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ABSTRACT

This research shows that members of different ideological groups in the United States can use different search terms when looking for information about political candidates, but that difference is not enough to yield divergent search results on Google. Search engines are central in information seeking during elections, and have important implications for the distribution of information and, by extension, for democratic society. Using a method involving surveys, qualitative coding, and quantitative analysis of search terms and search results, we show that the sources of information that are returned by Google for both liberal and conservative search terms are strongly correlated. We collected search terms from people with different ideological positions about Senate candidates in the 2018 midterm election from the two main parties in the U.S., in three large and politically distinct states: California, Ohio, and Texas. We then used those search terms to scrape web results and analyze them. Our analysis shows that, in terms of the differences arising from individual search term choices, Google results exhibit a mainstreaming effect that partially neutralizes differentiation of search behaviors, by providing a set of common results, even to dissimilar searches. Based on this analysis, this article offers two main contributions: first, in the development of a method for determining group-level differences based on search input bias; and second, in demonstrating how search engines respond to diverse information seeking behavior and whether that may have implications for public discourse.

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1. Introduction

Search engines are important mediators in the flow of news information to the public. Because of their scale, predominance, and role in information seeking during elections, search engines have significant implications for democratic society. Search results can be seen as a new type of metamedia (Metaxa et al., 2019), which can shape opinions, reinforce stereotypes, and impact voter preferences (Epstein, 2018; Kay et al., 2015; Knobloch-Westerwick, Johnson, Silver, et al., 2015).

A survey conducted in 2017 in five European countries and the United States showed that 56% of respondents go to search engines first when they are looking for information

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about politics, such as a political candidate. This is a far higher proportion than visiting specific websites (19.3%) or social media (11.0%). In the U.S., that dominance is above average, with 61.3% for search engines, 16.5% for specific sites, and 9.8% for social media (Dutton & Reisdorf, 2017). An analysis of browser histories showed that one out of every five news sessions (online events in which users read news) starts with the results of search, in comparison to 16% for social media sites (Bentley et al., 2019).

This dynamic of information-seeking behavior through search engines becomes more salient during elections, since the volume of searches increases after significant news events (Trevisan et al., 2016). Elections therefore make for a particularly interesting topic of investigation with regards to search engine use. This research focuses on search behavior and its effect during the United States midterm elections of 2018.

One concern is that curation by search engines may curtail the diversity of information, a key feature of democratic deliberation (Helberger et al., 2018; McQuail & Van Cuilenburg, 1983). However, there is a tension between information diversity and collective common ground. Divergent information could foster parallel interpretations of society and undermine the exchange of ideas. This conflicts with the deliberative model of democracy, which calls for the media to provide a public forum for such exchange in society (Helberger, 2019).

The tension between information diversity and collective common ground is made salient by advances in personalized curation algorithms (Diakopoulos et al., 2018). Such algorithmic approaches underlie concerns related to the filter bubble effect, the idea that algorithms react to users' preferences and profiles to supply them with personalized results that limit exposure to diverse information (Pariser, 2011). However, recent empirical research deflates the filter bubble, indicating that search and social media users are usually exposed to a mainstream selection of content (Bandy & Diakopoulos, 2020; Bechmann & Nielbo, 2018; Courtois et al., 2018; Müller et al., 2018; Puschmann, 2018). Still, the impact of user-centric personalization algorithms are a cause of public debate (Bruns, 2019; Thurman, 2019).

A complicating factor, particularly with respect to search engines, is the role of user-input biases in influencing how a dynamic curation algorithm responds to an individual. This relates more broadly to the notion of selective exposure to information – the mechanism through which people select information that is congruent to their viewpoints, either by preferring information that reinforces their views or avoiding information that challenges those views (Garrett, 2009a, 2009b; Knobloch-Westerwick, Johnson, Westerwick, et al., 2015; Stroud, 2010). In this research, we examine the role of user-input bias in relation to selective exposure, i.e., the self-induced 'customization' of search results produced through the choices of users. In particular, we are interested in the key element of agency when users trigger search engines: *search queries*. Are search engine users of different political ideologies different in the way they search for information about politics? And is that difference enough to surface substantially divergent search results?

To examine those questions, we first collect possible search terms from people with different ideological positions and use those terms to scrape results from Google. Both queries and results are then analyzed to better understand differences across ideological groups. In doing so, we contribute in two ways: first, in the development of a method for determining group-level input biases; and second, in demonstrating how search engines respond to diverse information seeking behavior. Our analysis shows that while there are significant differences in search behavior between liberals and conservatives, both groups largely see the same sources of information. This mainstreaming effect of search engines has implications for information intermediaries and society as a whole.

2. Related work

This research investigates the impact of search engines in politics and explores how search queries can be used as expressions of political interest. In this section, we review how previous research has approached these topics, and how our work relates.

2.1. Search and politics

The previous literature on the impact of search engines on political processes largely motivates the focus of the current study. Previous research has often focused on unequal representation of candidates and issues on search engines (Muddiman, 2013), the importance of candidate-controlled pages in establishing positive coverage in search results (Diakopoulos, 2019; Puschmann, 2018), how search bias differs from social media bias (Kulshrestha et al., 2019), and how search engines provide access to a handful of mainstream sites (Muddiman, 2013; Nechushtai & Lewis, 2019; Trielli & Diakopoulos, 2019). There have also been concerns raised regarding bias in page snippets, which can highlight more extreme partisan language used on websites (Hu et al., 2019). In some cases, unwanted bias can be reduced through greater transparency, such as by indicating the ideological leaning of websites (Epstein et al., 2017; Kulshrestha et al., 2019).

The effect of distortions in curation and representation of politics is not trivial. For instance the Search Engine Manipulation Effect (SEME) has been measured in a series of double-blind, randomized controlled experiments which show that biased search rankings have the potential to impact the outcome of elections (Epstein & Robertson, 2015). The experiments show that the voting preferences of undecided voters could be changed by 20% or more, and that some demographic groups are more susceptible to manipulation. These experimental findings underscore the need for additional field research into search engines and elections, which the current research contributes to.

2.2. Sources of bias

Research on search engine bias tends not to directly consider the effects and impact of user choices on the information the algorithm retrieves. Prior research has sought to determine the origin of bias, pointing to the impact of bias in the corpus of websites from which results are culled (Kulshrestha et al., 2017). But the curation of results is not purely the result of the algorithm and the corpus it selects results from. Search engines, and Google in particular, play into the specific user demand by favoring 'relevance' as a feature of a good result (How Search algorithms work, 2019). To Google, relevance is the result of matching users' search queries to information it has about webpages (How Search algorithms work, 2019). Even by establishing 'relevance' as a key factor, search engine companies impact the distribution of results (Goldman, 2008). User input bias in particular emerges from the interaction of the user with the system (Friedman & Nissenbaum, 1996) and humans affect the design and functioning of algorithms (Bozdag, 2013).

A range of previous work has focused on personalization resulting from the algorithmic aggregation of behavioral data (Bechmann & Nielbo, 2018; Courtois et al., 2018; Müller et al., 2018; Puschmann, 2018). For instance, recent algorithm audits have found that previous browsing history can impact the results for Google News search (Le et al., 2019) and standard Google search (Robertson, Lazer, et al., 2018). In contrast to these studies of personalization, this research examines the less studied role of user-input bias by focusing on the primary element of discretionary behavior that users employ when they interact with search algorithms: search query choice.

2.3. Search queries as expressions of preference

Search terms are the means through which users make their information desires explicit. By selecting specific keywords according to their personal preferences, individual users inject those preferences into the system.

Searching is in itself imbued with the bias of searchers (Baeza-Yates, 2018). In the context of information-seeking behavior, previously held beliefs are important determinants when searching information online (White & Horvitz, 2015). Previous research has also identified how differences in search behavior are related to demographic differences (Weber & Jaimes, 2011). Search users are more likely to choose not only high-quality results, but also results that are congruent with their political attitudes (Knobloch-Westerwick, Johnson, Westerwick, et al., 2015). When people seek information, they bring with them their beliefs when they choose which result to click on, a process related to selective exposure (Stroud, 2010; White, 2013).

Search can also be construed through the lens of Uses and Gratifications Theory (UGT), which posits that the audience is an active participant in mass media, making decisions on what to consume based on expected satisfaction (Katz et al., 1973). UGT was originally deployed to try to understand selection of mass media content by audiences (Katz et al., 1973), but the internet has provided a new perspective on UGT since computer-mediated communication has the element of interactivity (Ruggiero, 2000). That is, the internet has allowed audiences to express preferences more explicitly. Even before the advent of Google and social media, UGT was applied to analyze the way people looked for political information online (Kaye & Johnson, 2002).

In search, queries may serve as expressions of the political preferences of the searchers. Search data is a viable proxy for public interest, and it can be used to analyze behaviors and interests (Whyte, 2016). Research into the bias of representation of political candidates on search has focused more on results than on queries themselves, with several studies relying on the use of generic search terms, such as candidate names (Diakopoulos, 2019; Muddiman, 2013; Puschmann, 2018). But research has also shown that it is possible to predict, for instance, the political leaning of a blog based on the search terms that are used to search, find, and access it (Borra & Weber, 2012).

In this work, we seek to examine two interrelated questions: (1) *Do people from different ideological identities look for information about elections in distinct ways?; and* (2) *If those distinctions are present, are they enough to produce significant differences in content retrieved by Google?* The answer to those questions raises four possible scenarios. Either different ideological groups perform similar searches and a) see different results or b) see similar results; or different ideological groups perform different searches and either

c) see different results or d) see similar results. Scenarios a and b would mean that user biases in search query choice are minimal at the group-level, and that mechanisms of personalization would instead define whether results are differentiated. Scenarios c and d represent a situation in which user bias is reflected by the choice of search queries, and the algorithm then either tailors the results for each group (c), or produces a mainstream curation (d). The following section explains how we investigated search queries and search results to examine these various possible scenarios.

3. Methods

To investigate whether internet users of different ideological identities search for information differently, we developed a method that involves surveys, qualitative coding and categorization, and quantitative analysis of the distributions of those categories within ideological groups. Then, we analyzed the differences of web results that were generated by these from these search behaviors.

3.1. Data collection and preparation

We selected three states for our survey based on their historic partisan preference: California (historically Democratic), Texas (historically Republican), and Ohio (historically split) (Jones, 2017), and focused on the Senate races in those states.

For each Senate candidate in each state we conducted a separate survey on Mechanical Turk that was open only to participants located in that state. The survey solicited from participants five search query terms about one senate candidate. We asked an open-ended question: 'One of the candidates in this year's senate race in [state] is [candidate name]. If you were to search for information about that candidate, what search terms would you use?' We also asked for political affiliation information on a seven-point scale ranging from 'extremely liberal' to 'extremely conservative', with a middle option of 'Moderate; middle of the road'. Respondents could also answer with 'Haven't thought much about this'.

We conducted the surveys between October 22 and 24, 2018, two weeks before the 2018 midterm elections on November 6. Respondents were paid \$0.40 per response, which was estimated by calculating the average completion time of tasks (roughly two and a half minutes, according to pilot tests) and the state minimum wage (\$8.25 per hour). In total, 1,414 people responded to the survey, including 449 in California, 178 in Ohio, and 418 in Texas.

The search queries were then divided using the self-reported ideological identity of the respondents. We collapsed those categories into two groups to enable a clearer distinction between liberals and conservatives and to mitigate potential noise from different criteria for self-classification. The 369 respondents that self-identified in neutral categories ('Moderate' or 'Haven't thought much about this') were excluded from the analysis and the queries generated by the remaining 1,045 respondents were divided in a way that resulted in four groups of queries for each state: from liberals about the Democratic candidate, from liberals about the Republican candidate, from conservatives about the Democratic candidate, and from conservatives about the Republican candidate (Table 1).

Table 1. Number of search queries generated by survey.

State	Liberals on Democratic candidate	Liberals on Republican candidate	Conservatives on Democratic candidate	Conservatives on Republican candidate	State total
California	775	820	335	315	2,245
Ohio	275	255	200	160	890
Texas	630	545	445	470	2,090
Total	1,680	1,620	980	945	5,225

To make the ideological groups within state groups comparable in terms of the number of respondents, we downsampled the groups by randomly selecting responses from each larger group to match the number of responses from each smaller group (315 from California, 160 from Ohio, and 445 from Texas).

Our initial analysis indicated that some queries had the same words in a different order, or had misspellings. To cope with these variations, we processed the search terms through OpenRefine, a tool that helps cluster similar terms.[1] For instance, '2018 texas senate race' and 'senate race texas 2018' would be processed to belong to the same cluster. Variations of a query that included typographic errors, such as 'beto orourke', 'beto o'rourke', and 'beto ourourkke' were also clustered together.

This clustering resulted in 1878 unique search queries, 233 of which appear more than once across different groups of respondents (e.g., 'ohio senate race' appeared in all four groups related to Ohio). Counting the repeated appearances of search queries (included the multiple times a search query appears within a group), the final dataset included 3680 non-unique search queries.

These search queries were used in automated searches on Google.com on November 5th, 2018, one day prior to the election. To minimize any confounding effects of implicit result personalization, automated searches were made using a desktop browser configured with no user history, without being logged-in, and with language set to English (Epstein, 2018; Robertson, Lazer, et al., 2018). A remaining source of possible implicit personalization comes from the location of the server (Ohio, in this case). However, previous work has shown that personalization in politically-related searches is low (Robertson, Lazer, et al., 2018) and location personalization tends to have relevant impact only for searches related to local services and not political topics (Kliman-Silver et al., 2015). Other studies found personalization of 'politics' queries and personalization by location, but it is unclear if those two are related; that is, if that personalization in political topics came from geolocation or from other factors (Hannak et al., 2013). Data collected included the 10 items listed on the first page of results for each of the 1878 unique search queries.

3.2. Data analysis

We conducted our analysis in three phases. First, we analyzed to what extent search queries are different between groups according to a typological categorization. Second, we looked at the relationship between the overlap of searches between groups and the overlap of results between groups. And finally, we examined the extent to which the sources of search results differ.

3.2.1. Analyzing search queries

We first analyzed the search queries through a process of qualitative thematic coding (Braun et al., 2018). A first phase of open coding (Strauss & Corbin, 1998) was conducted by going over a sample of search queries for one candidate (Beto O'Rourke), in order to identify discrete conceptual categories of search queries. From that process, an initial typology of categories emerged, which was then used during a second phase of axial coding (Strauss & Corbin, 1998) on a sample of search queries about another candidate (Ted Cruz). In a second phase, the categorization was honed and improved, and applied to the rest of the search queries. By tabulating all search queries according to the thematic categories identified, each ideological group (liberals and conservatives) was then associated with a distribution of search terms across categories for each candidate (i.e., Texas conservative search terms about the Democratic candidate; Texas conservative search terms about the Republican candidate; etc).

To determine whether the political groups search differently, we compared distributions of search term categories between ideological groups relating to the same candidate (Texas liberals and conservatives about the Democratic candidate; Texas liberals and conservatives about the Republican candidate; etc). The differentiation among groups is done using a statistical test of independence. Because numbers in some cells are small, we use Fisher's exact test of independence[2].

3.2.2. Analyzing the relationship between search queries and search results

To determine the impact of search queries on search results we created distinct sets comprised of the unique queries for each intersection of ideological group and candidate (2 ideological groups × 6 candidates), resulting in 12 sets of query terms. We then compiled the search results we scraped using the queries from each set.

For any given pair of ideological groups searching for a candidate (e.g., California liberals and conservatives for Democratic candidate; California liberals and conservatives for Republican candidate, etc), there are search terms that are unique to liberals, others that are unique to conservatives, and others that are common to both groups. The same type of pattern is observed in search results: some links are seen only by inputting one set of search terms, others are seen by inputting either set of key terms.

The first step to ascertain whether different groups search similarly and whether that behavior produces similar results is to calculate the similarity of those sets of search terms and results across the pairs of ideological groups searching for the same candidate. To do that, we used the Szymkiewicz-Simpson coefficient (also known as the overlap coefficient), computed using the intersection of terms divided by the smaller of both sets. The overlap coefficient takes into account potential differences in set size (Vijaymeena & Kavitha, 2016).

We repeated the same calculations of similarity that we did for the search terms for the search results. In that way we can not only see the degree of similarity for both search terms and results, but also compare them, to see if the relative difference between the behavior of the ideological groups produces a larger or smaller difference in the output of the search algorithm (Figure 1).

3.2.3. Analyzing search results

Finally, we explored the extent of differences in search results. We first extracted the domain names of the links to gather information about the sources and types of

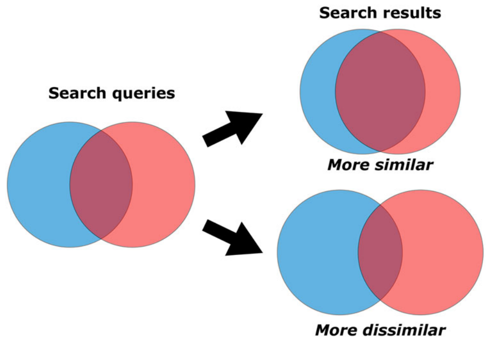

Figure 1. Conceptual representation of similarity of search terms and results per pair of ideological groups.

information provided. We then calculated the distributions of domains per ideological group (liberals and conservatives for all candidates) and compared them by calculating the Pearson correlations within the pairs, to determine if the distribution of impressions (the appearance of the link on a search result page) per domain was similar.

4. Results

4.1. Search queries

Through the process of qualitative thematic coding 11 categories of search queries were identified. The categories with the most frequent number of queries were General (the name of the candidate or description of the geographical scope or year of the election); Positions (generically or specifically asking about the issue stances of the candidates); and Background (political background of the candidate, such as previous positions, party affiliations, and past controversies). A full list of categories with descriptions and examples is in Table 2.

Next, we tabulated the counts of all search queries in every category for all candidates and ideological groups. Table 3 shows the comparison between liberal and conservative search queries for all candidates.

As seen in Table 3, the General category has a larger number of responses. This category is defined by the use of neutral language around variations of the name of the candidate or the election or the state and year (e.g., '2018 senate texas beto'). Queries in this category do not include any modifiers, such as 'bio' or 'stances'.

The results show that when it comes to searching for information about political candidates, liberals and conservatives can have different search behaviors, as evidenced by diverging distributions of search categories. This differentiation across ideological groups does not happen in every category, however.

To determine which differences are statistically significant, we computed Fisher's exact test, which provides a statistical measure of independence among two groups (liberal and conservative) searching for each of the six candidates. From the six candidates, three have significantly different distributions of search categories between liberals and conservatives: California Democratic candidate (p=0.002), the Texas Democratic candidate (p=0.014) and the Texas Republican candidate (p=0.010).

Table 2. Definitions and examples of categories.

Category	Definition	Examples
Background	Queries about the political background of the candidate, such as previous positions, party affiliations, and past controversies	'sherrod brown background'; 'party jim rennaci'
General	Queries that are just the name of the candidate or describe the geographical scope or year of the election	'california senate 2018'; 'california senate candidate dianne feinstein'
Moral question	Queries that simply question whether candidates are good or bad	'beto orourke pros cons'
Navigational	Queries that are tailored to reach a specific website	'wikipedia beto orourke'
Opponent	Queries about the direct opponent of the candidate in that race	'dianne feinstein opponent'; or 'ted cruz' when the topic of search is Beto O'Rourke
Other people	Queries about other specific persons that are not the opponent of the candidate	'barbra boxer'
Personal / bio	Queries about the personal background of the candidate (e.g., previous job, education, or family)	'de len biography'; 'kevin de len net worth'
Positions	Queries that either generically or specifically ask about the issue stances of the candidates	'beto stand issues'; 'beto policy weed'
Support level	Queries about how many supporters the candidate has, either in polls or donors	feinstein poll numbers; 'dianne feinstein donors'
Unclassified	Queries that were apparent errors by the respondents or that were ambiguous	'bing', 'cheer', 'ted cruz education' (Background or Position?)
Updates	Queries that try to obtain news about candidates, without mentioning specific websites	'kevin de leon interviews'

In the case of the California Democratic candidate, conservatives are more concerned with searches about the background of the candidate, and their biography. Liberals, on the other hand, are more interested in the candidate's positions on issues and on their opponent. Compare that to their Republican-supported opponent[3], for which some counts of search categories are different, but less so.

For the Texas Democratic candidate, liberals also tend to produce more queries on the issue positions of the candidate, but are also interested in personal and biographical information. Conservative users tend to include more navigational queries, which are meant to return results to websites that the searcher is specifically trying to get to. Where the Texas Republican candidate is concerned, users who report themselves to be conservative tend to be more interested in the background and personal and biographical information once again, and the liberal users are more concerned with campaign updates of the candidate.

Table 3. Distribution of categories of search queries per group.

State	California				Ohio				Texas			
Candidate	Democratic*		Rep.-supported		Democratic		Republican		Democratic*		Republican*	
Group	Con.	Lib.	Con.	Lib.	Con.	Lib.	Con.	Lib.	Con.	Lib.	Con.	Lib.
Background	59	37	34	24	22	23	33	26	62	70	83	59
General	183	185	203	205	95	88	86	94	218	199	200	247
Moral question	2	7	3	3	1	1	0	0	9	6	3	2
Navigational	9	6	6	4	3	1	1	1	16	5	7	10
Opponent	2	15	13	12	3	4	2	3	11	17	19	20
Other people	1	3	0	0	0	0	0	0	0	4	0	1
Personal / bio	18	12	14	16	4	11	10	5	21	32	39	27
Positions	38	44	36	39	28	27	22	29	70	81	73	60
Support level	2	5	2	7	4	5	6	2	12	17	12	12
Unclassified	0	0	3	4	0	0	0	0	15	5	8	0
Updates	1	1	1	1	0	0	0	0	11	9	0	7

*Indicates statistically significant difference of the counts, according to Fisher's Exact Test ($p-$ value < 0.05).

4.2. The impact of search queries on search results

The calculation of the similarity of search queries and the similarity of search results shows that a relatively small similarity of unique queries leads to a relatively higher similarity of unique URLs. To give an example using the rough counts of overlap, there are 195 unique search queries from conservatives and 170 from liberals about the California Democratic candidate. The number of overlapping search queries (that is, the same query for both groups) is 29. For the same candidate, there are 1056 unique URLs resulting from conservative search queries and 838 from liberal search queries, with 365 overlapping. These counts can be distilled into overlap coefficients – the higher the coefficient, the higher the overlap of sets. The average overlap coefficient of queries about candidates is 0.171. The average overlap coefficient of results about candidates is 0.448. This means that the average similarity between *result* sets across ideological groups is 2.6 times larger than the average similarity of *query* sets across ideological groups (Figure 2).

Noticeably, the overlap coefficient of queries and results is fairly similar across all candidates, even in those with a statistically significant difference in the distributions of search query categories across liberals and conservatives, as seen in the previous section (California Democratic, Texas Democratic and Texas Republican). That is, the distinctive behavior of searchers does not appear to systematically impact the relationship between the overlap of queries and results.

While there is a mainstreaming effect of the search engine (i.e., a set of common results is provided to dissimilar searches), it is not consistent across every candidate. The ratios between the overlap coefficient for queries and the overlap coefficient for results range from 2.2 to 3.3.

Even when there is no overlap in search queries, the results for the same candidates are very similar across different ideological groups. We found this when we computed the overlap coefficients again, but this time removing all the common search terms between

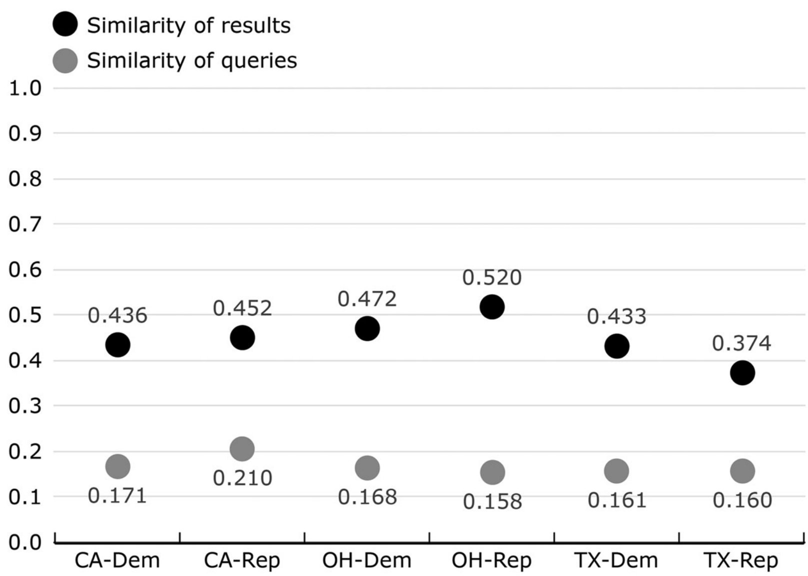

Figure 2. Similarity of search terms and of results between ideological groups.

liberals and conservatives. The expectation was that the similarity of results would be substantially smaller. However, the average reduction of the overlap coefficient was only 16% (Figure 3).

4.3. Search results

To further explore the differences in the search results, we aggregated all the links by website domain, so that instead of analyzing specific articles, we compare the sources of information. We find that the distribution of impressions across domains is heavily skewed, with a handful of websites concentrating a large proportion of impressions (one impression is an appearance of the domain on a search result page). On average, the top ten domains for each candidate represent 54% of impressions (SD = 9%; Median = 55%).

The distinctive behavior of searchers does not appear to substantially impact the frequency with which the domains appear in the results. For each pair of ideological groups (liberals and conservatives) we compared the similarity of impressions, by calculating the Pearson correlation between the distribution of impressions per domain for each pair of groups (Table 4). There is a very strong positive correlation (average of 0.985) between the number of impressions to domains that result from queries from liberals and conservatives about the same candidates. Even using the search terms that are unique for each group, the average correlation is 0.970. This indicates that no matter the uniqueness of search terms, the search engine appears to largely surface a similar set of sources for both groups. The correlation of results is similar across all candidates, even in those shown to have significantly different distributions of search query categories across liberals and conservative.

However, there are still some differences between what the ideological groups see. To investigate those, we calculated the proportion of impressions for domains that are unique to each ideological group. Tables 5 and 6 show the percentage of impressions that go to

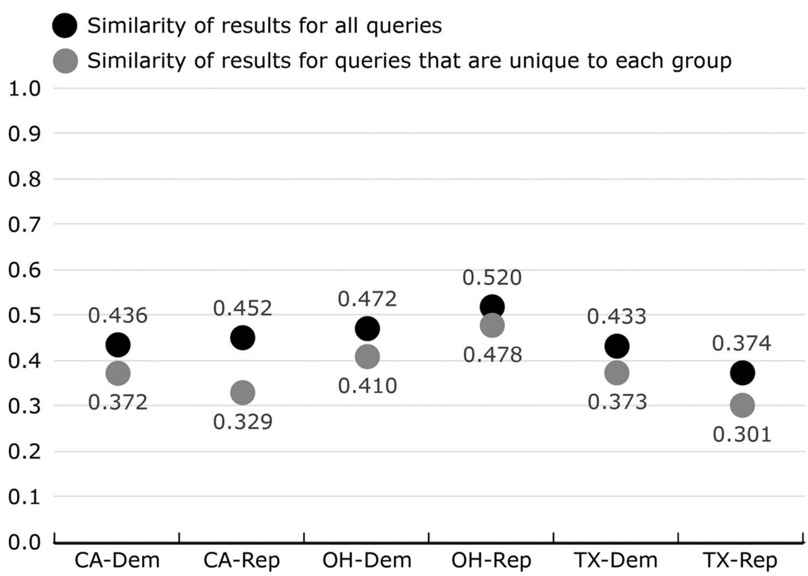

Figure 3. Similarity of results from unique search terms.

Table 4. Pearson correlation of impressions per domain between ideological groups.

State	Candidate	All results	Results of unique queries
California	Democratic	0.982	0.957
California	Rep-supported	0.994	0.975
Ohio	Democratic	0.983	0.970
Ohio	Republican	0.982	0.977
Texas	Democratic	0.982	0.980
Texas	Republican	0.986	0.959

domains that appear only for liberals and conservatives, as well as the most frequent unique domain for each ideological group. The proportion of impressions from unique domains by ideology is never more than 7.9% of impressions for any given group. The domains that appeared for only search queries that came from liberals account for an average of 4.2% of all impressions for that ideological group (SD = 1.1); for conservatives, the unique domains account for an average 6.0% of all impressions (SD = 1.4).

For any given candidate, the top unique domain for liberals accounts for, at most, 0.5% of impressions for the whole group. The top domains are scpr.org (Southern California Public Radio), newyorker.com (New Yorker Magazine), imdb.com (Internet Movie Database), capwiz.com (a website that shows bios of elected officials in the U.S.), factcheck.org (a fact-checking website run by the Annenberg Public Policy Center), and behindthebastards.com (a podcast).

The top unique domains for conservatives account for, at most, 0.4% of impressions. The top domains are oldest.org (a website that lists the oldest people in several categories), cadem.org (the official website of the Democratic Party in California), clevescene.com (Cleveland Scene, a local newspaper from Ohio), cantonrep.com (Canton Repository, a local newspaper in Ohio), texasstandard.org (local news organization), and google.com (links to books on Google Books).

5. Discussion

Previous work has shown how, in the 2018 U.S. elections, the sources curated by search media were relatively stable, while also pointing out the need to study the complex relationship between search and users and to align audited queries more closely with real user behavior (Metaxa et al., 2019). In this article, we address these issues by examining the extent to which partisan differences in search may generate different search results. We ask two interrelated questions: Do people from different ideological identities look for

Table 5. Unique domains for liberals.

State	Candidate	Queries that yielded unique results	Percentage of impressions to domains unique to liberals	Top domain unique to liberals	Percentage of impressions for top domain for liberals
California	Democratic	59	5.4%	scpr.org	0.5%
California	Rep.-supported	48	4.5%	newyorker.com	0.2%
Ohio	Democratic	33	4.9%	imdb.com	0.2%
Ohio	Republican	23	3.0%	capwiz.com	0.1%
Texas	Democratic	69	2.8%	factcheck.org	0.1%
Texas	Republican	94	4.8%	behindthebastards.com	0.1%

Table 6. Unique domains for conservatives.

State	Candidate	Queries that yielded unique results	Percentage of impressions to domains unique to conservatives	Top domain unique to conservatives	Percentage of impressions for top domain for conservatives
California	Democratic	74	5.9%	oldest.org	0.1%
California	Rep.-supported	60	5.3%	cadem.org	0.2%
Ohio	Democratic	38	3.9%	clevescene.com	0.3%
Ohio	Republican	42	5.5%	cantonrep.com	0.4%
Texas	Democratic	105	7.3%	texasstandard.org	0.1%
Texas	Republican	127	7.9%	google.com	0.2%

information about elections in distinct ways? And are those distinctions enough to produce significant differences in content retrieved by Google? Our results indicate that members of different ideological groups in the U.S. can indeed use significantly different categories of search terms when looking for political information, but that is not enough to yield substantially divergent results on Google.

We found a significant distinction in search behavior among liberals and conservatives for three of the six target candidates analyzed: the California Democrat, the Texas Democrat, and the Texas Republican. However, the specific context of the races may help account for some of the different search behaviors. In Texas, the Senate election was a particularly close race, which garnered national attention (Weber & Weissert, 2018). The California Democratic candidate is a long-time incumbent, in office since 1992, which may lead to differences in sourcing in search media (Metaxa et al., 2019). The familiarity of audiences with different candidates could interact with the type of information that users require. Future work may need to consider a range of factors that account for search behavior, including both individual preferences as well as context, such as the level of media attention for that race.

The results of this research speak to the role of search queries in the process of selective exposure (Garrett, 2009a, 2009b; Knobloch-Westerwick, Johnson, Westerwick, et al., 2015; Stroud, 2010). However, the user reaction to the search results, which is also an integral part of selective exposure, was not the focus of this study. Future work should seek to better understand how individual user behavior, biases, and selective exposure may interact with different forms of algorithmic personalization.

Our second question relates specifically to how Google's results respond to searchers' information demands. Our analysis demonstrates that Google results exhibit a mainstreaming effect that practically neutralizes differentiation of search queries. As noted, previous empirical research has shown a limited existence of filter bubbles resulting from implicit personalization (Bechmann & Nielbo, 2018; Courtois et al., 2018; Müller et al., 2018; Puschmann, 2018). Our results extend the prior work and show that even when taking into account self-induced differences produced through the query choices of users, the filter bubble effect is minimal. What we found instead is a *mainstreaming effect*, in which users see a highly similar set of curated media, regardless of how their ideology may have skewed their choice in search queries.

The underlying cause of that mainstreaming effect, however, needs further study. A straightforward explanation might be that mainstreaming is a value explicitly embedded in Google's algorithms. However, Google ostensibly favors 'relevance' as a feature of a good result (How Search algorithms work, 2019), and not shared exposure of content among searchers. It may be that the mainstreaming effect is the consequence of a limited set of possible websites from which Google can cull its results. After all, not every website has content on every candidate. Or it may be that Google's requirements of what constitutes a website good enough to receive impressions are stringent enough that only a handful of websites are selected for curation, and those websites are then referred to as sources of information for all users. Future work will be needed to disentangle these various possibilities.

5.1. Limitations

In presenting these findings it's important to also acknowledge some of the limitations of this study. First, since it was designed using a survey method to collect simulated search queries, our findings may not reflect real-life iterative search behavior, including the natural frequency of usage of various query terms or the impact of automated query suggestions. Other audit designs, such as panel studies using plugins to scrape real-users' results might address this limitation in future work (Puschmann, 2018; Robertson, Jiang, et al., 2018). Second, we focused our analysis on organic search results, rather than on the content present in widgets and information boxes, which may also convey relevant information (Diakopoulos, 2019). Finally, our results do not take into consideration the ordering of results, which can have an impact on attention and the decision of searchers to click on a link (Robertson, Jiang, et al., 2018). To accurately quantify that would require access to click-through data from Google or from other third parties (Trielli & Diakopoulos, 2019). While we do not believe these limitations undermine our core findings, they do offer avenues for potential future work.

Notes

1. The clustering algorithms used were the key collision fingerprint and Nearest Neighbor (Levenshtein) with a radius of 2.0 and block chars of 3.
2. Fisher's exact test is conducted in 2 × 2 tables. In larger tables, it is possible to conduct Monte Carlo simulations of thousands of permutations of internal tables. We conducted this test with 20,000 permutations.
3. California has nonpartisan primaries, and in 2018 the two contenders for the Senate election were Democrats. However, De Lon was favored by Republicans.

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