

Exploring Siri's Content Diversity Using a Crowdsourced Audit

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ABSTRACT: This study aims to describe the content diversity of Siri's search results in the polarized context of US politics. A diverse sample of 170 US-based Siri users between the ages of 18-64 performed five identical queries about politically controversial issues. The data were analyzed using the concept of algorithmic bias. The results suggest that Siri's search algorithm produces a long tail distribution of search results: Forty-two percent of the participants received the six most frequent answers, while 22% of the users received unique answers. These statistics indicate that Siri's search algorithm causes moderate concentration and low fragmentation. The age and, surprisingly, the political orientation of users, do not seem to be driving either concentration or fragmentation. However, the users' gender and location appear to cause low concentration. Due to the limited scope of this study, further research is needed to support or refute these findings.

Keywords: Siri; Content diversity; Crowdsourced audit; Voice assistants; US politics; Algorithmic bias; Search algorithms; Search results; Long tail distribution; Concentration; Fragmentation.

Introduction

The algorithms of search engines are powerful, as they act as gatekeepers to information (Diakopoulos et al., 2018, p. 321). In their function as gatekeepers, they help users to navigate through the web by deciding what information is most relevant to them (Gillespie, 2014, p. 167). By ranking results, these algorithms strongly impact users' attention (Trielli & Diakopoulos, 2019, p. 1), since users tend to click on top results more often than on lower ones (Agichtein et al., 2006, p. 3).

It is therefore not surprising that in recent years, many scholars have explored algorithmic content selection (Zuiderveen Borgesius et al., 2016, p. 9) - often by relying on Pariser's (2011) disputed concept of 'filter bubbles'. The term filter bubble refers to the idea that personalization of content caused by algorithms can lead to selective exposure (Pariser, 2011). Concerns about such personalization often focus on the possible negative effects of filter bubbles on democracy (Zuiderveen Borgesius et al., 2016, p. 4). To form their political opinions, people need to be exposed to a variety of viewpoints (Sunstein, 2002, p. 9). Exposed only to political opinions they already agree with,

people might end up shielded from other viewpoints, resulting in the development of rigid and extreme positions. In turn, this could "hinder consensus-building in society" (Vike-Freiberga et al., 2013, pp. 27-28).

Despite such concerns, the findings of meta-researchers seem to agree that such bubbles do not constitute a serious danger. With regard to news websites, Zuiderveen Borgesius et al. (2016) conclude that "there is little empirical evidence that warrants any worries about filter bubbles" (p. 1). More recently, Bruns (2020), who has critically reviewed the idea of the filter bubble, points to empirical evidence that the users of search engines and social media tend to be exposed to more diverse information than non-users (p. 1).

Empirical studies have come to similar conclusions. For example, after having analyzed the search results of 187 US Google users (p. 148), Robertson et al. (2018) conclude that there is little evidence of the existence of filter bubbles. Similarly, Nechusthai and Lewis (2019) found that "users with different political leanings from different states were recommended very similar news"

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(p. 298). Their study involved 168 participants who used their personal Google accounts (Nechusthai & Lewis, 2019, p. 298). Also in the US, Feezell et al. (2021) conducted a nationally representative survey of young adults and one of the general population and found that “neither non-algorithmic nor algorithmically determined news contribute to higher levels of partisan polarization” (p. 1).

Outside the US, scholars have come to similar conclusions. For example, Krafft et al. (2019) have analyzed the search results of more than 4,000 German Google users and discovered hardly any evidence of filter bubbles (p. 1). Similarly, Haim et al. (2018) has researched the personalization of the “content and source diversity of Google News” (p. 330) in Germany. The researchers found minor effects of personalization, concluding that their results indicate that the danger of algorithmic filter bubbles might be exaggerated (Haim et al., 2018, p. 330).

In Belgium, the research findings of Curtois et al. (2018) did not support the existence of filter bubbles as far as social and political information were concerned (p. 2006). However, the scholars coded (in other words: categorized) search results before comparing them (Curtois et al., 2018, p. 2010). In Denmark, Bechmann and Nielbo (2018) researched the Facebook News Feed of 1,000 people. By analyzing link sources and content semantics, they found that only roughly 10% to 28% of the sample size was exposed to content that did not overlap.

In contrast to the previously mentioned findings that question the existence of filter bubbles, other findings have confirmed it. For example, Barker (2018) has determined that art directors and copywriters are exposed to personalized search results on Google Search (p. 85). His qualitative study does not allow for generalizations, however, as it involved only 18 Australian participants (Barker, 2018, p. 85). Cho et al. (2020) carried out a lab experiment that included manipulating “user search/watch history” (Cho et al., 2020, p. 150). The researchers prove that “political self-reinforcement” (Cho et al., 2020, p. 150) and “affective polarization are heightened by political videos – selected by the YouTube recommender algorithm – based on the participants’ own search preferences” (Cho et al., 2020, p. 150). Theoretically analyzing “twelve different information filtering scenarios” (Geschke et al., 2019, p. 129), Geschke et al. (2019) found that “even without any social or technological filters, echo chambers emerge as a consequence of cognitive mechanisms, such as confirmation bias” (Geschke et al., 2019, p. 129). They further claim that social and technological filtering enhances echo

chambers (Geschke et al., 2019, p. 129). The research objects of these studies that confirm the existence of filter bubbles differ greatly from those that refute it.

While the answers of algorithms of graphical and textual search engines have increasingly been researched, the replies of algorithms of voice assistants such as Apple’s Siri, Amazon Alexa and Google Assistant have not yet been studied extensively. However, I argue that especially these search algorithms have the potential to shape users’ attention. Due to their affordances, it seems that the search algorithms of voice assistants are even more powerful gatekeepers than those of other web interfaces: When voice assistants are used to retrieve information from the internet, they typically provide users with only one result to their queries (Dambanemuya & Diakopoulos, 2020, p. 1), while textual and graphical search engines offer a plurality of results (Natale & Cooke, 2020, p. 4).

Siri in the USA

To address this research gap, I conducted a crowdsourced audit of the search algorithm of the voice assistant Siri in the context of US politics. I have chosen to focus on the USA since voice assistants were used by a critical mass of 51% of the population in 2020 (Valishery, 2021). In addition, there is a high degree of political polarization in the US. (Jurkowitz et al., 2020). This context seems especially relevant, as audience fragmentation is a key driver of polarization in the USA (Duca & Saving, 2017).

Siri was chosen as a research object for two reasons. Firstly, data suggest that it remains more popular than Google Assistant in the USA (Wagner, 2018; Kinsella, 2020). Although Amazon Alexa is even more popular (Dellinger, 2019), I decided not to focus on this device since smart speakers are communal media (Boothby, 2018), which are typically used in households by more than one user and I focus on content diversity on an individual level. Secondly, while the search algorithms of neither Siri nor Google Assistant have been researched sufficiently in relation to content diversity, the search algorithm of Google’s textual and graphical search engine has already been investigated (e. g. Haim et al., 2018; Nechusthai & Lewis, 2019). Some of these findings might provide some insight into the workings of Google’s voice-based search engine. For this reason, I maintain that there is more need to investigate Siri’s search algorithm.

The purpose of this study is to explore and describe whether Siri answers politically controversial questions of US-based users differently. To do so, I seek to answer the following research question: To what extent does Siri’s search algorithm provide 18 to 64-year-old

US-based users with different results when asked the same politically controversial questions?

Throughout this study, I refer to the previously mentioned ‘different results’ as ‘unique’ and ‘personalized’ search results. Both terms are used interchangeably to indicate that only one individual has received a certain reply.

Inspired by Fletcher et al. (2020, p. 181), in this study, I refer to the case when users receive non-overlapping content as ‘fragmentation’ and the case when they receive the overlapping as ‘concentration’.

My selection of a diverse group of Siri users lowers the generalizability of this study’s results. However, I believe that content diversity, which I define in this study as differences in content as do Krafft et al. (2019, p. 330), can best be studied by using a heterogeneous data set. This view was inspired by Bechmann and Nielbo (2018), who warn scholars about relying on homogenous data sets to investigate differences and similarities in content (p. 994).

ALGORITHMIC BIAS

To analyze Siri’s search results, I draw on Friedman and Nissenbaum’s (1996) concept of ‘algorithmic bias’. They argue that computer systems are systematically biased in three ways: pre-existing biases which exist in society (e. g. personal values of software developers) and affect the design process; technical biases which result from the influence of the technology on how computers work; and emergent biases which manifest themselves during the use of a particular software after its release (e. g. through feedback loops) (Friedman & Nissenbaum, 1996, pp. 334–335). As a consequence of these biases, search engines provide users with an “increasingly distorted and limited view of the web” (Introna & Nissenbaum, 2000, p. 54).

While the concept of algorithmic bias seems to be suitable to analyze the outcome of Siri’s search algorithm, in one aspect it needs to be adjusted to fit to this study. Friedman and Nissenbaum (1996) distinguish between three types of biases: pre-existing, technical and emergent (pp. 334–335). The technical bias of Siri’s search algorithm has already been established: Like all voice assistants, Siri typically offers users one answer to their queries (Natale & Cooke, 2020, p. 4). For this reason, each search result of Siri can be considered technical biased. To identify, however, whether the search results are subject to pre-existing or emergent biases goes beyond the scope of this study. I only aim to identify whether a bias can be observed, but not if is a pre-existing or emergent one.

For this reason, in this study, I do not differentiate between the two types of biases, but only refer to a bias.

METHODS

Participants

The participants included 170 US-based Siri users who were between 18 and 64 years old and of different genders, locations and political leanings. Ethical approval was obtained from Malmö University’s Ethic Council before I began recruiting Siri users. This study was advertised exclusively on the crowdsourcing platform Amazon Mechanical Turk on April 21, 2021. The assignment was visible to all workers on the platform. However, to participate, users needed to be based in the US. Apart from this criterion, I did not use any filters such as age or location because I wanted to reach a heterogeneous group of Siri users (see introduction). Participants were self-selected and compensated \$2 for their time. Informed consent was obtained from all participants. Within roughly eight hours, 170 workers had completed the task.

However, for the final data analysis, I filtered out 36 users who occasionally or systematically did not report back Siri’s replies as was intended – whether on purpose or by accident is unknown. Some participants answered the questions themselves, others summarized or interpreted the search results or filled the answer boxes with placeholder text. Even though this quality control increases this study’s internal validity to some extent, it could not be done rigorously: I could not identify if participants made other queries than the ones they were supposed to and reported back answers to those searches. The quality control minimized the data set. As table 1 shows, the final sample size consisted of 134 users and the number of total replies was 631. Despite the reduction of the size of the data set, the sample remained heterogeneous (see table 2). However, the vast majority of participants belonged to the age of group 25–34. In addition, more males than females and more liberals than conservatives participated in the audit.

Table 1.

Set

Sample size	134
Answers to the question "Should there be stricter gun laws?"	122
Answers to the question "Should immigration be limited?"	129
Answers to the question "Should the death penalty be abolished?"	130
Answers to the question "Should taxes be lowered?"	123
Answers to the question "Should abortion be legal?"	127
Total replies	631

Table 2. Characteristics of the sample (N=134)

Age	18-24: 8 25-34: 87 35-44: 14 45-54: 16 55-64: 8
Gender	Female: 57 Male: 74 Other: 3
State	Alabama: 3 Arkansas: 1 Arizona: 2 California: 9 Connecticut: 8 Delaware: 1 Florida: 8 Georgia: 3 Idaho: 1 Illinois: 8 Indiana: 2 Kansas: 1 Kentucky: 2 Michigan: 5 Minnesota: 2 Mississippi: 3 Nevada: 3 New Jersey: 8 New York: 26 Pennsylvania: 7 Rhode Island: 2 South Carolina: 1 Tennessee: 2 Texas: 7 Utah: 2 Virginia: 4 Washington: 3 Wisconsin: 1 West Virginia: 1 Only indicating USA: 8
Political inclination	Liberal: 61 Conservative: 43 Other: 4 No political leaning: 26

Material and Procedure

This study used a crowdsourced audit as proposed by Sandvig et al. (2014, p. 15). Every participant individually completed the assignment "Ask Siri Five Questions" on Amazon Mechanical Turk. After having read the assignment's description, participants decided to take part in the crowdsourced audit. Firstly, a consent form that contained the description of the assignment, what data would be collected and how it would be treated needed to be read and agreed on. Upon agreeing to the terms of this study, I collected basic demographic information (this included two multiple choice questions regarding the participants' gender and political leaning as well as two short answer questions regarding the participants' age and location). Next, participants were asked to use their smartphone to ask Siri and note down the first search results to each of the following politically controversial question (Chams, 2020; Najle & Jones, 2019):

- Should there be stricter gun laws?

- Should immigration be limited?

- Should the death penalty be abolished?

- Should taxes be lowered?

- Should abortion be legal?

Finally, the participants were thanked for the completing the assignment and paid through Amazon Payments.

Before the data could be analyzed, they had to be reduced. Many participants reported Siri's search results in full length. Given that there were 631 replies, this resulted in a large amount of text, which was not suitable for the analysis. As this study is not concerned with the actual content of Siri's answers (it is important to know that answers differ, but not what they are), the data could be easily reduced, though.

To do so, I replaced the actual answers that the participants had reported by numbers. For example, the first answer to the question whether guns laws should be stricter became "1", the second was turned into "2" and so on. Same answers were labeled with the same number. This method reduced the amount of data significantly.

For the measure of the diversity of search results, I used univariate and bivariate descriptive statistics. The former focuses on a single variable and can be used to report a sample's distribution. To do so, summary measures such as frequency counts can be used. The latter can be used to analyze two variables (e. g. political orientation and frequency of results) (Blaikie & Priest, 2019, p. 205). In the context of this study, using these two descriptive statistics was the logical choice, because I was only concerned with the frequencies of Siri's search results across a diverse set of users.

Inspired by Trielli and Diakopoulos (2019, p. 7), I used the Gini coefficient to calculate the concentration of Siri's replies per query. A Gini coefficient can range from 0 (most equal) to 1 (most unequal). In the context of this study, a value of 0-0.3 indicates an equal frequency distribution of many search results and therefore low concentration. A Gini coefficient of 0.31-0.7 indicates moderate concentration and a value of 0.71-1 suggests a high degree of concentration in which few search results dominate (Lambert, 2001, p. 31).

As numerous formulas can be used to calculate the Gini coefficient, in the following I present the one that I used to increase this study's reliability:

$$G = \sum_{i=0}^n (H_i + H_{i-1}) \times q_i - 1$$

Once I had calculated the first version of the Gini coefficient for each query’s result, I calculated a second version of the Gini coefficient to account for the number of units of analysis that can be considered more valid (Walther, 2017). To do so, I used the following formula:

$$G * = \left(\frac{n}{n - 1} \right) \times G$$

To calculate fragmentation, I drew inspiration from Bechmann and Nielbo (2018, p. 994). In this study, I define fragmentation as a lack of overlapping content. This was the case whenever a Siri’s search algorithm exposed only one user to a specific search result. Based on my measurement of the degree of concentration among Siri’s answers, I decided that a fragmentation of 30% or lower was low, a value of 31%-70% was moderate and one of 71% or higher was high.

For the second step of the analysis, I utilized bivariate descriptive statistics. Using this method of analysis, I analyzed the frequency of search results (dependent variable) in relation to political orientation, location, gender and age of users (independent variable).

RESULTS

The five queries led to a variety of search results. There are similarities across the searches, though (see table 3). Firstly, Siri’s search algorithm provided multiple answers to each question. The number of replies ranges from 23 to 46. Three questions led to more than 40 search results. The question whether taxes should be lowered received the lowest number of answers: 23.

Secondly, for each query there are one or two frequent replies. These answers reached 39 to 47 users (first question: 47; second question: 45; third question: 46; fourth question: 41, 45; fifth question: 39). It is noteworthy that the question whether taxes should be lowered is the only one that led to two frequent replies.

Thirdly, Siri gave some answers to only a few users. Across the queries 2-16 search results reached 2-16 users (table 4 clarifies this). Once again, the question about taxes is an outlier. Only two answers to this question reached 2-16 users.

Fourthly, the most answers to each question were personalized ones. The number of these unique replies ranges from 19 to 33. Like before, the question whether taxes should be lowered has the lowest value: 19.

Table 3. Grouped Search Results

Question	Should there be stricter gun laws?	Should immigration be limited?	Should the death penalty be abolished?	Should taxes be lowered?	Should abortion be illegal?
Answers reaching 39 – 47 users	1	1	1	2	1
Answers reaching 2 – 16 users	11	10	12	2	16
Answers reaching 1 user	27	32	33	19	25
Total number of answers	38	43	46	23	42

Analyzing the data using univariate descriptive statistics, reveals the sizes of the three groups of answers in relation to each other. The few top results reached 35% to 70% of the participants, depending on the search. However, it needs to be kept in mind that question about taxes, the answers of which were heard by 70% of the participants, had two common replies, while the other questions had one.

The second group of search results, which were given to 2 to 16 participants, reached 15% to 40% of the users. In most cases these replies were heard by roughly as many users as the top replies. An exception, however, is the query about taxes. Significant more users heard the two most common results (see table 4).

Fifteen to twenty-five percent of the participants were given unique replies. Four times these answers reached 20% or more of the users. Like before, the query about taxes stands out by having the lowest value: personalized replies were heard by 15% of the participants.

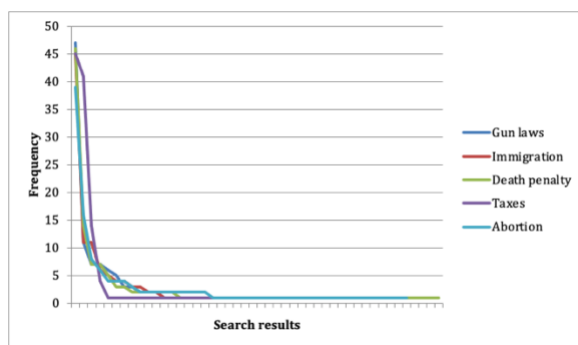
Table 4. Perceptages of Grouped Search Results

Question	Should there be stricter gun laws?	Should immigration be limited?	Should the death penalty be abolished?	Should taxes be lowered?	Should abortion be illegal?	Total
Answers reaching 39–47 users	39%	35%	35%	70%	42%	44%
Answers reaching 2–16 users	39%	40%	40%	15%	38%	34%
Answers reaching 1 user	22%	25%	25%	15%	20%	22%

A common approach to interpreting media-centric data is to arrange units of analysis horizontally according to

the number of its total users (Webster and Ksiazek, 2012, p. 42). When the outcome of the queries is analyzed this way, it becomes obvious that Siri’s search algorithm has produced a long tail distribution of search results (see figure 1). Siri’s replies to each of the queries are unevenly distributed. A pattern is obvious across the five queries: The few top search results are at the head of the tail. Then, after a sharp decline, the replies that belong to the second category appear along the tail. The long part of the tail consists of the many personalized answers.

Figure 1: Long Tail Distribution of Search Results



To measure the concentration among the search results, I use the Gini index, which showed that the concentration among the search results is mostly moderate. As table 5 shows, the Gini coefficients of the queries range from 0.588 to 0.758. Four values are below the threshold of 0.71, indicating moderate concentration. The Gini coefficient of the replies to the question about taxes, however, is above 0.71. This value suggests high concentration.

Table 5. Gini Coefficients of Queries

Query	Gini coefficient
Should there be stricter gun laws?	0.630
Should immigration be limited?	0.611
Should the death penalty be abolished?	0.599
Should taxes be lowered?	0.758
Should abortion be illegal?	0.588

To measure the fragmentation among the search results, I examined the percentage of non-overlapping content as previously explained. To do so, I turned to the unique answers. Table 4 already provided an overview of the percentages of these replies for each query. They range from 15% to 25%. In total, 22% of the users received a personalized answer.

According to previously defined criteria, the fragmentation of search results is low. For every query, and therefore in total as well, the percentage of non-overlapping content is below 31%. Even though the data suggest that Siri’s search algorithm causes only low

fragmentation, it needs to be emphasized that is caused fragmentation throughout the searches at all.

So far the analysis has shown that Siri’s search algorithm produced a long tail of replies and consequently caused moderate concentration and low fragmentation. This finding raises the question whether the identified concentration or fragmentation was driven by the political orientation, gender, age or location of users.

It appears that Siri does not provide one group of politically like-minded users disproportionately frequently with top results or unique answers. The most frequent answers to each of the five queries were given to liberals, conservatives, people with other political views, and users who have no political leaning. Unique answers also reached a politically diverse audience.

The data suggest Siri’s search algorithm is biased to some extent towards the gender of users. It caused concentration based on gender in relation to the most common answers: Siri provided men disproportionately often with the most frequent replies. However, Siri’s search algorithm provided female and male participants equally with unique search results.

It seems that Siri’s search algorithm is biased towards location. Siri appears to provide users from Pennsylvania more often with the top answers than others. Unique answers were given to a diverse set of participants. The data indicate that Siri’s search algorithm cause concentration but not fragmentation based on the location of users.

The data suggest that Siri’s search algorithm is not biased towards age. It seems that Siri’s top search results do not reach one age group disproportionately frequently. In addition, Siri provided users of different ages with personalized answers. The results indicate that Siri’s search algorithm does neither cause concentration nor fragmentation based on the age of users.

DISCUSSION

This study sought to discover to what extent Siri’s search algorithm provides 18 to 64-year-old US-based users with different answers to the same politically controversial questions. The main finding is that Siri’s search algorithm seems to produce a long tail distribution of search results. Across the audit’s five questions, it provided 42% of the users with six answers. At the same time, Siri presented 36% of the participants with replies that reached between 2 and 16 of users. In addition, 22% of the study’s participants were exposed to personalized search result. These data

indicate that Siri's search algorithm causes moderate concentration and low fragmentation.

EVALUATION OF FINDINGS

While still relatively low, the degree of fragmentation that Siri's search algorithm has caused is alarming. Several scholars have claimed that democracies benefit from the presentation of a variety of voices and viewpoints of public life in diverse media content (e. g. McQuail, 1992; Benson, 2013; Anderson, 2016). Diversity is important when it comes to political information (Diakopoulos et al., 2018, p. 337-338). However, personalized search results can undermine the diversity of political dialogue (Gillespie, 2014, p. 188). If users received strongly biased answers to the audit's politically controversial questions which correspond to their own world view, this would undermine information diversity. However, due to this study's focus, the content of the search results was not analyzed. It is therefore unknown to what extent ideological diversity or topical diversity among the results exists.

The concentration of search results is also worrying, even though it was mostly moderate. Scholars who are concerned with fragmentation claim that a unified body of relevant information should be accessible to the entire society (e. g. Gitlin, 2002; Sunstein, 2002). I mostly agree - especially when it comes to politically controversial questions. However, it is problematic that Siri's search algorithm decides how to answer these questions. Even if this study had analyzed the content of the six answers that 42% of the users heard, it would remain unclear why they were selected. The question arises whether the top search results managed to become "algorithmically recognizable" (Gillespie, 2017, p. 63); in other words, were these replies optimized to be found by Siri's search algorithm? Or were these results "privileged sources" (Diakopoulos et al., 2018, p. 331) selected by Siri? If so, their dominance might be based on some bias of the voice assistant (Trielli & Diakopoulos, 2019, p. 12). Due to the lack of transparency, these questions remain unanswered; in fact, they could not have been answered even if this study had had a different focus. It seems that Pasquale's (2015) view of algorithms in general also applies to Siri's: how it actually works is mysterious (p. 3). Since Siri's search algorithm gave some answers significantly more often than others, it is clear, however, that Siri promotes some search results over others - just as other algorithms do (see Gillespie, 2015, p. 1). By doing so, it "shapes the things people encounter" (Beer, 2009, p. 1000). Because these things are answers to politically controversial questions, Siri's search

algorithm actively influences the political information environment.

RELATION TO PREVIOUS RESEARCH

At first sight, the findings of this study challenge some of the research that was discussed in the introduction. This study's data have shown that Siri's search algorithm provides roughly 22% of users with unique search results. This result suggests that Siri's search algorithm causes low fragmentation. In contrast, the empirical research of Haim et al. (2018), Curtois et al. (2018), Robertson et al. (2018), Bechmann and Nielbo (2018), Nechusthai and Lewis (2019) and Krafft et al. (2019) claims that there is little evidence of filter bubbles. Despite their different geographical foci and methodological approaches, these scholars found no evidence of fragmentation. This study's results seem to contradict them.

However, upon closer examination, the data of this study and the results of some of the previously mentioned academic works are similar. For example, Krafft et al. (2019) found that, on average, around two to four results out of ten were personalized, although this depended on the search term (p. 1). Similarly, Bechmann and Nielbo (2018) reported that roughly 10% to 28% (depending on the methodological approach) of users were presented with different content (p. 990).

While the data of this study as well as the studies reviewed here are comparable, the scholars have interpreted their results differently. One reason might be that they focused exclusively on fragmentation. Because of this, their perspective tends to be quite narrow: for them fragmentation, often in the form of filter bubbles, either exists or not. This study offers a different, more nuanced, view by focusing on fragmentation and concentration. This wider approach can provide a clearer understanding of content diversity and therefore provide new insights into the frequency distribution of search results.

LIMITATIONS

Some limitations exist. First and foremost, the findings of this study are not representative. I tested Siri's search algorithm using only 170 Amazon participants. None of these Siri users were found by using probability sampling. As a result, I cannot generalize from this sample to the larger population of US-based Siri users. However, it was never the aim of this research to make claims about a population. Instead, this study has sought to provide a mere indication to what extent Siri provides 18 to 64-year-old US-based users with different answers to the same questions.

Secondly, a high internal validity of the data could not be guaranteed. The study's participants made the queries themselves. As I was not present during the data collection, I cannot assure that the Siri users reported back the replies to the queries they were supposed to make.

Thirdly, this study's results are necessarily constrained by its context. The five queries that were used in the audit have resulted in concentration and fragmentation alike. It is unknown whether other, perhaps less controversial, searches (or, for that matter, different participants) would yield answers that have a different frequency distribution. Similarly, the findings here are US-based. Search algorithms might work differently in different countries; in fact, there is evidence that they produce localized outcomes (Kitchin, 2017, p. 25). It is possible that users who are based outside the USA would receive different answers if they asked Siri the same questions.

Fourthly, this study's focus is highly limited. I decided to research only the extent to which Siri's search results differ. The contents of the search results, including ideological or topical differences, have been disregarded. As a consequence, the information that Siri provided users with was not analyzed. In addition, due to the focus of this study and especially because of its theoretical framework I excluded the perspective of the users themselves. Even though scholars such as Gillespie (2014) and Bucher (2017) are increasingly focusing on users in order to understand algorithms more holistically, I decided not to do this. This limitation is not problematic, however. My research question only focuses on the outcomes of Siri's search results and the concept of algorithmic bias enables me to analyze them.

Fifthly, the results might not be replicable. As algorithms are constantly tested (e. g. through a/b testing), developed further and changed, their outcomes are likely to vary over time (Gillespie, 2014, p. 178; Diakopoulos et al., 2018, p. 322). For this reason, the results of the audit, which was conducted on April 21, 2021, are time-based. If the same users had performed the same searches two weeks later, they might have received different replies.

FUTURE RESEARCH NEEDED

Due to this study's limitations, further research is needed. The small number of participants and the potentially low internal validity of the data were

identified as the main limitations. Therefore, research with representative sample sizes and a more closely controlled environment (e. g. by being in the same place with participants or being virtually connected via a program such as Zoom) would have to be conducted to support or challenge the finding that Siri's search algorithm causes both concentration and fragmentation. Such studies could use different search terms. However, they should not focus on a different location than the US because Siri's algorithm is likely to work differently in another country.

If future studies cannot falsify the assumption that Siri's search algorithm produces a long tail of search results, more diverse research would be needed. To avoid technological determinism, the role of Siri's users would need to be taken into consideration. This approach would be in line with the growing number of scholars who see algorithms as the entanglement between the technical and social (e. g. Seaver, 2013; Bozdog, 2013; Just & Latzer, 2017). For example, inspired by Bucher (2017), one could ask how users feel about receiving unique search results or the same as other user. Or: how do users react to the replies they receive? In addition to a crowdsourced audit, interviews with users could be conducted. By doing so, not only the frequency distribution of results, but also their impact, could be studied.

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Data Availability Statement

Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is not available.

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