systematic differences across liberal and conservative media. Roy et al. [52] use MFT to identify moral framing in political tweets and find that moral foundations toward entities differ highly across political ideologies.

Sentiments and topics on social media can be a good proxy for public opinion. Data from social media, such as Twitter, replicate consumer confidence and presidential job approval polls [53]. Twitter user sentiments are more predictive of the upcoming election than mainstream news media opinion polls [54]. We use Twitter data to understand how politically slanted news coverage influences its readers by identifying differences in moral foundations in readers' reactions to LEFT, BALANCED, and RIGHT.

III. Dataset

We present *NewsSlant*, a dataset to analyze political news and its influence on readers. The dataset includes news headlines, news tweets, and reader reactions to news tweets.

We collected news headlines from six major US news publishers, covering news stories relevant to the 2020 US presidential elections. To ensure balance in the dataset, we included two left-leaning (CNN and The Washington Post), two right-leaning (Fox News and Breitbart News), and two non-partisan (balanced) news publishers (USA Today and Business Insider). We obtained the political leaning of news publishers based on ratings from AllSides [13]. Allsides provides political inclination ratings to news publishers based on crowd-sourced annotations and expert reviews.

We used News API [55] to identify URLs for relevant news articles based on a set of keywords (see Table V in the appendix). To scrape news articles from the retrieved URLs, we used Newspaper3k [56]. We collected news articles published between March 25th 2020 (a month before Joe Biden announced his candidacy) and January 20th 2021 (Inauguration Day). We filtered out all the news headlines that didn't mention one of the two major parties' presidential candidates.

In addition to online news, we collected tweets published by the official Twitter handle of the same news publishers for the same period as the news headlines that mention one of the two candidates. We used Twitter's developer API [57] to collect the tweets. Additionally, we retrieved all reader reactions (response tweets) to the collected news tweets.

NewsSlant contains ≈36k news headlines and ≈25k news tweets and ≈4M reader reactions (response tweets) to the news tweets on Twitter. Table I shows the distribution of news headlines, tweets, and reader reactions for each news publisher. The dataset[1] and codebase[2] are publicly available.

[1]https://ieee-dataport.org/documents/newsslant

[2]https://github.com/ahaque2/NewsSlant

Publisher	Leaning	News	Tweets	Reactions
CNN	LEFT	6 485	6 108	1 704 194
The Washington Post	LEFT	4 678	6 999	1 051 062
Business Insider	BALANCED	4 803	3 872	41 731
USA Today	BALANCED	4 216	3 490	119 377
Fox News	RIGHT	8 327	872	648 719
Breitbart News	RIGHT	7 377	3 243	474 525

TABLE I: Distribution of news headlines, tweets, and reader reactions for each news publisher. Leaning from AllSides [13].

IV. Methodology

A. Analyzing News Headlines and Tweets

Detecting sentiment in the news is challenging as the sentiments expressed are often nuanced and not as explicit as on social media [58]. Further, popular traditional sentiment analysis approaches disregard the aspect for which the sentiment is expressed. This adds challenges when a sentence has mixed sentiments, i.e., positive toward some aspect and negative toward another. To overcome these challenges, we use NewsSentiment [59], a target-based sentiment analysis approach, to identify the sentiments in the news toward the two major parties' presidential candidates.

NewsSentiment uses a bidirectional GRU on top of a Language Model (LM) and is trained on political news articles. NewsSentiment can identify sentiments toward a specified target in a sentence. For any given sentence, it produces a positive, a negative, and a neutral sentiment score (toward a specified entity) between [0,1], with 0 indicating the lowest and 1 indicating the highest sentiment intensity.

A sentiment analysis approach that works for news text is usually unsuited for tweets. However, news tweets are similar to news headlines in writing style and are more formal than most tweets (i.e., unlikely to have spelling errors or Twitter-specific jargon). Hence, we use the same sentiment detection approach for news headlines and tweets.

We use bootstrapping to compute the confidence intervals and standard errors of the sentiment distributions. We employ Scipy[3] for bootstrapping. We also visually compare the sentiments between LEFT and RIGHT via distribution plots.

For a more fine-grained analysis, we identify the topic of the news. We use BERTopic [60] to identify the news topics. BERTopic is a transformer-based topic modeling approach that uses BERT to extract meaningful topics from text data. Unlike traditional topic modeling techniques, which rely on matrix factorization and probabilistic models, BERTopic leverages deep learning to better capture the semantic relationships between words.

We preprocess each tweet using the Tweet-preprocessor [61]. Further, we remove stopwords and unwanted texts common in tweets, such as mentions, URLs, and hashtags. We also remove common words in our dataset, such as party or politician names, that do not relate to any topic (see Table VI in the appendix for more details). We use a list of seed words to guide the topic modeling toward more meaningful clusters. To expand the list of seed words, we use a snowball strategy.

[3]https://docs.scipy.org

Entity	Source	Source Leaning		
		LEFT	BALANCED	RIGHT
Biden	Headlines	1.261	1.210	0.435
	Tweets	1.428	1.311	0.393
Trump	Headlines	0.194	0.233	0.322
	Tweets	0.215	0.242	0.494

TABLE II: Favorability scores across publisher groups.

We first generate topics with an empty seed word list and add seed words based on the top words in the identified topics. We repeat this process thrice, adding more seed words based on the identified topics and regenerating the topics. Each headline is labeled with at most one topic, and we stop after three iterations. We manually merge similar topics; for example, Covid-19 vaccines and Covid-19 cases/death related news are combined into one topic called Covid-19. Similarly, news on elections relating to mail-in ballots, voter fraud, and polls are combined into one topic, Elections, and so on. The list of seed words and the identified topics can be found in the Appendix.

We investigate differences in how news publishers (across political leaning) report news mentioning the two major parties presidential candidates. We identify *relative* slants in news coverage by comparing the relative *favorability* of news coverage of the same news stories within and across news publisher groups (LEFT, and RIGHT). Favorability score is computed as the ratio of the mean positive sentiment to the mean negative sentiment toward an entity. We compute favorability scores for both candidates separately for each news publisher group. We further analyze the differences in favorability toward each candidate on different topics.

We conduct statistical tests to confirm whether the differences in sentiments between LEFT and RIGHT are statistically significant. To pick a suitable statistical test to compare the distributions, we first identify if the compared distributions are Gaussian (i.e., normal distribution). To verify the normality of the distributions, we use the Shapiro-Wilks normality test [62]. Since none of the distributions are normal, we use the nonparametric Kruskal-Wallis H statistical test suitable for nonnormal distributions. We compute the effect size using epsilon square (ϵ^2) [63], which is well suited for the Kruskal-Wallis H test [64]. We interpret ϵ^2 (Table XII in the Appendix) based on interpretation from Field [65]. For all significance tests, we assume the null hypothesis to indicate a similar distribution of sentiments between LEFT and RIGHT and the alternative hypothesis to indicate they are different. We set the significance level, i.e., alpha, as 0.01 to accept or reject the null hypothesis.

B. Analyzing Reader Reactions

We adopt the RoBERTa model (Robustly Optimized BERT Pretraining Approach) [66] to identify moral foundations in reader reactions. RoBERTa is based on Bidirectional Encoder Representations from Transformers (BERT), a transformer-based deep-learning language representation model. While BERT advanced the state-of-the-art for eleven benchmarks NLP tasks, RoBERTa further improved GLUE [67], and SQuAD benchmarks [68, 69]. The RoBERTa model is retrained on ≈58 million tweets to capture the Twitter language specifics and fine-tuned on the Moral Foundation Twitter Corpus (MFTC) [70] to identify moral foundations in reader reactions. The MFTC contains ≈35k tweets annotated for moral foundations based on MFT. Each tweet is annotated with eleven labels (two for each of the five moral foundations and one for the nonmoral foundation). A tweet in the MFT corpus can have more than one label. However, we restrict to one label per tweet, choosing based on the majority label and randomly in case of a tie.

The RoBERTa model, fine-tuned to detect moral foundations, produces a softmax score for each tweet for the ten moral foundations and a score for the nonmoral foundation. Softmax is an exponential function that normalizes the output of a model to a probability distribution over predicted classes that sum up to one. We use the softmax scores as the moral foundation scores for a given tweet.

We analyze whether readers' reactions to the news on Twitter differ between LEFT and RIGHT. We use the shift in the moral foundation of readers' reactions as a metric for the comparison. Shift in the moral foundation measures how much the readers' reactions differ from the mean. It is computed as the change (in percent) in the moral foundation score from the mean for each moral foundation and is computed separately for each news publisher group. We identify the news topics and the moral foundations for which the shift is substantial.

We further compute user engagement for each news publisher group to identify differences in how engaging each news publisher is on Twitter. User engagement is the average number of reader reactions to each news tweet. We compute user engagement for each topic separately for LEFT, BALANCED, and RIGHT.

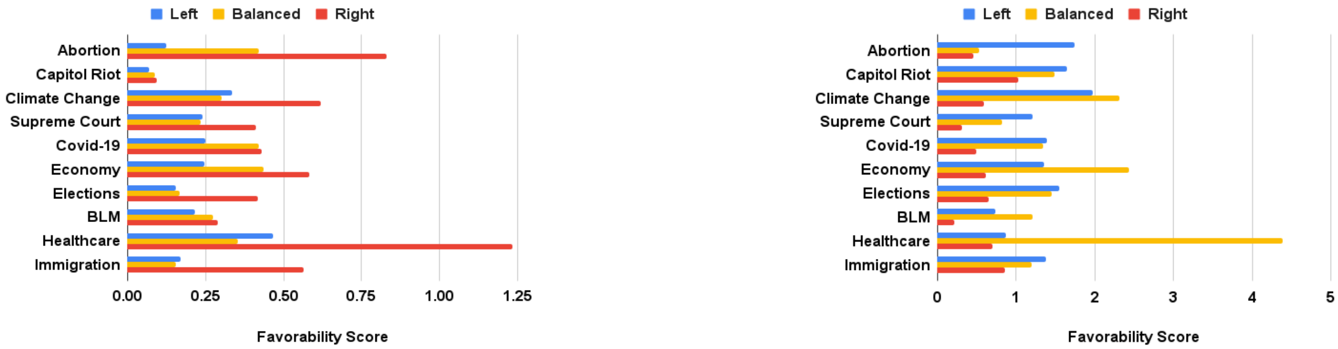
V. Results

A. News Headlines and Tweets

We compute bootstrapped standard error and confidence intervals for sentiment distributions toward the two candidates (see results in the appendix, Table X). The difference between low and high confidence intervals and the standard error is low, indicating that bootstrapped sample means are closely distributed around the actual distribution means and the sample represents the actual data well. Figure 4 (in the appendix) compares the sentiment distributions toward the two candidates between LEFT and RIGHT visually.

Table II shows the favorability scores toward the two candidates in headlines and tweets. Figure 1 and Figure 2 compare the favorability scores for the two candidates on different topics across news publisher groups. RIGHT has a higher favorability score for Trump for all news topics, and LEFT has a higher favorability score for Biden for all news topics in both, news headlines and tweets. BALANCED is more favorable to Biden than Trump, and in some cases even more favorable than LEFT. LEFT favors Biden and RIGHT favors Trump across all topics. Favorability is higher for Biden than Trump both in news headlines and tweets.

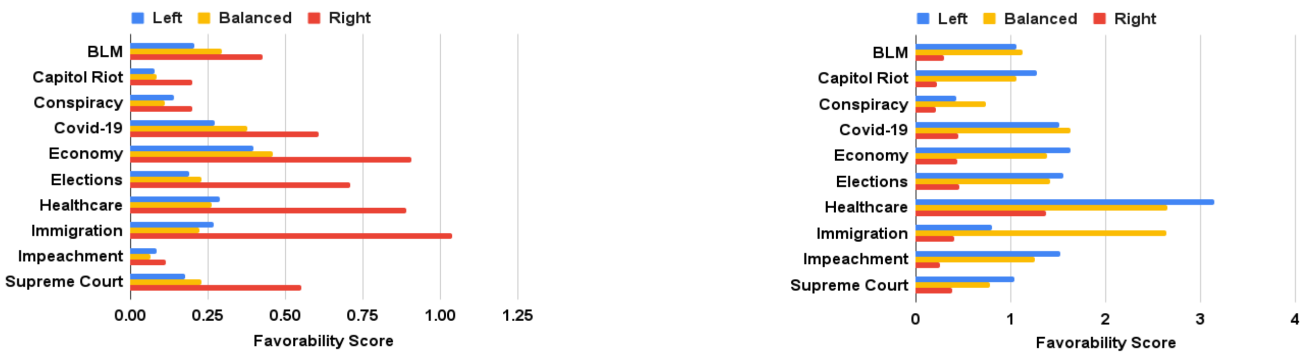
To isolate the differences between news coverage from LEFT and RIGHT, we conduct statistical significance tests. We



(a) Favorability toward Trump

(b) Favorability toward Biden

Fig. 1: Favorability scores of news headlines toward Trump and Biden across news topics for different publisher groups.



(a) Favorability toward Trump

(b) Favorability toward Biden

Fig. 2: Favorability scores of news on Twitter toward Trump and Biden across news topics for different publisher groups.

compare the sentiment distributions toward the two candidates between LEFT and RIGHT. The differences in sentiment distributions toward the two candidates are statistically significant for both, news headlines and tweets (see Table XIII in the appendix for detailed results). However, effect sizes vary, with news tweets showing a greater effect size than news headlines. For news headlines, the effects are moderate for negative sentiments and small for positive sentiments toward Biden, and the effects are very small for both positive and negative sentiments toward Trump. For news tweets, the effects are moderate toward Biden and small toward Trump for both sentiments.

To conduct a more fine-grained analysis, we identify topics in the news via topic modeling. For news headlines, 79 topics were identified that were manually merged into 20 topics. For news tweets, 90 topics were identified that were manually merged into 20 topics. Further, we manually identified ten topics (from the identified topics) corresponding to social and political issues in the news. The complete list of subtopics and topics (subtopics combined manually) can be found in the appendix; see Table VIII and Table IX. While most topics discussed are common across news headlines and tweets, some are exclusive. Common topics include Capitol Riots, Climate Change, Supreme Court, Covid-19, Elections, Economy, BLM (Black Lives Matter), Healthcare, and Immigration. Topics exclusive to news headlines are Abortion and Climate Change. Topics exclusive to news tweets are Conspiracy Theory and Impeachment. We further compare sentiment distributions across news topics (Table XIV and Table XV in the appendix show the results). We compare only those news topics for which there are at least ten data points to compare (i.e., a minimum of ten headlines or tweets on the topic for each candidate). For headlines, all topics show a statistically significant difference between LEFT and RIGHT with a few exceptions. News on healthcare and Capitol Riots don't show a statistically significant difference for either candidate for either sentiment. News on BLM and Climate Change show statistically significant differences with moderate effect sizes, but only for Biden. In contrast, news on Immigration shows statistically significant differences with moderate effect sizes but only for Trump. For news on Twitter, topics including Economy and Elections show significant differences with moderate effect sizes for both sentiments and for both candidates. In contrast, news on Immigration and Conspiracy Theory doesn't show a significant difference between LEFT and RIGHT for any sentiment for either candidate. News on Impeachment and BLM shows a significant difference in both sentiments for Biden with large effects, but not for Trump.

Topic	Slant	Nonmoral	Care	Harm	Authority	Subversion	Fairness	Cheating	Loyalty	Betrayal	Purity	Degradation
BLM	LEFT	**−5**	10	**47**	−2	−3	**20**	−4	2	**22**	**0**	**−3**
	RIGHT	**3**	16	**25**	−7	−12	**−1**	−14	2	**−5**	**85**	**19**
Economy	LEFT	−5	**−5**	−24	1	8	−6	23	1	1	−17	−17
	RIGHT	−13	**22**	−5	14	18	1	24	1	14	−12	−15
Conspiracy Theory	LEFT	**−3**	−19	−12	**−10**	−1	−3	**21**	**−10**	−3	**1**	**1**
	RIGHT	**5**	−5	−9	**20**	0	−14	**−14**	**1**	−9	**−5**	**−4**
Capitol Riots	LEFT	−13	**30**	**40**	9	18	0	−10	6	46	−3	9
	RIGHT	−13	**−3**	**65**	0	16	12	−5	0	55	−10	2
Impeachment	LEFT	−7	−12	**−18**	24	23	4	−7	**0**	**6**	−2	15
	RIGHT	−12	−1	**14**	27	29	0	−9	**33**	**26**	−6	4
Healthcare	LEFT	**−5**	**14**	**4**	8	8	7	**4**	−2	−2	**−6**	**−1**
	RIGHT	**4**	**−1**	**−2**	1	0	12	**−2**	−2	−3	**−26**	**−30**
Immigration	LEFT	**3**	**32**	34	**−9**	**−12**	6	−16	**−1**	**−8**	**10**	**16**
	RIGHT	**−7**	**76**	21	**20**	**16**	10	−13	**25**	**21**	**−17**	**−10**

TABLE III: Shift in the mean moral foundation scores for each topic from the overall mean across news publisher group. Values are in percent (%). We highlight major shifts based on differences in the shift between responses to LEFT and RIGHT. ■ Change (> 20%), and ■ Change (>5%) in opposite directions.

	Source Leaning		
	Left	Balanced	Right
User Engagement	210	21	272

TABLE IV: User engagement for news publisher groups.

Finding 1: News

News sources of the LEFT and RIGHT show signs of political slant in election-related news. The difference in the news coverage of presidential candidates between LEFT and RIGHT is statistically significant, and the effect size varies across social and political issues. The slant is more prominent in the news on Twitter than in headlines. The slant on Twitter appears to be more aligned with the political leaning for the news from RIGHT than LEFT.

B. Reader Reactions

The differences in moral foundations in readers' reactions to LEFT and RIGHT are statistically significant for all moral foundations except loyalty. However, the effects are very small (See Table XVI in the appendix for more details).

Table III shows the shift in moral foundations across news topics (i.e., social and political issues) in readers' reactions to the news from LEFT, and RIGHT. A more detailed result can be found in the appendix (Table XVII). Certain topics fetch more discussion containing moral foundations than the mean for a news publisher group. Topics for which the aggregate moral foundation scores increase across all news publisher groups include Supreme Court, Economy, Capitol Riots, and Impeachment. For discussions related to Elections, Conspiracy Theory, BLM, and Healthcare, the aggregate moral foundation scores decrease in readers' reactions to the RIGHT but increase in readers' reactions to the LEFT. Immigration is the only topic for which the aggregate moral foundation score decreases for the LEFT but increases for the RIGHT. The only topic for which the aggregate moral foundation score decreases across all news publisher groups is Covid-19.

User engagement differs substantially between LEFT, BALANCED, and RIGHT. BALANCED is the least engaging and the RIGHT is the most. Table IV shows the overall user engagement across different news publishers grouped based on political leaning. User engagement is substantially higher for LEFT and RIGHT than BALANCED. Figure 3 compares the user engagement between LEFT and RIGHT across different social and political issues. Few topics have close to equal engagement between LEFT and RIGHT. Topics such as Conspiracy Theory, and Healthcare are more engaging topics for the audience on LEFT (readers responding to LEFT). In contrast, topics like Impeachment, Supreme Court, Elections, Immigration, Capitol Riots, Covid-19, Economy, and BLM are more engaging for the audience on RIGHT (readers responding to RIGHT). BALANCED has the lowest user engagement for all topics.

Finding 2: Reader Reactions

Moral foundations differ significantly between readers' reactions to LEFT and RIGHT. The shift in moral foundations across news topics (i.e., social and political issues) differs between readers' reactions to LEFT and RIGHT. News from the RIGHT is most engaging, followed by the news from LEFT, while the news from BALANCED is least engaging.

VI. Discussion

We find that news from partisan news publishers shows signs of political slant. This corroborates earlier findings that found systematic differences between liberal and conservative media based on moral framing of the news [51], and that political headlines are slanted congenially with respect to the preferences of the news publishers' typical readers [29]. However, our findings contradict earlier findings that mainstream news outlets in the US present news in a largely nonpartisan

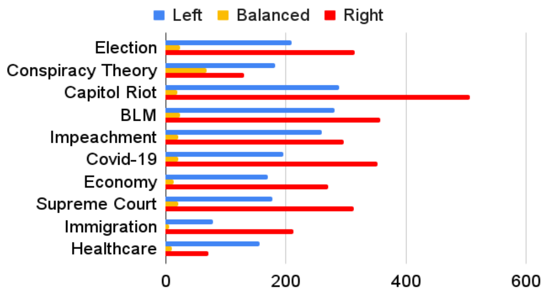


Fig. 3: User engagement for different news topics.

manner and do not show favoritism toward either Democrats or Republicans [25].

The distribution of sentiments toward the presidential candidates differs significantly between LEFT and RIGHT across news headlines and tweets. However, the effects are greater for tweets than headlines, suggesting more variance in political slant on Twitter. Further, news tweets are more sentimental (i.e., higher mean sentiment score) than news headlines. The increased sentiment in news on Twitter aligns with news publishers' political leaning more for RIGHT than LEFT. News on Twitter from LEFT and BALANCED are more favorable than the headlines for both candidates. However, for news from RIGHT, the favorability in the news on Twitter (compared to news headlines) increases for Trump but decreases for Biden.

Favorability is higher for Biden than Trump across all publishers. This may be because Trump is the incumbent president amidst a global pandemic (Covid-19) with a lot of negative news that mentions him. The RIGHT has substantially higher negative sentiments toward Biden in both the news headlines and tweets. In contrast, the negative sentiment toward Trump doesn't vary as much across news publisher groups. Prior research found evidence that news publishers express their ideology not by directly advocating for the preferred political party but by disproportionately criticizing the other party [25]. The substantial difference in the negative sentiment toward Biden suggests that the RIGHT may be using disproportionate criticism against Biden to advocate relative support for Trump.

Our findings corroborate earlier findings that suggest liberals and conservatives rely on different moral foundations [49]. The shifts in moral foundations in readers' reactions differ across news topics between LEFT, and RIGHT. Covid-19 is the only topic for which the readers' reactions show a consistent shift (i.e., increment or decline) for all moral foundations across all news publisher groups. Covid-19 is also the only topic for which the discussions containing moral foundations decrease across all news publisher groups. Perhaps because many Covid-19 related discussions are about facts and figures, such as symptoms, infection rate, death toll, and so on, and may not contain a moral foundation. Care/Harm and degradation are the only moral foundations that increase in readers' reactions to Covid-19 related news, while all other moral foundations decline. For some topics, the shift is in the opposite direction. This is true for readers' reactions to news on topics such as BLM, Conspiracy Theory, Healthcare, and Immigration.

A. *Threats to Validity*

Determining the political slant of a news publisher is a challenging problem. While we take good care of doing a careful analysis to get insights, our methodology has some threats to validity that need to be acknowledged. *First*, the presumed political leaning of news publishers is determined based on political bias ratings from Allsides. Though these ratings are generally considered correct and have been used in many prior studies to identify political bias in news reporting, these may not be accurate. Further, it is difficult to classify any news publisher as purely left-leaning or right-leaning as they may have mixed stances on different political and social issues. *Second*, we only used two news publishers for each news publisher group. Including more news publishers can potentially change the results. *Third*, we use data from Twitter to understand readers' reactions to the news from LEFT and RIGHT. Though Twitter is a good proxy for public opinion [53, 54], and has been used by previous studies as a sentinel tool to monitor public opinion [71]. Data from Twitter can only account for the audience that uses the platform. Further, opinions on Twitter may not necessarily reflect readers' true opinions, and we do not check if the tweets are from real accounts or bots. Though the estimated proportion of bots on Twitter is low, they may play a more vital role in discussions on contentious social and political issues. Thus, any generalization based on the results should be made with caution.

B. *Limitations and Directions*

Although we use state-of-the-art models to conduct the analysis, our analysis still has limitations. *First*, we define political slant based on favorable and unfavorable news, which is determined based on the sentiments toward a political entity. While sentiment toward a political entity (over a period of time) could be a good indicator of the political slant of a news publisher, it is far from perfect. *Second*, we look at the two major parties presidential candidates to identify the political slant in the news. However, the news mentions many other political entities that may reveal a different slant. *Third*, topic modeling via BERTopic used to identify news topics (social and political issues) assumes only one topic per news tweet, while a news tweet can potentially discuss more than one topic. All of the above observations suggest important directions for future work. Incorporating changes in framing within topical news [72], and adopting a more nuanced approach to the attribution of blame in political discourse [73, 74] can enhance the efficacy of our methods. We leave this for future work.

VII. Conclusion

Our results demonstrate that news publishers show signs of political slant in election-related news in news headlines and on Twitter. News on Twitter is more slanted than news headlines, and the slant on Twitter is better aligned with the political leaning for the RIGHT than LEFT. Further, moral foundations differ between readers' reactions to the news from

LEFT and RIGHT. Consumers of different news publishers often focus on different aspects (moral foundations) of a social or political issue, making it more challenging to reach a consensus or effective conflict resolution.

Algorithmic content filtering, often used on social media platforms to recommend content to readers could potentially exacerbate political polarization by recommending content that aligns with a user's existing political opinions. The increased use of social media for news consumption and the abundance of choices of news sources make political polarization more likely. Our research highlights the need to identify better ways of disseminating news with reduced polarizing effects.

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APPENDIX

Keywords
Trump, Biden, Election, President, Democratic, Republican

TABLE V: Keywords used to identify news related to the 2020 US presidential elections.

Keywords
Donald, Trump, Joe, Biden, President

TABLE VI: Keywords removed during pre-processing before topic modeling.

Topic	Keywords
Covid-19	drug, outbreak, flu, infection, contagious, treatment, prescription, Covid, test, virus, ventilator, deaths, cases, pandemic, epidemic, corona, coronavirus, Covid19, patients, symptom
Covid-19 Lockdown	lockdown, shutdown, mask, distancing, masks
Covid-19 Vaccination	vaccine, vaccination, cure, moderna, pfizer, astrazeneca, j&j, dose
Covid-19 Educational_impact	education, school, student, teacher, children, homeschool, schools, students, teachers
Economy	economy, industry, business, financial, finance, fiscal, economic, job, jobless, investing, investor, billion, gdp, debt, liquidity, inflation, stimulus, bill, stocks, market, employment, unemployment, checks, cheques, recession, bull, bullish, bear, bearish, dow, s&p, nasdaq, trade, trading, tax, loan, labor, buyback, selloff, wealth, wealthy, billionare, millionare'
Climate Change	earth, green, pollution, ozone, deforestation, greenhouse, wildfire, climate, warming, temperature, flood, drought, glacier, environment, environmental, carbon, emission, gas, fracking
Capitol Riots	capitol, riot, siege, rioter, mob
Elections	voter, absentee, ballot, fraud, mailin, stolen, voting, Election, black voters
Immigration	Immigration, immigrant, refugee, border, wall, migration, h1b, visa
Black Lives Matter	blm, floyd, police, brutality, defund, protest, protesters, officer, black lives matter, injustice, racism, racial, supremacist
Abortion	abortion, wade, roe
Supreme Court	supreme, court, coney, barret, packing, justice, judge
National Security	security, military, weapons, attack, defense, gun, shooting, pentagon
International News	international, country, global, china, chinese, beijing, shanghai, iran, irani, iranian, tehran, afghanistan, afghan, afghani, afghanistani, kabul, russia, russian, moscow, britain, british, brit, brexit, london, Korea, Korean, kim, venezuelan, venezuela, syrian, syriaworld, worldwide

TABLE VII: List of seed words used for topic modeling news headlines and tweets

Topic	SubTopics
Election	Elections, voting fraud, Election polls, black voters, georgia runoff
Covid-19	new cases, symptoms and precautions, vaccine, public advisory, drugs and treatment, testing, school reopenings, Covid-19 supplies
Economy	economic stimulus, taxes, markets

TABLE VIII: Topics formed by manually merging subtopics in news headlines. Subtopics are identified by BERTopic.

Topics	SubTopics
Election	Election, vote, Election fraud, electoral college, presidential debate, Election polls and opinions, biden inauguration, tulsa rally
Covid-19	new cases, Covid-19 response, face covering and mask, vaccine, school reopening, public advisory, Covid-19 treatment
Economy	economic stimulus, taxes
Conspiracy Theory	conspiracy theories, and fact-check

TABLE IX: Topics formed by manually merging subtopics in news tweets. Subtopics are identified by BERTopic.

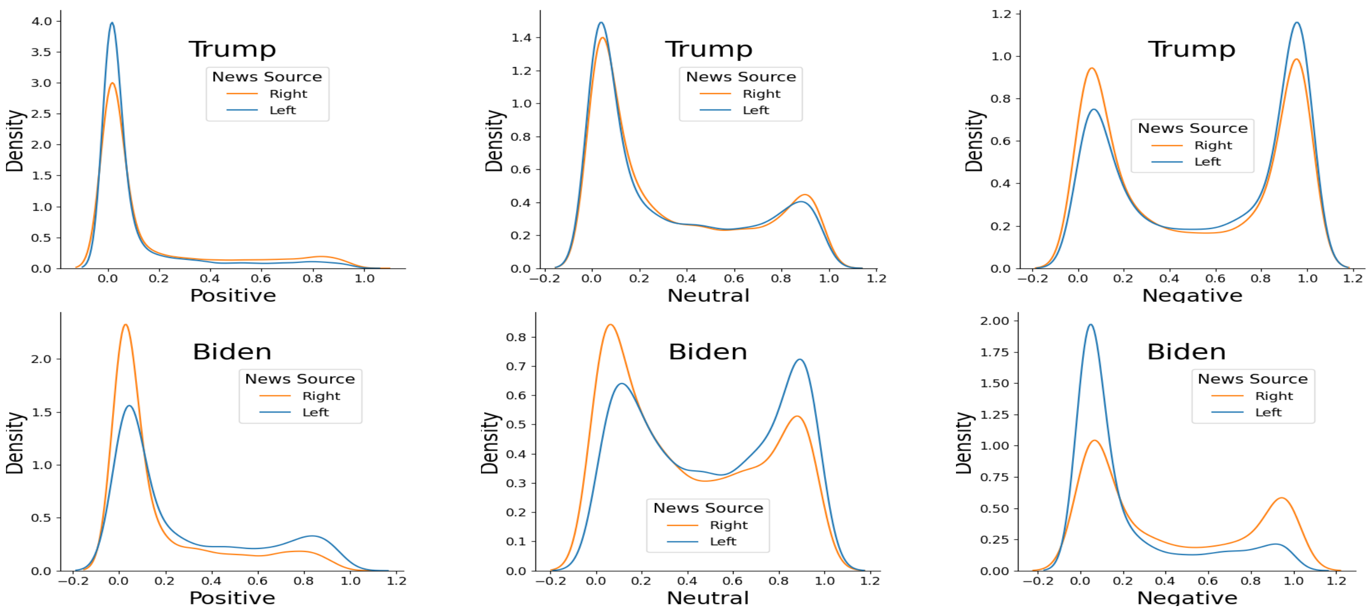

Fig. 4: Comparing sentiment distributions in headlines between LEFT and RIGHT. To ensure a fair comparison, we downsample the bigger sample and compare an equal number of samples in each case.

Source	Entity	Sentiment	Confidence-Interval$_{Low}$	Confidence-Interval$_{High}$	Standard-Error
RIGHT	Biden	Positive	0.250	0.261	0.003
		Negative	0.370	0.376	0.002
		Neutral	0.324	0.330	0.002
	Trump	Positive	0.255	0.264	0.002
		Negative	0.391	0.394	0.001
		Neutral	0.326	0.332	0.002
LEFT	Biden	Positive	0.300	0.313	0.003
		Negative	0.275	0.293	0.005
		Neutral	0.318	0.327	0.002
	Trump	Positive	0.202	0.214	0.003
		Negative	0.380	0.384	0.001
		Neutral	0.323	0.329	0.002

TABLE X: Bootstrapping mean errors for sentiment distributions.

Pub	Headlines						Tweets					
	Trump			Biden			Trump			Biden		
	Positive	Negative	Neutral	Positive	Negative	Neutral	Positive	Negative	Neutral	Positive	Negative	Neutral
LEFT	0.110	0.568	0.322	0.275	0.218	0.507	0.129	0.598	0.274	0.329	0.230	0.441
CENTER	0.128	0.550	0.321	0.294	0.243	0.463	0.134	0.551	0.316	0.314	0.239	0.447
RIGHT	0.162	0.503	0.335	0.178	0.409	0.413	0.207	0.419	0.373	0.175	0.447	0.378

TABLE XI: Mean sentiment scores of news headlines and tweets toward Trump and Biden for news publishers grouped based on political leaning.

	Effect Size	Interpretation
Epsilon-Square (ϵ^2)	[0.00, 0.01)	Negligible
	[0.01, 0.06)	Small
	[0.06, 0.14)	Medium
	[0.14, 1.00]	Large

TABLE XII: Effect size and their corresponding interpretations. Interpretations based on Field [65].

Entity	Sentiment	Tweets		Headlines	
		p-value	ϵ^2	p-value	ϵ^2
Biden	Negative	0.00*	0.078	0.00*	0.068
	Positive	0.00*	0.090	0.00*	0.041
Trump	Negative	0.00*	0.036	0.00*	0.007
	Positive	0.00*	0.012	0.00*	0.005

TABLE XIII: Statistical test comparing sentiment distributions toward the two major parties' presidential candidates in news headlines and tweets between LEFT and RIGHT.

Topics	Positive Sentiment				Negative Sentiment			
	Biden		Trump		Biden		Trump	
	p-value	ϵ^2	p-value	ϵ^2	p-value	ϵ^2	p-value	ϵ^2
Abortion	0.05	0.04	0.00*	0.12	0.00*	0.09	0.00*	0.10
Healthcare	1.00	0.00	0.03	0.04	0.75	0.00	0.06	0.03
Capitol Riots	0.07	0.01	0.08	0.00	0.03	0.02	0.30	0.00
Supreme court	0.00*	0.06	0.00*	0.02	0.00*	0.07	0.00*	0.02
Economy	0.00*	0.03	0.00*	0.04	0.00*	0.03	0.00*	0.05
BLM	0.00*	0.03	0.09	0.00	0.00*	0.07	0.15	0.00
Climate Change	0.00*	0.07	0.06	0.01	0.00*	0.10	0.26	0.01
Elections	0.00*	0.05	0.00*	0.05	0.00*	0.03	0.00*	0.09
Immigration	0.29	0.01	0.00*	0.06	0.18	0.01	0.00*	0.02
Covid-19	0.00*	0.03	0.00*	0.01	0.00*	0.07	0.00*	0.01

TABLE XIV: Statistical test comparing sentiment toward Trump and Biden in news headlines between LEFT and RIGHT.

Topics	Positive Sentiment				Negative Sentiment			
	Biden		Trump		Biden		Trump	
	p-value	ϵ^2	p-value	ϵ^2	p-value	ϵ^2	p-value	ϵ^2
Economy	0.00*	0.12	0.00*	0.02	0.00*	0.06	0.00*	0.03
Conspiracy Theory	0.10	0.02	0.32	0.00	0.01	0.05	0.02	0.01
Elections	0.00*	0.08	0.00*	0.04	0.00*	0.05	0.00*	0.10
Immigration	0.59	0.01	0.06	0.07	0.56	0.01	0.22	0.03
Impeachment	0.00*	0.14	0.86	0.00	0.00*	0.16	0.23	0.01
BLM	0.00*	0.10	0.00*	0.02	0.00*	0.15	0.00*	0.02
Supreme Court	0.03	0.06	0.00*	0.03	0.00*	0.08	0.00*	0.03
Covid-19	0.00*	0.08	0.00*	0.00	0.00*	0.03	0.00*	0.02

TABLE XV: Statistical test comparing sentiment toward Trump and Biden in news tweets between LEFT and RIGHT.

Moral Foundations	$p-$value	ϵ^2
Care	0.00*	0.0011
Subversion	0.00*	0.0001
Cheating	0.00*	0.0002
Harm	0.00*	0.0004
Fairness	0.00*	0.0011
Betrayal	0.00*	0.0004
Authority	0.00*	0.0001
Loyalty	0.156	0.0000
Purity	0.00*	0.0001
Degradation	0.00*	0.0000

TABLE XVI: Statistical test comparing moral foundations between readers' reaction from LEFT and RIGHT.

Topic	Slant	Nonmoral	Care	Harm	Authority	Subversion	Fairness	Cheating	Loyalty	Betrayal	Purity	Degradation
Election	LEFT	−1	−13	−13	0	1	−1	9	1	−1	−6	−5
	BALANCED	−2	−9	−16	1	1	0	13	3	1	−9	−11
	RIGHT	1	−9	−16	2	−1	−1	5	4	−4	−5	−8
Covid-19	LEFT	5	18	19	−7	−8	−9	−10	−7	−9	−2	5
	BALANCED	4	16	14	−11	−8	−12	−15	−6	−12	−5	32
	RIGHT	8	19	13	−7	−12	−8	−16	−9	−15	−8	6
BLM	LEFT	−5	10	47	−2	−3	20	−4	2	22	0	−3
	BALANCED	−15	6	80	3	6	18	9	−3	35	0	6
	RIGHT	3	16	25	−7	−12	−1	−14	2	−5	85	19
Supreme Court	LEFT	−5	−5	−18	18	4	58	7	1	−6	14	−3
	BALANCED	−6	−18	−11	19	16	11	−2	−3	−5	9	24
	RIGHT	−7	−10	−19	23	10	34	14	−1	−1	2	−11
Economy	LEFT	−5	−5	−24	1	8	−6	23	1	1	−17	−17
	BALANCED	−10	−2	−13	7	15	−3	30	−4	5	−24	−14
	RIGHT	−13	22	−5	14	18	1	24	1	14	−12	−15
Conspiracy Theory	LEFT	−3	−19	−12	−10	−1	−3	21	−10	−3	1	1
	BALANCED	14	−12	−30	−24	−24	−6	6	−11	−19	−1	−24
	RIGHT	5	−5	−9	20	0	−14	−14	1	−9	−5	−4
Capitol Riots	LEFT	−13	30	40	9	18	0	−10	6	46	−3	9
	BALANCED	−15	−3	57	5	22	5	0	−3	56	3	−1
	RIGHT	−13	−3	65	0	16	12	−5	0	55	−10	2
Impeachment	LEFT	−7	−12	−18	24	23	4	−7	0	6	−2	15
	BALANCED	−11	13	−3	40	22	16	−6	26	17	17	5
	RIGHT	−12	−1	14	27	29	0	−9	33	26	−6	4
Healthcare	LEFT	−5	14	4	8	8	7	4	−2	−2	−6	−1
	BALANCED	−2	−9	44	−5	−5	−5	0	−4	−5	42	−2
	RIGHT	4	−1	−2	1	0	12	−2	−2	−3	−26	−30
Immigration	LEFT	3	32	34	−9	−12	6	−16	−1	−8	10	16
	BALANCED	−7	27	27	7	18	9	−12	60	23	33	−34
	RIGHT	−7	76	21	20	16	10	−13	25	21	−17	−10

TABLE XVII: Shift in the mean moral foundation scores for each topic from the overall mean for a given news publisher group. Values are in percent (%).