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# Algorithmic Bias or Algorithmic Reconstruction? A Comparative Analysis Between AI News and Human News

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Despite a substantial body of scholarship at the intersection of artificial intelligence (AI) and journalism, it remains relatively unexplored as to how AI-generated news is different from news produced by professional journalists in terms of news bias. To fill the gap, this study compares human versus GPT-2-generated news in terms of the linguistic features, tone, and bias toward gender and race/ethnicity on two highly controversial issues, namely abortion and immigration, using news transcripts from CNN and Fox News. In doing so, the study adopts a mixed-method content analysis approach, including dictionary and coreference analysis, topic modeling and semantic network analysis, and manual content analysis. The results reveal that although AI news differs from human news in terms of language features and thematic areas, machine news is not necessarily more biased compared to human news regarding gender and race/ethnicity. Implications are discussed for future scholarship on

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algorithmic bias in lieu of the roles that AI-generated news may play in journalism and democracy.

*Keywords: Artificial Intelligence, news framing, news bias, algorithmic bias, automated journalism, gender bias, race/ethnicity bias*

Recent advances in artificial intelligence (AI) have made the automation of journalistic tasks possible (Broussard et al., 2019; Jones & Jones, 2019). Machine-learning algorithms can automatically generate news content with limited to no human intervention (Primo & Zago, 2015). For instance, Narrative Science, an automated journalism provider, has been automating sports news stories based on existing game data since its launch in 2010 (Lee, Bulitko, & Ludvig, 2021). The recent launch of ChatGPT in 2022 demonstrates the greater potential of AI algorithms to mimic human language and automate text generation at scale (Adami, 2023).

Despite significant development, scholars have raised concerns regarding the potential drawbacks of automated journalism (Thurman, Dörr, & Kunert, 2017). Whether and how algorithm bias may be manifested in automated news remains understudied. Algorithms may learn bias and stereotypes from human-generated contents, which can have harmful impacts on social equity at large. This study takes an initial step to examine algorithmic bias in automated journalism by investigating how AI-generated news is similar or distinct from news produced by professional journalists in terms of news bias. Specifically, the study trains the GPT-2 language model based on news from CNN and Fox News related to two controversial issues: abortion and immigration. It compares human and machine-generated news, paying particular attention to linguistic features, tone, and bias toward gender and race/ethnicity. Beyond methodological contributions, the present study advances existing literature by juxtaposing AI- and human-generated texts on contentious topics, providing a foundation for future research on automated journalism and algorithmic bias in news media. The analysis has implications for the reconceptualization of framing theory in the emergent media environment with AI technologies and automated journalism.

## Literature Review

### *Media Bias and Frames*

Media bias refers to "the influence of journalists' belief systems on the texts they produce" (Entman, 2010, p. 393). Often because of the highly politicized media landscape, media bias is positioned along the ideological spectrum (Groseclose & Milyo, 2005) wherein those studying and analyzing media bias align or categorize beliefs made apparent in the media content, resulting in designations of media as being politically biased toward liberal, conservative, or moderate.

The recent scholarship has contributed nuanced and far-reaching research in the areas of media bias and the frames that are used to determine the themes and salient concepts in today's media environment. For instance, scholars have broadened their understanding of media bias to include sentiment and emotional words to establish a larger understanding of media bias in tandem with emerging computational techniques, such as topic modeling and machine learning, to identify media bias at scale (Spinde, Hamborg, & Gipp, 2020). The expansion of these types of techniques attempt to combine linguistic word choice, topic mapping, and sentence level biases toward tool-based analyses of the vast landscape of digital news now readily available to online readers (Krieger, Spinde, Ruas, Kulshrestha, & Gipp, 2022).

### *Media Bias Toward Gender and Immigrants*

The study of media bias, specifically news bias against women, has remained a perennial topic of inquiry ranging from political events through coverage of violence to female qualifications, resulting in mixed findings (Bauer, 2022; Meyers, 1996). Some studies have found that gendered positioning of women and men in the news plays a role in effectively shaping perceptions (Peng, 2018), as well as the coverage frequency of the gender of world leaders or people of interest (Hooghe, Jacobs, & Claes, 2015; Van der Pas & Aaldering, 2020). In contrast, other studies have found that there is no difference in the way that women are perceived in terms of their expertise and competence in major news sources when compared with men (Greve-Poulsen, Larsen, Pedersen, & Albæk, 2023).

Simultaneously, bias against immigrants in the media has a historical legacy (Dovidio, Hewstone, Glick, & Esses, 2010). Large-scale global events tend to exacerbate perceptions that news is biased against immigrants, wherein immigrants may be seen as to blame for negative events or economic developments in their emigrated nation (Ahmed, Chen, & Chib, 2021). The United States has a unique context as a nation of immigrants and as a country with varying ethnicities and a combination of long-arrived immigrants, generational immigrants, and newcomers. Therefore, the study of immigrant bias in the news in the United States holds particular importance because immigrants do not represent a monolith but rather an array of languages, locations, cultures, and reasons for immigration (Massey, 1981).

### *Algorithmic Bias in Media and Journalism*

Algorithmic bias is defined as unfair decisions made by AI systems for or against an individual or group based on their inherent or acquired characteristics such as race, gender, and class (Mehrabi, Morstatter, Saxena, Lerman, & Galstyan, 2021; Mitchell, Potash, Barocas, D'Amour, & Lum, 2021). It is posited that involving algorithms in the information production and dissemination may have negative consequences (Graefe & Bohlken, 2020). AI-powered news generation tools may reproduce social stereotypes or biases manifested in human-generated news as machine-learning algorithms are trained on existing news (Selbst, Boyd, Friedler, Venkatasubramanian, & Vertesi, 2019). What is more, algorithms rank and recommend content based on user preferences to increase product satisfaction and adoption rates (Hermann, 2022). It may lead to the issue of "echo chambers" and "filter bubbles" wherein the audience is only exposed to like-minded information (Urman, Makhortykh, & Ulloa, 2022).

In general, the definition of algorithmic bias centers around the harmful consequences from prejudiced decisions made by AI. In the context of automated journalism, such bias can be attributed to the training data and model mechanisms. In this study, we focus on stereotypes related to a group of people manifested in the language of automated news.

### *Gender and Race-Based Algorithmic Bias*

Gender bias is widely documented in algorithmic bias literature (Bivens, 2017; Zhao, Wang, Yatskar, Ordonez, & Chang, 2017). Caliskan, Bryson, and Narayanan (2017) found that algorithms associate female names with family and arts more than with career words and sciences when they learn word connections from written texts. In terms of online visual content, when retrieving pictures from Bing, images of women are more frequently associated with warm attributes, such as "emotional," whereas photos of males are more likely to be associated with agentic characteristics such as "logical" (Gutierrez, 2021).

Similarly, racial bias in human society can be extended to algorithms. Because of inherent biases contained in the training data, algorithms may make unfair decisions against certain immigration groups based on race and ethnicity (Laupman, Schippers, & Papaléo Gagliardi, 2022; Phillips, Jiang, Narvekar, Ayyad, & O'Toole, 2011). For instance, a study by Obermeyer, Powers, Vogeli, and Mullainathan (2019) demonstrates racial disparities in a widely used algorithm for risk prediction in the health sector. That is, an equally sick Black patient can get less financial assistance compared with their White counterparts based on the prediction of the algorithm.

### *Research Questions*

As stated in the literature review, media coverage may reflect human stereotypes with respect to gender and race/ethnicity. Biased media portrayal of a particular gender or race may skew public opinion of the group negatively (Beyer & Matthes, 2015), which can in turn harm individual development, policy decisions on gender and race-related issues, and social equity at large (Facchini, Mayda, & Puglisi, 2017). Given the significance, we propose the following two research questions with a special emphasis on gender and racial bias in the news.

*RQ1: To what extent does AI news approximate human news in terms of gender and race/ethnicity?*

*RQ2: To what extent is AI news distinct from human news in terms of overall tone?*

## Methods

### *Data Collection, Preprocessing, and Language Model Training*

To compare gender and racial biases between human and machine-generated news related to abortion and immigration, this study focuses on the two mainstream cable networks in the United States, CNN and Fox News, to make sure that the news in the dataset represents both sides of the political ideological spectrum. Data were collected from Nexis Uni using the keywords shown in Table 1. In addition, our search includes only articles that have more than 600 characters to ensure document quality. CNN also has another two source types ("Newswires & Press Releases" and "Web-based Publications") in addition to news transcripts, whereas Fox News has only news transcripts. To make sure the documents are comparable, we include another search criterion, "Source Type," for CNN documents, which we limit to "News Transcripts." The publication date is limited to 2012–2022.

***Table 1. Search Keywords.***

| | |
|---|---|
| "abortion" AND publication ("CNN") | "abortion" AND publication ("Fox News") |
| "immigration" AND publication ("CNN") | "immigration" AND publication ("Fox News") |

We followed a five-step process for data cleaning (see Figure 1): (1) delete duplicated news; (2) remove a list of phrases that are often included during news transcribing; (3) exclude articles that mention a keyword of interest only once; (4) identify the first and last sentence a keyword is present within each news transcript, and retrieve that portion as the unit of analysis because a news transcript often covers multiple topics not related to abortion or immigration;[1] (5) remove texts that contain less than 600 characters after the filtering and cleaning to ensure document quality. Lastly, 500 articles were randomly selected from each of the topic-news network categories as the training data for the subsequent news generation models.

[1] Some articles may address other topics in addition to abortion—for instance, Syrian opposition forces. To exclude irrelevant information, we identify the first and last sentence that the keyword ("abortion") is present in an article and retrieve that portion in between the two sentences for further analysis.

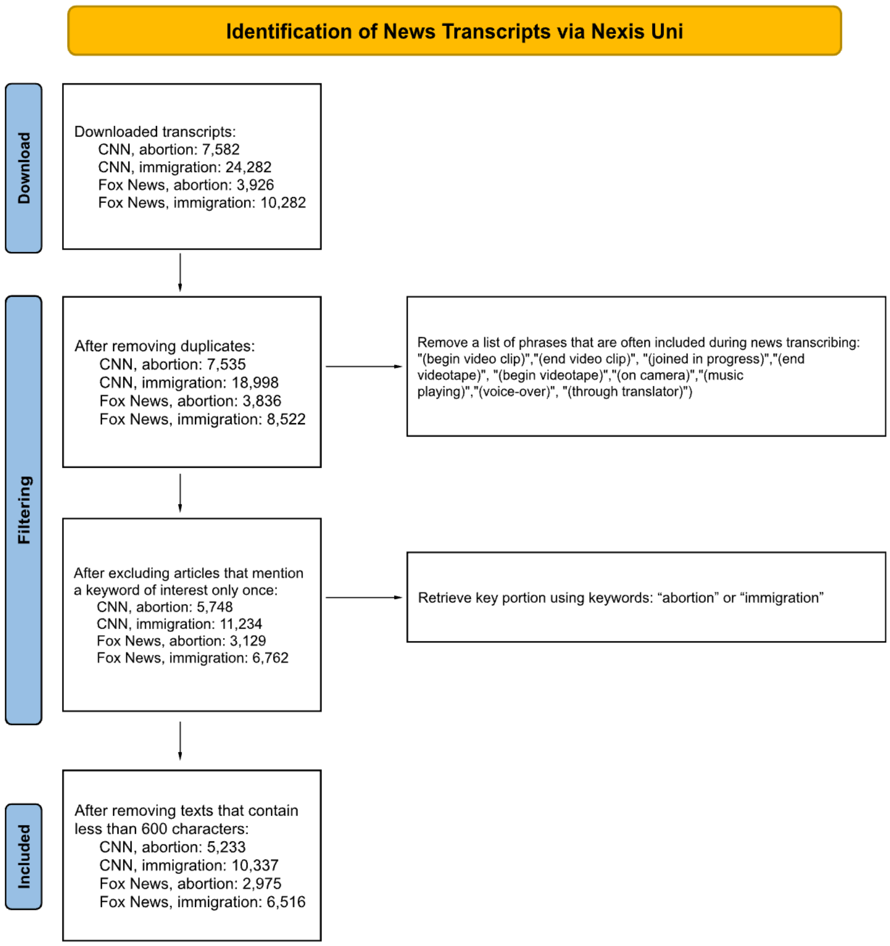



***Figure 1. Identification of news transcripts via Nexis Uni.***

As for model training, GPT-2 was utilized as the pretrained language model on English Web texts from 45 million links (Radford et al., 2019). Two separate language models were also trained using the sample news of abortion and immigration (batch size = 5). A prompt, “abortion” or “immigration,” was given to the model to generate an equal number of news related to the topic (with the parameters $k$ = 5, $p$ = .92). Detailed codes can be found on Hugging Face, which provides the open-source implementation of the GPT-2 architecture (Wolf et al., 2020). Table 2 presents sample news generated by the language model on abortion and immigration, respectively. Table 3 also summarizes the average number of characters and words for both human and machine-generated news.

***Table 2. Machine-Generated Sample News.***

| Abortion | Immigration |
|---|---|
| *"We're seeing these issues getting more attention, especially among White women, the ones who have been the hardest hit in terms of abortion and contraception and access to care. Now, all of this has led to a lot of women looking for a safe place to have their kids, who want to go to college."* | *"Immigration has always been a source of instability for some. What's clear now is that Trump is trying to exploit that weakness by saying something like this on immigration. I mean, if I'm president, I don't want my country to become a sanctuary for illegal immigrants because I'm tired of illegal immigration."* |

***Table 3. Average Number of Characters/Average Number of Words Before and After Cleaning.***

| | Abortion | | | Immigration | | |
|---|---|---|---|---|---|---|
| | Human | | Machine | Human | | Machine |
| | Before cleaning | After cleaning | | Before cleaning | After cleaning | |
| CNN | 33578/6104 | 15408/2780 | 2666/518 | 32540/5905 | 14127/2561 | 2695/521 |
| Fox News | 39218/7130 | 22490/4078 | 2608/518 | 41342/7477 | 25776/4665 | 2609/512 |

## ***Mixed-Method Content Analysis***

Our analytical methods include (i) dictionary-based bias measurement, (ii) coreference analysis, (iii) topic modeling and semantic network analysis, and (iv) manual content analysis. It is notable that we have preprocessed news articles by removing punctuation and stop words for analysis purposes.

### *Dictionary-Based Analysis*

We applied the dictionaries of gender-specific nouns constructed by Dacon and Liu (2021) to our news dataset. For example, "she," "women," and "congresswoman" are included in the female keyword set, and "his" and "male" are included in the male keyword set. Their dictionary contains 465 masculine and feminine gender possessive nouns. With respect to racial bias, four categories were considered (i.e., White, Black, Hispanic or Latino, and Asian). Our ethnicity-related word list includes "White," "Black," "Hispanic or Latino," and "Asian," as well as nationalities such as "Russian," "Chinese," and "Mexican." We compare the total number of keywords in human or machine-generated news to understand whether gender/ethnic bias in news media is learned by AI and appears in machine-generated news.

### *Coreference Analysis*

Although dictionary-based keyword searches can reveal the disparity of how often gender- or ethnicity-related words are used between machine- and human-written news, it cannot capture pronouns (e.g., "she" or "he") used to refer to the same entity. To get a more accurate measure of bias, we run a coreference analysis using *neuralcoref* built in spaCy to find both nouns and pronouns of an entity (Honnibal & Montani, 2017). We then compare the reference counts in machine- and human-written news.

*Topic Modeling and Semantic Network Analysis*

To understand whether algorithms and human-written news report the same topic differently, we conduct topic modeling and semantic network analysis (the Analysis of Topic Model Networks approach introduced by Walter & Ophir, 2019; see also Nah, Luo, & Joo, 2023) to visualize the major thematic areas in the news. This method treats the co-occurrence of topics across documents as frame elements and uses Latent Dirichlet Allocation (LDA) topic modeling and network clustering algorithms to detect and visualize media frames (Walter & Ophir, 2019, pp. 250–251). Following their three-step process, LDA topic modelling was trained on each of our human and machine-generated news. Because each of the samples contain only 500 articles, the training is implemented on the entire document instead of randomly selecting a small portion as demonstrated in the previous literature (Maier et al., 2018). A 10-fold cross-validation was first performed on each candidate model with the number of topics (*k*) ranging from 2 to 100 (2, 5, and 10–100 with skips of 10) and different values of alpha (0.01, 0.05, 0.1, 0.2, 0.5). The optimal *k* was then determined based on the maximum point for the second derivative of the perplexity scores of all candidate models, meaning that larger numbers will give diminishing returns in minimizing perplexity scores. Table 4 shows the optimal *k* and alpha values for each of the sample news corpus. We then qualitatively evaluate the top 50 keywords, top 50 exclusive words (FREX words), and top 50 documents most representative of each topic to interpret the topics identified by LDA (Walter & Ophir, 2019). Figures 3–4 and 7–8 show the topic clusters. The nodes represent individual topics. The edges represent co-occurrence of topics in documents based on pairwise cosine similarity. The node size shows the prevalence of topics in the corpus, and its color represents the topic community detected by the Eigen algorithm based on the leading eigenvector of the community matrix. All the figures are created using Gephi (Bastian, Heymann, & Jacomy, 2009).

***Table 4. The Optimal k and Alpha Values for Each of the Sample News Corpus.***

| | Abortion | | Immigration | |
|---|---|---|---|---|
| | Human | Machine | Human | Machine |
| CNN | 20; 0.2 | 20; 0.5 | 20; 0.2 | 20; 0.2 |
| Fox News | 20; 0.5 | 20; 0.2 | 20; 0.1 | 20; 0.2 |

*Manual Content Analysis*

We also conducted a manual content analysis to measure felt bias and tones. A separate coding scheme for news on abortion and immigration was created with a set of variables that examine the degree of gender and ethnicity bias, as well as overall tones or frames of the gender and immigration issues. For the news stories on abortion, we coded the overall tone and bias toward gender (male and female). For the news stories on immigration, we coded a set of questions related to bias against immigrants of different race/ethnicity (White, Black, Hispanic or Latino, and Asian) in addition to overall tone. Table 5 presents sample news with bias against females and immigrants:

***Table 5. Sample News With Bias against Females and Immigrants.***

| Bias against females | Bias against immigrants |
|---|---|
| *"We have some of the issues that are just very raw right now. We're doing things that don't make any sense. When it comes to something like abortion,* ***why is it that if you kill a pregnant woman you get two charges of murder, but you can kill a baby with nothing?*** *There are so many things that don't make any sense."* | *"And the fact that we are going to be dealing with the fallout from this* ***immigration mess that was created by these illegal aliens*** *is going to be very challenging for the president."* |

After a series of intensive coder training sessions, three trained graduate students coded all articles. First, 10% was randomly sampled from each of 500 news articles by the cable networks (i.e., CNN or Fox News) and content producers (i.e., human or machine) categories for the coder training purpose. Second, 20% of the news articles were randomly chosen to assess intercoder reliability using Krippendorff's alpha, which yielded an acceptable intercoder reliability with the range between 0.7 and 0.9 (Abortion: tone: 0.89, bias against females: 0.82, bias against males: 0.76; Immigration: tone: 0.70, bias against immigrants: 0.80, bias against White: 0.71, bias against Black: 0.73, bias against Hispanic or Latino: 0.80, bias against Asian: 0.79). Then, the trained coders coded the remaining 70% of news stories independently.

## Results

### *Abortion*

#### *Linguistic Analysis*

Figure 2 shows the gender keyword rates of human and machine news article sets across CNN and Fox News. Interestingly, for CNN, the gender keyword rate of machine news is higher than its counterpart (i.e., machine news used more female keywords), and the rates for Fox News show the opposite trend, although the keyword rate of CNN human news is lower than that of Fox News.

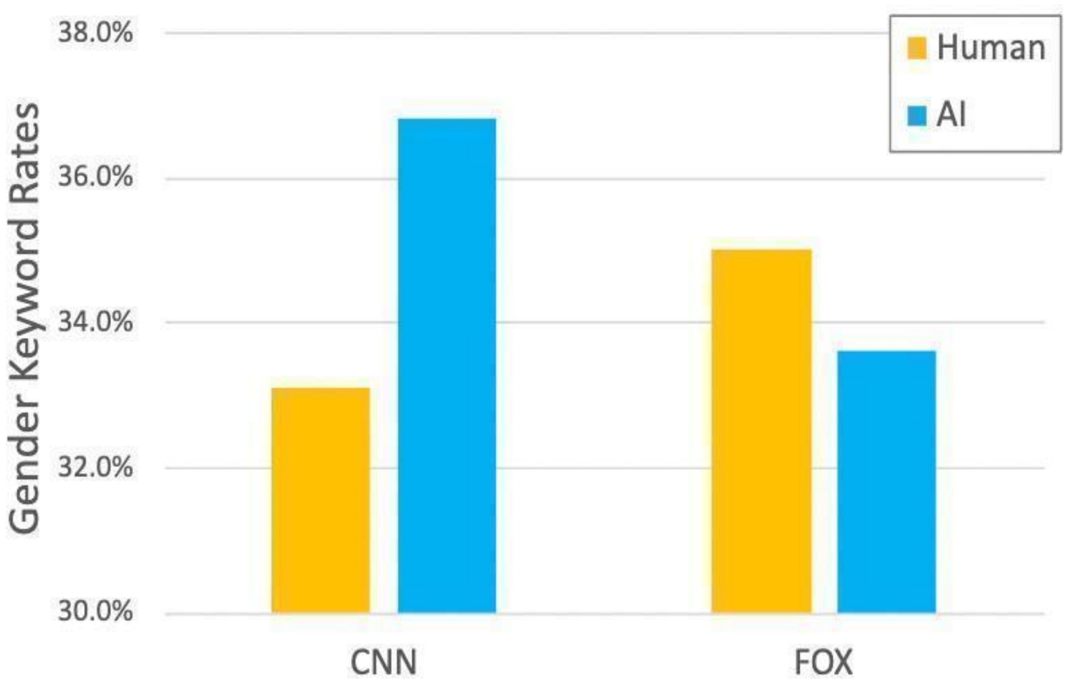



***Figure 2. Gender keyword rates of human and machine news across CNN and Fox News.***
*Note.* The rate is calculated as the number of female keywords divided by the number of male keywords.

Table 6 shows the top gender keywords in human and machine news. The total number of words for human news is much larger than its counterpart because all the news articles were used in the dataset for the analysis purpose. The results indicate that the proportion of pronouns, such as she, he, her, and his, are very high, dominating other keywords. However, CNN's machine news uses more "women/woman" than pronouns, resulting in a higher rate of female keywords compared with CNN's human news. In contrast, for Fox News, the use of pronouns referring to men is significantly higher than female keywords, although "women/woman" keywords are highly ranked. This implies that the proportion of pronouns used are higher than that of other gender keywords. The coreference analysis shows that pronouns in human news mostly refer to politicians, including Donald Trump, Hillary Clinton, and Mitt Romney. Conversely, in machine news, the top referents include "a person" and "a woman" while pronouns rarely refer to those politicians. This is because machine news emphasizes the topic of abortion from a broader perspective rather than the debates of real politicians.

To further understand the topic of "Abortion," a list of the most used nouns and adjectives was generated in each news set, as shown in Table 7. The analysis shows that machine news focuses more on the topic of "Abortion" than human news. The machine news has key words as "women," "rights," and "issue," whereas the human news has key words as "Trump," "people," and "country." In comparison, machine-generated articles of Fox News dealt more with legal and religious content (e.g., "law" and "catholic"), whereas CNN's machine news used more words related to women's rights.

***Table 6. Top-Ranked Gender Keywords in Human and Machine News on Abortion.***

| CNN | | | | Fox News | | | |
|---|---|---|---|---|---|---|---|
| Human | | AI | | Human | | AI | |
| Female | Male | Female | Male | Female | Male | Female | Male |
| She (8.66%: 2,789) | He (38.54%: 12,409) | Woman (16.07%: 767) | He (42.58%: 2,032) | She (9.75%: 4,224) | He (35.21%: 15,254) | Women (10.90% : 422) | He (41.27%: 1,598) |
| Woman (5.75%: 1,850) | His (12.89%: 4,152) | She (5.26%: 251) | His (13.29%: 634) | Her (5.65%: 2,449) | His (10.65%: 4,615) | She (7.36%: 285) | His (10.28%: 398) |
| Her (5.25%: 1,692) | Him (6.47%: 2,084) | Her (2.79%: 133) | Him (5.66%: 270) | Woman (4.11%: 1,779) | Him (6.29%: 2,724) | Her (4.05%: 157) | Him (7.23%: 280) |
| Female (0.96%: 309) | Governor (2.69%: 865) | Mother (0.78%: 37) | Governor (3.73%: 178) | Female (1.62%: 703) | Governor (2.60%: 1,126) | Female (0.65%: 25) | Governor (4.31%: 167) |
| Mother (0.66%: 212) | Man (2.09%: 673) | Wife (0.34%: 16) | Man (1.49%: 71) | Mother (0.42%: 184) | Male (2.15%: 931) | Mother (0.54%: 21) | Guy (2.61%: 101) |
| Wife (0.41%: 133) | King (1.30%: 418) | Female (0.25%: 12) | Mr (1.38%: 66) | Congress woman (0.34%: 147) | Man (2.08%: 902) | Girl (0.26%: 10) | Man (1.86%: 72) |
| Daughter (0.32%: 103) | Male (1.08%: 347) | Congresswoman (0.23%: 11) | Gay (0.75%: 36) | Wife (0.33%: 145) | Guy (1.92%: 832) | Congress woman (0.21%: 8) | Mr (1.34%: 52) |
| Girls (0.27%: 88) | Mr (1.01%: 324) | Daughter (0.21%: 10) | Guy (0.59%: 28) | Girls (0.33%: 145) | Host (1.40%: 607) | Daughter (0.18%: 7) | Host (0.88%: 34) |
| Congresswoman (0.25%: 80) | Himself (0.95%: 306) | Girls (0.19%: 9) | Congressman (0.52%: 25) | Mrs (0.30%: 129) | Mr (1.11%: 480) | Lady (0.15%: 6) | Gay (0.80%: 31) |
| Mrs (0.20%: 65) | Guy (0.80%: 258) | Lady (0.15%: 7) | Male (0.42%: 20) | Daughter (0.27%: 116) | Mayor (0.93%: 401) | Mrs (0.13%: 5) | Male (0.77%: 30) |

*Note.* The numbers in parentheses indicate the percentage and total number of times that keyword is used.

***Table 7. Top-Ranked Nouns and Adjectives in News Articles on Abortion.***

| CNN | | | | Fox News | | | |
|---|---|---|---|---|---|---|---|
| Human | | AI | | Human | | AI | |
| Noun | Adjective | Noun | Adjective | Noun | Adjective | Noun | Adjective |
| President | New | Abortion | Republican | People | New | Abortion | Right |
| People | Many | President | Important | President | Good | People | Republican |
| Trump | Republican | People | Supreme | Trump | Right | President | Good |
| Abortion | Last | Issue | Political | News | Last | Country | Important |
| Time | Right | Court | Right | Time | Many | Issue | Able |
| Court | Much | States | Good | Way | Great | Party | New |
| States | Good | Women | Democratic | Country | First | Right | Supreme |
| State | Political | Country | New | Today | Next | Way | Democratic |
| Way | Supreme | Rights | Able | State | Former | Law | First |
| Country | First | Right | Many | States | Much | Court | Catholic |

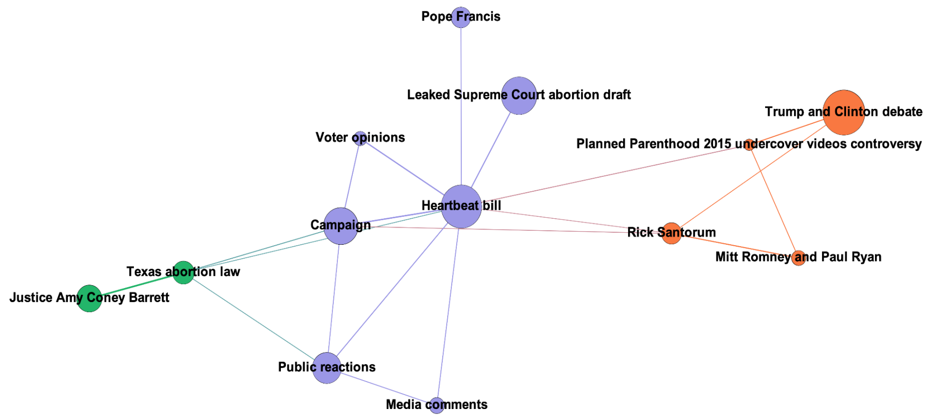
*Topic Networks*

The community detection algorithm identified three topic communities for human news corpus in CNN and Fox News. Figure 3(a) shows that the major community in the middle for the CNN abortion corpus focuses on public, politicians, and media reactions to the overturn of Roe v. Wade, as well as several major events and important forms of abortion restrictions. The second community on the right centers around Trump and Clinton and other politicians' views on abortion issues. The third community on the left emphasizes the legislative aspect of abortion, which mainly covers Justice Amy Coney Barrett's position on abortion along with the extreme abortion law in Texas. In contrast, the major topic community for Fox News focuses on debates on abortion rights, views of Catholic churches, and ramifications associated with abortion, as shown in Figure 3(b).

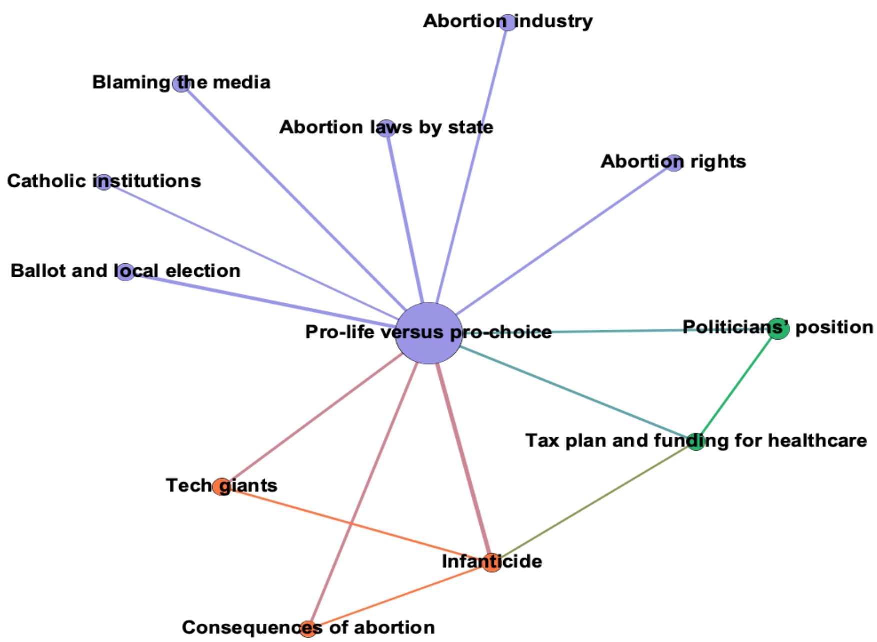
As for AI news on abortion, Figure 4 shows that the first community on the left side of the CNN network focuses on campaign, election, voting, and senate races along with Trump's opinion on abortion. The second community broadly covers the constitutional and legislative foundation of abortion and its associations with women's healthcare and funding for health in general. The machine news generated by the Fox News model focuses on similar topics, although religion is one main topic, which is not present in the CNN machine news.

In sum, the human and machine news on abortion have two major differences. First, human news shows more in-depth interpretations of abortion. For instance, human news from CNN covers Rick Santorum's, Mitt Romney's, and Paul Ryan's stances on abortion whereas machine news can only broadly refer to senators' views shown in races without being able to explain or debate about a single politician's view. Second, machine news only captures the major topics and framing categories representative in human news. For example, the abortion industry, which is often addressed in relation to the controversies of selling fetal tissue for profit, is not present in machine news. Similarly, blaming the media for its slant against Republicans and Trump is also absent from the machine news. The differences are due in part to the model training. Machines may not be as capable as human beings of reporting different views of an issue, and more so when the training data is unbalanced.

This means that the news generation model is more likely to capture topics and frames more prevalent in the human news (e.g., voting, election, and Trump's positions) and tends to ignore content, which is less prevalent, as seen in the cases of abortion industry and blaming the media.

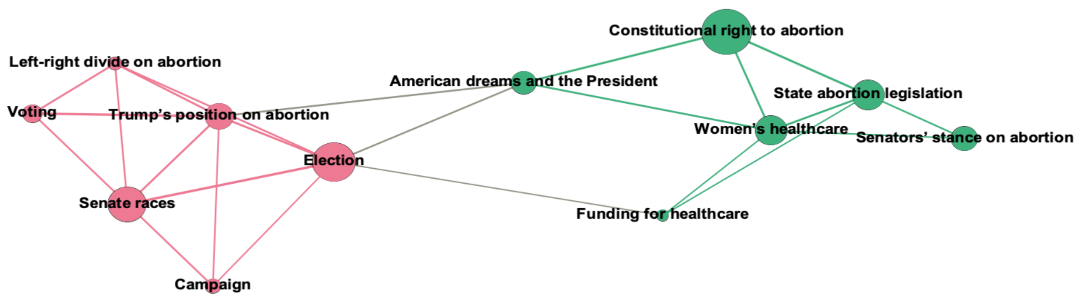



***(a) CNN***

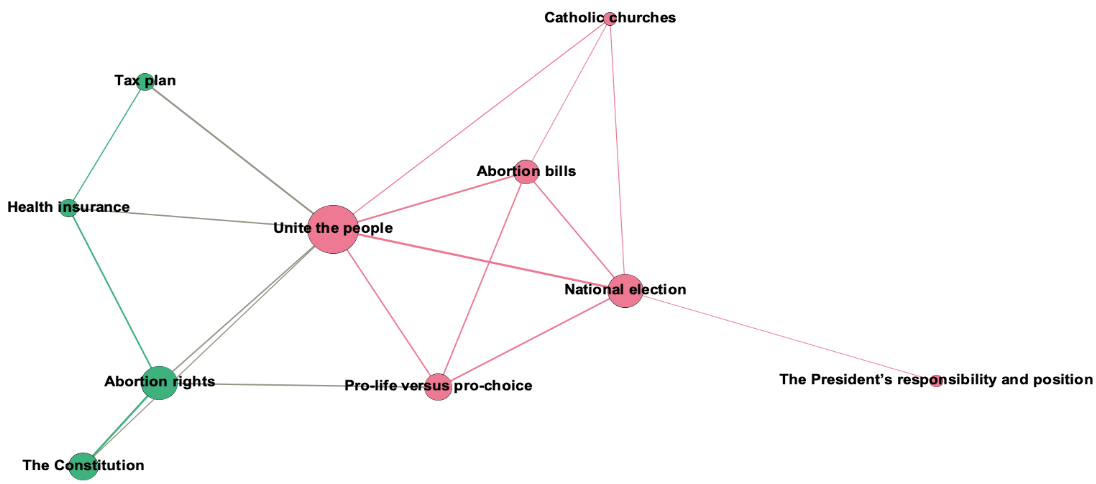



***(b) Fox News***

***Figure 3. The topic network of human news on abortion by CNN vs. Fox News.***
*Note.* The nodes represent individual topics. The edges represent co-occurrence of topics in news articles. The node size shows the prevalence of topics in the corpus, and its color represents the topic community detected by the Eigen algorithm based on the leading eigenvector of the community matrix.




***(a) CNN***




***(b) Fox News***

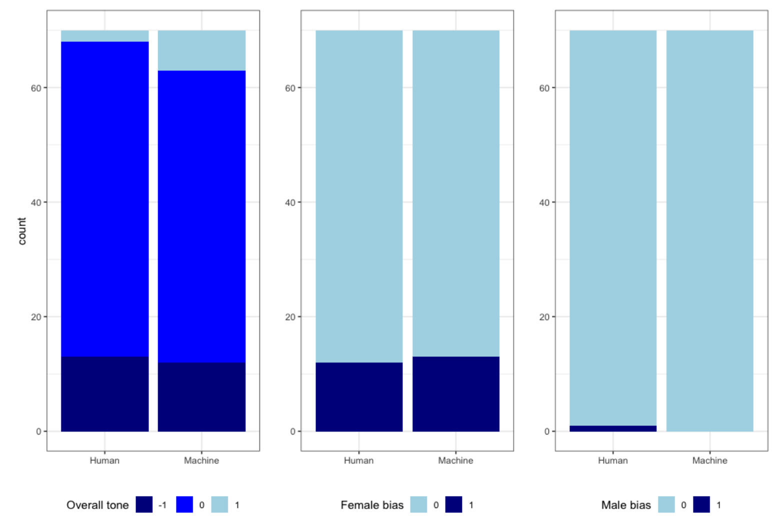
***Figure 4. The topic network of machine news on abortion by CNN vs. Fox News.***

*Manual Content Analysis*

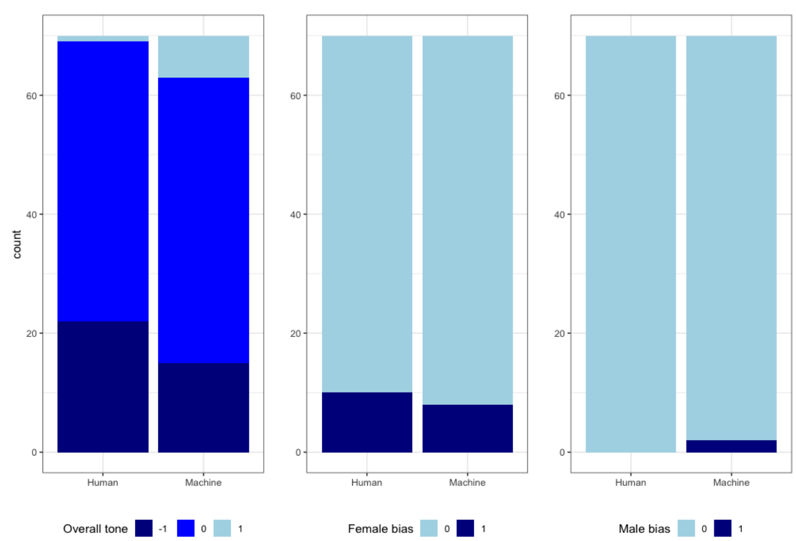
The results from the content analysis demonstrate that human and machine news are similar in terms of gender bias, while they slightly differ in the overall tone. As shown in Figure 5(a) and Figure 5(b), machine news from the CNN language model has slightly more news with bias against females compared with human news (17% vs. 19%). Conversely, human news from Fox News language model shows a slightly higher level of bias against females than machine news (14% vs. 13%). But these differences are not significant (CNN: $x^2$ = 0.048696, df = 1, $p$ = .8253; Fox News: $x^2$ = 0.25501, df = 1, $p$ = .6136). In addition, CNN machine news has fewer articles with male bias (male = 0.1 % vs. female = 0%), whereas Fox News machine news shows slightly more biases against males (male = 0% vs. female = 0.3%, Male bias: CNN: $x^2$ = 1.0072, df = 1, $p$ = .3156; Fox News: $x^2$ = 2.029, df = 1, $p$ = .1543).

In terms of overall tone, the majority of the human news articles are neutral (CNN: Human 79% vs. Machine 73%; Fox News: Human 67% vs. Machine 68%). This is followed by negative news (CNN:

Human 17% vs. Machine 17%; Fox News: Human 31% vs. Machine 21%). Only a small portion of human articles are positive (CNN: Human 2.9% vs. Machine 10%; Fox News: Human 1.4% vs. Machine 10%). The machine news has a lower volume of negative news and more positive news compared with the human news, and this difference is more prevalent in Fox News corpus (CNN: $x^2$ = 2.9687, df = 2, $p$ = .2266; Fox News: $x^2$ = 5.8349, df = 2, $p$ = .05407).




***(a) CNN***




***(b) Fox News***

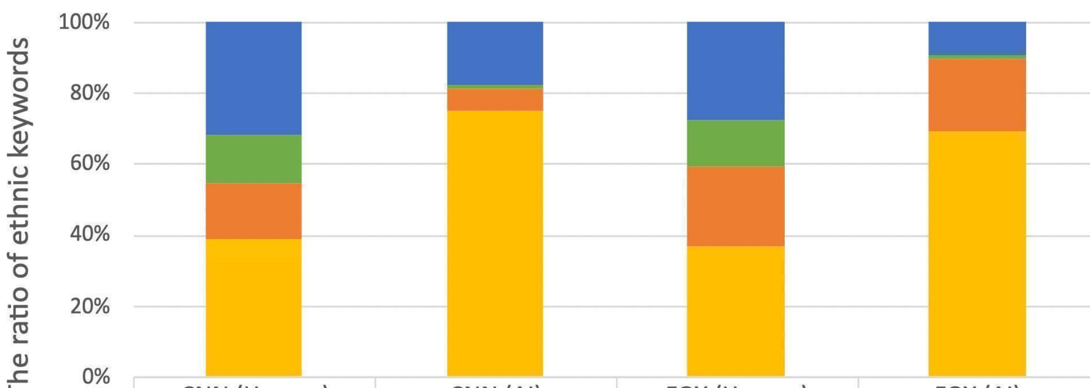
***Figure 5. Content analysis results of abortion news.***

*Note.* The first panel shows the news article count for the overall tone variable: −1 = negative, 0 = neutral, 1 = positive. The second and third panel show the news article count for the two questions: bias against females and bias against males. 1 = "Yes," 0 = "No."

### *Immigration*

*Linguistic Analysis*

The frequency of each set of words was first examined representing the four ethnic groups used in immigration news articles: White, Black, Asian, and Hispanic or Latino. Figure 6 shows the ratio of ethnic keywords. In human news, it was observed that words related to White are frequently used more than other ethnic groups, and Hispanic or Latino-related words are followed by White. In terms of CNN and Fox News' human news, the percentages of White words are 38.5% (CNN) and 36.6% (Fox News), and the percentages of Hispanic or Latino words are 32.1% (CNN) and 27.6% (Fox News). This is probably because Hispanic- or Latino-related words, including certain countries such as Mexico, appeared frequently on both CNN and Fox News because of President Trump's immigration policy. The percentages of White-related words used in machine news account for 74.6% (CNN) and 68.9% (Fox News). In contrast, although Asian received the smallest proportion of human news compared with other ethnic groups, they were rarely covered in the machine news (Asian = 1.37%, CNN and 1.07%, Fox News). These results imply that the news generation model trained on the human news disproportionately used ethnic words.




| | CNN (Human) | CNN (AI) | FOX (Human) | FOX (AI) |
|---|---|---|---|---|
| Hispanic | 32.06% | 17.81% | 27.60% | 9.63% |
| Asian | 13.79% | 1.37% | 13.48% | 1.07% |
| Black | 15.65% | 6.16% | 22.32% | 20.32% |
| White | 38.50% | 74.66% | 36.61% | 68.98% |

***Figure 6. The ratio of ethnic keywords in the human and machine news of CNN vs. Fox News***

The most frequently used nouns and adjectives in the immigration news were then analyzed. As shown in Table 8, both human and machine news have "president" and "Trump" as top-ranked nouns. Findings indicate that the news generation model deals with the immigration policy of President Trump.

However, findings also show that the machine news used more specific words related to President Trump's immigration policy, such as "wall" or "illegal," unlike the human news. Notably, there was no significant difference between CNN and Fox News.

***Table 8. Top-Ranked Nouns and Adjectives in News Articles on Immigration.***

| CNN | | | | Fox News | | | |
|---|---|---|---|---|---|---|---|
| Human | | AI | | Human | | AI | |
| Noun | Adjective | Noun | Adjective | Noun | Adjective | Noun | Adjective |
| President | New | President | Republican | People | New | People | Good |
| People | Last | Immigration | Good | President | Good | President | Great |
| Trump | Right | People | Political | Trump | Right | Immigrants | Able |
| Immigration | Good | Country | Important | Time | Last | Country | Right |
| Time | Republican | Issue | Able | Country | Many | Border | Important |
| Lot | Political | Border | New | News | Grant | Way | New |
| Way | Many | Democrats | First | States | First | Democrats | Republican |
| Country | First | Trump | Last | Immigration | Next | Trump | Much |
| States | Much | Wall | Bipartisan | Border | Much | Issue | First |
| Border | Next | Problem | Illegal | Years | Political | States | Illegal |

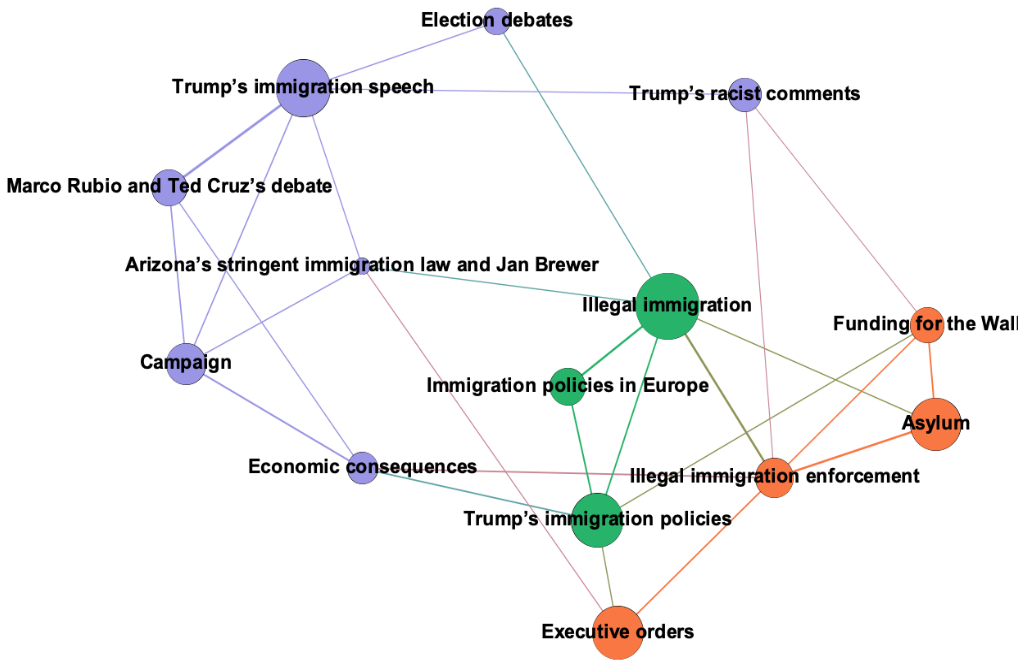
*Topic Networks*

Figure 7 shows that CNN news consisted of three topic communities. The first frame situates immigration issues in the context of campaign, election, and legislation. The second cluster centers around the policy side of immigration. The last group of news articles covers aspects supplemental to major campaign and electoral debates, and policy design on immigration issues such as enforcement, funding sources, and individual asylum seekers. In contrast, human news from Fox News has four topic communities. The major one in the middle (orange color) focuses on immigration reform of GOP leaders and funding sources necessary to implement their policy agenda. Another topic cluster at the top of the network graph (purple) emphasizes policies on welfare, sanctuary cities, and border security, as well as Biden's failing. The rest of the two communities consist of topics related to Trump's position and comments on immigration.

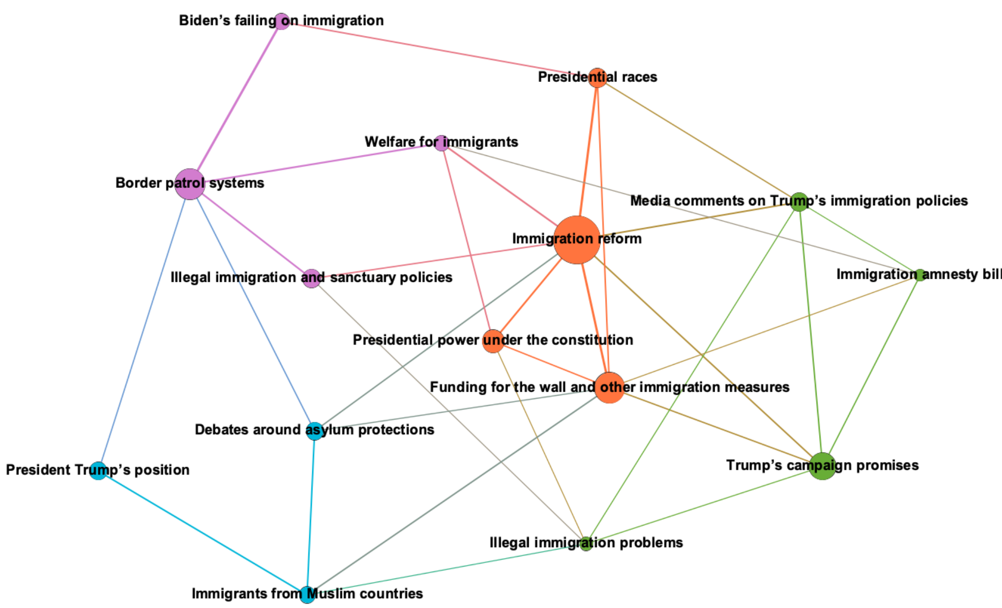
Similar to the case of abortion, the machine news on immigration includes fewer topic communities with less diverse topics. The first cluster of CNN machine news on the left centers around the President's immigration plans and the associated campaigns, executive orders, legislative process, and social impact in religion and trade. The second topic community covers policies that restrict immigration as well as their potential pros and cons with a focus on illegal immigration (e.g., the Wall). As for the machine news generated by the Fox News model, the topic community on the right side of the network graph covers several main topics in human news such as the presidential race and voting, welfare for immigrants, and Trump's position on immigration issues. Interestingly, the topic of "racism" addresses White nationalism and racial animus associated with the surge of illegal immigration. News articles of this topic also criticize

Republicans' immigration agenda. The other topic community centers around illegal immigration and border security, which frames illegal immigrants as a national security issue.

In sum, the machine news employs similar major frames to describe immigration issues compared with the human news, as seen in the cases of the illegal immigration frame in CNN and the national security frame in Fox News. Similar to the case of abortion, the news generation models are more likely to ignore topics that are less prevalent in human news. There exists some exception where machine news reconstructs content from human news that is not explicitly observable. For instance, articles criticizing the racism in immigration policies are not identified in the topic network of human news. In contrast, racism is represented as an individual topic in the topic network of machine news. Presumably, the news generation model learns from the articles under media comments on Trump's immigration policies where critique outweighs the support toward his agenda.




***(a) CNN***




***(b) Fox News***

***Figure 7. The topic network of human news by CNN vs. Fox News.***

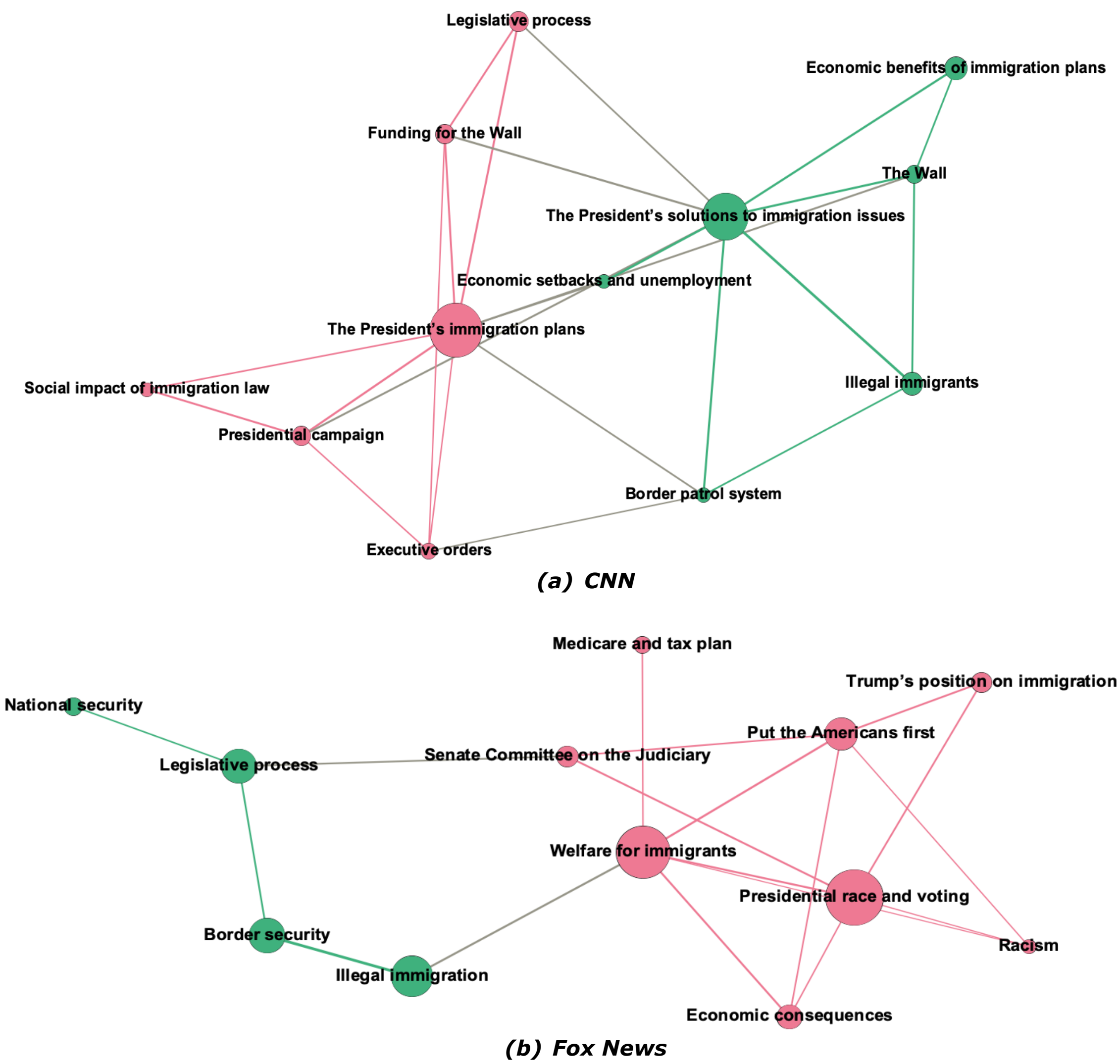


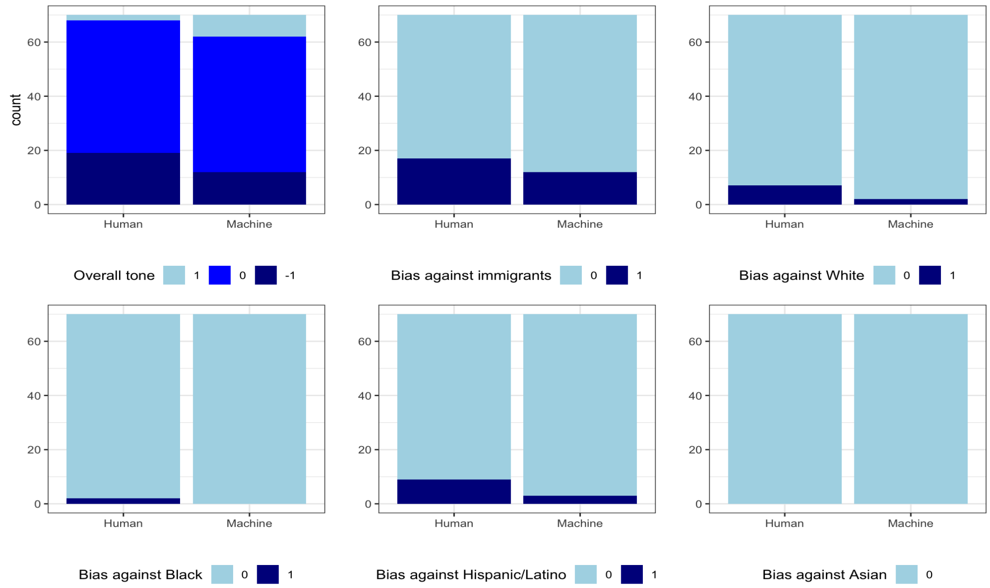

***Figure 8. The topic network of machine news by CNN vs. Fox News.***

*Manual Content Analysis*

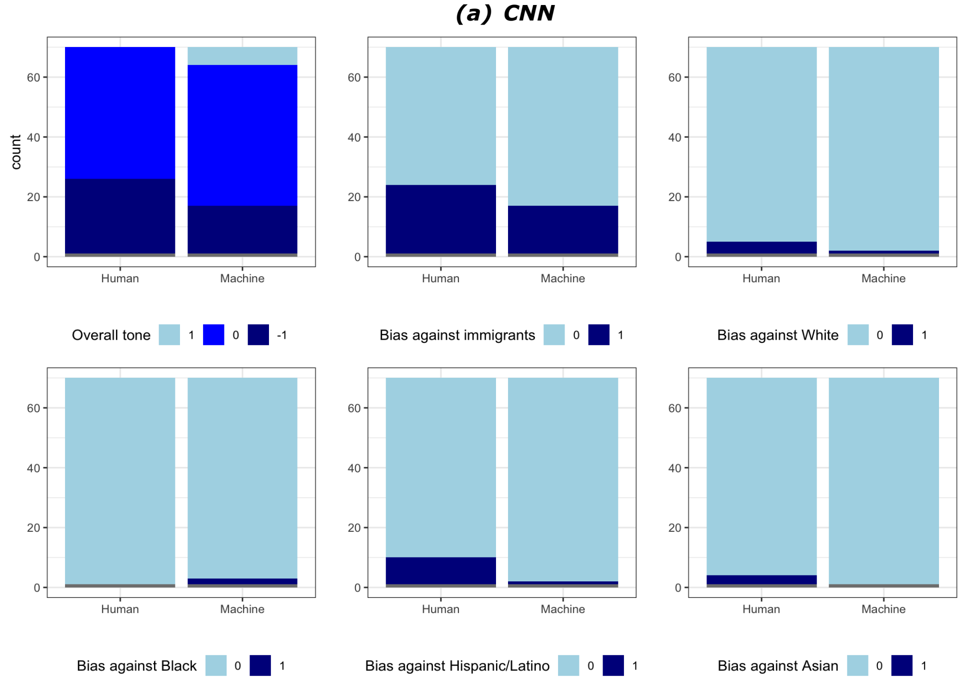
Results from the manual content analysis indicate that human and machine news differ in the following aspects: (1) Human news contains more negative articles compared with machine news whereas machine news has more positive content. (2) Human news shows a higher level of bias against immigrants overall compared with machine news. This contrast is slightly stronger in Fox News. (3) Human and machine news provide similar patterns in terms of bias against specific ethnic groups, with bias against Black being one exception. As shown in Figure 9(a) and 9(b), CNN human news contains more negative news and less positive news compared with machine news ($x^2$ = 5.1907, df = 2, $p$ =

.07462). Fox News overall presents a similar pattern ($x^2$ = 8.0745, df = 2, $p$ = .01765). In addition, 24% of human news from CNN contains content showing bias against immigrants in general (vs. 17% of machine news, $x^2$ = 1.0873, df = 1, $p$ = .2971). As for Fox News, 33% of human news shows this type of bias, whereas only 23% of the machine news was observed having immigrant bias ($x^2$ = 1.7514, df = 1, $p$ = .1857).

With respect to bias against specific ethnic groups, human news contains more content showing bias against White, Hispanic or Latino, and Asian groups compared with machine news regardless of the media outlets. More human news shows bias against White compared with machine news in both CNN and Fox News (CNN: $x^2$ = 2.9686, df = 1, $p$ = .08489; Fox News: $x^2$ = 1.8677, df = 1, $p$ = .1717). Human news from the CNN model has a slightly higher number of articles showing bias against Black people compared with its machine counterparts, whereas Fox News is the opposite (2.8% vs. 0%; CNN: $x^2$ = 2.029, df = 1, $p$ = .1543; Fox News: $x^2$ = 2.0294, df = 1, $p$ = .1543). Both news outlets have more articles showing content that are biased against Hispanic or Latinos, which is more prevalent in human news (CNN: $x^2$ = 3.2812, df = 1, $p$ = .07008; Fox News: $x^2$ = 6.9, df = 1, $p$ = .00862). No significant difference is observed in bias against Asians (CNN: both show 0%; Fox News: $x^2$ = 3.0667, df = 1, $p$ = .07991). In general, Fox News contains more content biased against immigrants across the ethnic groups.




***(a) CNN***




***(b) Fox News***

***Figure 9. Content analysis results of immigration news by CNN vs. Fox News.***

*Note.* The overall tone variable: −1 = negative, 0 = neutral, 1 = positive; bias against ethnic groups: 1 = "Yes," 0 = "No."

## Discussion and Conclusion

The present study compares human versus machine-generated news in terms of linguistic features, tones, and bias toward gender and race/ethnicity regarding two highly controversial issues: abortion and immigration. Overall, our results reveal that (1) human news contains more diversified topics, whereas machine-generate news is more focused on the topic of interest; (2) human and machine news exhibit sharply distinct linguistic word choice; and (3) machine news is relatively more positive and at the same time less biased relative to human news, although there is a disproportionate use of ethnic words related to White.

In terms of abortion, CNN machine news contained more female keywords compared to CNN human news, whereas pronouns referring to men dominate female keywords in machine news for Fox News. Top referents in machine news are often more general (e.g., a person) compared to specific politicians frequently mentioned in human news. Moreover, the results indicate that machine news focuses more on the topic of abortion itself, whereas human news tends to emphasize politicians' views and actions associated with the abortion issue. These findings are corroborated by the results from topic networks where machine news tends to capture the major topics of human news and cover less of the abortion issue in more nuanced forms than its counterpart.

As for immigration news, White-related words are used more often compared to other racial words. According to the manual coding, both CNN and Fox News contain fewer articles that show bias against White people compared to bias against other ethnic groups. It is our speculation that White-related words are associated with news content on politicians' debates about immigration policy, whereas Hispanic or Latino-related words point toward such topics as the Wall, Trump's speech on immigration, and so on. In addition, the discrepancies between CNN and Fox News in terms of the number of racial words align with the results. From the manual coding, the results indicate that Fox News has more articles showing bias against ethnic groups.

Given that machine news tends to convey news content, which is already more salient in human-generated texts, AI news production may alter the frame-building process, largely determined by external forces, organizational pressures, journalistic routines and attitudes, and ideology (Scheufele, 1999). Presumably, algorithm designers and creators, coupled with human biases represented in the training data, can affect what gets "selected" into the news ("gatekeeping"), which agenda becomes more salient ("agenda setting"), and how the issues are framed ("framing"). Furthermore, individual-level frame setting with the acceptance and reconstruction of media frames may interact with audience predispositions of AI and algorithms such as trust in AI and AI news credibility (e.g., Cloudy, Banks, & Bowman, 2021; Lee, Nah, Chung, & Kim, 2020). That is, audiences with higher levels of AI acceptance may be more inclined to trust machine news or perceive it as more accurate compared to journalist-written news content. It is plausible that this may raise concerns over misinformation and polarization, suggesting that AI technologies may spread fake news or limit diverse media exposure (Kreps, McCain, & Brundage, 2022). In this vein, future research should consider testing whether there are differences between human- and machine-generated news in terms of news quality and the impact on public news consumption. Specifically, future studies may examine whether AI technologies are indeed more likely to diffuse rumors (Vosoughi, Roy, & Aral, 2018) and how the formation of an "echo chamber" may vary with AI recommendation systems mediating the information selection process (Möller, Trilling, Helberger, & van Es, 2018).

Despite potential issues concerning AI news production, our findings suggest that machine news is more focused on the topic of interest, whereas human news contains more extensive and diversified topic patterns. This implies that AI models may have the potential to capture news content that is more specifically related to the topic of interest compared with human-generated news content. Thus, it is plausible that machines may be more accurate and concise in reporting facts about a certain topic than opinion-based news content. In this vein, human and AI news can go in tandem, being complementary rather than contradictory when it comes to news production. Future research may examine the concept of news accuracy and bias by comparing the performance of machines and professional journalists in covering factual versus opinionated content.

In fact, emerging research has begun to explore AI in the newsroom in terms of the juxtapositions and questions that the merge between AI and journalism may create. For instance, Moran and Shaikh (2022) explored this exact tension between AI's ability to report facts but questioning whether journalism's role was to simply report content or rather contextualize situations to further elucidate news truths. In addition, it is relevant to note that AI in the newsroom does not solely pertain to the co-creation of content or news but also to task-assistance and work efficiency (Munoriyarwa, Chiumbu, & Motsaathebe, 2021). One example of how AI-assisted task-efficiency may also overlap with content creation or journalism is through machine-learning suggestions of headlines, which journalists may then reflect on and decide on a course (Stenbom, Wiggberg, & Norlund, 2021). In this way, AI can assist with the "first round" of content creation but allow for human nuance and decision making, as well as checking for bias or other areas of concern.

Notwithstanding the theoretical and practical implications, several limitations remain. First, our data are temporal and local. The contents of news articles can differ by years and are influenced by other time-variant factors, such as political events. Therefore, future research may group news articles by presidential terms and assess how the linguistic features, tone, and biases depicted in news articles may vary across time periods to provide a more holistic picture of the impact of AI language models on journalism. Second, machine-generated news by the language model may differ depending on the input prompt. Future research, using input prompts other than "abortion" and "immigration," which were used in this study, should validate the quality of news stories in terms of word choices, types of sources, and issues, as well as tones/frames. Third, this study used news transcripts as the training data because it is the only available document type published by Fox News on Nexis Uni. Future research may continue examining differences in human- and machine-generated news with complete news articles. Lastly, the measurement of bias toward gender and race/ethnicity in our coding schemes may be oversimplified because these concepts are fluid, multifaceted, and often more subtle. Future scholarship should further develop a solid conceptual and operational definition of bias that can be more testable for bias toward gender and race/ethnicity.

In conclusion, this study provides a foundation for future research to compare machine versus human news concerning automated journalism and news bias. The results and their related implications enable us to pose a fundamental question of whether and how AI-generated news may reflect news bias represented in human news ("algorithmic bias") or reconstruct human news in distinct ways ("algorithmic reframing" or "algorithmic reconstruction"). Future scholarship may continue this line of research from a comparative news perspective and shed light on how audiences receive, perceive, and respond to AI-constructed news, potentially resulting in democratic outcomes such as an enhanced level of news trust, literacy, knowledge, and civic action. In doing so, future scholarship may revisit framing theory (e.g., Scheufele, 1999) to test how machine versus human news may operate in tandem or in similar but distinct ways in terms of news production and consumption processes and outcomes.

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