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Partisan Media Sentiment Toward Artificial Intelligence

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Abstract

Artificial intelligence (AI) is becoming pervasive across society. However, its deployment appears to be a divisive issue. This research examines aversion to AI across the partisan divide. We analyze partisan media sentiment towards AI, a powerful driver of public opinion towards social issues. We conduct a text analysis of media articles on AI (N = 7,840) from several liberal-leaning and conservative-leaning media outlets. Results demonstrate that liberal-leaning media show a greater aversion to AI than conservative-leaning media. Furthermore, a mediation analysis suggests that liberal-leaning media are more concerned with AI magnifying social biases in society than conservative-leaning media, which drives the partisan media differences. Moreover, the results also show that media sentiment towards AI became more negative after George Floyd's death, an event that heightened sensitivity about social biases in society. Implications for how these partisan media differences can polarize public opinion and policymaker support towards AI are discussed.

Keywords: artificial intelligence, partisanship, political bias, media, sentiment analysis

Artificial intelligence (AI) is becoming pervasive across society. It is increasingly employed in important decisions such as job recruitment, government resource allocation, and disease detection (Esteva et al., 2017; Frank et al., 2019; Margetts & Dorobantu, 2019). However, the deployment of AI for such tasks remains a divisive issue. Some people are embracing AI-enabled decision-making and viewing it as the future. For example, some scholars have argued that AI significantly augments the capabilities of humans and completes tasks with greater speed and accuracy (Frank et al., 2019). Yet, others are hesitant to embrace the use of AI in important decision-making. For instance, many scholars have argued that AI can result in privacy violations, threaten employment, and widen the gap between the privileged and the disadvantaged groups (Frank et al., 2019; Horvitz & Mulligan, 2015; Zou & Schiebinger, 2018). As such, it is increasingly important to understand which sections of society might be more amiable to AI and which sections might be opposed to AI.

In this research, we examine the heterogeneous reactions to AI across political lines. Indeed, AI is increasingly entering the political sphere. Lawmakers are turning their attention toward AI and seeking to understand whether and how to regulate AI (Lohr, 2019). However, neither the left nor the right has declared a clear ideological stance on the deployment of AI-enabled decision-making. That is, while some lawmakers from both parties have called for regulation and oversight (Harwell, 2019; Lohr, 2019), it is still unclear whether the liberal and conservative parties will demonstrate a partisan divide over AI. Will one partisan group emerge to be a supporter of AI while the other group becomes an opponent?

To that end, we seek to assess partisan reactions toward AI by analyzing partisan media sentiment towards AI. Media sentiment is a powerful driver of public opinion (King et al., 2017; McCombs & Shaw, 1972). Research suggests that partisan media can change people’s voting behaviors (DellaVigna & Kaplan, 2007), reinforce existing political beliefs (Finkel et al., 2020), and shape attitudes towards political parties (Tokita et al., 2021).

Moreover, the media that people consume can change the composition of opinions in the national conversation in concordance with the ideological direction of the media articles (King et al., 2017). Further, people have preferences toward politically congenial media sources, and this selective exposure polarizes partisan attitudes (Iyengar & Hahn, 2009). More directly, partisan media can shape policymakers' and political leaders' attitudes towards contentious issues (Cook et al., 1983). In that, political leaders often turn to media to understand and predict public sentiment on hot-button issues and subsequently shape their policies accordingly (Clinton & Enamorado, 2014). Thus, examining partisan media sentiment towards AI is a harbinger of how liberal and conservative stakeholders might react differently toward AI.

Notably, psychological theories on political ideology generate opposing predictions for how liberal versus conservative media might differ in their sentiment towards AI. One possibility is that conservative media will demonstrate a more negative sentiment towards AI than liberal media. This is because conservatives tend to prefer the status quo and are resistant to social change (Jost et al., 2018). More directly, conservatives tend to shun new technological advances that might hurt jobs and reduce employment (Jost et al., 2018). And, AI is a massive disruptor of labor (Frank et al., 2019). More specifically, the proliferation of AI has raised concerns about "technological unemployment," suggesting that around half of the US employment is at risk of automation due to the developments in AI (Frey & Osborne, 2017). Thus, given that conservative media reflects values of preserving employment opportunities, conservative media may show a greater aversion to AI than liberal media.

However, other theories predict that liberal media may show a greater aversion towards AI than conservative media. First, AI can lead to huge gains in productivity levels by automating tasks. In fact, the productivity gains from AI can add nearly $15 trillion to the world economy by 2030 (Holmes, 2019). As conservatives tend to value efficiency and

corporate productivity (Peck, 2014), conservative media might not be averse to the employment disruption caused by AI.

A second theory suggests that liberal media tends to be more cognizant of social justice, rights, and welfare (Fryberg et al., 2012). Crucially, a large volume of research has documented that AI embeds and magnifies social biases against minority and unprivileged groups (Zou & Schiebinger, 2018). For example, a widely used algorithm in the health sector displayed significant racial bias and was found to be deprioritizing Black patients' health over White patients' health (Obermeyer et al., 2019). Furthermore, automated speech recognition systems employed by companies like Amazon and Google misclassified Black speakers at a higher rate than White speakers (Koenecke et al., 2020). The biases displayed by AI extend beyond racial biases. AI has also been shown to exhibit gender biases in language processing (Caliskan et al., 2017). And, AI-based search engines displayed an underrepresentation of women in search results for leadership roles (Kay et al., 2015). Thus, given that liberals tend to be more sensitive to social justice issues and the evidence of social bias in AI, liberal media might show a greater aversion towards AI than conservative media.

Alternatively, one might surmise that liberal media's aversion to AI could be driven by privacy concerns. Indeed, the proliferation of AI has raised concerns over the control of personal information due to AI's ability to monitor, collect, and analyze data (Acquisti et al., 2015; Puntoni et al., 2021). Given the sophisticated techniques and tools offered by AI, it is possible to infer sensitive information from anonymized data (Mayer et al., 2016). Consequently, people can feel exploited by AI collecting data because they are unaware of how their personal data is used and with what consequences (Acquisti et al., 2015). Importantly, liberals tend to be more sensitive than conservatives to the privacy violations presented by algorithms (Madan et al., 2022; Turow et al., 2018). Thus, it is possible that liberal media may be more averse to AI due to these privacy concerns. However, concerns

about privacy are highly uncertain and context-dependent because the way in which personal data is collected and managed is often invisible (Acquisti et al., 2015). Studies have also shown that people display a privacy paradox, a phenomenon in which there is a mismatch between attitudes and behaviors toward privacy (Norberg et al., 2007). Therefore, even if liberals are more concerned about AI-driven privacy violations, this may not necessarily lead to an aversion to AI due to the uncertainty surrounding privacy preferences.

In sum, we predict that liberal media will show a greater aversion to AI than conservative media. We examine this proposition by performing a text analysis of media articles written about AI. Moreover, we also predict that the partisan differences towards AI are most likely driven by liberal media's higher social bias concerns, and not by an emphasis on employment concerns or privacy concerns.

Preregistration

The hypotheses, design, and planned analysis were preregistered (https://aspredicted.org/yw78h.pdf). The procedural details and additional data analysis are available in the Supplementary Material. Data, analysis codes, and outputs are available on the Open Science Framework (https://osf.io/e9h6q/?view_only=5341cdf58f434d748520d33699b9e08c).

Emotional Tone Analysis

This analysis served to test our hypothesis that articles from liberal-leaning media outlets are more negative towards AI than articles from conservative-leaning media outlets. We tested this proposition using a dataset of media articles from both liberal-leaning media and conservative-leaning media.

Method

We compiled our dataset of articles based on the following criteria: 1) the media outlet had a partisan rating on AllSides' Media Bias Rating Chart (AllSides, 2021), and 2) the

articles from the media outlet were available on the Dow Jones & Company's Factiva database (https://global.factiva.com/). There were five liberal-leaning media outlets (Washington Post, The Guardian, USA Today, CNN, and New York Times [NYT]) and four conservative-leaning media outlets (The Daily Mail, New York Post, Wall Street Journal [WSJ], and Fox News) that met these two criteria. We then downloaded articles from these outlets based on the following four criteria. First, the article must include the key terms "algorithm" or "artificial intelligence." Second, we included articles that were written from May 25, 2019, to May 25, 2021. Third, we selected articles written in English. Fourth, we set Factiva's search setting to remove any duplicate articles. The articles were initially downloaded in HTML format from Factiva. The texts were converted to corpus form in Excel. In so doing, we removed articles that exceeded Excel's cell limit of 32,767 characters. There were 425 articles that exceeded this limit. After removing these articles, there were 7,844 articles that met these four selection criteria. Then, we removed Fox News from our analysis because there were only four articles from Fox News. These four articles increased the standard error by a factor of 3. Note that including these articles in the dataset does not change the pattern of results (Supplementary Material, Table 1). Further, including the 425 articles that exceeded the limit also does not change the pattern of results (Supplementary Material, Table 4 and Table 5). Thus, our final dataset included 7,840 articles (without Fox News).

Emotional tone analysis was performed using LIWC, an automated text analysis tool (Pennebaker et al., 2015). Through this tool, we were able to capture a measure of emotional tone for each article. This metric measures the percentage of positive emotional words in a piece of text and subtracts the percentage of negative emotional words. Thus, it indicates a relative measure of positive emotional tone for the text at hand (range 0-100). In addition to emotional tone, the LIWC analysis also measures analytical thinking, clout, and authenticity

of the text, which were used as controls in the analysis. Additionally, we used the date of the articles and the media outlets' format (print vs. TV) as controls.

Results

We performed a nested analysis of variance (ANOVA) with the emotional tone of the articles as the dependent variable and the political leaning of the media outlet as the independent variable. Individual media outlets were nested within the political leaning variable. The analysis revealed that liberal-leaning media (M = 40.98) expressed a more negative tone towards AI than conservative-leaning media (M = 43.95, b = -2.96, SE = 0.82, $F(1, 7832) = 13.12$, $p < .001$, $\eta_p^2 = 0.002$). See Figure 1 for means of the emotional tone across the individual media outlets.

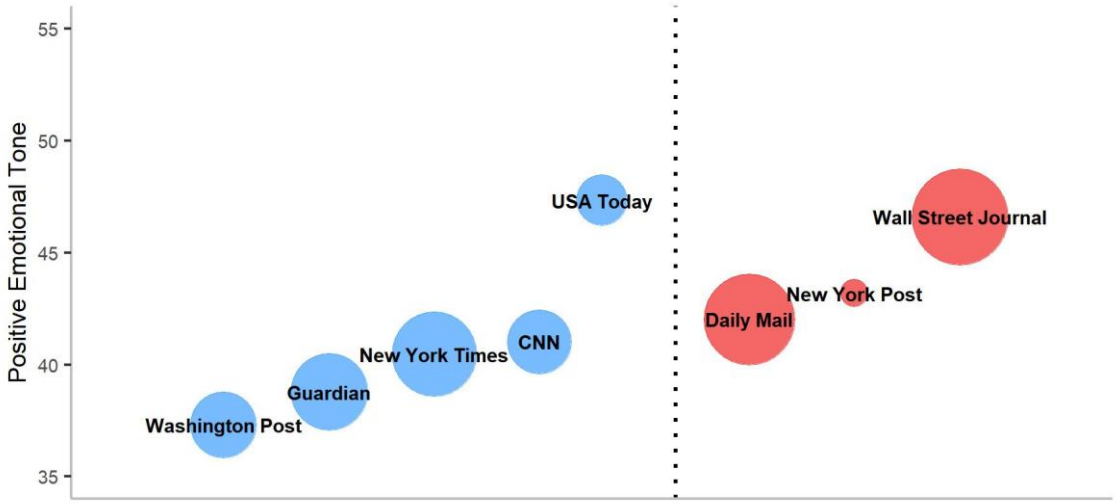


Figure 1. Mean Emotional Tone across Media Outlets.

Note. The y-axis reports values of emotional tone of the articles, where higher values represent a more positive emotional tone towards AI. The size of each bubble represents the number of articles in each media outlet (M = 980 articles, Range = 98 – 1,966 articles). The blue bubbles represent liberal media, and the red bubbles represent conservative media. The dotted line separates the liberal media outlets and the conservative media outlets. The data shows that the articles from the conservative-leaning media outlets tend to have a higher positive emotional tone towards AI than the articles from the liberal-leaning media outlets.

Robustness Checks. We ran four robustness checks to corroborate the results. First, we reran the nested ANOVA analysis with some added controls. Specifically, we controlled for analytical thinking, clout, authenticity, media outlet format (print vs. TV), and the publication date of the article (Supplementary Material, Table 3). Analytical thinking captures the degree of formal and logical thinking in the text. We added analytical thinking as a control because a more analytical article may come across as less emotionally charged. Clout measures the level of confidence in the text. Clout was added as a control because articles with higher clout can influence the overall tone of the articles by being perceived as more positive in emotion. Authenticity measures the extent to which the text is personal or disclosing. Articles with higher authenticity scores may present a tone of sincerity and emotional resonance, which may influence tone. Further, we added the date of the article to control for the potential longitudinal trends (i.e., changes in ownership of the media outlet and media trends). Lastly, we added a dummy variable for whether the article was in TV or print format (TV = 1, print = 0) to control for differences in the article format. We controlled for media outlet format because TV format and print format may follow different norms that can impact tone. For example, TV format may result in more emotionally charged content to attract the viewer's attention. We again find that liberal-leaning media expressed a more negative tone towards AI than conservative-leaning media (b = -3.20, SE = 0.82, $F(1,7827) = 15.26$, $p < 0.001$, $\eta_p^2 = 0.002$).

Second, we also looked at a subset of the articles, comparing only the articles from NYT with the articles from WSJ. We selected these two media outlets because they are similar in terms of quality and readership. We again see that the liberal-leaning outlet (NYT) had a more negative sentiment towards AI than the conservative-leaning media outlet (WSJ) (Supplementary Material, Table 6).

Third, we sought to demonstrate that the partisan bias is specific to articles about AI. It is possible that liberal-leaning media outlets are more negative than conservative media outlets

in general, not just for AI-related content. Therefore, to show that the effects are particular to AI, we compiled a dataset of articles from the same media outlets about 'food'. We find no difference in tone between liberal-leaning media and conservative-leaning media for these articles (b = 0.65, SE = 1.09, $F(1, 2999) = 0.35$, $p = 0.55$, $\eta_p^2 < 0.001$). Thus, the partisan bias observed seems to be specific to articles about AI. See Supplementary Material, Table 7 and Table 8 for more information.

Finally, to ensure that our findings are not particular to the LIWC sentiment tool, we also ran the analysis with a different measure of emotional tone. Specifically, we used the tone measure from the R package called sentimentr (Rinker, 2017). We again found a convergent pattern of results (Supplementary Material, Table 9).

Sensitivity Analysis. As a sensitivity analysis, we performed a post-hoc power analysis. To do so, we conducted additional analysis to determine the dependency of the data (intraclass correlation [ICC]= 0.027). Since the ICC value was almost zero, we treated the observations as independent. This assumption of independence allowed us to use the G*Power software to determine the sample size needed to find a small effect (Cohen's f = 0.1) with high power of 95% (Faul et al., 2007). The G*Power calculations indicated necessitating 1,302 observations. Since our sample size was greater than 7,000, our study had a very high chance of finding even smaller effects.

Social Bias Concerns

Next, we sought to examine how the differences in emotional tone between liberal and conservative media outlets are driven by different levels of social bias concerns. We also tested the alternative accounts of privacy concerns and employment concerns that could explain the differences.

Method

We created custom dictionaries to measure social bias, privacy, and employment concerns. To do so, we listed the social bias, privacy and employment concerns as the categories and generated a list of words that belonged to each concern category. We relied on a sample of articles and a thesaurus to compile a list of words associated with each concern category. The full list of words in each custom dictionary is listed in the Supplementary Material. We encoded these custom dictionaries into LIWC and performed a text analysis on the 7,840 articles. This analysis allowed us to measure the proportion of social bias, privacy, and employment-related words present in each article.

Results

We conducted a mediation analysis using a Sobel test (Sobel, 1982). The emotional tone of the articles was the dependent variable, the political leaning of the media outlet was the predictor variable, and the social bias, privacy, and employment concerns were the parallel mediators (see Figure 2 for details). The analysis showed that only social bias concerns was a significant mediator (z = -2.41, p = 0.016). Specifically, liberal media were more concerned about social bias than conservative media (b = 0.06, SE = 0.02, F(1, 7832) = 6.32, p = 0.012, η_p^2 = 0.001), which in turn contributed to the decrease in emotional tone (b = -2.78, SE = 0.40, F(1, 7829) = 49.39, p < .001, η_p^2 = 0.006).

Privacy concerns (z = 0.27, p = 0.789) and employment concerns (z = -0.48, p = 0.631) were not shown to be significant mediators. Privacy concerns cannot explain the difference in tone because privacy concerns did not have an effect on the overall emotional tone (b = -0.10, SE = 0.35, p = 0.788, F(1, 7829) = 0.07, η_p^2 < .001). Similarly, employment concerns cannot explain the difference in emotional tone because liberal and conservative media were similarly concerned about employment (b = -0.02, SE = 0.03, F(1, 7832) = 0.24, p = 0.62, η_p^2 < .001). Thus, articles from the liberal-leaning media outlets were more likely to

express social bias concerns, and these social bias concerns explained why the articles from liberal media outlets had a more negative tone towards AI. See Figure 2 for the detailed results. Note, mediation analysis performed using PROCESS macro finds the same pattern of results (see Supplementary Material).

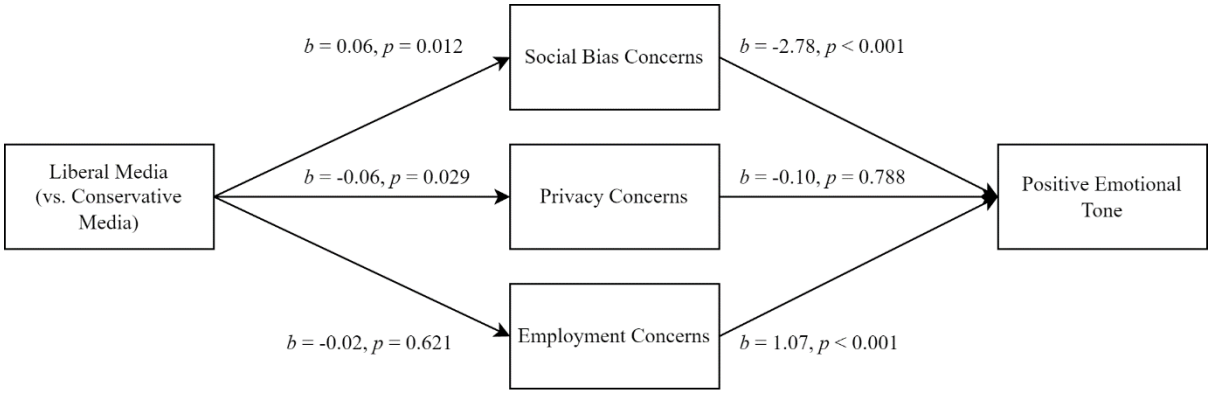


Figure 2. Parallel mediation model depicting the relationship between political leaning of media outlets and emotional tone towards AI.

Note. The analysis shows that liberal-leaning media tend to have less positive tone towards AI and this effect is mediated by higher social bias concerns expressed in the liberal-leaning media. Privacy concerns and employment concerns do not explain the relationship. AI = Artificial Intelligence.

Natural Experiment

The mediation analysis provides initial support for the role of social bias concerns in explaining the differences in emotional tone between the liberal and conservative media outlets. However, the analysis is limited by its correlational nature. Therefore, to provide further support for the role of social bias concerns, we examined the impact of George Floyd's death on the media sentiment towards AI. George Floyd's death (May 25, 2020) and the subsequent Black Lives Matter protests sparked a national conversation on the prevailing social biases in society (Dunivin et al., 2022). We predicted that this heightened recognition

of social biases in society should reduce media support for AI, even though the event was not directly related to the domain.

Method

We wanted to test the impact of George Floyd's death on media articles about AI. As George Floyd's death triggered national outrage, we assumed that this event also may have heightened social bias concerns in media. If social bias concern indeed leads to a more negative tone for AI-related articles, then we should observe a corresponding decrease in emotional tone, right around George Floyd's death in such AI-related articles. Note, we do not make specific predictions for whether liberal or conservative media would be more affected by Floyd's death because different outcomes are possible. One could argue that Floyd's death might impact liberal-leaning media more as they are already sensitive to social biases. However, while the interpretation of relatively ambiguous issues and events may depend on one's values and beliefs, that may be less the case for events that are less amenable to alternative interpretations like Floyd's death (Kunda, 1990). As a result, Floyd's death could have affected conservative media to the same extent as liberal media. As such, we a priori predicted that Floyd's death would lead to greater negative tone for AI-related articles, but we did not make a prediction for whether this effect would vary across liberal and conservative media.

We turned to interrupted time series models to obtain unbiased estimates of the causal effect of George Floyd's death on social bias concerns and emotional tone for AI-related articles. The first interrupted time series analysis looked at the effect of George Floyd's death on the level of social bias concerns in the articles. The model regressed social bias concerns on the political leanings of the media outlets, media outlets nested within the political leaning variable, Floyd's death, time, and the interaction between Floyd's death and the time variable. Floyd's death is a binary indicator variable that equals 1 when the article is written

on and after his death and 0 otherwise. The time variable is the difference in the number of days between the date of Floyd's death (May 25, 2020) and the article's publication date. Second, we ran another interrupted time series model that looked at the impact of George Floyd's death and social bias concerns on the emotional tone of the media articles. The model regressed emotional tone on the political leanings of the media outlets, media outlets nested within the political leaning variable, Floyd's death, time, social bias concerns, and interaction between Floyd's death and the time variable. Then, we set up a mediation model and used the results of the interrupted time series analysis to get the respective a-path and b-path coefficients.

Results

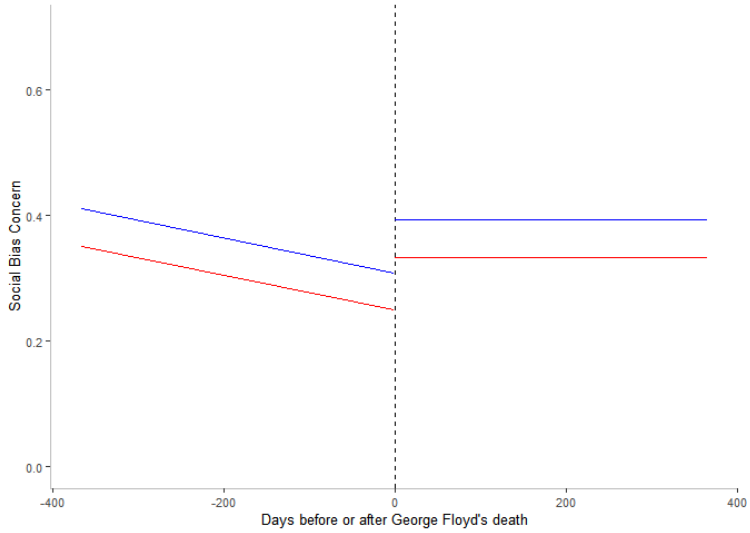
The first interrupted time series analysis compared social bias concerns before and after Floyd's death. The analysis regressed social bias concerns on the political leaning of the outlets, nested effects of media type within political leaning, George Floyd's death (1 = after death, 0= before death), a time variable and the interaction between Floyd's death and the time variable. The results indicate that social bias concerns increased after Floyd's death (b = 0.08, SE = 0.03, F(1,7829) = 9.45, p < 0.01, η_p^2 = 0.001). See Supplementary Material, Table 11 for more information. Note, we reran the same model but included the interaction between political leaning and Floyd's death. The results reveal that the interaction between political leaning and Floyd's death was not significant (b = -0.01, SE = 0.03, F(1, 7828) = 0.11, p = 0.736, η_p^2 < 0.001), indicating that liberal and conservative media showed an equivalent increase in social bias concerns after Floyd's death. This suggests that this event was sufficiently impervious to alternative interpretations, causing heightened social bias concerns for conservative media akin to liberal media.

Then, we performed another interrupted time series model comparing the emotional tone of media articles on AI before and after Floyd's death. The analysis regressed tone on

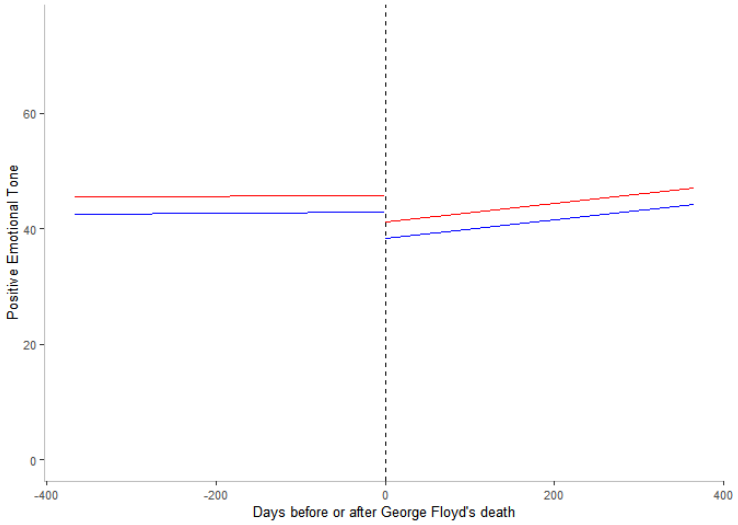
the political leaning of the outlets, nested effects of media type within political leaning, George Floyd's death, a time variable, the interaction between Floyd's death and the time variable, and social bias concerns. The results indicate that social bias concerns contributed to the decrease in emotional tone (b = -2.67, SE = 0.39, $F(1, 7828) = 45.73$, $p < 0.001$, η_p^2 = 0.006). See Supplementary Material, Table 12 for more information. Note, we reran the same model but included the interaction term between political ideology and Floyd's death. We again see that the effects are similar for liberal and conservative media.

We conducted a conditional mediation model using the Sobel test to demonstrate that the differences in tone after George Floyd's death was driven by the heightened social biases in society. In other words, the effect of Floyd's death on emotional tone through social bias concerns was tested at time 0 (i.e., date of Floyd's death). A Sobel test showed that social bias concerns was a significant mediator (z = -2.82, $p < 0.01$). Thus, these results further support the notion that social bias concerns drive the negative media sentiment towards AI. See Figure 3 and Figure 4 for the graph and Supplementary Material for detailed results.

To corroborate these results, we ran two robustness checks. First, we ran the same conditional mediation model by restricting the window of observations to two months before and after Floyd's death (Supplementary Material, Table 13 and Table 14). The results again indicated that social bias concerns was a significant mediator (z = -2.68, $p < 0.01$). Second, we reran this conditional mediation model for New York Times and Wall Street Journal articles only. Again, the Sobel test for mediation was significant (z = -2.06, $p < 0.05$). See Supplementary Material, Table 15 and Table 16.



a



b

Figure 3. Interrupted time series graphs showing the increase in social bias concerns and decrease in positive tone after Floyd's death.

Note. a. Interrupted time series graph depicting the increase in social bias concerns after George Floyd's death. The y-axis represents the social bias concern, and the x-axis represents the difference in days between the article's date and the date of George Floyd's death. The red line represents conservative media, and the blue line represents liberal media. b. Interrupted time series graph showing the decrease in positive tone after George Floyd's death. The y-axis represents the positive emotional tone.

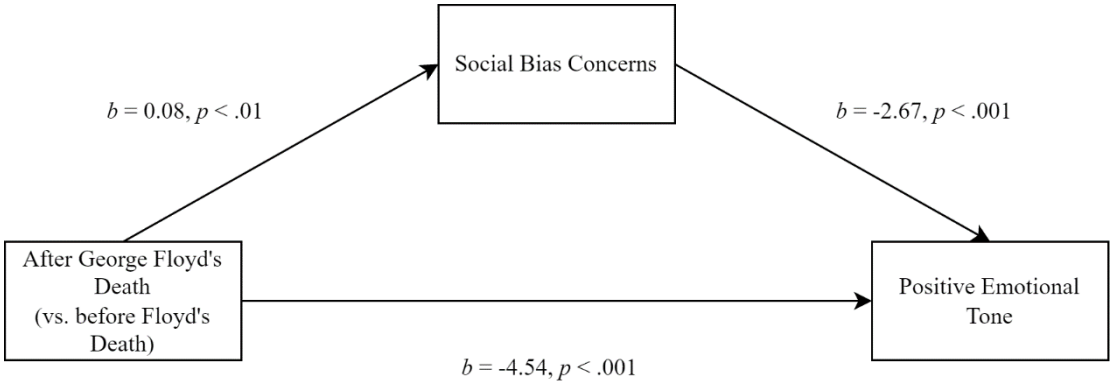


Figure 4. Mediational analysis depicting the reduction in positive emotional tone after George Floyd's death (evaluated at time 0).

Note. The mediational model shows that the effect of George Floyd's death on emotional tone can be explained by the heightened social bias concerns. The results show that, George Floyd's death led to heightened social bias concerns, which in turn led to the drop in positive tone in AI-related articles.

Discussion

The current research sought to understand support for AI by analyzing partisan media sentiment towards AI. We observed a difference in sentiment towards AI across liberal-leaning and conservative-leaning media outlets. Specifically, we find that liberal-leaning media show a higher aversion to AI than conservative-leaning media. These partisan media differences towards AI are driven by liberal-leaning media's greater concern about AI's ability to magnify societal biases. Furthermore, the results suggest that the partisan media differences cannot be explained by differences in employment concerns or privacy concerns. Privacy concerns were not shown to be a significant mediator because it did not explain the difference in tone. Further, employment concerns could not explain the difference in tone because there was no difference in employment concerns between left and right-leaning media outlets. Notably, we see that media sentiment towards AI became more negative after George Floyd's death. In this natural experiment, we did not test any partisan differences.

Instead, we used George Floyd's death to test if the difference in social bias concerns led to a difference in emotional tone. The results indicated that this event heightened sensitivity towards social biases in society and consequently influenced sentiment towards AI in both liberal and conservative media. Thus, these results provide convergent support for the notion that media reactions to AI are influenced by social bias concerns.

Our work adds to the growing literature investigating people's reactions to AI (Dietvorst & Bharti, 2020; Kim & Duhachek, 2020; Ward et al., 2013). Moreover, a large volume of literature has examined how liberals and conservatives differ in their attitudes towards important societal issues (Duckitt et al., 2002; Graham & Nosek, 2009; Jost et al., 2009). We extend these streams of literature by demonstrating political differences can also manifest in reactions towards AI.

This work also opens future research opportunities. Additional research can be performed to see how the partisan media's sentiment towards AI actually shapes the public discourse around AI. For example, future research can demonstrate how the sentiment of social media conversations on AI changes as a function of partisan media reporting of AI.

Moreover, our analysis was based on articles from U.S. and U.K. media outlets. It is possible that the partisan divide in other countries may not be as strong or polarized as shown in this research. Moreover, partisan divide over AI may even reverse in some countries depending on socio-historic factors. Thus, the future work can examine the diversity of partisan reactions to AI across countries.

Altogether, our research findings have important implications for political discussions around AI. Media sentiment is a harbinger of public sentiment and policymakers' stance. The partisan media differences observed here might subsequently lead to differences in public opinion towards AI. Concerningly, these partisan media differences could lead to political polarization in attitudes towards AI. Furthermore, political leaders, who take cues from the

media, may subsequently shape their policies toward AI in concordance with these observed partisan differences.

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