

This is a post-print version of the article published in *Social Science Computer Review* and accessible via the following link:

<https://journals.sagepub.com/doi/suppl/10.1177/08944393211006863>

To cite this article:

Urman, A., Makhortykh, M., & Ulloa, R. (2021). The Matter of Chance: Auditing Web Search Results Related to the 2020 U.S. Presidential Primary Elections Across Six Search Engines. *Social Science Computer Review*.
<https://doi.org/10.1177/08944393211006863>

The Matter of Chance: Auditing Web Search Results Related to the 2020 U.S. Presidential Primary Elections Across Six Search Engines

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Abstract: We examine how six search engines filter and rank information in relation to the queries on the U.S. 2020 presidential primary elections under the default — that is nonpersonalized — conditions. For that, we utilize an algorithmic auditing methodology that uses virtual agents to conduct large-scale analysis of algorithmic information curation in a controlled environment. Specifically, we look at the text search results for “us elections,” “donald trump,” “joe biden,” “bernie sanders” queries on Google, Baidu, Bing, DuckDuckGo, Yahoo, and Yandex, during the 2020 primaries. Our findings indicate substantial differences in the search results between search engines and multiple discrepancies within the results generated for different agents using the same search engine. It highlights that whether users see certain information is decided by chance due to the inherent randomization of search results. We also find that some search engines prioritize different categories of information sources with respect to specific candidates. These observations demonstrate that algorithmic curation of political information can create information inequalities between the search engine users even under nonpersonalized conditions. Such inequalities are particularly troubling considering that search results are highly trusted by the public and can shift the opinions of undecided voters as demonstrated by previous research.

Keywords: search engines, web search elections, U.S. elections, algorithmic auditing

Search engines play a crucial role in today’s high-choice media environment (Van Aelst et al., 2017). The rapid growth of the volume of available information dictates the need for large-scale filtering and ranking of information sources. Without automated mechanisms for prioritizing reliable and relevant sources, users would be overwhelmed by the abundance of information. Thus, search engines turn into major information gatekeepers (Laidlaw, 2010; Schulz et al., 2005; Wallace, 2018) with their ranking and filtering mechanisms directing the information that is received by the users. By doing so, these mechanisms of algorithmic curation can influence users’ beliefs and decisions and, in some cases, also reinforce their existing biases (Noble, 2018; White & Horvitz, 2015).

The leverage of search engine algorithms on information filtering and ranking is of particular concern in the context of political campaigns. Previous research has shown that merely the way the results are ranked can shift the voting preferences of undecided voters by 20% or more with the potential shift being as high as 80% for some demographic groups (Epstein & Robertson, 2015). While the effect size depends on the share and demographics of undecided voters as well as the level of Internet penetration in the country, it highlights the potential influence that search engines have over election outcomes. Hence, search engine corporations are increasingly called to take responsibility for preventing biases in search results and providing citizens with consistent and reliable information (Elgesem, 2008; Hinman, 2008).

The present study builds on the previous research on diversity, biases, and discrepancies in political web search results (i.e., Diakopoulos et al., 2018; Haim et al., 2018; Puschmann, 2019; Robertson, Jiang, et al., 2018; Steiner et al., 2020). Using an algorithmic auditing

methodology (Mittelstadt, 2016) that builds on that proposed by Haim and colleagues (Haim et al., 2017; Haim, 2020), we investigate the curation of information on search engines under the default — that is, nonpersonalized — filtering and ranking conditions. Our methodological approach helps to further advance the field of algorithmic impact auditing as it allows tracing the effects of randomization of search results at scale. In-built randomization is a factor that can lead to major differences in search output (Makhortykh et al., 2020), yet it has been largely overlooked in the previous search engine auditing studies (i.e., Haim et al., 2018; Hannak et al., 2013; Puschmann, 2019; Robertson, Jiang, et al., 2018; Robertson, Lazer, et al., 2018; Trielli & Diakopoulos, 2019). The details on the methodology are outlined in the relevant section.

We contribute to the existing research on the representation of political topics in search results by examining how search engines distribute information about the candidates for the U.S. 2020 presidential elections during the primaries using a set of the following search queries: “us elections,” “joe biden,” “donald trump,” and “bernie sanders.” We compare our observations to those of the previous studies conducted in the context of the 2016 U.S. presidential elections (Kulshrestha et al., 2019; Trielli & Diakopoulos, 2019) and discuss potential implications of our observations.

In the current study, we explore the differences in the search results provided by six major search engines (Google, Yahoo!, Bing, DuckDuckGo, Baidu, and Yandex) for the queries related to the 2020 U.S. presidential elections during the early stage of the election campaign. Specifically, we scrutinize the results mentioning the U.S. elections, incumbent president Donald Trump, Bernie Sanders, and Joe Biden. We included queries on both, Sanders and Biden, as they were the two major contenders for the Democratic presidential nomination at the time when the experiment was conducted—1 week before the so-called Super Tuesday (the day when the biggest number of the U.S. states hold primaries).

In the context of politics, search engines are of utmost importance since, at least in the Western democracies, they are the first place where people look for political information (Dutton et al., 2017). At the same time, the general public tends to highly trust web search output (Pan et al., 2007; Schultheiß et al., 2018) despite the fact that several studies have shown that search results can exhibit racial and gender biases (Kay et al., 2015; Noble, 2018; Singh et al., 2020). Because the way search results are ranked can shift political opinions of undecided voters (Epstein & Robertson, 2015), it is important to investigate how political information is curated by search engines. To do so, we examine the differences in search outputs for the queries related to the 2020 U.S. presidential elections and aim to answer the following research questions:

Research Question 1: How large are the differences in the results provided by various search engines under the default (i.e., nonpersonalized) selection and prioritization of information related to the 2020 U.S. presidential elections?

Research Question 2: Are there differences in the results provided by the same search engine to identical users under the default conditions?

Research Question 3: Do the levels of discrepancies vary between searches about different political actors in relation to the 2020 U.S. presidential elections?

Research Question 4: Are there differences in the types of information sources prioritized by search engines for queries about different political candidates?

Related Work: Algorithmic Impact Auditing and Political Search Results

Algorithmic systems are essential elements of digital platform infrastructure. The need to assess their performance led to the formation of the set of methods collectively known as algorithmic auditing that is “a process of investigating the functionality and impact of decision-making algorithms” (Mittelstadt, 2016, P. 4994). While functionality auditing examines how algorithms arrive at certain decisions and outputs, impact auditing aims to find out which algorithmic outputs are prevalent and infer whether these outputs are biased in some way (Kroll et al., 2017; Sandvig et al., 2014). Algorithmic impact auditing of search engines is of paramount importance because they influence citizens’ political information-seeking behavior by filtering and ranking politics-related information (Trevisan et al., 2018).

Since differences in search output can shift the opinions of undecided voters (Epstein & Robertson, 2015), biases in political search results can affect election outcomes and the general political landscape. In recent years, a number of studies that used algorithmic auditing in the context of political searches was conducted. Methodologically, such studies fall into three categories: those that rely on manually generated data (i.e., the ones collected from individual users or generated by the researchers themselves by manually querying search engines), those that rely on virtual agents simulating users’ browsing behavior to generate and collect the data, and those that combine these two approaches.

The studies, which use manually generated data, primarily look on the effects of search personalization in the context of information behavior. Two of these studies investigated political filter bubbles on Google using crowd-sourced search results and found no evidence of bubbles’ presence (Courtois et al., 2018; Robertson, Jiang, et al., 2018). Still, using a similar methodology another study found significant differences in personalized search results related to the U.S. presidential elections of 2016 (Robertson, Lazer, et al., 2018). Finally, a study that relied on the manual collection of the data by the researchers has assessed the diversity of search results in response to politically salient queries in the German context (Steiner et al., 2020). According to the findings, a certain degree of diversity is present even for the top results (depending on the query), but diversity generally increases for the long tail of search results.

The growing number of studies uses virtual agents to audit algorithmic content curation by search engines. One of the earliest studies (Feuz et al., 2011) on personalization of search results simulated browsing behavior of three different information-seeking personas on Google. The researchers found that results are affected by personalization and the effect increases overtime; the longer the virtual personas used the search engine, the more different were the results. Another study examined Google search results in the context of 2017 federal elections in Germany (Unkel & Haim, 2019). Specifically, the study simulated browsing activity of five information-oriented personas and showed the prevalence of general news websites and resources controlled by political parties in the results. Another study used a single virtual agent to query Google for a set of political queries that are

germane to different ideological groups (Democrats vs. Republicans as the study was conducted in the U.S. context) and assess whether search engine results can be biased by the searcher's political orientation (Trielli & Diakopoulos, 2019). Another study that used a single virtual agent (Kulshrestha et al., 2019) investigated bias in Google's search results during the 2016 U.S. presidential election primaries. The authors found that Google's results tend to be biased in the direction of a specific candidate's political leaning (i.e., those related to "Donald Trump" exhibit a slight conservative bias and those related to "Hillary Clinton"—a slight liberal bias).

Besides studies relying exclusively on manual or agent-based data collection, there is some research combining the two approaches. The first study that combined virtual agent-based testing with crowd-sourced data for search engine auditing examined effects of different factors on search personalization (Hannak et al., 2013). The authors used virtual agents to generate a set of nonpersonalized results and compared them with the personalized results obtained from actual users. The study found that personalization significantly affects search results on both Bing and Google that were examined. In another study (Puschmann, 2019), the author asked the users to install a plug-in that queried Google for political searches at regular time intervals thus mimicking users' behavior and isolating potential bias related to the differences in the time when the searches were performed. The analysis revealed discrepancies in the ways different German parties were represented in Google Search and Google News in the run-up to the 2017 German federal elections.

The mentioned studies, with the exception of the one by Hannak and colleagues (2013) and the one by Steiner and colleagues (2020), have focused on one search engine—Google—and did not compare potential differences in algorithmic information curation between the search engines. This is understandable because Google currently dominates the global search market with around 90% of the market share (Statcounter, 2020) and is the engine that is the most commonly used by the majority of Western users. However, other search engines should not be overlooked because they are still used by millions of users across the globe and in some cases dominate regional search markets (i.e., Baidu is the leader on the Chinese market, and Yandex has around 50% of the market share in Russia; Statcounter, 2020). Furthermore, including other engines in the analysis allows testing whether some of them exhibit more biases than others and check whether the choice of a search engine itself affects the quality of information a user is exposed. Therefore, the first contribution to the existing scholarship that we aim to do is to compare politics-related results obtained through the six most popular search engines worldwide (Statcounter, 2020).

Apart from the lack of comparative research on search engine performance, aforementioned studies tend to look at the effects of personalization on search results and potential biases stemming from different variables (i.e., ideological bias of the searchers). None of them, however, has explored for the inherent randomization and volatility of search results. As search engines constantly and continuously update the results, the results inevitably change all the time. Hannak and colleagues (2013) have acknowledged the existence of this effect and attempted to control for it in their study by adding a control virtual agent. However, it is unclear if adding a single control agent is enough—that is, if noise affects all identical results equally. In addition, the scope of the differences in search results due to continuous search updates and inherent randomization has not been extensively examined to date. The only evidence on the level influence of these effects on search outputs comes from a commercial

tool that tracks the volatility of search results for the same user throughout the day (SEMrush, n.d.) and from a study that found significant differences in the results for a singular “coronavirus” query when executed by several identical users at the exact same time under the same default filtering and ranking conditions (Makhortykh et al., 2020). With the present study, we aim to partially address this gap by examining the effects of the continuous search updates on the results through a systematic comparison of the results across several search queries and engines.

Method

Data Collection

Using automated agents to simulate browsing behavior of Internet users, we collected the HTML search results from the six most popular search engines according to Statcounter (2020): Google, Bing, Yahoo, Baidu, Yandex, and DuckDuckGo. Extending the methodology adopted by Haim et al. (2017), we built a cloud-based infrastructure to set up a controlled environment that allowed us to isolate external factors (e.g., time or location) and block the effects of search engine’s in-built randomization (Makhortykh et al., 2020). Thus, our methodology addresses a potential limitation of earlier algorithmic auditing studies that did not account for the randomization effects (Kulshrestha et al., 2019; Puschmann, 2019; Steiner et al., 2020; Trielli & Diakopoulos, 2019; Unkel & Haim, 2019). Although one study looked at this effect for a singular query (“coronavirus”) in the context of COVID-19 (Makhortykh et al., 2020), none, to date, examined the influence of randomization in the context of political search results, which is a gap we aim to address.

To implement the study, we used a cloud-based infrastructure made of 100 CentOS virtual machines deployed via Amazon Elastic Compute Cloud (EC2) and located in the Frankfurt EC2 region. We chose this particular region outside of the United States because (1) we considered that the usage of any region inside the United States might introduce biases in search results due to geolocation-based personalization as Republicans and Democrats are not evenly distributed across states; (2) we did not have the resources to afford more than one EC2 geographic region to counteract this potential effect (e.g., by selecting one pro-Republican and one pro-Democratic region), further, at the time of the analysis, EC2 had no clusters available in pro-Republican states; and (3) we selected Frankfurt because it serves as a base for many international companies and has a high share of English-speaking population.

All the machines were t3a.medium Amazon EC2 instances based on AMD EPYC 7,000 series processors. Each machine had two CPUs, four gigabyte (GB) RAM, and 20 GB hard drive. Because the machines were generated using the same Centos-based Amazon machine image with the same set of software installed (e.g., same Centos packages and browser versions), they had the same hardware and software specifications. Besides, all machines were located in the same range of Internet protocol (IPs) performed identical searches at the same time. Hence, the searches were conducted in a fully controlled environment that accounted for potential factors that could have led to the discrepancies in search results (e.g., due to personalization). The only difference between the machines related to their unique IP addresses—though they all belonged to the same IP range provided by EC2 and should not have affected the results due to, that is, location-based

personalization. We do acknowledge, however, that this is a limitation of the present study, and future research should investigate the potential effects of the said discrepancy.

Each virtual machine hosted two browsers: Firefox and Chrome. In each browser (“agent”), we installed two extensions: a tracker and a bot. The tracker collected metadata (e.g., time stamps) and the full HTML of all pages that were visited within the browser that were sent to an external storage server. The bot emulated user browsing behavior by searching query terms from the predefined list (which included terms “us elections,” “joe biden,” “donald trump,” and “bernie sanders”) and navigating through the search results. The queries were selected based on the event that the search was centered on. We opted for generic actor names (e.g., instead of actor names accompanied by descriptions) to retrieve the least biased results about the actors. The focus on the three aforementioned actors is explained by the fact that ahead of the primary elections, Joe Biden and Bernie Sanders were the major contenders for the Democratic nomination, and Donald Trump was then-incumbent President running for the reelection. We added a generic “us elections” term to get a broader overview of search results at the time, which would not be biased toward one of the candidates. In the present study, we entered identical queries into search engines without accounting for potential differences in the ways search engine algorithms handle multiword queries. We opted for this to achieve maximum consistency between the searches which we deemed necessary as our study is focused on impact auditing. Future studies that focus on functionality auditing of web search algorithms might investigate, however, how multiword queries are handled by different algorithms.

Table 1. The Total Number of Agents That Completed the Task per Search Engine and Browser.

Browser	Baidu	Bing	DDG	Google	Yahoo!	Yandex
Firefox	15	16	17	17	15	16/6 (*)
Chrome	16	15	17	16	16	16/13 (*)

Note. The first row displays the name of the search engine (DDG is an abbreviation for DuckDuckGo), and the first column shows the name of the browser. (*) $\frac{1}{4}$ We obtained fewer results for Yandex for the “U.S. elections” query because it triggered the bot detection algorithm of Yandex which blocked some of the agents.

The navigation through the retrieved search results was organized in browser sessions, which consisted of three steps: (1) visiting the main landing page of a search engine, (2) inputting a query from the predefined list into the search text box, and “clicking” on the search button, and (3) navigating through the search results.

Each agent collected at least the top 50 results by visiting multiple result pages or by scrolling down the page (in case of infinite scrolling configuration of the search result page, such as in the case of DuckDuckGo). Immediately after each search session, the browsers were cleaned to prevent previous searches from affecting the following sessions. The bot removed both the data accessed by the browser (i.e., browsing history and cache) and the browser data that can be retrieved by the search engines’ algorithms (i.e., local storage,

session storage, and cookies). At the time of the data collection, none of the search engines was forcing the users to accept or reject their cookie policies. Hence, none of the agents accepted engine-specific policies.

Regardless of the search engine, each search session lasted less than 3 min. Each subsequent session started 7 min after the beginning of the previous one to guarantee at least a 4-min gap between sessions. Therefore, the agents were always synchronized at the beginning of all sessions to isolate the potential effect of time on search results.

The 200 agents were deployed on February 26, 2020, 1 day after the Democratic debate and almost a week before Super Tuesday, when 14 states hold democratic primary elections. The search engines (Baidu, Bing, DuckDuckGo, Google, Yandex, and Yahoo) selected for this study were equally distributed among the agents, so that 32 of 33 agents (15 of 16 from each browser group) were assigned to each search engine. During our collection, the expected amount of agents was slightly decreased because of the issues: (1) bot detection in Yandex via occasionally appearing captchas, and (2) a few browser crashes due to the limited volume of RAM available on the machines. The total number of agents providing data for each browser–engine combination is provided below (Table 1).

Data Analysis

After collecting the data, we used BeautifulSoup (Python; Richardson, 2020.) and rvest (R; Wickham & RStudio, 2019) packages to extract search results from the HTML for each query and filter out the URLs not related to the search results (e.g., ads). The latter decision is explained by our implicit interest in the default mechanisms for search filtering and ranking, not in the ads displayed by the engines. Then, for each query, we compared the URLs of the search results obtained by each possible pair of agents. We used two similarity metrics—Jaccard Index (JI) and Rank Biased Overlap (RBO).

JI measures the overlap between two sets of results and shows the size of the intersection between the sets over the union. JI has been used to measure similarities in search results by previous studies personalization of web search (Hannak et al., 2013; Kliman-Silver et al., 2015; Puschmann, 2019). The values of the JI vary from 0 to 1, with 1 indicating that the compared sets are identical, and 0 that they are completely different.

Although JI is valuable for assessing the similarity between two sets of results, it does not take into account their ranking. Yet, the latter feature is especially relevant for the present study due to the proven effect of search ranking on voting preferences (Epstein & Robertson, 2015). For this reason, we also used RBO metric that accounts for the order in which results are presented and is frequently utilized in the studies on search engines (Cardoso & Magalhães, 2011; Robertson, Jiang, et al., 2018; Robertson, Lazer, et al., 2018). Specifically, RBO takes into consideration three important characteristics of web search: incompleteness (there are too many search results so it is not possible to scrape all of them), indefiniteness (chosen result range is arbitrary), and top-weightedness (variation between the top results is more important than the one between the lower ones) of the results (Webber et al., 2010). The formula for RBO is as follows:

$$\text{RBO}(S, T, p) = (1 - p) \sum_{d=1}^{\infty} p^{d-1} \cdot A_d,$$

where S and T are two infinite rankings, d is the depth to which their agreement is computed, A is the level of agreement (which is equal to a Jaccard similarity of top d results), and the persistence parameter p determines the importance of top results: The lower the value of p , the more weight is assigned to the top results.

For each of the four queries, we calculated JI for the overall set of results and for top 10 results, and RBO ($p = .95$ and $p = .8$) for all the result pairs. Setting p to $.95$ allowed us to conduct a more systemic analysis of the differences between result pairs, whereas $p = .8$ enabled us to put more emphasis on the first few results (Webber et al., 2010).

After calculating JI and RBO, we aggregated the data for each search engine examined in the study. To make sure that the agents' browsers did not cause the discrepancies between the search results, we aggregated data separately for Chrome and for Firefox. This also allowed us to check whether search results differ between the two browsers for otherwise identical agents. Afterward, we calculated the mean values for JI and RBO between the sets of agents with different combinations of search engines and browsers they were produced by.

We produced a linear mixed effect model using the lme4 and lmerTest R packages (Bates et al., 2020; Kuznetsova et al., 2020) to fit the data and calculate the statistical significance for our main independent variables: browser and search engine. The model allows us to control for (1) the effects of multiple comparisons of each agent, that is, the search results of an agent are used several times, one per comparison against the search results of the other agents, and (2) the effects of the machine combination, that is, since each machine contains two agents (one per browser), we need to control for pairing the same machines several times.

To assess whether there are qualitative differences in the types of content prioritized by the search engines in response to different queries, we have first aggregated data about the domains that appeared most frequently in the top 20 results for each search engine–query combination. Then, we have manually coded the results based on the following categories:

- think tank/academic websites (i.e., academic articles/think tank reports),
- social media sites (i.e., Facebook, Twitter),
- reference work (i.e., dictionaries, encyclopedic notes, Wikipedia),
- news aggregators (i.e., *Google News*),
- legacy media (i.e., *New York Times*),
- infotainment (i.e., soft news websites such as BuzzFeed),
- government (i.e., White House website),
- fact-checking websites (i.e., PolitiFact),
- commerce (i.e., online shops),
- campaign (i.e., official candidate–affiliated campaign websites),
- alternative media (i.e., digital-born partisan outlets such as Conservapedia), and

- not available (i.e., the link points to a site/page that is no longer available at the time of the analysis).

The coding was performed by one of the authors and then thoroughly checked by the two other authors to ensure agreement between them. All the disagreements arising from the checks were resolved via consensus-coding in a series of group discussions.

To answer our research questions, we first looked at the differences in the results obtained for the “us elections” query via different search engines (e.g., Google vs. Yahoo; Research Question 1), then by different agents using the same browser (e.g., when both agents used Google; Research Question 2). Then, we repeated these two steps for the queries related to specific politicians (i.e., “bernie sanders,” “donald trump,” “joe biden”) and checked the discrepancies between the results obtained for each query (Research Question 3). Finally, we have qualitatively examined and categorized the types of domains in top 20 results for different search engines and analyzed the differences in the types of sources prioritized by each engine for specific politicians (Research Question 4).

Results

Differences in Search Results on “us elections” Query

In response to Research Question 1, we find significant discrepancies between filtering and ranking mechanisms utilized by different search engines for the “us elections” query on both, Chrome and Firefox browsers (see Supplemental Material for the complete statistical summary). We observe that 115 of 120 (95.8%) similarity values between different search engines are lower than .35, including all the JI values for the top 10 search results (Figure 1). The ranking of the results is also highly volatile that means even in the nonpersonalized setting, users of the same search engine are unlikely to see the same results. While some discrepancies in the results provided by different search engines are expected, given that they utilize different algorithms to filter and rank results, the magnitude of discrepancies suggests that users of these platforms get fundamentally different sets of information.

The most similar results are provided by DuckDuckGo and Yahoo search engines. However, in this case, the two engines share just under half of all the results ($n = 50$) results (measured by JI overall) and around a third of the top 10 results (JI for top 10). The similarities are even lower when the ranking is taken into account (RBO) with the ordering of top results (RBO, $p = .8$) in most cases being more volatile than the overall ordering of the results (RBO, $p = .95$). This finding echoes that of Steiner and colleagues (2020) who found that the differences in search results are higher for the lower positioned results. Still, for the second most similar pair, Bing and Yandex, the top results are more similar in terms of both, order and composition as indicated by higher top 10 JI and RBO with $p = .8$. Hence, the findings regarding the volatility of search results with different rankings are contextual.

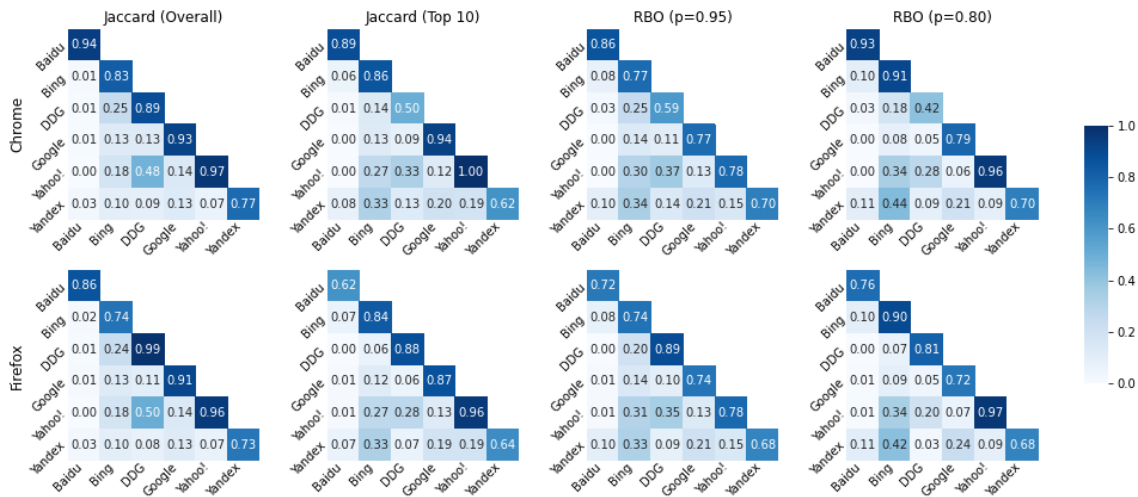


Figure 1. Cross-engine and cross-browser similarities in search results for the “us elections” search query. The columns show the different similarity measures used, and the rows show the results for Chrome (top) and Firefox (bottom) browsers.

The discrepancies in the results between different search engines can have important consequences for the public sphere because the users of different engines get different (political) information. However, most Western markets, including the United States, are currently dominated by Google. The Google’s share of the U.S. search market is estimated to be just under 90%, slightly lower than Google’s market share worldwide (Statcounter, 2020). This means that even if the results provided by Google are very different from those on other platforms, it does not affect about 90% of the U.S. public. However, what does affect the Western public is the high degree of randomization that creates discrepancies in the information curation even in the nonpersonalized context.

Concerning Research Question 2, we observed variations in search results within the same search engine for both Chrome and Firefox browsers (diagonal values in the plots in Figure 1). The only search engine in our sample did not randomize the selection of the top 10 results for the “us elections” query was Yahoo accessed from Chrome (but not from Firefox), and even in this case, the ordering of the results showed some variation between the agents. Since such variation happens under the nonpersonalized conditions, it is seemingly random and, most likely, attributed to the fact that search engine algorithms constantly adapt their output to provide the results viewed as the most relevant to the users at the given time. This constant output adaptation means that users of the same search engine are likely to receive different results even when they conduct searches at the same time and no personalization is involved. Even though the within-engine discrepancies are not as high as cross-engine ones, their effect on the public opinion is still important because the ranking of the search results can shift voters’ opinion (Epstein & Robertson, 2015).

In terms of the browser differences, we only found significant differences between Firefox and Chrome for DuckDuckGo (the statistical table is reported in Supplemental Material, Table A1). In this case, the search results obtained in Firefox are more consistent than those obtained in Chrome for all our response variables. One potential explanation of this is that DuckDuckGo’s search algorithm takes a user’s browser into account when making curation

decisions. If true, this is problematic since browser is a semantically nonmeaningful signal and its influence on search results can increase information inequalities between users of different browsers.

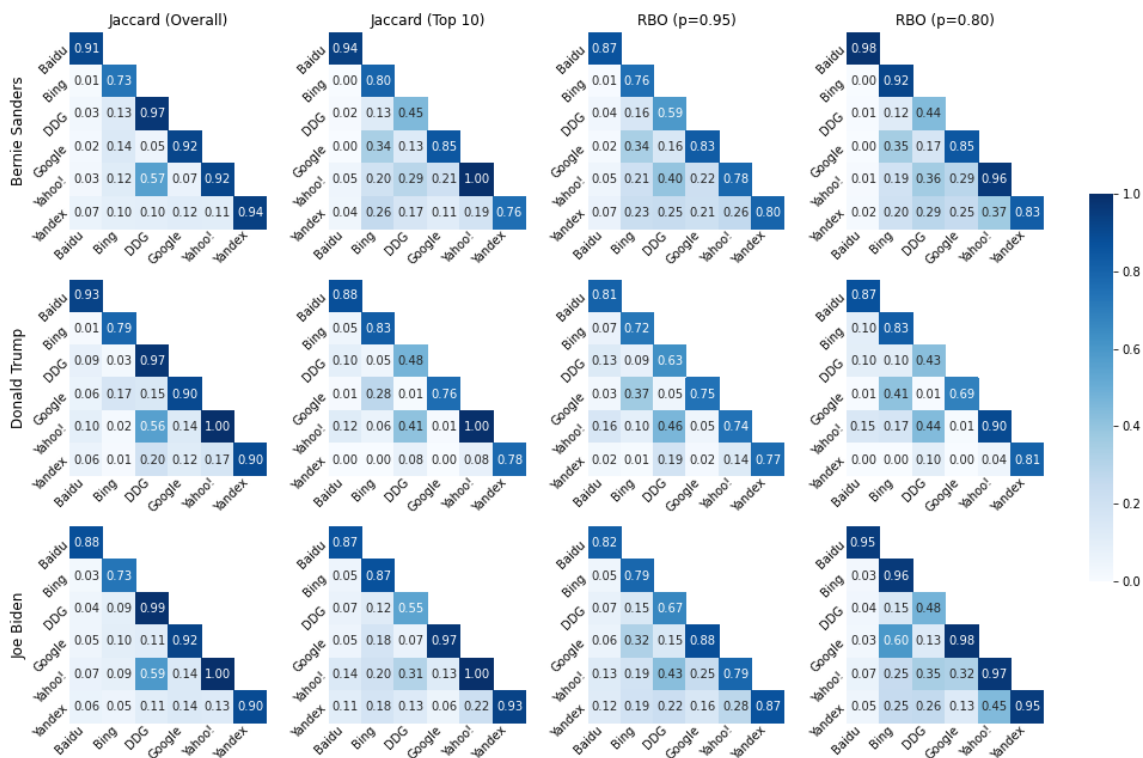


Figure 2. Similarities in search results across engines by relevant political candidate query, Chrome browser.

Discrepancies in the Stability of Search Results for Different Political Candidates

To answer Research Question 3, we compared the differences in the results for different political candidate queries. Similarly to the search results for the “us elections” query, there are large discrepancies for the queries related to specific political candidates (see Figure 2 for Chrome and Figure 3 for Firefox). On average, cross-engine dissimilarities for all the political candidates–related queries are slightly higher than those for the “us elections” query.

We found significant differences between the browsers depending on the query (statistically significant values are reported in Table 2; for the complete statistical tables see Supplemental Material, see Sections B.1, C.1, D.1). The results are in line with the findings for the “us elections” query: DuckDuckGo shuffles the results for Chrome users more than it does for Firefox users. For the “bernie sanders” query, we also observed some browser differences for Bing and Yahoo.

Looking only at the results for the same-engine comparisons and controlling for different browsers, we found statistically significant differences in terms of consistency of search results between the three queries (see Supplemental Material, Section E). These differences depend on the search engine that is being used, but overall “joe biden”- and “bernie

sanders”-related results are less volatile than “donald trump” ones in terms of JI (top 10), RBO (p ¼ .8) and RBO (p ¼ .95; see Supplemental Material, Section F).

Prioritization of Source Types

In order to infer qualitative differences between the results for queries on different political candidates and, thus, answer Research Question 4, we examined the top 20 results most frequently obtained through each engine for each of the three candidate-related queries (see Figures 4–6). We found that search engines, in general, prioritize different categories of search results, and in some cases (i.e., Baidu, Yahoo, and Yandex), there are large discrepancies between different candidate queries.

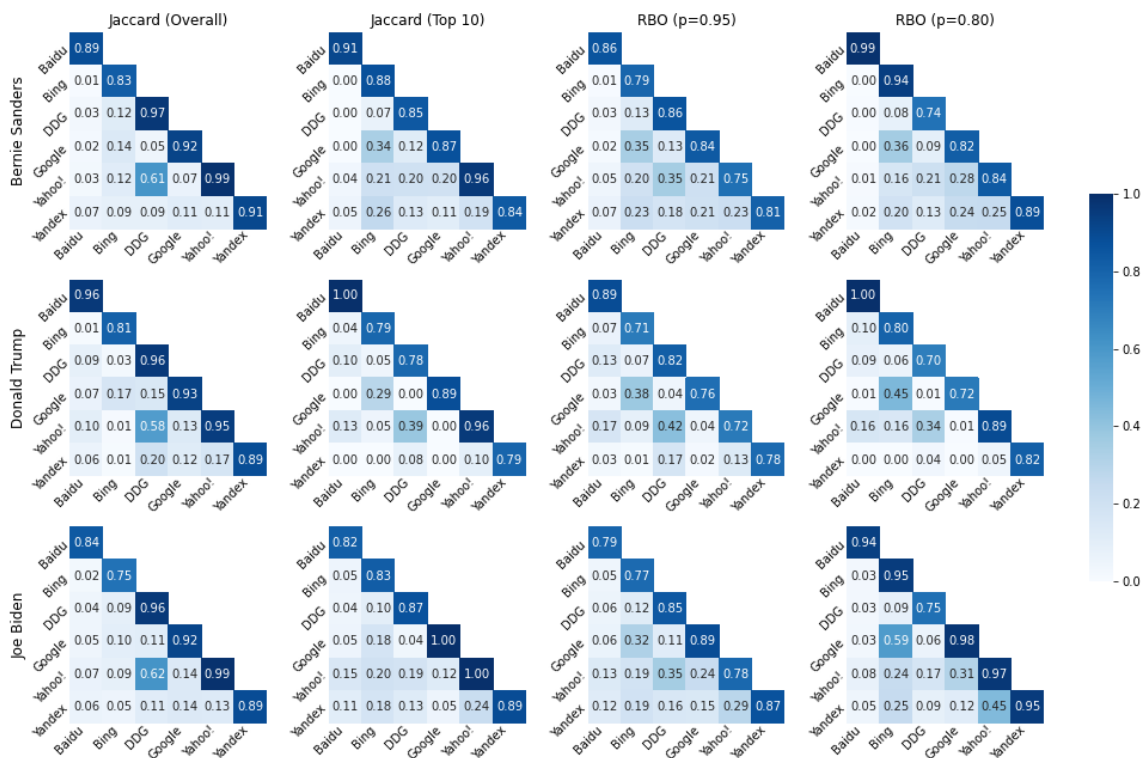


Figure 3. Similarities in search results across engines by relevant political candidate query, Firefox browser.

Table 2. p Values for Statistically Significant Effects of Browser in Politician Queries.

Search query	Engine	JI (Overall)	JI (Top 10)	RBO (p = .8)	RBO (p = .95)
bernie sanders	Bing	.016	—	—	—
	DDG	—	<.0001	.0296	.0001
	Yahoo	—	—	.0303	—
joe biden	DDG	—	.0035	.0002	.0036

donald trump	—	—	—	—	—
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Note. The first column shows the query term used. The second column refers to the search engine. JI = Jaccard Index; RBO = Rank Biased Overlap.

On Google, the prioritization of results is consistent for all three candidates with legacy media dominating search outputs. This is similar to what was observed in a study on Google search results in relation to the 2017 German federal elections (Unkel & Haim, 2019). Overall, legacy media results were more prevalent in the outputs of Google and Bing than those of the other search engines. The only major difference we observed on Google for different queries is that the results for “bernie sanders” did not contain a link to Sanders’ campaign website, unlike those for “donald trump” and “joe biden.” In addition, we found that the candidates-controlled campaign websites were less prevalent in Google results during the 2020 primaries than during the 2016 primaries when almost a quarter of top 10 results were made of candidate-affiliated websites (Kulshrestha et al., 2019). Still further longitudinal studies are necessary to properly verify this claim. As we conducted a snapshot experiment, we cannot state whether how persistent and systematic this observation is.

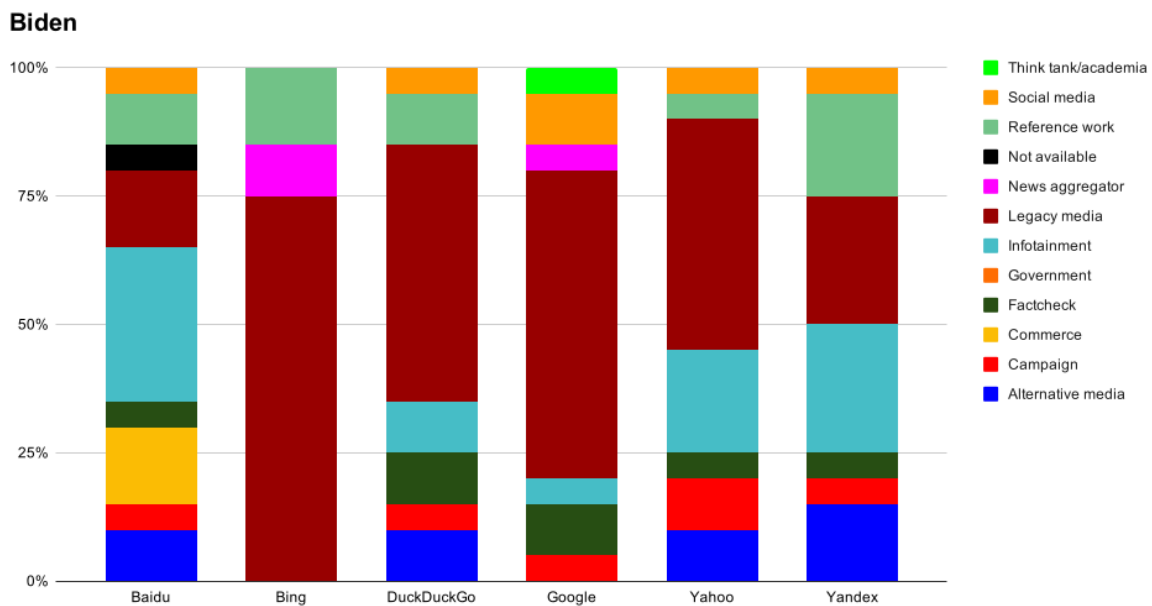


Figure 4. Information sources referenced in top 20 search results for “joe biden.”

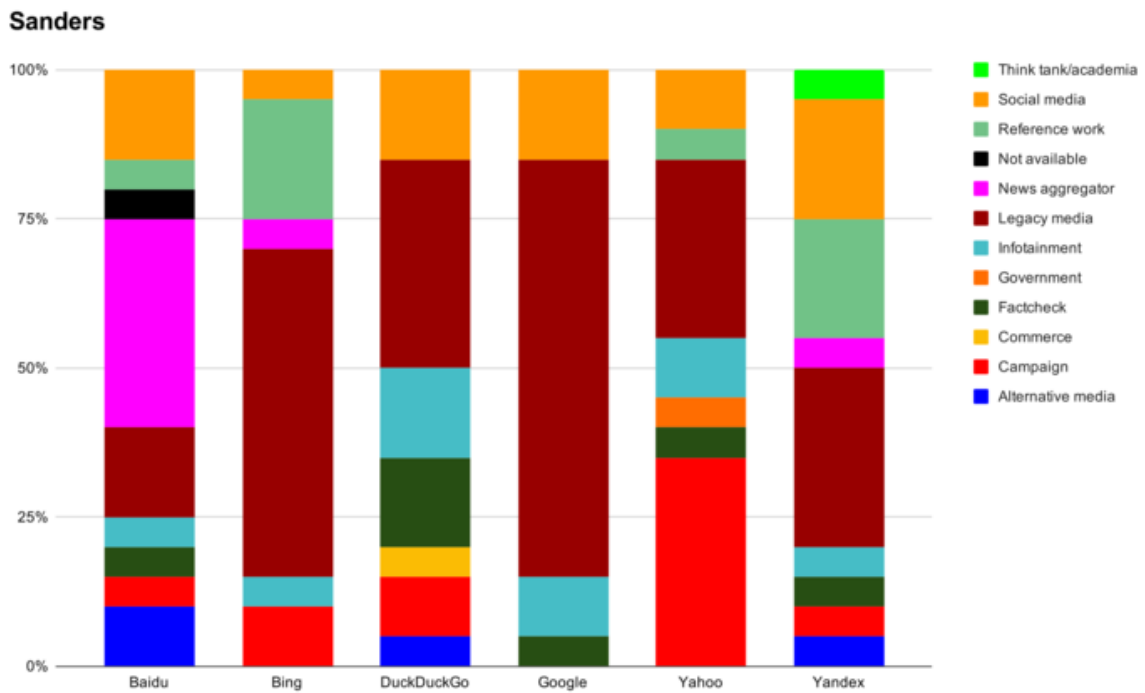


Figure 5. Information sources referenced in top 20 search results for “bernie sanders”.

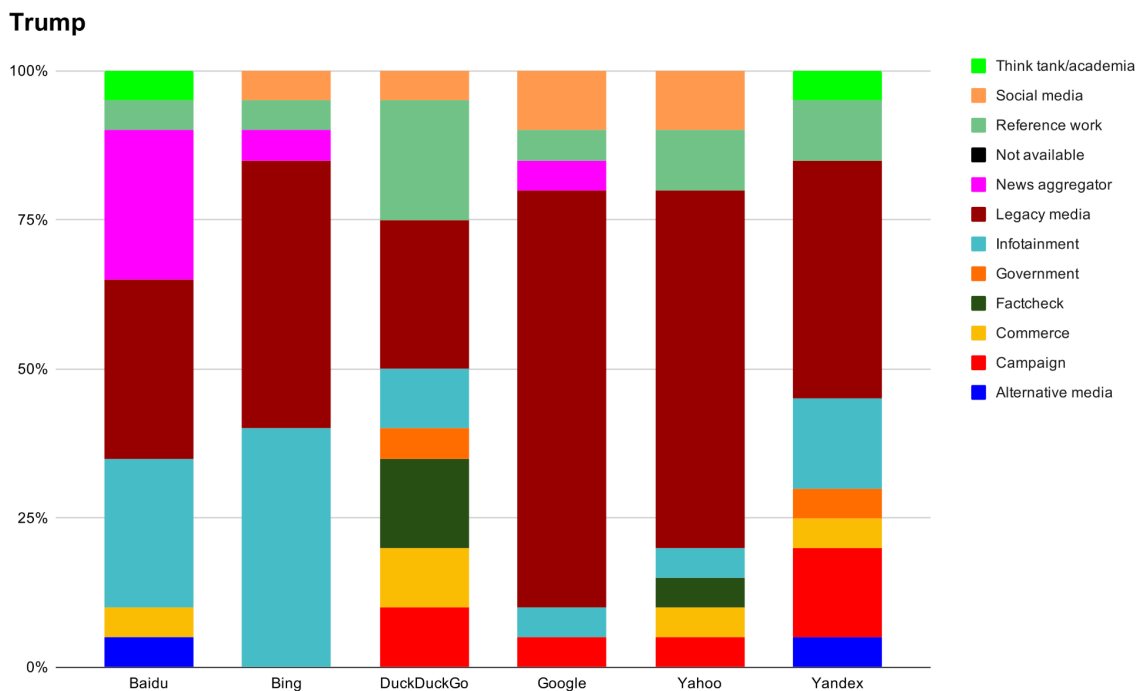


Figure 6. Information sources referenced in top 20 search results for “donald trump”.

More pronounced differences across candidates were observed on Bing and Yahoo, the second and third most popular engines in the United States with 6.55% and 3.65% of the search market, respectively (Statcounter, 2020). In terms of potential biases, Yahoo displayed a high ratio of pro-Sanders results with around 40% of the top 20 results linking to

outlets related to his campaign, while for Biden and Trump the ratio was 10% and 5%, respectively. However, as we conducted a snapshot experiment, we cannot say how stable the observed effect is overtime.

Discussion

Our findings highlight two major issues related to the ways search engine filter and rank political information. The first issue is a number of differences in the search outputs produced by algorithmic curation mechanisms of different search engines (Research Question 1). While some variation in the selection of information sources is expected as the engines clearly employ different algorithms to retrieve and rank the results, our study indicates that even under the nonpersonalized conditions, search results show varying degrees of volatility and prioritize different types of sources depending on the query. These discrepancies, even if they are to be expected due to the differences in algorithms, can lead to information inequalities between the individuals who use different search engines, in particular, as some of the engines seem to prioritize sources which are more supportive (e.g., Yahoo for Sanders) or critical (e.g., Yandex for Biden) of specific candidates. We suggest that this observation warrants further studies into how usage of different search engines affects the populations from the social science perspective.

While the effects of these inequalities might be somehow limited in the United States where over 90% of the public are using Google as their default engine (Statcounter, 2020), in the countries where the search market is not dominated by a single engine, the cross-engine discrepancies can have a larger effect on the public sphere. Such contexts include, for instance, East Asian states such as China, Japan, and South Korea, as well as post-Soviet countries such as Russia, Kazakhstan, and Belarus, where local search corporations serve as major competitors for Western tech giants (Statcounter, 2020).

The second troubling issue is the volatility of search results within the same search engine (RQ2). The randomization of search results is not necessarily a negative phenomenon, because it allows the Figure 6. Information sources referenced in top 20 search results for “donald trump.” engines to present the most relevant information by updating the ranking of sources and can potentially diversify users’ information diets (Helberger et al., 2018). On the other hand, such volatility makes search outputs less predictable and might lead to information inequalities between the users of the same engine by randomizing their access to information. We also find that the volatility of search results differs across different candidate queries (RQ3), with the results related to the two Democratic candidates being more stable than those for “donald trump” query.

In addition, our analysis has revealed qualitative differences in the composition of top results across the three political candidate queries (RQ4). For instance, we observed that Yahoo contained a much higher share of campaign websites for the “bernie sanders” query compared to other engines and queries. Such discrepancy might indicate a potential pro-Sanders bias in the output, but without a longitudinal study, it is not possible to verify how systematic this bias is. Further longitudinal research utilizing similar methodology is required to enhance our understanding of how resilient the observations coming from the current study are as we conducted a snapshot experiment and cannot state whether our observations indicate a presence of a systematic bias. Still, the observed differences in

search results across political queries, engines and browsers are already troubling, because the ranking of political search results can affect voters' decisions (Epstein & Robertson, 2015).

In contrast to earlier research focusing on the effects of personalization on political information dissemination via search engines (i.e. Hannak et al., 2013; Puschmann, 2019; Unkel & Haim, 2019), our study highlights the need for taking into account search results' volatility that is present on all search engines we audited. Whereas personalization does not significantly alter election-related search results, at least on Google in the context of the German Federal elections (Unkel & Haim, 2019), our findings show that built-in randomization can strongly affect the composition and the ranking of results. It prompts the need to go beyond the current scholarship's focus on search personalization and its influence on promotion of specific biases (e.g., the ones related to gender and race; Noble, 2018) and discuss to what degree inherent volatility of the results can create informational inequalities which make users receive different information under identical conditions. Similar to the search queries related to the emergencies like the COVID-19 pandemic (Makhortykh et al., 2020), in the case of political queries such randomization, can result in some part of the population being less informed or even misinformed about important societal developments. Whether the users get to see certain information or not becomes, thus, a matter of chance that is in stark contradiction with the public's general perception of search results as accurate and trustworthy ("2020 Edelman Trust Barometer," n.d.; Pan et al., 2007) as well as the framing of the search process as unbiased and scientific by the search companies (Sweeney, 2013).

Funding

The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This paper has been written within the project "Reciprocal relations between populist radical-right attitudes and political information behaviour: A longitudinal study of attitude development in high-choice information environments" lead by Silke Adam (U of Bern) and Michaela Maier (U of Koblenz-Landau) and sponsored by the SNF (100001CL_182630/1) and DFG (MA 2244/9-1).

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Supplementary material

Table of Contents

A. Statistical Tests for "us elections" query.....	2
A.1 Comparison of Browsers for "us elections" query.....	2
Response: Jaccard.....	2
Response: Jaccard Top-10.....	3
Response: RBO (p=0.95).....	4
Response: RBO (p=0.8).....	5
A.2 Comparison of Search Engines for "us elections" query.....	6
Response: Jaccard.....	6
Response: Jaccard Top-10.....	6
Response: RBO (p=0.95).....	7
Response: RBO (p=0.8).....	8
B. Statistical Tests for "bernie sanders" query.....	9
B.1 Comparison of Browsers for "us elections" query.....	9
Response: Jaccard.....	9
Response: Jaccard Top-10.....	10
Response: RBO (p=0.95).....	11
Response: RBO (p=0.8).....	11
B.2 Comparison of Search Engines for "bernie sanders" query.....	12
Response: Jaccard.....	12
Response: Jaccard Top-10.....	13
Response: RBO (p=0.95).....	14
Response: RBO (p=0.8).....	15
C. Statistical Tests for "donald trump" query.....	15
C.1 Comparison of Browsers for "donald trump" query.....	16
Response: Jaccard.....	16
Response: Jaccard Top-10.....	16
Response: RBO (p=0.95).....	17
Response: RBO (p=0.8).....	18
C.2 Comparison of Search Engines for "donald trump" query.....	19
Response: Jaccard.....	19
Response: Jaccard Top-10.....	20
Response: RBO (p=0.95).....	21
Response: RBO (p=0.8).....	21
D. Statistical Tests for "joe biden" query.....	22
D.1 Comparison of Browsers for "joe biden" query.....	22
Response: Jaccard.....	22
Response: Jaccard Top-10.....	23
Response: RBO (p=0.95).....	24
Response: RBO (p=0.8).....	25
D.2 Comparison of Search Engines for "joe biden" query.....	26
Response: Jaccard.....	26
Response: Jaccard Top-10.....	27
Response: RBO (p=0.95).....	28
Response: RBO (p=0.8).....	28
E. Comparison of politician-like queries withing search engines.....	29

Response: Jaccard.....	29
Response: Jaccard Top-10.....	30
Response: RBO (p=0.95).....	31
Response: RBO (p=0.8).....	31
F. Comparison of politician-like queries controlling by all factors.....	32
Response: Jaccard.....	32
Response: Jaccard Top-10.....	33
Response: RBO (p=0.95).....	34
Response: RBO (p=0.8).....	34

A. Statistical Tests for "us elections" query

A.1 Comparison of Browsers for "us elections" query

Response: Jaccard

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: jaccard ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)

Data: subdf

REML criterion at convergence: -5752.8

Scaled residuals:

Min	1Q	Median	3Q	Max
-13.1561	-0.2648	0.0226	0.1494	8.7211

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	5.429e-05	0.007368
agent2	(Intercept)	5.679e-03	0.075356
agent1	(Intercept)	4.453e-03	0.066734
Residual		2.090e-03	0.045712

Number of obs: 2038, groups: machine_combination, 1495; agent2, 179; agent1, 93

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	9.440e-01	2.556e-02	2.448e+02	36.932	< 2e-16 ***
browserFirefox	-4.868e-02	2.761e-02	1.679e+02	-1.763	0.07971 .
engineBing	-1.163e-01	3.676e-02	2.451e+02	-3.164	0.00175 **
engineDDG	-5.418e-02	3.559e-02	2.442e+02	-1.522	0.12920
engineGoogle	-1.536e-02	3.615e-02	2.449e+02	-0.425	0.67133
engineYahoo!	2.676e-02	3.620e-02	2.460e+02	0.739	0.46052
engineYandex	-1.700e-01	3.827e-02	2.471e+02	-4.442	1.35e-05 ***
browserFirefox:engineBing	8.868e-04	3.907e-02	1.683e+02	0.023	0.98192
browserFirefox:engineDDG	9.801e-02	3.815e-02	1.675e+02	2.569	0.01106 *
browserFirefox:engineGoogle	4.323e-02	3.847e-02	1.681e+02	1.124	0.26272
browserFirefox:engineYahoo!	4.168e-02	3.910e-02	1.686e+02	1.066	0.28806
browserFirefox:engineYandex	3.888e-02	4.696e-02	1.686e+02	0.828	0.40877

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

(Intr) brwsrF engnBn engnDDG engnGg engnY! engnYn brwF:B bF:DDG brwF:G brF:Y!


```

browserFrfrx -0.531
engineBing -0.695 0.369
engineDDG -0.718 0.382 0.499
engineGoogl -0.707 0.376 0.492 0.508
engineYaho! -0.706 0.375 0.491 0.507 0.499
engineYandx -0.668 0.355 0.465 0.480 0.472 0.472
brwsrFrfrx:B 0.375 -0.707 -0.540 -0.270 -0.265 -0.265 -0.251
brwsrFr:DDG 0.385 -0.724 -0.267 -0.535 -0.272 -0.272 -0.257 0.511
brwsrFrfrx:G 0.381 -0.718 -0.265 -0.274 -0.540 -0.269 -0.255 0.507 0.520
brwsrFrfr:Y! 0.375 -0.706 -0.261 -0.269 -0.265 -0.533 -0.251 0.499 0.511 0.507
brwsrFrfrx:Y 0.312 -0.588 -0.217 -0.224 -0.221 -0.221 -0.469 0.415 0.426 0.422 0.415
convergence code: 0
Model failed to converge with max|grad| = 0.00216689 (tol = 0.002, component 1)

```

Response: Jaccard Top-10

Linear mixed model fit by REML. t-tests use Satterthwaite's method [`lmerModLmerTest`]
 Formula: `jaccotop10 ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)`
 Data: `subdf`

REML criterion at convergence: -2107.7

Scaled residuals:

Min	1Q	Median	3Q	Max
-4.8403	-0.3722	0.0307	0.2115	9.8368

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.0009883	0.03144
agent2	(Intercept)	0.0239715	0.15483
agent1	(Intercept)	0.0224131	0.14971
Residual		0.0125251	0.11192

Number of obs: 2038, groups: machine_combination, 1495; agent2, 179; agent1, 93

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	0.89139	0.05500	235.84248	16.206	< 2e-16 ***
browserFirefox	-0.15870	0.05726	168.74932	-2.771	0.00621 **
engineBing	-0.03403	0.07911	236.28394	-0.430	0.66749
engineDDG	-0.38616	0.07657	235.05204	-5.044	9.14e-07 ***
engineGoogle	0.04351	0.07779	235.93328	0.559	0.57652
engineYahoo!	0.10865	0.07793	237.10221	1.394	0.16457
engineYandex	-0.27136	0.08241	238.76236	-3.293	0.00114 **
browserFirefox:engineBing	0.15514	0.08102	169.09470	1.915	0.05719 .
browserFirefox:engineDDG	0.29870	0.07908	168.18859	3.777	0.00022 ***
browserFirefox:engineGoogle	0.12862	0.07978	169.04424	1.612	0.10878
browserFirefox:engineYahoo!	0.13656	0.08112	169.46715	1.683	0.09413 .
browserFirefox:engineYandex	0.17570	0.09741	169.72004	1.804	0.07305 .

 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

	(Intr)	brwsrF	engnBn	engDDG	engnGg	engnY!	engnYn	brwF:B	bF:DDG	brwF:G	brF:Y!
browserFrfrx	-0.516										
engineBing	-0.695	0.359									
engineDDG	-0.718	0.371	0.499								
engineGoogl	-0.707	0.365	0.492	0.508							

```

engineYaho! -0.706 0.364 0.491 0.507 0.499
engineYandx -0.667 0.344 0.464 0.479 0.472 0.471
brwsrFrFx:B 0.365 -0.706 -0.525 -0.262 -0.258 -0.257 -0.243
brwsrFr:DDG 0.373 -0.724 -0.260 -0.519 -0.264 -0.264 -0.249 0.511
brwsrFrFx:G 0.370 -0.718 -0.257 -0.266 -0.524 -0.261 -0.247 0.507 0.520
brwsrFrF:Y! 0.364 -0.706 -0.253 -0.262 -0.257 -0.518 -0.243 0.498 0.511 0.507
brwsrFrFx:Y 0.303 -0.588 -0.211 -0.218 -0.214 -0.214 -0.457 0.415 0.426 0.422 0.415

```

Response: RBO (p=0.95)

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: rbo_95 ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)
Data: subdf

REML criterion at convergence: -3948.7

Scaled residuals:

```

  Min      IQ  Median      3Q      Max
-4.9900 -0.3979  0.0240  0.2390  8.3798

```

Random effects:

```

Groups          Name          Variance Std.Dev.
machine_combination (Intercept) 0.0005483 0.02342
agent2           (Intercept) 0.0076564 0.08750
agent1           (Intercept) 0.0095810 0.09788
Residual                            0.0050011 0.07072

```

Number of obs: 2038, groups: machine_combination, 1495; agent2, 179; agent1, 93

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	0.86423	0.03360	214.70327	25.720	< 2e-16 ***
browserFirefox	-0.08288	0.03262	167.93736	-2.541	0.01195 *
engineBing	-0.09407	0.04833	215.15770	-1.947	0.05289 .
engineDDG	-0.26817	0.04677	213.92278	-5.734	3.32e-08 ***
engineGoogle	-0.09685	0.04752	214.79434	-2.038	0.04278 *
engineYahoo!	-0.08466	0.04761	215.87886	-1.778	0.07677 .
engineYandx	-0.16680	0.05036	217.62644	-3.312	0.00108 **
browserFirefox:engineBing	0.07050	0.04614	168.19459	1.528	0.12840
browserFirefox:engineDDG	0.19350	0.04504	167.24969	4.297	2.93e-05 ***
browserFirefox:engineGoogle	0.06788	0.04545	168.30664	1.494	0.13714
browserFirefox:engineYahoo!	0.08497	0.04622	168.67352	1.838	0.06776 .
browserFirefox:engineYandx	0.08757	0.05551	169.16331	1.578	0.11650

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

```

(Intr) brwsrF engnBn engDDG engnGg engnY! engnYn brwF:B bF:DDG brwF:G brF:Y!
browserFrFx -0.484
engineBing -0.695 0.336
engineDDG -0.718 0.348 0.500
engineGoogl -0.707 0.342 0.492 0.508
engineYaho! -0.706 0.341 0.491 0.507 0.499
engineYandx -0.667 0.323 0.464 0.479 0.472 0.471
brwsrFrFx:B 0.342 -0.705 -0.492 -0.246 -0.242 -0.241 -0.228
brwsrFr:DDG 0.350 -0.724 -0.244 -0.487 -0.248 -0.247 -0.234 0.511
brwsrFrFx:G 0.347 -0.718 -0.241 -0.249 -0.491 -0.245 -0.232 0.506 0.520
brwsrFrF:Y! 0.341 -0.706 -0.237 -0.245 -0.241 -0.486 -0.228 0.498 0.511 0.507
brwsrFrFx:Y 0.284 -0.588 -0.198 -0.204 -0.201 -0.201 -0.429 0.415 0.426 0.422 0.415

```

Response: RBO (p=0.8)

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: rbo_80 ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)

Data: subdf

REML criterion at convergence: -1574.3

Scaled residuals:

Min	1Q	Median	3Q	Max
-4.4305	-0.4232	0.0458	0.2217	5.7322

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.002188	0.04678
agent2	(Intercept)	0.011521	0.10734
agent1	(Intercept)	0.016846	0.12979
Residual		0.017457	0.13212

Number of obs: 2038, groups: machine_combination, 1495; agent2, 179; agent1, 93

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	0.93227	0.04420	206.19512	21.094	< 2e-16 ***
browserFirefox	-0.09593	0.04184	167.94975	-2.293	0.023093 *
engineBing	-0.01853	0.06361	207.24252	-0.291	0.771113
engineDDG	-0.51262	0.06147	204.82107	-8.340	1.08e-14 ***
engineGoogle	-0.14334	0.06252	206.36713	-2.293	0.022862 *
engineYahoo!	0.02573	0.06266	207.47717	0.411	0.681720
engineYandex	-0.23605	0.06647	211.76684	-3.551	0.000472 ***
browserFirefox:engineBing	0.09161	0.05920	168.36862	1.547	0.123650
browserFirefox:engineDDG	0.22999	0.05771	166.63698	3.986	0.000100 ***
browserFirefox:engineGoogle	0.06326	0.05833	168.71031	1.085	0.279687
browserFirefox:engineYahoo!	0.10260	0.05933	168.55464	1.729	0.085584 .
browserFirefox:engineYandex	0.12156	0.07135	170.67013	1.704	0.090231 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

(Intr)	brwsrF	engnBn	engDDG	engnGg	engnY!	engnYn	brwF:B	bF:DDG	brwF:G	brF:Y!	
browserFrFx	-0.487										
engineBing	-0.695	0.338									
engineDDG	-0.719	0.350	0.500								
engineGoogl	-0.707	0.344	0.491	0.508							
engineYahoo!	-0.705	0.343	0.490	0.507	0.499						
engineYandex	-0.665	0.324	0.462	0.478	0.470	0.469					
brwsrFrFx:B	0.344	-0.703	-0.497	-0.247	-0.243	-0.243	-0.229				
brwsrFr:DDG	0.353	-0.725	-0.245	-0.489	-0.250	-0.249	-0.235	0.510			
brwsrFrFx:G	0.349	-0.717	-0.243	-0.251	-0.494	-0.246	-0.232	0.504	0.520		
brwsrFrF:Y!	0.343	-0.705	-0.239	-0.247	-0.243	-0.490	-0.228	0.496	0.511	0.508	
brwsrFrFx:Y	0.286	-0.586	-0.198	-0.205	-0.202	-0.201	-0.436	0.412	0.427	0.421	0.414

A.2 Comparison of Search Engines for "us elections" query

Response: Jaccard

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: jaccard ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)
Data: subdf

REML criterion at convergence: -36722.3

Scaled residuals:

Min	1Q	Median	3Q	Max
-9.8246	-0.3578	-0.0078	0.3606	5.3976

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.000e+00	0.0000000
agent2	(Intercept)	3.377e-05	0.0058115
agent1	(Intercept)	3.388e-05	0.0058202
browser	(Intercept)	1.596e-07	0.0003995
Residual		2.033e-04	0.0142590

Number of obs: 6637, groups: machine_combination, 4005; agent2, 179; agent1, 179; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)	
(Intercept)	0.013855	0.001267	10.399383	10.932	4.97e-07	***
engines_Baidu-DDG	-0.003405	0.001368	800.323431	-2.489	0.013	*
engines_Baidu-Google	-0.001605	0.001378	800.620999	-1.165	0.244	
engines_Baidu-Yahoo!	-0.011900	0.001400	801.679909	-8.501	< 2e-16	***
engines_Baidu-Yandex	0.020623	0.001608	792.928943	12.821	< 2e-16	***
engines_Bing-DDG	0.229403	0.001369	802.880103	167.514	< 2e-16	***
engines_Bing-Google	0.114711	0.001377	799.011637	83.317	< 2e-16	***
engines_Bing-Yahoo!	0.167255	0.001400	801.875053	119.462	< 2e-16	***
engines_Bing-Yandex	0.084766	0.001613	809.568100	52.561	< 2e-16	***
engines_DDG-Google	0.105032	0.001705	483.855589	61.594	< 2e-16	***
engines_DDG-Yahoo!	0.479521	0.001722	487.987434	278.400	< 2e-16	***
engines_DDG-Yandex	0.071928	0.001889	522.909088	38.069	< 2e-16	***
engines_Google-Yahoo!	0.129410	0.001731	490.605103	74.758	< 2e-16	***
engines_Google-Yandex	0.113973	0.001901	529.376300	59.967	< 2e-16	***
engines_Yahoo!-Yandex	0.056281	0.001917	532.680918	29.353	< 2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

convergence code: 0

boundary (singular) fit: see ?isSingular

Response: Jaccard Top-10

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: jacctop10 ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)

Data: subdf

REML criterion at convergence: -26194.9

Scaled residuals:

Min	1Q	Median	3Q	Max
-5.1249	-0.3260	-0.0321	0.2853	9.1889

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.000e+00	0.0000000
agent2	(Intercept)	9.967e-04	0.031571
agent1	(Intercept)	8.981e-04	0.029968

```

browser          (Intercept) 7.884e-05 0.008879
Residual          9.108e-04 0.030179
Number of obs: 6637, groups: machine_combination, 4005; agent2, 179; agent1, 179; browser, 2

```

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	0.061965	0.008478	2.044701	7.309	0.0171 *
engines_Baidu-DDG	-0.055757	0.005732	419.003649	-9.727	< 2e-16 ***
engines_Baidu-Google	-0.052943	0.005773	418.890355	-9.171	< 2e-16 ***
engines_Baidu-Yahoo!	-0.053319	0.005864	419.378036	-9.092	< 2e-16 ***
engines_Baidu-Yandex	0.013480	0.006755	420.515588	1.996	0.0466 *
engines_Bing-DDG	0.037483	0.005734	419.788063	6.537	1.83e-10 ***
engines_Bing-Google	0.062807	0.005773	419.013786	10.879	< 2e-16 ***
engines_Bing-Yahoo!	0.208913	0.005864	419.534429	35.625	< 2e-16 ***
engines_Bing-Yandex	0.264007	0.006752	421.835188	39.100	< 2e-16 ***
engines_DDG-Google	0.011498	0.007894	371.765103	1.456	0.1461
engines_DDG-Yahoo!	0.242587	0.007960	372.467799	30.475	< 2e-16 ***
engines_DDG-Yandex	0.039040	0.008628	378.626392	4.525	8.10e-06 ***
engines_Google-Yahoo!	0.064182	0.007991	372.939894	8.032	1.27e-14 ***
engines_Google-Yandex	0.133363	0.008657	379.534443	15.406	< 2e-16 ***
engines_Yahoo!-Yandex	0.124684	0.008723	380.285031	14.293	< 2e-16 ***

```

---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
convergence code: 0
boundary (singular) fit: see ?isSingular

```

Response: RBO (p=0.95)

```

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: rbo_95 ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)
Data: subdf

```

REML criterion at convergence: -27931.4

Scaled residuals:

Min	1Q	Median	3Q	Max
-4.3397	-0.4261	-0.0161	0.3647	5.3031

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	1.403e-13	3.745e-07
agent2	(Intercept)	6.204e-04	2.491e-02
agent1	(Intercept)	5.408e-04	2.325e-02
browser	(Intercept)	3.045e-05	5.518e-03
Residual		7.094e-04	2.664e-02

Number of obs: 6637, groups: machine_combination, 4005; agent2, 179; agent1, 179; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	0.079702	0.005952	2.614099	13.392	0.001762 **
engines_Baidu-DDG	-0.066225	0.004552	438.151952	-14.550	< 2e-16 ***
engines_Baidu-Google	-0.071770	0.004584	437.920822	-15.656	< 2e-16 ***
engines_Baidu-Yahoo!	-0.071976	0.004657	438.678196	-15.456	< 2e-16 ***
engines_Baidu-Yandex	0.021282	0.005362	439.902935	3.969	8.42e-05 ***
engines_Bing-DDG	0.143178	0.004554	439.237961	31.440	< 2e-16 ***
engines_Bing-Google	0.063067	0.004584	438.293658	13.757	< 2e-16 ***
engines_Bing-Yahoo!	0.223475	0.004657	438.904286	47.987	< 2e-16 ***

engines_Bing-Yandex	0.254050	0.005361	441.838793	47.385	< 2e-16	***
engines_DDG-Google	0.023378	0.006223	377.679596	3.757	0.000199	***
engines_DDG-Yahoo!	0.279278	0.006275	378.571252	44.503	< 2e-16	***
engines_DDG-Yandex	0.039026	0.006807	386.422319	5.734	1.98e-08	***
engines_Google-Yahoo!	0.052152	0.006300	379.167096	8.278	2.16e-15	***
engines_Google-Yandex	0.130837	0.006831	387.608162	19.154	< 2e-16	***
engines_Yahoo!-Yandex	0.073975	0.006883	388.508537	10.747	< 2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
convergence code: 0
boundary (singular) fit: see ?isSingular

Response: RBO (p=0.8)

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: rbo_80 ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)
Data: subdf

REML criterion at convergence: -18314.5

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.9570	-0.4259	0.0071	0.3608	4.2815

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.0000000	0.00000
agent2	(Intercept)	0.0014840	0.03852
agent1	(Intercept)	0.0012271	0.03503
browser	(Intercept)	0.0001537	0.01240
Residual		0.0031302	0.05595

Number of obs: 6637, groups: machine_combination, 4005; agent2, 179; agent1, 179; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)	
(Intercept)	0.101393	0.011273	1.882299	8.994	0.014620	*
engines_Baidu-DDG	-0.084542	0.007363	518.469900	-11.482	< 2e-16	***
engines_Baidu-Google	-0.097356	0.007415	517.749237	-13.130	< 2e-16	***
engines_Baidu-Yahoo!	-0.095693	0.007534	519.490938	-12.701	< 2e-16	***
engines_Baidu-Yandex	0.006272	0.008680	520.270269	0.723	0.470216	
engines_Bing-DDG	0.024038	0.007370	520.819008	3.262	0.001179	**
engines_Bing-Google	-0.011789	0.007416	519.094469	-1.590	0.112500	
engines_Bing-Yahoo!	0.237549	0.007535	520.216997	31.525	< 2e-16	***
engines_Bing-Yandex	0.331605	0.008684	524.188412	38.185	< 2e-16	***
engines_DDG-Google	-0.053472	0.009795	401.633188	-5.459	8.39e-08	***
engines_DDG-Yahoo!	0.136270	0.009882	403.296144	13.789	< 2e-16	***
engines_DDG-Yandex	-0.037864	0.010760	416.956260	-3.519	0.000481	***
engines_Google-Yahoo!	-0.034742	0.009924	404.406091	-3.501	0.000516	***
engines_Google-Yandex	0.116982	0.010804	419.356467	10.827	< 2e-16	***
engines_Yahoo!-Yandex	-0.011246	0.010893	420.778695	-1.032	0.302461	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
convergence code: 0
boundary (singular) fit: see ?isSingular

B. Statistical Tests for "bernie sanders" query

B.1 Comparison of Browsers for "us elections" query

Response: Jaccard

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: jaccard ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)

Data: subdf

REML criterion at convergence: -6102.4

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.7102	-0.4353	0.0197	0.2927	12.8798

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	1.409e-05	0.003753
agent2	(Intercept)	2.201e-03	0.046913
agent1	(Intercept)	4.136e-03	0.064314
Residual		2.701e-03	0.051972

Number of obs: 2258, groups: machine_combination, 1537; agent2, 192; agent1, 96

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	0.909725	0.020517	189.589718	44.340	< 2e-16 ***
browserFirefox	-0.011024	0.017902	166.464863	-0.616	0.5389
engineBing	-0.174685	0.029524	190.330285	-5.917	1.5e-08 ***
engineDDG	0.060930	0.028548	188.652320	2.134	0.0341 *
engineGoogle	0.006559	0.029000	189.236797	0.226	0.8213
engineYahoo!	0.007027	0.029014	189.558048	0.242	0.8089
engineYandex	0.027131	0.029044	190.230746	0.934	0.3514
browserFirefox:engineBing	0.061620	0.025381	168.134029	2.428	0.0162 *
browserFirefox:engineDDG	0.010162	0.024699	165.353888	0.411	0.6813
browserFirefox:engineGoogle	0.013795	0.024929	166.571360	0.553	0.5807
browserFirefox:engineYahoo!	0.044427	0.025315	166.451331	1.755	0.0811 .
browserFirefox:engineYandex	-0.006441	0.025154	167.298795	-0.256	0.7982

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

(Intr)	brwsrF	engnBn	engDDG	engnGg	engnY!	engnYn	brwF:B	bF:DDG	brwF:G	brF:Y!	
browserFrFx	-0.442										
engineBing	-0.695	0.307									
engineDDG	-0.719	0.318	0.499								
engineGoogl	-0.707	0.313	0.492	0.508							
engineYaho!	-0.707	0.313	0.491	0.508	0.500						
engineYandx	-0.706	0.312	0.491	0.508	0.500	0.500					
brwsrFrFx:B	0.312	-0.705	-0.450	-0.224	-0.221	-0.221	-0.220				
brwsrFr:DDG	0.321	-0.725	-0.223	-0.444	-0.227	-0.227	-0.226	0.511			
brwsrFrFx:G	0.318	-0.718	-0.221	-0.228	-0.448	-0.225	-0.224	0.506	0.520		
brwsrFrF:Y!	0.313	-0.707	-0.217	-0.225	-0.221	-0.442	-0.221	0.499	0.513	0.508	
brwsrFrFx:Y	0.315	-0.712	-0.219	-0.226	-0.223	-0.223	-0.447	0.502	0.516	0.511	0.503

Response: Jaccard Top-10

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: jacctop10 ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)

Data: subdf

REML criterion at convergence: -3045.4

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.8942	-0.5392	0.0001	0.4503	7.7916

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.0006679	0.02584
agent2	(Intercept)	0.0050696	0.07120
agent1	(Intercept)	0.0188896	0.13744
Residual		0.0102972	0.10148

Number of obs: 2258, groups: machine_combination, 1537; agent2, 192; agent1, 96

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)	
(Intercept)	0.941024	0.039962	148.325020	23.548	< 2e-16	***
browserFirefox	-0.013000	0.028285	168.263530	-0.460	0.64639	
engineBing	-0.140327	0.057508	148.935605	-2.440	0.01586	*
engineDDG	-0.491117	0.055605	147.587207	-8.832	2.77e-15	***
engineGoogle	-0.090829	0.056488	148.068773	-1.608	0.10998	
engineYahoo!	0.058994	0.056512	148.307272	1.044	0.29823	
engineYandex	-0.182246	0.056564	148.789937	-3.222	0.00156	**
browserFirefox:engineBing	0.052888	0.040104	169.854801	1.319	0.18902	
browserFirefox:engineDDG	0.159345	0.038987	166.634955	4.087	6.78e-05	***
browserFirefox:engineGoogle	0.019089	0.039393	168.596770	0.485	0.62861	
browserFirefox:engineYahoo!	-0.009252	0.039997	168.275026	-0.231	0.81736	
browserFirefox:engineYandex	0.051879	0.039770	169.305894	1.304	0.19384	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

(Intr)	brwsrF	engnBn	engDDG	engnGg	engnY!	engnYn	brwF:B	bF:DDG	brwF:G	brF:Y!	
browserFrFx	-0.368										
engineBing	-0.695	0.256									
engineDDG	-0.719	0.265	0.499								
engineGoogl	-0.707	0.261	0.492	0.508							
engineYaho!	-0.707	0.260	0.491	0.508	0.500						
engineYandx	-0.706	0.260	0.491	0.508	0.500	0.500					
brwsrFrFx:B	0.260	-0.703	-0.376	-0.187	-0.184	-0.184	-0.184				
brwsrFr:DDG	0.267	-0.725	-0.186	-0.369	-0.189	-0.189	-0.189	0.510			
brwsrFrFx:G	0.264	-0.718	-0.184	-0.190	-0.373	-0.187	-0.187	0.505	0.521		
brwsrFrF:Y!	0.260	-0.707	-0.181	-0.187	-0.184	-0.368	-0.184	0.497	0.513	0.509	
brwsrFrFx:Y	0.262	-0.711	-0.182	-0.188	-0.185	-0.185	-0.373	0.500	0.517	0.511	0.503

Response: RBO (p=0.95)

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: rbo_95 ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)

Data: subdf

REML criterion at convergence: -5195.3

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.9502	-0.3593	-0.0084	0.2876	7.3957

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.002398	0.04897
agent2	(Intercept)	0.001885	0.04342
agent1	(Intercept)	0.008847	0.09406
Residual		0.002217	0.04708

Number of obs: 2258, groups: machine_combination, 1537; agent2, 192; agent1, 96

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	0.865571	0.026693	138.305702	32.427	< 2e-16 ***
browserFirefox	-0.001450	0.017449	170.485230	-0.083	0.933893
engineBing	-0.109011	0.038411	138.838937	-2.838	0.005220 **
engineDDG	-0.274974	0.037146	137.665772	-7.403	1.2e-11 ***
engineGoogle	-0.034586	0.037733	138.087898	-0.917	0.360957
engineYahoo!	-0.083507	0.037748	138.289345	-2.212	0.028593 *
engineYandex	-0.065342	0.037779	138.698183	-1.730	0.085929 .
browserFirefox:engineBing	0.020832	0.024413	163.493650	0.853	0.394741
browserFirefox:engineDDG	0.095367	0.024047	168.765669	3.966	0.000108 ***
browserFirefox:engineGoogle	0.003338	0.024305	170.943935	0.137	0.890921
browserFirefox:engineYahoo!	-0.017142	0.024673	170.437729	-0.695	0.488134
browserFirefox:engineYandex	-0.003268	0.024536	171.496064	-0.133	0.894196

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

	(Intr)	brwsrF	engnBn	engDDG	engnGg	engnY!	engnYn	brwF:B	bF:DDG	brwF:G	brF:Y!
browserFrFx	-0.343										
engineBing	-0.695	0.238									
engineDDG	-0.719	0.246	0.499								
engineGoogl	-0.707	0.242	0.492	0.508							
engineYaho!	-0.707	0.242	0.491	0.508	0.500						
engineYandx	-0.707	0.242	0.491	0.508	0.500	0.500					
brwsrFrFx:B	0.245	-0.693	-0.355	-0.176	-0.173	-0.173	-0.173				
brwsrFr:DDG	0.249	-0.726	-0.173	-0.343	-0.176	-0.176	-0.176	0.503			
brwsrFrFx:G	0.246	-0.718	-0.171	-0.177	-0.347	-0.174	-0.174	0.498	0.521		
brwsrFrF:Y!	0.242	-0.707	-0.168	-0.174	-0.171	-0.343	-0.171	0.490	0.513	0.522	
brwsrFrFx:Y	0.244	-0.711	-0.169	-0.175	-0.172	-0.172	-0.347	0.493	0.530	0.511	0.503

Response: RBO (p=0.8)

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: rbo_80 ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)

Data: subdf

REML criterion at convergence: -2334.4

Scaled residuals:

Min	1Q	Median	3Q	Max
-4.3219	-0.5208	0.0167	0.2249	6.3630

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.0003591	0.01895

```

agent2      (Intercept) 0.0032672 0.05716
agent1      (Intercept) 0.0110980 0.10535
Residual                    0.0160351 0.12663
Number of obs: 2258, groups: machine_combination, 1537; agent2, 192; agent1, 96

```

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	0.981113	0.032308	166.961350	30.368	< 2e-16 ***
browserFirefox	0.003848	0.025225	202.508689	0.153	0.87891
engineBing	-0.060564	0.046553	168.514312	-1.301	0.19505
engineDDG	-0.539083	0.044896	165.330342	-12.007	< 2e-16 ***
engineGoogle	-0.132697	0.045655	166.552255	-2.907	0.00415 **
engineYahoo!	-0.016492	0.045689	166.952364	-0.361	0.71858
engineYandex	-0.144938	0.045754	167.718450	-3.168	0.00183 **
browserFirefox:engineBing	0.008107	0.035911	205.149901	0.226	0.82162
browserFirefox:engineDDG	0.076198	0.034702	199.413537	2.196	0.02926 *
browserFirefox:engineGoogle	-0.021174	0.035153	203.712744	-0.602	0.54761
browserFirefox:engineYahoo!	-0.077796	0.035672	202.573259	-2.181	0.03034 *
browserFirefox:engineYandex	-0.010141	0.035505	203.951526	-0.286	0.77546

```

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Correlation of Fixed Effects:

```

(Intr) brwsrF engnBn engDDG engnGg engnY! engnYn brwF:B bF:DDG brwF:G brF:Y!
browserFrFx -0.430
engineBing -0.694 0.298
engineDDG -0.720 0.309 0.499
engineGoogl -0.708 0.304 0.491 0.509
engineYaho! -0.707 0.304 0.491 0.509 0.500
engineYandx -0.706 0.303 0.490 0.508 0.500 0.499
brwsrFrFx:B 0.302 -0.701 -0.439 -0.217 -0.214 -0.213 -0.213
brwsrFr:DDG 0.312 -0.727 -0.217 -0.430 -0.221 -0.221 -0.221 0.509
brwsrFrFx:G 0.308 -0.718 -0.214 -0.222 -0.434 -0.218 -0.218 0.503 0.522
brwsrFrF:Y! 0.304 -0.707 -0.211 -0.219 -0.215 -0.430 -0.215 0.496 0.514 0.508
brwsrFrFx:Y 0.305 -0.710 -0.212 -0.220 -0.216 -0.216 -0.435 0.498 0.517 0.510 0.502
convergence code: 0
Model failed to converge with max|grad| = 0.00267193 (tol = 0.002, component 1)

```

B.2 Comparison of Search Engines for "bernie sanders" query

Response: Jaccard

```

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: jaccard ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)
Data: subdf

```

REML criterion at convergence: -38073.9

Scaled residuals:

Min	1Q	Median	3Q	Max
-13.8010	-0.2851	-0.0285	0.2514	5.0431

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.000e+00	0.000000

```

agent2      (Intercept) 8.216e-05 0.009064
agent1      (Intercept) 5.778e-05 0.007602
browser     (Intercept) 0.000e+00 0.000000
Residual                    3.617e-04 0.019018
Number of obs: 7677, groups: machine_combination, 4074; agent2, 192; agent1, 192; browser, 2

```

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	8.901e-03	1.728e-03	5.222e+02	5.153	3.65e-07 ***
engines_Baidu-DDG	2.172e-02	1.888e-03	7.988e+02	11.508	< 2e-16 ***
engines_Baidu-Google	1.334e-02	1.902e-03	7.991e+02	7.013	4.98e-12 ***
engines_Baidu-Yahoo!	1.867e-02	1.932e-03	8.005e+02	9.665	< 2e-16 ***
engines_Baidu-Yandex	5.711e-02	1.920e-03	8.055e+02	29.737	< 2e-16 ***
engines_Bing-DDG	1.150e-01	1.888e-03	8.022e+02	60.904	< 2e-16 ***
engines_Bing-Google	1.332e-01	1.903e-03	8.020e+02	69.999	< 2e-16 ***
engines_Bing-Yahoo!	1.093e-01	1.933e-03	8.028e+02	56.540	< 2e-16 ***
engines_Bing-Yandex	8.261e-02	1.918e-03	8.022e+02	43.074	< 2e-16 ***
engines_DDG-Google	4.069e-02	2.378e-03	5.022e+02	17.112	< 2e-16 ***
engines_DDG-Yahoo!	5.783e-01	2.400e-03	5.053e+02	240.975	< 2e-16 ***
engines_DDG-Yandex	8.400e-02	2.388e-03	5.034e+02	35.173	< 2e-16 ***
engines_Google-Yahoo!	5.740e-02	2.412e-03	5.080e+02	23.797	< 2e-16 ***
engines_Google-Yandex	1.060e-01	2.400e-03	5.059e+02	44.175	< 2e-16 ***
engines_Yahoo!-Yandex	9.865e-02	2.424e-03	5.105e+02	40.698	< 2e-16 ***

```

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
convergence code: 0
boundary (singular) fit: see ?isSingular

```

Response: Jaccard Top-10

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: jaccotop10 ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)

Data: subdf

REML criterion at convergence: -29867.6

Scaled residuals:

Min	1Q	Median	3Q	Max
-4.9982	-0.3460	-0.0364	0.3465	7.8219

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.0000145	0.003808
agent2	(Intercept)	0.0006027	0.024551
agent1	(Intercept)	0.0006692	0.025869
browser	(Intercept)	0.0001022	0.010108
Residual		0.0009846	0.031378

Number of obs: 7677, groups: machine_combination, 4074; agent2, 192; agent1, 192; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	2.306e-04	8.586e-03	1.395e+00	0.027	0.982
engines_Baidu-DDG	6.607e-03	4.863e-03	5.027e+02	1.359	0.175
engines_Baidu-Google	-2.886e-04	4.900e-03	5.035e+02	-0.059	0.953
engines_Baidu-Yahoo!	4.315e-02	4.976e-03	5.032e+02	8.671	<2e-16 ***
engines_Baidu-Yandex	4.723e-02	4.940e-03	5.048e+02	9.561	<2e-16 ***
engines_Bing-DDG	9.854e-02	4.862e-03	5.024e+02	20.265	<2e-16 ***

engines_Bing-Google	3.388e-01	4.900e-03	5.033e+02	69.148	<2e-16	***
engines_Bing-Yahoo!	2.035e-01	4.976e-03	5.034e+02	40.894	<2e-16	***
engines_Bing-Yandex	2.598e-01	4.937e-03	5.036e+02	52.630	<2e-16	***
engines_DDG-Google	1.241e-01	6.586e-03	4.174e+02	18.847	<2e-16	***
engines_DDG-Yahoo!	2.475e-01	6.641e-03	4.183e+02	37.261	<2e-16	***
engines_DDG-Yandex	1.498e-01	6.614e-03	4.181e+02	22.652	<2e-16	***
engines_Google-Yahoo!	2.067e-01	6.670e-03	4.196e+02	30.983	<2e-16	***
engines_Google-Yandex	1.133e-01	6.639e-03	4.186e+02	17.071	<2e-16	***
engines_Yahoo!-Yandex	1.914e-01	6.696e-03	4.200e+02	28.580	<2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

convergence code: 0

Model failed to converge with max|grad| = 0.106145 (tol = 0.002, component 1)

Response: RBO (p=0.95)

Linear mixed model fit by REML. t-tests use Satterthwaite's method [`'lmerModLmerTest'`]

Formula: `rbo_95 ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)`

Data: `subdf`

REML criterion at convergence: -34727.5

Scaled residuals:

Min	1Q	Median	3Q	Max
-4.6231	-0.4584	-0.0280	0.4810	4.6119

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.0000000	0.00000
agent2	(Intercept)	0.0003933	0.01983
agent1	(Intercept)	0.0004151	0.02037
browser	(Intercept)	0.0001345	0.01160
Residual		0.0005250	0.02291

Number of obs: 7677, groups: machine_combination, 4074; agent2, 192; agent1, 192; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	6.244e-03	9.023e-03	1.299e+00	0.692	0.5916
engines_Baidu-DDG	2.634e-02	3.820e-03	4.797e+02	6.896	1.7e-11 ***
engines_Baidu-Google	9.471e-03	3.848e-03	4.803e+02	2.461	0.0142 *
engines_Baidu-Yahoo!	4.255e-02	3.908e-03	4.802e+02	10.888	< 2e-16 ***
engines_Baidu-Yandex	6.158e-02	3.880e-03	4.815e+02	15.872	< 2e-16 ***
engines_Bing-DDG	1.375e-01	3.819e-03	4.795e+02	36.004	< 2e-16 ***
engines_Bing-Google	3.381e-01	3.849e-03	4.803e+02	87.847	< 2e-16 ***
engines_Bing-Yahoo!	2.000e-01	3.908e-03	4.804e+02	51.165	< 2e-16 ***
engines_Bing-Yandex	2.211e-01	3.878e-03	4.805e+02	57.011	< 2e-16 ***
engines_DDG-Google	1.396e-01	5.212e-03	4.102e+02	26.788	< 2e-16 ***
engines_DDG-Yahoo!	3.717e-01	5.255e-03	4.109e+02	70.724	< 2e-16 ***
engines_DDG-Yandex	2.057e-01	5.233e-03	4.105e+02	39.313	< 2e-16 ***
engines_Google-Yahoo!	2.052e-01	5.276e-03	4.117e+02	38.892	< 2e-16 ***
engines_Google-Yandex	2.033e-01	5.254e-03	4.112e+02	38.707	< 2e-16 ***
engines_Yahoo!-Yandex	2.378e-01	5.298e-03	4.123e+02	44.887	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

convergence code: 0

boundary (singular) fit: see `?isSingular`

Response: RBO (p=0.8)

Linear mixed model fit by REML. t-tests use Satterthwaite's method [`'lmerModLmerTest'`]

Formula: `rbo_80 ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)`

Data: `subdf`

REML criterion at convergence: -21470.8

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.2779	-0.5267	-0.0294	0.4932	4.8220

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	4.670e-06	0.002161
agent2	(Intercept)	1.947e-03	0.044120
agent1	(Intercept)	1.918e-03	0.043790
browser	(Intercept)	8.221e-04	0.028672
Residual		2.981e-03	0.054602

Number of obs: 7677, groups: machine_combination, 4074; agent2, 192; agent1, 192; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	3.294e-04	2.190e-02	1.238e+00	0.015	0.9901
engines_Baidu-DDG	3.727e-03	8.469e-03	5.003e+02	0.440	0.6600
engines_Baidu-Google	2.906e-04	8.532e-03	5.009e+02	0.034	0.9728
engines_Baidu-Yahoo!	1.294e-02	8.665e-03	5.008e+02	1.493	0.1361
engines_Baidu-Yandex	1.583e-02	8.603e-03	5.024e+02	1.839	0.0664 .
engines_Bing-DDG	1.037e-01	8.468e-03	5.002e+02	12.241	<2e-16 ***
engines_Bing-Google	3.557e-01	8.533e-03	5.010e+02	41.681	<2e-16 ***
engines_Bing-Yahoo!	1.793e-01	8.665e-03	5.011e+02	20.696	<2e-16 ***
engines_Bing-Yandex	1.995e-01	8.598e-03	5.012e+02	23.207	<2e-16 ***
engines_DDG-Google	1.311e-01	1.148e-02	4.172e+02	11.416	<2e-16 ***
engines_DDG-Yahoo!	2.895e-01	1.158e-02	4.181e+02	25.009	<2e-16 ***
engines_DDG-Yandex	2.062e-01	1.153e-02	4.174e+02	17.886	<2e-16 ***
engines_Google-Yahoo!	2.809e-01	1.162e-02	4.188e+02	24.169	<2e-16 ***
engines_Google-Yandex	2.484e-01	1.157e-02	4.183e+02	21.466	<2e-16 ***
engines_Yahoo!-Yandex	3.109e-01	1.167e-02	4.197e+02	26.633	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

convergence code: 0

Model failed to converge with $\max|\text{grad}| = 0.00230499$ (tol = 0.002, component 1)

C. Statistical Tests for "donald trump" query

C.1 Comparison of Browsers for "donald trump" query

Response: Jaccard

Linear mixed model fit by REML. t-tests use Satterthwaite's method [`'lmerModLmerTest'`]

Formula: `jaccard ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)`

Data: subdf

REML criterion at convergence: -6854.8

Scaled residuals:

Min	1Q	Median	3Q	Max
-2.9690	-0.4603	-0.0063	0.2848	13.3648

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	2.402e-05	0.004901
agent2	(Intercept)	3.030e-03	0.055044
agent1	(Intercept)	3.489e-03	0.059071
Residual		1.802e-03	0.042447

Number of obs: 2258, groups: machine_combination, 1537; agent2, 192; agent1, 96

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	9.268e-01	2.060e-02	2.302e+02	44.996	< 2e-16 ***
browserFirefox	1.780e-02	2.039e-02	1.790e+02	0.873	0.3839
engineBing	-1.358e-01	2.963e-02	2.307e+02	-4.583	7.5e-06 ***
engineDDG	4.789e-02	2.868e-02	2.296e+02	1.670	0.0963 .
engineGoogle	-2.340e-02	2.911e-02	2.297e+02	-0.804	0.4223
engineYahoo!	6.956e-02	2.912e-02	2.301e+02	2.388	0.0177 *
engineYandex	-2.983e-02	2.912e-02	2.298e+02	-1.025	0.3066
browserFirefox:engineBing	-1.308e-04	2.887e-02	1.798e+02	-0.005	0.9964
browserFirefox:engineDDG	-2.224e-02	2.816e-02	1.785e+02	-0.790	0.4308
browserFirefox:engineGoogle	-5.367e-03	2.839e-02	1.789e+02	-0.189	0.8503
browserFirefox:engineYahoo!	-4.614e-02	2.883e-02	1.789e+02	-1.600	0.1113
browserFirefox:engineYandex	-1.665e-02	2.860e-02	1.789e+02	-0.582	0.5612

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

	(Intr)	brwsrF	engnBn	engDDG	engnGg	engnY!	engnYn	brwF:B	bF:DDG	brwF:G	brF:Y!
browserFrfrx	-0.491										
engineBing	-0.695	0.341									
engineDDG	-0.718	0.353	0.499								
engineGoogl	-0.708	0.347	0.492	0.508							
engineYaho!	-0.707	0.347	0.492	0.508	0.500						
engineYandx	-0.707	0.347	0.492	0.508	0.500	0.500					
brwsrFrfrx:B	0.347	-0.706	-0.499	-0.249	-0.245	-0.245	-0.245				
brwsrFr:DDG	0.355	-0.724	-0.247	-0.494	-0.251	-0.251	-0.251	0.511			
brwsrFrfrx:G	0.353	-0.718	-0.245	-0.253	-0.498	-0.249	-0.249	0.507	0.520		
brwsrFrfr:Y!	0.347	-0.707	-0.241	-0.249	-0.246	-0.491	-0.246	0.499	0.512	0.508	
brwsrFrfrx:Y	0.350	-0.713	-0.243	-0.251	-0.248	-0.248	-0.494	0.504	0.516	0.512	0.504

Response: Jaccard Top-10

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: jaccotop10 ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)

Data: subdf

REML criterion at convergence: -2583

Scaled residuals:

Min	1Q	Median	3Q	Max
-4.1699	-0.4710	0.0207	0.2965	7.9511

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.000000	0.00000
agent2	(Intercept)	0.007879	0.08877
agent1	(Intercept)	0.020055	0.14162
Residual		0.013301	0.11533

Number of obs: 2258, groups: machine_combination, 1537; agent2, 192; agent1, 96

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	0.87962	0.04320	169.94158	20.361	< 2e-16 ***
browserFirefox	0.06117	0.03455	172.64433	1.770	0.0784 .
engineBing	-0.05022	0.06217	170.65705	-0.808	0.4203
engineDDG	-0.41453	0.06013	169.28102	-6.894	1.03e-10 ***
engineGoogle	-0.11447	0.06105	169.45021	-1.875	0.0625 .
engineYahoo!	0.12038	0.06109	169.87225	1.971	0.0504 .
engineYandex	-0.09304	0.06106	169.63212	-1.524	0.1295
browserFirefox:engineBing	-0.08163	0.04902	175.08306	-1.665	0.0977 .
browserFirefox:engineDDG	0.03586	0.04767	171.52404	0.752	0.4530
browserFirefox:engineGoogle	-0.01240	0.04809	172.62547	-0.258	0.7968
browserFirefox:engineYahoo!	-0.08617	0.04885	172.65236	-1.764	0.0795 .
browserFirefox:engineYandex	-0.06200	0.04845	172.59661	-1.280	0.2023

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

(Intr)	brwsrF	engnBn	engDDG	engnGg	engnY!	engnYn	brwF:B	bF:DDG	brwF:G	brF:Y!
browserFrFx	-0.411									
engineBing	-0.695	0.285								
engineDDG	-0.718	0.295	0.499							
engineGoogl	-0.708	0.291	0.492	0.508						
engineYaho!	-0.707	0.290	0.491	0.508	0.500					
engineYandx	-0.707	0.291	0.492	0.508	0.501	0.500				
brwsrFrFx:B	0.289	-0.705	-0.418	-0.208	-0.205	-0.205	-0.205			
brwsrFr:DDG	0.298	-0.725	-0.207	-0.413	-0.211	-0.210	-0.211	0.511		
brwsrFrFx:G	0.295	-0.718	-0.205	-0.212	-0.415	-0.209	-0.209	0.506	0.521	
brwsrFrF:Y!	0.290	-0.707	-0.202	-0.209	-0.206	-0.410	-0.205	0.498	0.513	0.508
brwsrFrFx:Y	0.293	-0.713	-0.203	-0.210	-0.207	-0.207	-0.413	0.503	0.517	0.512

convergence code: 0
boundary (singular) fit: see ?isSingular

Response: RBO (p=0.95)

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: rbo_95 ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)

Data: subdf

REML criterion at convergence: -4790.1

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.5045	-0.3899	-0.0018	0.2495	6.7850

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.001331	0.03649

```

agent2      (Intercept) 0.002855 0.05343
agent1      (Intercept) 0.007969 0.08927
Residual                    0.003759 0.06131
Number of obs: 2258, groups: machine_combination, 1537; agent2, 192; agent1, 96

```

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	0.80494	0.02688	163.74001	29.946	< 2e-16 ***
browserFirefox	0.04351	0.02088	168.40027	2.084	0.0387 *
engineBing	-0.08110	0.03868	164.41988	-2.097	0.0376 *
engineDDG	-0.18151	0.03741	163.11546	-4.851	2.85e-06 ***
engineGoogle	-0.05988	0.03798	163.27919	-1.576	0.1169
engineYahoo!	-0.06219	0.03801	163.67630	-1.636	0.1037
engineYandex	-0.03442	0.03800	163.44998	-0.906	0.3663
browserFirefox:engineBing	-0.04529	0.02946	167.33422	-1.538	0.1260
browserFirefox:engineDDG	0.01359	0.02881	167.27650	0.472	0.6378
browserFirefox:engineGoogle	-0.04003	0.02907	168.40620	-1.377	0.1703
browserFirefox:engineYahoo!	-0.05773	0.02952	168.41115	-1.955	0.0522 .
browserFirefox:engineYandex	-0.03782	0.02928	168.36001	-1.292	0.1983

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

```

(Intr) brwsrF engnBn engDDG engnGg engnY! engnYn brwF:B bF:DDG brwF:G brF:Y!
browserFrFx -0.400
engineBing -0.695 0.278
engineDDG -0.718 0.287 0.499
engineGoogl -0.708 0.283 0.492 0.508
engineYaho! -0.707 0.283 0.491 0.508 0.500
engineYandx -0.707 0.283 0.492 0.508 0.501 0.500
brwsrFrFx:B 0.284 -0.700 -0.410 -0.204 -0.201 -0.201 -0.201
brwsrFr:DDG 0.290 -0.725 -0.201 -0.402 -0.205 -0.205 -0.205 0.508
brwsrFrFx:G 0.287 -0.718 -0.200 -0.206 -0.405 -0.203 -0.203 0.503 0.521
brwsrFrF:Y! 0.283 -0.707 -0.197 -0.203 -0.200 -0.400 -0.200 0.495 0.513 0.514
brwsrFrFx:Y 0.285 -0.713 -0.198 -0.205 -0.202 -0.202 -0.402 0.500 0.522 0.512 0.504

```

Response: RBO (p=0.8)

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: rbo_80 ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)
Data: subdf

REML criterion at convergence: -1917.5

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.7763	-0.5061	0.0169	0.3004	6.8509

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	1.002e-10	1.001e-05
agent2	(Intercept)	4.265e-03	6.531e-02
agent1	(Intercept)	1.695e-02	1.302e-01
Residual		1.944e-02	1.394e-01

Number of obs: 2258, groups: machine_combination, 1537; agent2, 192; agent1, 96

Fixed effects:

Estimate	Std. Error	df	t value	Pr(> t)
----------	------------	----	---------	----------


```

(Intercept)      8.703e-01  3.871e-02  1.515e+02  22.485 < 2e-16 ***
browserFirefox   6.573e-02  2.836e-02  1.545e+02   2.318 0.02179 *
engineBing       -4.334e-02  5.576e-02  1.527e+02  -0.777 0.43820
engineDDG        -4.560e-01  5.384e-02  1.505e+02  -8.470 2.06e-14 ***
engineGoogle     -1.829e-01  5.468e-02  1.509e+02  -3.344 0.00104 **
engineYahoo!     3.164e-02  5.474e-02  1.515e+02   0.578 0.56415
engineYandex     -5.890e-02  5.471e-02  1.512e+02  -1.077 0.28331
browserFirefox:engineBing -7.082e-02  4.041e-02  1.594e+02  -1.753 0.08158 .
browserFirefox:engineDDG  4.438e-04  3.906e-02  1.524e+02   0.011 0.99095
browserFirefox:engineGoogle -5.831e-02  3.949e-02  1.551e+02  -1.477 0.14180
browserFirefox:engineYahoo! -6.964e-02  4.011e-02  1.548e+02  -1.736 0.08450 .
browserFirefox:engineYandex -6.077e-02  3.978e-02  1.548e+02  -1.528 0.12861
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Correlation of Fixed Effects:

```

(Intr) brwsrF engnBn engDDG engnGg engnY! engnYn brwF:B bF:DDG brwF:G brF:Y!
browserFrFx -0.400
engineBing -0.694 0.278
engineDDG -0.719 0.288 0.499
engineGoogl -0.708 0.283 0.491 0.509
engineYaho! -0.707 0.283 0.491 0.508 0.501
engineYandx -0.708 0.283 0.491 0.509 0.501 0.500
brwsrFrFx:B 0.281 -0.702 -0.408 -0.202 -0.199 -0.198 -0.199
brwsrFr:DDG 0.290 -0.726 -0.202 -0.401 -0.206 -0.205 -0.205 0.510
brwsrFrFx:G 0.287 -0.718 -0.199 -0.206 -0.404 -0.203 -0.203 0.504 0.521
brwsrFrF:Y! 0.283 -0.707 -0.196 -0.203 -0.200 -0.400 -0.200 0.496 0.513 0.508
brwsrFrFx:Y 0.285 -0.713 -0.198 -0.205 -0.202 -0.202 -0.402 0.500 0.518 0.512 0.504
convergence code: 0
boundary (singular) fit: see ?isSingular

```

C.2 Comparison of Search Engines for "donald trump" query

Response: Jaccard

```

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: jaccard ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)
Data: subdf

```

REML criterion at convergence: -44721.3

Scaled residuals:

```

   Min      1Q  Median      3Q      Max
-9.2712 -0.3560 -0.0044  0.3729  5.8130

```

Random effects:

```

Groups          Name          Variance Std.Dev.
machine_combination (Intercept) 6.827e-06 0.002613
agent2           (Intercept) 3.995e-05 0.006321
agent1           (Intercept) 4.211e-05 0.006489
browser          (Intercept) 1.190e-06 0.001091
Residual                            1.428e-04 0.011949

```

Number of obs: 7677, groups: machine_combination, 4074; agent2, 192; agent1, 192; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	1.141e-02	1.500e-03	4.659e+00	7.608	0.000849 ***
engines_Baidu-DDG	7.656e-02	1.373e-03	6.884e+02	55.744	< 2e-16 ***
engines_Baidu-Google	5.355e-02	1.383e-03	6.881e+02	38.716	< 2e-16 ***
engines_Baidu-Yahoo!	8.796e-02	1.404e-03	6.878e+02	62.628	< 2e-16 ***
engines_Baidu-Yandex	4.834e-02	1.394e-03	6.898e+02	34.668	< 2e-16 ***
engines_Bing-DDG	1.473e-02	1.374e-03	6.888e+02	10.721	< 2e-16 ***
engines_Bing-Google	1.587e-01	1.384e-03	6.898e+02	114.618	< 2e-16 ***
engines_Bing-Yahoo!	4.115e-03	1.404e-03	6.876e+02	2.930	0.003506 **
engines_Bing-Yandex	4.258e-04	1.393e-03	6.877e+02	0.306	0.760051
engines_DDG-Google	1.390e-01	1.776e-03	4.782e+02	78.255	< 2e-16 ***
engines_DDG-Yahoo!	5.576e-01	1.792e-03	4.807e+02	311.095	< 2e-16 ***
engines_DDG-Yandex	1.919e-01	1.787e-03	4.824e+02	107.373	< 2e-16 ***
engines_Google-Yahoo!	1.235e-01	1.803e-03	4.843e+02	68.510	< 2e-16 ***
engines_Google-Yandex	1.062e-01	1.791e-03	4.802e+02	59.320	< 2e-16 ***
engines_Yahoo!-Yandex	1.618e-01	1.808e-03	4.832e+02	89.491	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Response: Jaccard Top-10

Linear mixed model fit by REML. t-tests use Satterthwaite's method [`lmerModLmerTest`']

Formula: `jacctop10 ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)`

Data: `subdf`

REML criterion at convergence: -33106.1

Scaled residuals:

Min	1Q	Median	3Q	Max
-7.2345	-0.4500	-0.0214	0.3627	5.1511

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	4.422e-12	2.103e-06
agent2	(Intercept)	1.195e-04	1.093e-02
agent1	(Intercept)	1.738e-04	1.318e-02
browser	(Intercept)	4.091e-07	6.396e-04
Residual		6.889e-04	2.625e-02

Number of obs: 7677, groups: machine_combination, 4074; agent2, 192; agent1, 192; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	4.635e-02	2.511e-03	2.565e+01	18.456	2.51e-16 ***
engines_Baidu-DDG	5.389e-02	2.681e-03	7.670e+02	20.101	< 2e-16 ***
engines_Baidu-Google	-4.039e-02	2.700e-03	7.659e+02	-14.960	< 2e-16 ***
engines_Baidu-Yahoo!	7.721e-02	2.741e-03	7.650e+02	28.166	< 2e-16 ***
engines_Baidu-Yandex	-4.613e-02	2.723e-03	7.691e+02	-16.943	< 2e-16 ***
engines_Bing-DDG	2.493e-04	2.680e-03	7.631e+02	0.093	0.926
engines_Bing-Google	2.398e-01	2.701e-03	7.646e+02	88.784	< 2e-16 ***
engines_Bing-Yahoo!	1.247e-02	2.740e-03	7.598e+02	4.553	6.17e-06 ***
engines_Bing-Yandex	-4.272e-02	2.718e-03	7.604e+02	-15.717	< 2e-16 ***
engines_DDG-Google	-4.129e-02	3.400e-03	4.926e+02	-12.144	< 2e-16 ***
engines_DDG-Yahoo!	3.545e-01	3.432e-03	4.960e+02	103.272	< 2e-16 ***
engines_DDG-Yandex	3.071e-02	3.416e-03	4.944e+02	8.989	< 2e-16 ***
engines_Google-Yahoo!	-3.902e-02	3.446e-03	4.969e+02	-11.323	< 2e-16 ***
engines_Google-Yandex	-4.642e-02	3.429e-03	4.954e+02	-13.535	< 2e-16 ***
engines_Yahoo!-Yandex	4.386e-02	3.463e-03	4.992e+02	12.664	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
convergence code: 0
boundary (singular) fit: see ?isSingular

Response: RBO (p=0.95)

Linear mixed model fit by REML. t-tests use Satterthwaite's method [`'lmerModLmerTest'`]
Formula: `rbo_95 ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)`
Data: `subdf`

REML criterion at convergence: -38490.9

Scaled residuals:

Min	1Q	Median	3Q	Max
-6.8115	-0.3709	0.0242	0.4396	4.9614

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	6.322e-06	0.002514
agent2	(Intercept)	1.511e-04	0.012293
agent1	(Intercept)	1.712e-04	0.013084
browser	(Intercept)	8.280e-07	0.000910
Residual		3.220e-04	0.017944

Number of obs: 7677, groups: machine_combination, 4074; agent2, 192; agent1, 192; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	0.068077	0.002513	426.304599	27.093	< 2e-16 ***
engines_Baidu-DDG	0.063290	0.002510	547.663603	25.216	< 2e-16 ***
engines_Baidu-Google	-0.034456	0.002528	547.468362	-13.631	< 2e-16 ***
engines_Baidu-Yahoo!	0.097339	0.002567	547.294878	37.921	< 2e-16 ***
engines_Baidu-Yandex	-0.043600	0.002548	548.585723	-17.110	< 2e-16 ***
engines_Bing-DDG	0.009077	0.002510	547.587729	3.616	0.000327 ***
engines_Bing-Google	0.307000	0.002529	548.212508	121.383	< 2e-16 ***
engines_Bing-Yahoo!	0.023445	0.002567	546.855344	9.134	< 2e-16 ***
engines_Bing-Yandex	-0.058837	0.002547	546.925811	-23.103	< 2e-16 ***
engines_DDG-Google	-0.022523	0.003360	434.515188	-6.703	6.34e-11 ***
engines_DDG-Yahoo!	0.375583	0.003389	435.935605	110.822	< 2e-16 ***
engines_DDG-Yandex	0.114274	0.003376	435.842691	33.851	< 2e-16 ***
engines_Google-Yahoo!	-0.021268	0.003403	436.866813	-6.249	9.81e-10 ***
engines_Google-Yandex	-0.046971	0.003387	435.645578	-13.868	< 2e-16 ***
engines_Yahoo!-Yandex	0.066890	0.003416	437.342607	19.579	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
convergence code: 0
unable to evaluate scaled gradient
Model failed to converge: degenerate Hessian with 1 negative eigenvalues

Response: RBO (p=0.8)

Linear mixed model fit by REML. t-tests use Satterthwaite's method [`'lmerModLmerTest'`]
Formula: `rbo_80 ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)`
Data: `subdf`

REML criterion at convergence: -27161.7

Scaled residuals:

```

  Min      1Q  Median      3Q      Max
-5.2171 -0.3499 -0.0027  0.4649  6.2392

```

Random effects:

```

Groups          Name          Variance Std.Dev.
machine_combination (Intercept) 0.000e+00 0.000000
agent2           (Intercept) 6.594e-04 0.025680
agent1           (Intercept) 6.787e-04 0.026052
browser          (Intercept) 8.563e-05 0.009254
Residual                1.443e-03 0.037992

```

Number of obs: 7677, groups: machine_combination, 4074; agent2, 192; agent1, 192; browser, 2

Fixed effects:

```

              Estimate Std. Error      df t value Pr(>|t|)
(Intercept)    0.096763   0.008215   1.811932  11.779 0.010108 *
engines_Baidu-DDG -0.003761   0.005148  551.585037  -0.731 0.465387
engines_Baidu-Google -0.089580   0.005185  551.493601 -17.278 < 2e-16 ***
engines_Baidu-Yahoo!  0.061160   0.005266  551.451972  11.615 < 2e-16 ***
engines_Baidu-Yandex -0.095963   0.005227  552.560939 -18.360 < 2e-16 ***
engines_Bing-DDG -0.016071   0.005149  552.023810  -3.121 0.001897 **
engines_Bing-Google  0.337638   0.005188  552.673115  65.075 < 2e-16 ***
engines_Bing-Yahoo!  0.067594   0.005265  551.553579  12.837 < 2e-16 ***
engines_Bing-Yandex -0.094772   0.005224  551.551302 -18.140 < 2e-16 ***
engines_DDG-Google -0.089291   0.006876  433.726362 -12.985 < 2e-16 ***
engines_DDG-Yahoo!  0.293810   0.006936  435.224124  42.358 < 2e-16 ***
engines_DDG-Yandex -0.026629   0.006906  434.517786  -3.856 0.000133 ***
engines_Google-Yahoo! -0.088711   0.006962  435.585073 -12.742 < 2e-16 ***
engines_Google-Yandex -0.096472   0.006932  434.927955 -13.917 < 2e-16 ***
engines_Yahoo!-Yandex -0.053023   0.006993  436.719500  -7.583 2.05e-13 ***

```

```

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
convergence code: 0
boundary (singular) fit: see ?isSingular

```

D. Statistical Tests for "joe biden" query

D.1 Comparison of Browsers for "joe biden" query

Response: Jaccard

```

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: jaccard ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)
Data: subdf

```

REML criterion at convergence: -5942.5

Scaled residuals:

```

  Min      1Q  Median      3Q      Max
-5.3593 -0.2846  0.0002  0.2915 11.6410

```

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	7.664e-05	0.008754
agent2	(Intercept)	3.544e-03	0.059530
agent1	(Intercept)	2.526e-03	0.050263
Residual		2.817e-03	0.053074

Number of obs: 2258, groups: machine_combination, 1537; agent2, 192; agent1, 96

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	0.882560	0.020280	264.879707	43.519	< 2e-16 ***
browserFirefox	-0.022267	0.022398	180.616863	-0.994	0.321484
engineBing	-0.149840	0.029119	264.595654	-5.146	5.20e-07 ***
engineDDG	0.105944	0.028141	261.908080	3.765	0.000206 ***
engineGoogle	0.041277	0.028581	262.595999	1.444	0.149875
engineYahoo!	0.117441	0.028630	264.108059	4.102	5.46e-05 ***
engineYandex	0.015232	0.028597	263.081668	0.533	0.594727
browserFirefox:engineBing	0.037444	0.031667	181.019050	1.182	0.238589
browserFirefox:engineDDG	0.009032	0.030858	178.987662	0.293	0.770082
browserFirefox:engineGoogle	0.018143	0.031121	179.798153	0.583	0.560642
browserFirefox:engineYahoo!	0.018339	0.031630	180.273970	0.580	0.562771
browserFirefox:engineYandex	0.020996	0.031354	179.904044	0.670	0.503938

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

(Intr)	brwsrF	engnBn	engDDG	engnGg	engnY!	engnYn	brwF:B	bF:DDG	brwF:G	brF:Y!
browserFrFx	-0.558									
engineBing	-0.696	0.388								
engineDDG	-0.721	0.402	0.502							
engineGoogl	-0.710	0.396	0.494	0.511						
engineYaho!	-0.708	0.395	0.493	0.510	0.503					
engineYandx	-0.709	0.396	0.494	0.511	0.503	0.502				
brwsrFrFx:B	0.395	-0.707	-0.566	-0.284	-0.280	-0.279	-0.280			
brwsrFr:DDG	0.405	-0.726	-0.282	-0.559	-0.287	-0.287	-0.287	0.513		
brwsrFrFx:G	0.401	-0.720	-0.280	-0.289	-0.563	-0.284	-0.285	0.509	0.522	
brwsrFrF:Y!	0.395	-0.708	-0.275	-0.285	-0.280	-0.556	-0.280	0.501	0.514	0.510
brwsrFrFx:Y	0.398	-0.714	-0.278	-0.287	-0.283	-0.282	-0.560	0.505	0.519	0.514

Response: Jaccard Top-10

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: jacctop10 ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)

Data: subdf

REML criterion at convergence: -3565.6

Scaled residuals:

Min	1Q	Median	3Q	Max
-5.8152	-0.4207	0.0000	0.3685	9.1425

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.0005793	0.02407
agent2	(Intercept)	0.0046714	0.06835
agent1	(Intercept)	0.0138438	0.11766
Residual		0.0080593	0.08977

Number of obs: 2258, groups: machine_combination, 1537; agent2, 192; agent1, 96

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	8.657e-01	3.531e-02	1.636e+02	24.521	< 2e-16 ***
browserFirefox	-1.884e-02	2.700e-02	1.740e+02	-0.698	0.48617
engineBing	6.676e-03	5.073e-02	1.635e+02	0.132	0.89547
engineDDG	-3.006e-01	4.905e-02	1.619e+02	-6.129	6.51e-09 ***
engineGoogle	9.911e-02	4.981e-02	1.624e+02	1.990	0.04832 *
engineYahoo!	1.343e-01	4.989e-02	1.632e+02	2.691	0.00786 **
engineYandex	6.009e-02	4.984e-02	1.627e+02	1.206	0.22966
browserFirefox:engineBing	3.133e-03	3.817e-02	1.749e+02	0.082	0.93467
browserFirefox:engineDDG	1.104e-01	3.712e-02	1.720e+02	2.974	0.00336 **
browserFirefox:engineGoogle	3.695e-02	3.748e-02	1.736e+02	0.986	0.32565
browserFirefox:engineYahoo!	1.885e-02	3.812e-02	1.742e+02	0.494	0.62162
browserFirefox:engineYandex	-6.289e-04	3.777e-02	1.737e+02	-0.017	0.98673

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

	(Intr)	brwsrF	engnBn	engDDG	engnGg	engnY!	engnYn	brwF:B	bF:DDG	brwF:G	brF:Y!
browserFrFx	-0.400										
engineBing	-0.696	0.278									
engineDDG	-0.720	0.288	0.501								
engineGoogl	-0.709	0.284	0.493	0.510							
engineYaho!	-0.708	0.283	0.493	0.509	0.502						
engineYandx	-0.708	0.283	0.493	0.510	0.502	0.501					
brwsrFrFx:B	0.283	-0.705	-0.406	-0.204	-0.201	-0.200	-0.200				
brwsrFr:DDG	0.291	-0.727	-0.202	-0.399	-0.206	-0.206	-0.206	0.513			
brwsrFrFx:G	0.288	-0.720	-0.201	-0.207	-0.402	-0.204	-0.204	0.508	0.524		
brwsrFrF:Y!	0.283	-0.708	-0.197	-0.204	-0.201	-0.399	-0.201	0.499	0.515	0.512	
brwsrFrFx:Y	0.286	-0.715	-0.199	-0.206	-0.203	-0.202	-0.400	0.504	0.521	0.515	0.506

Response: RBO (p=0.95)

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: rbo_95 ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)

Data: subdf

REML criterion at convergence: -6401

Scaled residuals:

Min	1Q	Median	3Q	Max
-5.9239	-0.3067	-0.0028	0.2066	7.3749

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.001332	0.03650
agent2	(Intercept)	0.001048	0.03237
agent1	(Intercept)	0.005200	0.07211
Residual		0.001350	0.03674

Number of obs: 2258, groups: machine_combination, 1537; agent2, 192; agent1, 96

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	0.816990	0.020434	138.374880	39.982	< 2e-16 ***
browserFirefox	-0.010696	0.013173	181.164801	-0.812	0.41788
engineBing	-0.030281	0.029369	138.335489	-1.031	0.30432
engineDDG	-0.138748	0.028400	137.145854	-4.885	2.84e-06 ***
engineGoogle	0.066865	0.028845	137.486227	2.318	0.02192 *

engineYahoo!	-0.029367	0.028880	138.106590	-1.017	0.31100
engineYandex	0.050720	0.028857	137.695743	1.758	0.08103 .
browserFirefox:engineBing	0.006800	0.018391	173.754399	0.370	0.71202
browserFirefox:engineDDG	0.053409	0.018099	178.891318	2.951	0.00359 **
browserFirefox:engineGoogle	0.013307	0.018289	181.152457	0.728	0.46781
browserFirefox:engineYahoo!	0.008767	0.018600	181.505112	0.471	0.63797
browserFirefox:engineYandex	0.011409	0.018427	181.152354	0.619	0.53660

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

(Intr) brwsrF engnBn engDDG enngG engnY! engnYn brwF:B bF:DDG brwF:G brF:Y!
browserFrFx -0.344
engineBing -0.696 0.239
engineDDG -0.719 0.247 0.501
engineGoogl -0.708 0.243 0.493 0.510
engineYaho! -0.708 0.243 0.492 0.509 0.501
engineYandex -0.708 0.243 0.493 0.509 0.502 0.501
brwsrFrFx:B 0.246 -0.695 -0.354 -0.177 -0.175 -0.174 -0.175
brwsrFr:DDG 0.250 -0.728 -0.174 -0.342 -0.177 -0.177 -0.177 0.506
brwsrFrFx:G 0.248 -0.720 -0.172 -0.178 -0.345 -0.175 -0.175 0.501 0.524
brwsrFrF:Y! 0.243 -0.708 -0.169 -0.175 -0.173 -0.343 -0.172 0.492 0.515 0.525
brwsrFrFx:Y 0.246 -0.715 -0.171 -0.177 -0.174 -0.174 -0.344 0.497 0.534 0.515 0.506

convergence code: 0
Model failed to converge with max|grad| = 0.00207129 (tol = 0.002, component 1)

Response: RBO (p=0.8)

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: rbo_80 ~ browser * engine + (1 | agent1) + (1 | agent2) + (1 | machine_combination)
Data: subdf

REML criterion at convergence: -3731.5

Scaled residuals:

Min	1Q	Median	3Q	Max
-5.8694	-0.3108	0.0043	0.2445	8.4232

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.0000000	0.00000
agent2	(Intercept)	0.0002155	0.01468
agent1	(Intercept)	0.0086548	0.09303
Residual		0.0093675	0.09679

Number of obs: 2258, groups: machine_combination, 1537; agent2, 192; agent1, 96

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	9.503e-01	2.525e-02	1.138e+02	37.641	< 2e-16 ***
browserFirefox	-5.239e-03	1.224e-02	1.969e+02	-0.428	0.66908
engineBing	7.142e-03	3.635e-02	1.145e+02	0.196	0.84457
engineDDG	-4.567e-01	3.508e-02	1.126e+02	-13.019	< 2e-16 ***
engineGoogle	2.936e-02	3.567e-02	1.134e+02	0.823	0.41212
engineYahoo!	1.665e-02	3.570e-02	1.138e+02	0.466	0.64192
engineYandex	6.755e-06	3.568e-02	1.136e+02	0.000	0.99985
browserFirefox:engineBing	3.581e-03	1.758e-02	2.128e+02	0.204	0.83879
browserFirefox:engineDDG	6.292e-02	1.670e-02	1.911e+02	3.768	0.00022 ***

```

browserFirefox:engineGoogle 1.421e-03 1.705e-02 2.022e+02 0.083 0.93367
browserFirefox:engineYahoo! 4.672e-03 1.731e-02 1.977e+02 0.270 0.78755
browserFirefox:engineYandex 5.939e-03 1.718e-02 2.009e+02 0.346 0.72985
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Correlation of Fixed Effects:

```

(Intr) brwsrF engnBn engDDG engnGg engnY! engnYn brwF:B bF:DDG brwF:G brF:Y!
browserFrFx -0.312
engineBing -0.695 0.217
engineDDG -0.720 0.225 0.500
engineGoogl -0.708 0.221 0.492 0.509
engineYaho! -0.707 0.221 0.491 0.509 0.501
engineYandx -0.707 0.221 0.491 0.509 0.501 0.500
brwsrFrFx:B 0.217 -0.696 -0.318 -0.156 -0.154 -0.154 -0.154
brwsrFr:DDG 0.229 -0.733 -0.159 -0.308 -0.162 -0.162 -0.162 0.510
brwsrFrFx:G 0.224 -0.718 -0.156 -0.161 -0.313 -0.158 -0.158 0.500 0.526
brwsrFrF:Y! 0.221 -0.707 -0.153 -0.159 -0.156 -0.312 -0.156 0.492 0.518 0.508
brwsrFrFx:Y 0.222 -0.713 -0.154 -0.160 -0.157 -0.157 -0.313 0.496 0.522 0.512 0.504
convergence code: 0
boundary (singular) fit: see ?isSingular

```

D.2 Comparison of Search Engines for "joe biden" query

Response: Jaccard

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: jaccard ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)

Data: subdf

REML criterion at convergence: -44799.8

Scaled residuals:

	Min	1Q	Median	3Q	Max
	-7.8027	-0.2687	0.0181	0.2931	5.1795

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	6.004e-06	0.002450
agent2	(Intercept)	4.396e-05	0.006630
agent1	(Intercept)	4.003e-05	0.006327
browser	(Intercept)	0.000e+00	0.000000
Residual		1.419e-04	0.011910

Number of obs: 7677, groups: machine_combination, 4074; agent2, 192; agent1, 192; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	2.523e-02	1.296e-03	4.815e+02	19.46	<2e-16 ***
engines_Baidu-DDG	1.864e-02	1.382e-03	6.759e+02	13.49	<2e-16 ***
engines_Baidu-Google	2.067e-02	1.389e-03	6.721e+02	14.87	<2e-16 ***
engines_Baidu-Yahoo!	4.460e-02	1.413e-03	6.752e+02	31.57	<2e-16 ***
engines_Baidu-Yandex	3.771e-02	1.401e-03	6.742e+02	26.91	<2e-16 ***
engines_Bing-DDG	6.695e-02	1.381e-03	6.741e+02	48.47	<2e-16 ***
engines_Bing-Google	7.667e-02	1.390e-03	6.721e+02	55.16	<2e-16 ***
engines_Bing-Yahoo!	6.347e-02	1.413e-03	6.740e+02	44.93	<2e-16 ***


```

engines_Bing-Yandex 2.847e-02 1.400e-03 6.715e+02 20.34 <2e-16 ***
engines_DDG-Google 8.808e-02 1.789e-03 4.714e+02 49.25 <2e-16 ***
engines_DDG-Yahoo! 5.796e-01 1.805e-03 4.739e+02 321.07 <2e-16 ***
engines_DDG-Yandex 8.781e-02 1.799e-03 4.747e+02 48.80 <2e-16 ***
engines_Google-Yahoo! 1.150e-01 1.816e-03 4.779e+02 63.30 <2e-16 ***
engines_Google-Yandex 1.149e-01 1.804e-03 4.737e+02 63.67 <2e-16 ***
engines_Yahoo!-Yandex 1.042e-01 1.820e-03 4.763e+02 57.25 <2e-16 ***

```

```

---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
convergence code: 0
boundary (singular) fit: see ?isSingular

```

Response: Jaccard Top-10

Linear mixed model fit by REML. t-tests use Satterthwaite's method [`'lmerModLmerTest'`]

Formula: `jacctop10 ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)`

Data: `subdf`

REML criterion at convergence: -27485.4

Scaled residuals:

```

      Min       1Q   Median       3Q      Max
-3.7483 -0.3324  0.0608  0.2375 11.4652

```

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.000e+00	0.000000
agent2	(Intercept)	7.228e-04	0.026885
agent1	(Intercept)	4.372e-04	0.020910
browser	(Intercept)	6.581e-05	0.008113
Residual		1.392e-03	0.037316

Number of obs: 7677, groups: machine_combination, 4074; agent2, 192; agent1, 192; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	5.301e-02	7.339e-03	1.898e+00	7.224	0.0214 *
engines_Baidu-DDG	1.607e-03	4.752e-03	5.523e+02	0.338	0.7353
engines_Baidu-Google	-6.313e-05	4.779e-03	5.491e+02	-0.013	0.9895
engines_Baidu-Yahoo!	9.597e-02	4.860e-03	5.525e+02	19.748	<2e-16 ***
engines_Baidu-Yandex	5.846e-02	4.818e-03	5.500e+02	12.133	<2e-16 ***
engines_Bing-DDG	5.939e-02	4.747e-03	5.488e+02	12.510	<2e-16 ***
engines_Bing-Google	1.258e-01	4.779e-03	5.474e+02	26.328	<2e-16 ***
engines_Bing-Yahoo!	1.495e-01	4.856e-03	5.488e+02	30.799	<2e-16 ***
engines_Bing-Yandex	1.251e-01	4.813e-03	5.466e+02	26.001	<2e-16 ***
engines_DDG-Google	3.537e-04	6.282e-03	4.162e+02	0.056	0.9551
engines_DDG-Yahoo!	1.960e-01	6.337e-03	4.179e+02	30.928	<2e-16 ***
engines_DDG-Yandex	7.387e-02	6.308e-03	4.170e+02	11.710	<2e-16 ***
engines_Google-Yahoo!	7.327e-02	6.364e-03	4.190e+02	11.514	<2e-16 ***
engines_Google-Yandex	1.620e-03	6.334e-03	4.178e+02	0.256	0.7983
engines_Yahoo!-Yandex	1.767e-01	6.390e-03	4.196e+02	27.659	<2e-16 ***

```

---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
convergence code: 0
boundary (singular) fit: see ?isSingular

```

Response: RBO (p=0.95)

Linear mixed model fit by REML. t-tests use Satterthwaite's method [`'lmerModLmerTest'`]

Formula: `rbo_95 ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)`

Data: `subdf`

REML criterion at convergence: -38088.9

Scaled residuals:

Min	1Q	Median	3Q	Max
-4.9635	-0.3656	-0.0118	0.3108	7.9731

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.0000000	0.00000
agent2	(Intercept)	0.0005276	0.02297
agent1	(Intercept)	0.0004231	0.02057
browser	(Intercept)	0.0001227	0.01108
Residual		0.0003286	0.01813

Number of obs: 7677, groups: machine_combination, 4074; agent2, 192; agent1, 192; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	4.771e-02	8.791e-03	1.296e+00	5.427	0.075834 .
engines_Baidu-DDG	1.742e-02	3.979e-03	4.256e+02	4.377	1.51e-05 ***
engines_Baidu-Google	1.525e-02	4.006e-03	4.248e+02	3.808	0.000161 ***
engines_Baidu-Yahoo!	8.164e-02	4.070e-03	4.255e+02	20.059	< 2e-16 ***
engines_Baidu-Yandex	7.459e-02	4.037e-03	4.252e+02	18.475	< 2e-16 ***
engines_Bing-DDG	8.885e-02	3.978e-03	4.251e+02	22.333	< 2e-16 ***
engines_Bing-Google	2.750e-01	4.007e-03	4.247e+02	68.634	< 2e-16 ***
engines_Bing-Yahoo!	1.415e-01	4.069e-03	4.251e+02	34.783	< 2e-16 ***
engines_Bing-Yandex	1.465e-01	4.036e-03	4.246e+02	36.286	< 2e-16 ***
engines_DDG-Google	8.534e-02	5.521e-03	3.886e+02	15.458	< 2e-16 ***
engines_DDG-Yahoo!	3.426e-01	5.566e-03	3.891e+02	61.553	< 2e-16 ***
engines_DDG-Yandex	1.442e-01	5.542e-03	3.888e+02	26.013	< 2e-16 ***
engines_Google-Yahoo!	1.955e-01	5.586e-03	3.894e+02	34.993	< 2e-16 ***
engines_Google-Yandex	1.077e-01	5.563e-03	3.891e+02	19.352	< 2e-16 ***
engines_Yahoo!-Yandex	2.369e-01	5.608e-03	3.896e+02	42.239	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

convergence code: 0

boundary (singular) fit: see `?isSingular`

Response: RBO (p=0.8)

Linear mixed model fit by REML. t-tests use Satterthwaite's method [`'lmerModLmerTest'`]

Formula: `rbo_80 ~ engines_ + (1 | agent1) + (1 | agent2) + (1 | browser) + (1 | machine_combination)`

Data: `subdf`

REML criterion at convergence: -24428.7

Scaled residuals:

Min	1Q	Median	3Q	Max
-5.5253	-0.3632	-0.0001	0.3235	5.8919

Random effects:

Groups	Name	Variance	Std.Dev.
machine_combination	(Intercept)	0.0000000	0.00000

```

agent2      (Intercept) 0.0021570 0.04644
agent1      (Intercept) 0.0017845 0.04224
browser     (Intercept) 0.0006293 0.02508
Residual                    0.0019896 0.04461
Number of obs: 7677, groups: machine_combination, 4074; agent2, 192; agent1, 192; browser, 2

```

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	2.971e-02	1.955e-02	1.301e+00	1.520	0.3269
engines_Baidu-DDG	8.604e-04	8.271e-03	4.532e+02	0.104	0.9172
engines_Baidu-Google	2.315e-03	8.325e-03	4.520e+02	0.278	0.7810
engines_Baidu-Yahoo!	3.985e-02	8.460e-03	4.531e+02	4.711	3.29e-06 ***
engines_Baidu-Yandex	1.977e-02	8.391e-03	4.527e+02	2.356	0.0189 *
engines_Bing-DDG	8.891e-02	8.269e-03	4.526e+02	10.753	< 2e-16 ***
engines_Bing-Google	5.622e-01	8.327e-03	4.520e+02	67.525	< 2e-16 ***
engines_Bing-Yahoo!	2.169e-01	8.457e-03	4.526e+02	25.644	< 2e-16 ***
engines_Bing-Yandex	2.246e-01	8.388e-03	4.518e+02	26.772	< 2e-16 ***
engines_DDG-Google	6.660e-02	1.137e-02	3.987e+02	5.859	9.75e-09 ***
engines_DDG-Yahoo!	2.297e-01	1.146e-02	3.994e+02	20.042	< 2e-16 ***
engines_DDG-Yandex	1.446e-01	1.141e-02	3.990e+02	12.666	< 2e-16 ***
engines_Google-Yahoo!	2.875e-01	1.151e-02	3.998e+02	24.989	< 2e-16 ***
engines_Google-Yandex	9.405e-02	1.146e-02	3.993e+02	8.209	3.11e-15 ***
engines_Yahoo!-Yandex	4.181e-01	1.155e-02	4.001e+02	36.201	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
convergence code: 0
boundary (singular) fit: see ?isSingular

E. Comparison of politician-like queries withing search engines

Response: Jaccard

```

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: jaccard ~ politician + (1 | engines_) + (1 | browser) + (1 | agent1) + (1 | agent2) + (1 | agent_combination) + (1 | machine_combination)
Data: subdf

```

REML criterion at convergence: -20453.6

Scaled residuals:

Min	1Q	Median	3Q	Max
-4.9468	-0.4452	0.0552	0.5394	5.9005

Random effects:

Groups	Name	Variance	Std.Dev.
agent_combination	(Intercept)	0.0005174	0.02275
machine_combination	(Intercept)	0.0000000	0.00000
agent2	(Intercept)	0.0016921	0.04114
agent1	(Intercept)	0.0016931	0.04115
engines_	(Intercept)	0.0051241	0.07158
browser	(Intercept)	0.0000000	0.00000
Residual		0.0044819	0.06695

Number of obs: 8658, groups: agent_combination, 1443; machine_combination, 768; agent2, 192; agent1, 192; engines_, 6; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	9.073e-01	2.956e-02	5.042e+00	30.698	6.27e-07 ***
politicianDonald Trump	8.521e-03	1.762e-03	7.051e+03	4.835	1.36e-06 ***
politicianJoe Biden	-8.172e-03	1.762e-03	7.051e+03	-4.637	3.60e-06 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

(Intr) pltcDT
pltcDnldTr -0.030
politicnJBdn -0.030 0.500
convergence code: 0
boundary (singular) fit: see ?isSingular

Response: Jaccard Top-10

Linear mixed model fit by REML. t-tests use Satterthwaite's method [`'lmerModLmerTest'`]

Formula: `jaccotop10 ~ politician + (1 | engines_) + (1 | browser) + (1 | agent1) + (1 | agent2) + (1 | agent_combination) + (1 | machine_combination)`

Data: `subdf`

REML criterion at convergence: -9530.5

Scaled residuals:

Min	1Q	Median	3Q	Max
-4.8028	-0.5167	0.0872	0.5867	4.8079

Random effects:

Groups	Name	Variance	Std.Dev.
agent_combination	(Intercept)	0.004049	0.06363
machine_combination	(Intercept)	0.000000	0.00000
agent2	(Intercept)	0.004252	0.06521
agent1	(Intercept)	0.004252	0.06520
engines_	(Intercept)	0.011701	0.10817
browser	(Intercept)	0.002483	0.04983
Residual		0.015008	0.12251

Number of obs: 8658, groups: agent_combination, 1443; machine_combination, 768; agent2, 192; agent1, 192; engines_, 6; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	8.421e-01	5.696e-02	4.274e+00	14.79	7.85e-05 ***
politicianDonald Trump	-1.580e-02	3.225e-03	7.056e+03	-4.90	9.82e-07 ***
politicianJoe Biden	4.239e-02	3.225e-03	7.056e+03	13.14	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

(Intr) pltcDT
pltcDnldTr -0.028
politicnJBdn -0.028 0.500
convergence code: 0
boundary (singular) fit: see ?isSingular

Response: RBO (p=0.95)

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: rbo_95 ~ politician + (1 | engines_) + (1 | browser) + (1 | agent1) +
(1 | agent2) + (1 | agent_combination) + (1 | machine_combination)
Data: subdf

REML criterion at convergence: -18437.2

Scaled residuals:

Min	1Q	Median	3Q	Max
-5.4949	-0.4546	0.0551	0.5333	5.6292

Random effects:

Groups	Name	Variance	Std.Dev.
agent_combination	(Intercept)	0.0019422	0.04407
machine_combination	(Intercept)	0.0000000	0.00000
agent2	(Intercept)	0.0014980	0.03870
agent1	(Intercept)	0.0014976	0.03870
engines_	(Intercept)	0.0017116	0.04137
browser	(Intercept)	0.0008291	0.02879
Residual		0.0051943	0.07207

Number of obs: 8658, groups: agent_combination, 1443; machine_combination, 768; agent2, 192; agent1, 192; engines_, 6; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	7.948e-01	2.681e-02	2.532e+00	29.65	0.000276 ***
politicianDonald Trump	-3.726e-02	1.897e-03	7.056e+03	-19.64	< 2e-16 ***
politicianJoe Biden	2.012e-02	1.897e-03	7.056e+03	10.60	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

(Intr) pltcDT
pltcnDnldTr -0.035
politicnJBdn -0.035 0.500
convergence code: 0
boundary (singular) fit: see ?isSingular

Response: RBO (p=0.8)

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: rbo_80 ~ politician + (1 | engines_) + (1 | browser) + (1 | agent1) +
(1 | agent2) + (1 | agent_combination) + (1 | machine_combination)
Data: subdf

REML criterion at convergence: -9310.2

Scaled residuals:

Min	1Q	Median	3Q	Max
-5.1111	-0.4612	0.0477	0.5787	5.0111

Random effects:

Groups	Name	Variance	Std.Dev.
agent_combination	(Intercept)	1.261e-02	1.123e-01

```

machine_combination (Intercept) 1.819e-05 4.265e-03
agent2 (Intercept) 9.341e-10 3.056e-05
agent1 (Intercept) 0.000e+00 0.000e+00
engines_ (Intercept) 1.732e-02 1.316e-01
browser (Intercept) 1.578e-03 3.973e-02
Residual 1.465e-02 1.210e-01
Number of obs: 8658, groups: agent_combination, 1443; machine_combination, 768; agent2, 192; agent1, 192; engines_, 6;
browser, 2

```

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	8.511e-01	6.075e-02	5.903e+00	14.01	9.4e-06 ***
politicianDonald Trump	-6.360e-02	3.186e-03	7.213e+03	-19.96	< 2e-16 ***
politicianJoe Biden	5.165e-02	3.186e-03	7.213e+03	16.21	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

```

(Intr) pltcDT
pltcnDnldTr -0.026
politcnJBdn -0.026 0.500
convergence code: 0
boundary (singular) fit: see ?isSingular

```

F. Comparison of politician-like queries controlling by all factors

Response: Jaccard

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: jaccard ~ politician + (1 | engines_) + (1 | browser) + (1 | agent1) + (1 | agent2) + (1 | agent_combination) + (1 | machine_combination)
Data: subdf

REML criterion at convergence: -20453.6

Scaled residuals:

Min	1Q	Median	3Q	Max
-4.9468	-0.4452	0.0552	0.5394	5.9005

Random effects:

Groups	Name	Variance	Std.Dev.
agent_combination	(Intercept)	0.0005174	0.02275
machine_combination	(Intercept)	0.0000000	0.00000
agent2	(Intercept)	0.0016921	0.04114
agent1	(Intercept)	0.0016931	0.04115
engines_	(Intercept)	0.0051241	0.07158
browser	(Intercept)	0.0000000	0.00000
Residual		0.0044819	0.06695

Number of obs: 8658, groups: agent_combination, 1443; machine_combination, 768; agent2, 192; agent1, 192; engines_, 6; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	9.073e-01	2.956e-02	5.042e+00	30.698	6.27e-07 ***
politicianDonald Trump	8.521e-03	1.762e-03	7.051e+03	4.835	1.36e-06 ***
politicianJoe Biden	-8.172e-03	1.762e-03	7.051e+03	-4.637	3.60e-06 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
(Intr) pltcDT
pltcDnldTr -0.030
politicnJBdn -0.030 0.500
convergence code: 0
boundary (singular) fit: see ?isSingular

Response: Jaccard Top-10

Linear mixed model fit by REML. t-tests use Satterthwaite's method [`'lmerModLmerTest'`]
Formula: `jaccotop10 ~ politician + (1 | engines_) + (1 | browser) + (1 | agent1) + (1 | agent2) + (1 | agent_combination) + (1 | machine_combination)`
Data: `subdf`

REML criterion at convergence: -9530.5

Scaled residuals:
Min 1Q Median 3Q Max
-4.8028 -0.5167 0.0872 0.5867 4.8079

Random effects:

Groups	Name	Variance	Std.Dev.
agent_combination	(Intercept)	0.004049	0.06363
machine_combination	(Intercept)	0.000000	0.00000
agent2	(Intercept)	0.004252	0.06521
agent1	(Intercept)	0.004252	0.06520
engines_	(Intercept)	0.011701	0.10817
browser	(Intercept)	0.002483	0.04983
Residual		0.015008	0.12251

Number of obs: 8658, groups: agent_combination, 1443; machine_combination, 768; agent2, 192; agent1, 192; engines_, 6; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	8.421e-01	5.696e-02	4.274e+00	14.79	7.85e-05 ***
politicianDonald Trump	-1.580e-02	3.225e-03	7.056e+03	-4.90	9.82e-07 ***
politicianJoe Biden	4.239e-02	3.225e-03	7.056e+03	13.14	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
(Intr) pltcDT
pltcDnldTr -0.028
politicnJBdn -0.028 0.500
convergence code: 0
boundary (singular) fit: see ?isSingular

Response: RBO (p=0.95)

Linear mixed model fit by REML. t-tests use Satterthwaite's method [`'lmerModLmerTest'`]

Formula: rbo_95 ~ politician + (1 | engines_) + (1 | browser) + (1 | agent1) +
(1 | agent2) + (1 | agent_combination) + (1 | machine_combination)
Data: subdf

REML criterion at convergence: -18437.2

Scaled residuals:

Min	1Q	Median	3Q	Max
-5.4949	-0.4546	0.0551	0.5333	5.6292

Random effects:

Groups	Name	Variance	Std.Dev.
agent_combination	(Intercept)	0.0019422	0.04407
machine_combination	(Intercept)	0.0000000	0.00000
agent2	(Intercept)	0.0014980	0.03870
agent1	(Intercept)	0.0014976	0.03870
engines_	(Intercept)	0.0017116	0.04137
browser	(Intercept)	0.0008291	0.02879
Residual		0.0051943	0.07207

Number of obs: 8658, groups: agent_combination, 1443; machine_combination, 768; agent2, 192; agent1, 192; engines_, 6; browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	7.948e-01	2.681e-02	2.532e+00	29.65	0.000276 ***
politicianDonald Trump	-3.726e-02	1.897e-03	7.056e+03	-19.64	< 2e-16 ***
politicianJoe Biden	2.012e-02	1.897e-03	7.056e+03	10.60	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

(Intr)	pltcDT
pltcnDnldTr	-0.035
politcnJBdn	-0.035 0.500

convergence code: 0
boundary (singular) fit: see ?isSingular

Response: RBO (p=0.8)

Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']

Formula: rbo_80 ~ politician + (1 | engines_) + (1 | browser) + (1 | agent1) +
(1 | agent2) + (1 | agent_combination) + (1 | machine_combination)
Data: subdf

REML criterion at convergence: -9310.2

Scaled residuals:

Min	1Q	Median	3Q	Max
-5.1111	-0.4612	0.0477	0.5787	5.0111

Random effects:

Groups	Name	Variance	Std.Dev.
agent_combination	(Intercept)	1.261e-02	1.123e-01
machine_combination	(Intercept)	1.819e-05	4.265e-03
agent2	(Intercept)	9.341e-10	3.056e-05
agent1	(Intercept)	0.000e+00	0.000e+00
engines_	(Intercept)	1.732e-02	1.316e-01

browser (Intercept) 1.578e-03 3.973e-02
Residual 1.465e-02 1.210e-01
Number of obs: 8658, groups: agent_combination, 1443; machine_combination, 768; agent2, 192; agent1, 192; engines_, 6;
browser, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)	
(Intercept)	8.511e-01	6.075e-02	5.903e+00	14.01	9.4e-06	***
politicianDonald Trump	-6.360e-02	3.186e-03	7.213e+03	-19.96	< 2e-16	***
politicianJoe Biden	5.165e-02	3.186e-03	7.213e+03	16.21	< 2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

(Intr) pltcDT
pltcnDnldTr -0.026
politicnJBdn -0.026 0.500
convergence code: 0
boundary (singular) fit: see ?isSingular