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RESEARCH ARTICLE

Examining the Existence of Google's Search Engine Bias Based on Gender in the United States Congress

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ABSTRACT: This study analyzes visual data from the Google image results of the 535 members of Congress to investigate the existence of visibility bias (an undue amount of coverage in comparison to their counterparts). The quasi-experimental approach separates congresspeople by gender to look for significant deviation based on visual representation. The images were processed with a Haar Cascade Classifier to identify the number of people in each photo, and the results were confirmed by human review. Through t-tests, significant differences were found between the representation of congressmen and congresswomen in terms of the average number of photos without the searched-for politician (a photo result without the searched-for politician) and the sharing of photo representation with the same gender (being featured in a photo with someone of the same gender). The odds-ratio test, which compared zero photos to non-zero photo representations, found significant differences regarding the number of photos alone of the searched-for politician, the number of photos without the searched-for politician, and photos with the same gender as the searched-for politician. These findings offer insight into measuring visual visibility bias in news aggregation and suggest discrepancies in political gender representation between men and women.

KEYWORDS: Media Studies, Gender Bias, Politics, Computer Vision Search.

Introduction

The 118th Congress which served the United States from January 2023 to January 2025 was made up of 28.6% of women while the United States population in 2023 was made up of 50.4% women.[1,2] With an unrepresentative congressional body based on gender, the public often attributes the imbalance to "female unelectability" which is the idea that women are seen as suffering in elections due to inherent biases from voters that are rooted in American culture, therefore causing them to lose elections.[3] These inherent biases can come from media biases, which are any deviation from neutral coverage. Researchers at the University of Vienna, Austria, determined that one way to define media bias is to split it into three types: agenda bias, visibility bias, and tonality bias.[4] Agenda bias is the selectivity of coverage, visibility bias is a relatively undue amount of coverage, and tonality bias is the deviation from a neutral tone when creating associations. In a political sphere, an agenda bias against a female politician would be exclusively covering male politicians. She would not be on the "agenda" of coverage. Visibility bias occurs when two figures are presented, but one is given an undue amount of coverage. Finally, tonality bias is about the connotation elicited from the creation of an association. Associating a figure with an increasing environmental crisis or scandal is an example of associations that reveal negative tonality bias. An example of a visual tonal negative bias is emphasizing poor skin, making them look sickly and tired, to associate with the degenerative parts of aging.

History of Media's Gender Bias:

The media has historically caused biases against women. Bhatia and Bhatia, while working with the University of Pennsylvania, found that media representation of women was made more masculine in 2021 as compared to the 1990s, correlating with the increase in roles of women in the workplace.[5] These trends reflect and suggest a societal attitude that paid work is a masculine domain. Not only were women found to be seen as subordinate, but men were found to be depicted as being in power. When examining autocomplete algorithmic search bias, Lin and his colleagues from the School of Journalism and Communication at Renmin University of China found that the bias was "consistent with long-standing societal discrimination" against women.[6] Furthermore, the media reflects societal gender bias by quoting women three times less often.[7] Yet, they also discovered that more women are represented than males numerically. This means that there are a few influential men, while there are many non-influential women quoted and used as sources.

The Impact of Media Bias on Voters:

Imbalances present in the media can have negative cognitive effects on viewers. The profound impacts of media and its bias on voter behavior can be attributed to its power over the opinions of consumers on issues of salience and sentiment.[8] However, there is disagreement about the degree to which media bias informs the development of bias in an individual. Bissel and Parrott argue that bias is not only from the media but also from preconceived notions and societal ideas.[9] Hopmann, Van Aelst, and Legnante, on the other hand, had findings that support the ability of media to significantly shift bias in voters switching their vote through all three types of bias (agenda, visibility, and tonality), especially tonality.[10] This difference can be explained by the different data utilized by these research efforts. While Bissel and Parrot interviewed people, Hopmann and his colleagues scraped data online. Thus, Hopmann, Van

Aelst, and Legnante could have overestimated the role of media as the sole source of bias by exclusively using online data. However, these researchers agreed that media representation contributes to one's formation of categories used to classify others. Morgan and his colleagues differentiated first-order and second-order beliefs by stating that if one were to see the underrepresentation of women, one would not be convinced "there are fewer women in the real world (a first-order belief), but it may well be taken as an indicator of devaluation and restriction that supports the cultivation of traditional gender roles (a second-order belief)." [11] The second-order cognitive effects of media bias against a group can impact a person's perception of them. Thus, although perception is not fully derived from media, it is heavily informed and thus can be studied as a large contributor to perceptions of people seen and interacted with largely digitally.

Search Engine Bias:

There are several types of news media, one of which is the news aggregator. These aggregators collect and publish news stories and are a key gatekeeper of what is shown to viewers, taking on the responsibility of curating content. One such aggregator is the search engine Google. With 16.4 billion total Google searches a day, Google serves as a primary search engine for 65% of Americans.[12, 13] Thus, the results from the search engine at Google could point to a possible bias against women, which could be a contributing factor to a bias against female politicians. For this reason, this analysis will focus on Google. In addition, "[in] the current environment, people just are not going to search much past page one," making it the only page that will be sampled from to reflect the searching behavior of the average American.[14] Since there is no "First Page" in the "Photos tab", the study will sample from the photo results under the "All" section of Google. Another reason the "All" tab is being used is to record the number of photos when it is not explicitly stated.

The United States Congressional Structure:

The United States's direct democratic bicameral legislature creates unique potential for analyzing representation in the hands of voters. The 17th Amendment of the U.S. Constitution, ratified in the year of 1913, changed the upper house of Congress (the Senate) from being appointed by state legislatures to being directly elected by the people. Direct representation has "switched candidate focus from winning in the state legislature to winning in the statewide electorate." [15] Thus, the legislative branch, as opposed to the executive and judicial branches, is the only branch of the United States national government that is voted on directly by its citizens. In addition, the upper house has two representatives per state, while the lower house is proportional to the population, creating congressional districts and providing a more granular look into American voting behavior.

How to Study Different Types of Bias:

The current research connects gender bias to politics by examining facial attributes in photographs, revealing an emphasis on studying visual tonality bias.[16] Such face attributes included skin quality, facial expression, and the size of the face. However, there is a lack of research on visual visibility bias (the amount of coverage) at the intersection of gender bias and politics. Therefore, this study will examine visual visibility bias. Currently, there has been extensive research done covering bias against political parties in search engines and generative AI such as ChatGPT.[17] When examining such AI models, researchers have examined output to replicate user experience while studying search engines that draw from the data from all possible results.

RQ: How do Google's photo search results of the 118th Congress differ based on the politician's gender, revealing an existence or lack of bias?

Methods

This study operates under Wallace's gatekeeping theory.[18] This theory argues that the people are part of determining issue salience, but also that the media has an instrumental role in determining what people deem important.

By looking at image data where it is not directly asked for, the bias is revealed by the organic supplement of results by the Google search engine's algorithm. This methodology is supported by McGee, who used Irish limericks (a type of joke in poetry) to elicit the political bias of ChatGPT.[19] McGee asked for limericks regarding Democrats and Republicans and coded the different types of jokes to determine which were harsher and which were more light-hearted. Similarly, this study will use the equalizing phrase "articles" during the search, which will indirectly reveal bias in the types of photos the Google algorithm provides.

I used a quasi-experimental research design since this framework aligns with the equal treatment of the same across all searches (same search format), and the fact that there are two preexisting groups. There are only cisgender representatives in the 118th Congress, which served from January 3, 2023, to January 3, 2025.[20] Although gender does not exist in a binary, for this study, there are only two genders present to study: women and men. Thus, the independent variable is the gender of the congressperson put into the search.

The dependent variables are quantitative. The dependent variables are the number of first-page photo results, the number of photos without the politicians, and the number of photos with both the politician and someone else. These can all reveal favorability or bias toward candidates, according to Kim et al., who found that negative visibility bias (the disproportionately low amount of coverage someone receives) can be visually determined by how much coverage figures have to share their coverage with others.[21] Each dependent variable is meant to determine whether coverage is shared and who/what the coverage is being shared with. By not sharing coverage, the politician receives the main focus, indicating a stronger bias toward them. If both genders are disproportionately sharing coverage, with one gender, the gender not being represented in either is being biased against.

The procedure of the study is as follows:

1) Search "[Politician First Name] + [Politician Last Name] + articles" on Google
2) Download the first-page photo results in the "All" section of Google results into folders for each politician.
   a) Video thumbnails are counted as an image.
   b) The sampling is exclusively from the Google first page search results, inspired by the findings of Buddenbrock that American users significantly draw the majority of their search information exclusively from Google's first page results.[14]
3) Analyze each photo with a Haar Cascade Classifier in Google Colab to determine the number of people in the photos and manually review the analyzed output for accuracy.
4) Record each person's total photos, photos alone, photos without them, photos with someone else of the same gender, and photos with someone else of the opposite gender, as informed by Haar Cascade Classifier output data.
5) Conduct a paired t-test (men vs. women) in Python and an Odds Ratio in Logarithmic Regression test in Google Sheets. Examine the p-value and see if there is a statistically significant difference between the Google first-page photo search results for men and women in the U.S. Congress.
   a) Both tests are conducted for each dependent variable (10 tests total)

Steps 1-3 are repeated for each of the 535 members in the 118th U.S. Congress, analyzing the first-page Google results.

During sampling, there are several possible ethical concerns with the sampling procedure. Google utilizes data such as previous websites visited, keywords, and localization to determine the influence of search results. Previous data consideration can be mitigated by creating a new Google account and deleting history after each search. Keyword search differences have been eliminated by using the same search template, "[Politician First Name] + [Politician Last Name] + articles." Localization is kept constant in California, which is a limitation of the study. Since California is a largely Democratic state, there is the possibility of Google using localized data to augment democratic candidates. There are 63 women registered as Democrats and 59 women registered as Republicans in the 118th Congress. Since the difference between these numbers is 4, it is unlikely that the Google search localization of California will increase the representation of women, but it should be acknowledged that this could possibly impact the results of this study.

Data collection was done over 4 days (January 8, 2025 - January 12, 2025). It was important to conduct this research over as short a time frame as possible since a figure can become highly associated with a contentious issue or election, increasing its coverage in the course of a week, month, or year. The analysis is cross-sectional, meaning data collection needs to be as close together as possible in time to avoid a temporal aspect changing the results. Thus, measuring across too large a time frame does not allow for comparable data. However, the end-to-end collection took over 10 hours, so it is important to ensure high-quality and accurate collection. The 118th Congress served from January 3, 2023, to January 3, 2025. The sampling was done at the completion of the term in order not to be impacted by recent political decisions made during their term. However, this study does not account for which politicians were running as incumbents, nor did it consider which politicians' terms did not end on January 3, 2025.

To identify faces, the Haar Cascade Classifier scans images searching for features of a human face. One ethical concern with the Haar Cascade Classifier is the accuracy rate of this program, which is 96.6%.[22] To ensure the counting of faces is closer to 100%, each result is reviewed visually in step 3 of the procedure. This program draws a rectangle around the face, making finding errors during review easier. Since it could not identify the specific person searched, this process also needed to be manually readjusted to determine whether the politician was in the photo and fix incorrect outputs for "Photos alone" and "Photos without them" dependent variables. This program serves to make processing and collection faster and more standardized.

The statistical tests of the t-test and odds ratio were chosen due to their unique abilities to capture the complexity of the dataset and investigate bias from two different perspectives. An advantage of the t-test is that it takes into account the different frequencies within the data. However, the t-statistic output can only be examined relative to other outputs within the study. The odds ratio test, on the other hand, takes into account how there are many zeros in the data by analyzing zero vs. non-zero photo data points between male and female congresspeople for each dependent variable. This loses some complexity of the data set by simplifying the frequencies, but the odds-ratio test outputs percent values that are easily interpretable independently of other values in the study.

Results and Discussion

Results

On average, congresswomen were represented with 0.5533 photos each, while congressmen were represented with 0.6512 photos each, meaning men were represented with 17.69% more photos than women. The majority of data was zero for every dependent variable, which can be seen in Figures 1 and 2, which display histograms of the total number of photos of congressmen and congresswomen.

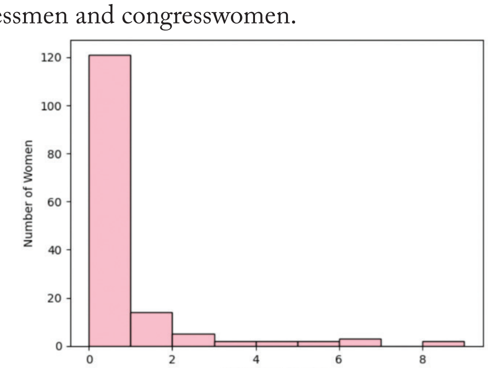

Figure 1: Histogram of Number of Total Photos for Each Female Congressman: Frequencies of photos are on the x-axis, while each congresswoman's number of total photos is plotted on the y-axis. The majority of results display 0 photos, which was expected since the search explicitly only asks for articles.

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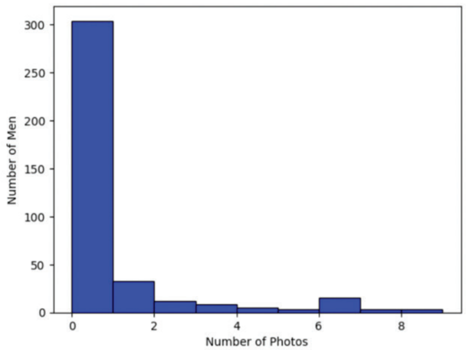

Figure 2: Histogram of Number of Total Photos for Each Male Congressman: Frequencies of photos are on the x-axis, while each congressmen's number of total photos is plotted on the y-axis. There were more men represented in this histogram than women in Figure 1, since there are more men in Congress. Thus, the x axes are the same, but men's y axis for men goes to 300 men.

To best represent this data, the Odds Ratio test and sample t-tests were used. This study operated with a 95% confidence interval, so any findings with a p-value less than 0.05 were considered significant because a p-value less than 0.05 suggests there is a 95% chance that the findings were not by random chance. The odds ratio test produced percentages that represented the percentage chance men have of being represented the same as women. The Odds Ratio test was set up such that the percentage takes into account the "negative" portrayal for each dependent variable: fewer photos, fewer photos alone, more photos without them, and sharing space with men disproportionately more than with women. The lower the percentage, the greater the representation of men compared to women. This is because the lower the percentage is, the test revealed there is a lower chance that there is over the men experiencing a greater representation as women. There were fewer women, but this test was a ratio test, so this did not present a problem with the uneven dataset for statistical analysis. The odds ratio between men and women considering the number of total photos, there was a 96% chance that men would be represented the same as women ($p=0.8722$). It was found that men had less than a 7.2% likelihood of having portrait photos alone as infrequently as women ($p<0.01$). For the number of photos without them, men have a 36.97% chance of having as many photos without them as women ($p=0.0269$). Men shared representation with men 28.93% of the time compared to women sharing representation with other women ($p=0.0104$). When considering photos that showed the opposite gender, men were 20% less likely to have women than women were to have men ($p=0.6169$).

Sample t-tests check if a sample mean is within the population with a certain confidence level. In this test, women's data was the "sample," while men were the "population." Therefore, this test determines if the women's mean average representation is significantly different than men's mean average representation. This test checks if the mean for women could reasonably be representative of the data for men. This study will continue to look for a 95% confidence, which is a p-value of less than 0.05. For sample t-tests, the preconditions must be met: the sample has at least 10, and the population has a normal distribution. Although the raw data is not normal, the t-test will be operating with the assumption of the central limit theorem: as the number of data points increases, the sampling distribution will approach normality. With over 40 data points, the t-tests between men and women can be conducted (Table 1).

Table 1: T-Tests Results: Summary of t-tests done for each independent variable, testing if the average photo count of congresswomen's data could be reasonably representative of men's photo frequencies. The findings regarding photos without them and the same gender are statistically significant. Since they both have negative t-statistics, the congresswomen's average is too low to be reasonably representative of the congressmen's data, so men had more photos without them and depicted other men than women.

Value	Total Photos	Photos Alone	Photos Without Them	Same Gender	Opposite Gender
t-statistic	-1.4636	-0.5358	-6.3379	-3.5877	0.3977
p-value	0.0727	0.2965	>0.0001	0.0002	0.6543

The t-statistic output is non-standard and is relative to the other findings. The greater the absolute value of the t-statistic is, the less representative the women's mean can be for the men's data. Figure 3 displays how having a negative t-statistic (in this case, Photos Without Them) in this study means men have more photos in the comparison because the congresswoman's mean is too low to be representative of the congressman's data.

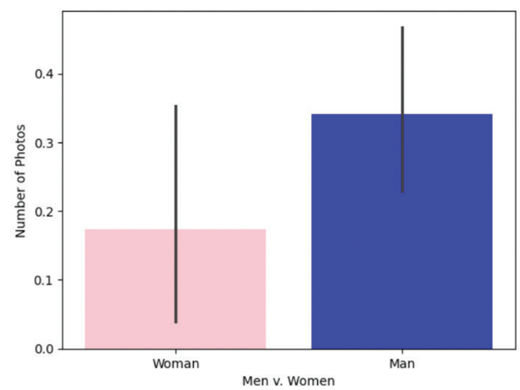

Figure 3: Men versus Women, Photos Without Them: Average values are graphed with error bars that represent the standard deviation. Congressmen, on average, have a greater average number of photos that do not include them in their search results than congresswomen.

Discussion:

This project has the potential to explain a factor of uneven representation of women serving in the U.S. Congress. If significant bias in search engines is found in this study, future studies can study the impact of search engine bias on users. They can conduct further examination similarly to how linkages between issue salience and media are studied (with convolutional neural networks that aim to find and evaluate similarities between them to suggest a causational impact).

This study supports Asr et al.'s findings that female representation is tokenism– representative small efforts to give the appearance of equality while not supplying it.[7] Initially, this study had the assumption that the more photos without the politician, the worse their representation is. The t-statistic of -6.3379 displayed in Figure 3 reveals that men had signifi-

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cantly more photos without them than women. Yet, according to the odds ratio test, congressmen only have a 7% chance of being alone in a photo as infrequently as congresswomen. This finding, coupled with the fact that men, on average, had 18% more photos than women, reveals that the representation of men is so much greater than that of women that men have more photos alone and more photos without them than women do. Peng's study found that male politicians are often portrayed as dominant, portraying them as angry, while women are represented with kindness, portraying them as happy.[16] Furthermore, according to researchers from the University of California, Santa Barbara, being depicted alone can assert dominance since taking up the frame alone increases the salience of a person.[23] This reality is reflected in the findings that are overwhelmingly in favor of men. Thus, the women's photos that are included are minimal, while men's photos offer a more complete view of the political actor, suggesting tokenism when representing women.

However, the people whom men and women share their representation with are also important. Men shared the photo representation with women 28% of the time, and women shared the frame with other women. Thus, men are sharing space with other men more than how much women are sharing space with women. This difference is also shown by the -3.5877 t-statistic output when comparing whether men and women share photo representation with the same gender. This means that when searching for a female politician, there is a higher likelihood of seeing a man than finding a woman when searching for a male politician. Men are benefiting from other men's overrepresentation through their grouping based on gender. The relatively high t-statistic (compared to the other findings), high absolute value, along with its great significance ($p=0.0002$), reveals the significant difference between male and female congressional representation on Google. This overemphasis on gender exclusively for men can delegitimize womens' role in government.24 The second-order cognitive effect thus would not only be seeing women as less valuable in political spaces but seeing men as more deserving politicians, thus making it extremely difficult to overcome the hurdle determined to be the most significant obstacle during the market and campaign for a female politician, being a woman.[25]

Overall, there appears to be a significant bias against congresswomen in comparison to congressmen on the news media aggregator Google. The higher overall representation of men, coupled with more photos without them, suggests tokenism. In addition, the grouping of men bolsters each other's representation, while women share their representation with men.

Conclusion

Wallace's contemporary gatekeeping model updates what was previously thought of as media aggregates playing a dominant role in comparison to users; users now have the power to influence what the algorithm deems valuable content.[18] Considering that the American people predominantly vote for males and that they influence Google algorithms with search and engagement metrics, it is reasonable to question whether Google's bias is intentional or if the Google algorithm simply reflects user bias. Thus, it is important to distinguish between correlational and causational effects of Google representation impacting voters or voters impacting Google representation. Vargo and Guo suggest that the biases from users are amplified by algorithms, exacerbating existing discrimination in digital spaces.[8] Thus, with this study alone, it is impossible to conclude whether the bias is completely from users or completely from Google. While this study suggests the existence of bias against female congresswomen on Google, it cannot point out the cause. Future studies can examine causes by drawing from Kim et al.'s findings to support that short-term bias is dynamic and not "exogenous to the political process."[21] This could include studying a congress while it is serving, unlike this study, which sampled data after their term concluded. Future researchers can also analyze dynamic bias over time and integrate Google's parent company, Alphabet Inc., to test if the bias toward or against congresspeople is correlated with lobbying efforts. Since this study has data collected only includes the congress from 2023-2025, future research can include more terms and record data with a selenium bot (automated method of web scraping) instead of manually for a more accurate cross-sectional analysis. In the political sphere, this study reveals the importance of search engine representation in determining the importance of a political candidate. Thus, politicians can aim to shape search results during campaigns or acknowledge unfavorable coverage.

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