SOCIAL MEDIA AND THE FILTER BUBBLE: CURATED FLOWS THEORY, FACEBOOK, AND NEWS DIVERSITY

by

ALEXANDER PIPPIN

CYNTHIA C. PEACOCK, COMMITTEE CHAIR
MARY M. MEARES
WILSON J. LOWREY

A THESIS

Submitted in partial fulfillment of the requirements for the degree of Master of Arts in the
Department of Communication Studies
in the Graduate School of
The University of Alabama

TUSCALOOSA, ALABAMA

2022

ABSTRACT

I utilize curated flows theory to explore the case for a filter bubble on Facebook, as well as exploring the impacts of this potential filter bubble environment on climate change misinformation. Three hypothesized are utilized in this research. I hypothesize that individuals who use Facebook to seek out news will have a less balanced repertoire of left-leaning and right-leaning news sources are more likely to deny the seriousness of climate change, and are less likely to believe the news media is effectively providing accurate information on climate change than those who use other platforms. To test these hypotheses, I utilize data from the 2020 Reuters Institute Digital News Report survey (Newman et al.) as well as three bootstrapped analyses of covariance (*ANCOVA*) tests. Hypothesis 1 is found to be partially supported, providing evidence for the existence of a filter bubble effect created by Facebook's News Feed algorithm.

ACKNOWLEDGEMENTS

I thank all my committee members—Dr. Peacock, Dr. Lowrey, and Dr. Meares—for their support for this project. This is my most ambitious piece of academic writing to date and undergoing this project without their support would have been impossible. This thanks is not only in regard to their support during the writing of this thesis, but also to their classes I took prior to beginning this project. These classes were invaluable in shaping how I think about many of the subjects discussed herein.

CONTENTS

ABSTRACT ii

ACKNOWLEDGEMENTS iii

LIST OF TABLES v

RATIONALE OF STUDY 1

LITERATURE REVIEW 4

Selective Exposure and Curated Flows 4

Echo Chambers and Filter Bubbles 5

The Case Against Filter Bubbles 6

Personalization and Curation 9

The Filter Bubble and Facebook 11

Misinformation 13

METHODOLOGY 16

Sample 16

Measures 17

News Platform 17

Denial of the Seriousness of Climate Change 20

Belief the News Media is Providing Accurate Information on Climate Change 20

Data Analysis 21

DISCUSSION, LIMIATIONS, AND CONCLUSION 23

Discussion 23

Limitations 26

Conclusion 26

REFERENCES 28

APPENDIX 32

LIST OF TABLES

1. H1 Tests of Between-Subjects Effects 32

2. H1 Parameter Estimates 33

3. H2 Tests of Between-Subjects Effects 34

4. H2 Parameter Estimates 35

5. H3 Tests of Between-Subjects Effects 36

6. H3 Parameter Estimates 37

RATIONALE OF STUDY

About two-thirds of Americans believe that social media, a large source of algorithmically driven news diets, has a negative impact on society (Auxier, 2020). Americans with this opinion largely point to misinformation and fake news, followed by the concerns of partisanship, bias, and echo chambers (Auxier, 2020). This perceived environment of misinformation and echo chambers on social media foregrounds the widely held belief that Democrats and Republicans cannot agree on “basic facts” (Dimok, 2020). Despite the public perception of a society divided by the algorithmic curation of social media feeds, there is academic debate about the extent to which this is accurate (Bakshy et al., 2015; Fletcher & Nielson, 2018). Those who question the influence of algorithms in the creation of an ideological bubble online often suggest that individual social media users (rather than algorithms) are primarily responsible for their exposure to politically cross-cutting news content, or that which is not aligned with one's political beliefs (Bakshy et al., 2015).

The existence and cause of ideological bubbles online can be understood along the lines of different theories, concepts, and language. Largely, the arguments against the existence of filter bubbles are in line with selective exposure theory (Bakshy et al., 2015; Scharkow et al., 2019; Zimmer et al., 2019), while those that support the existence of a filter bubble are in line with curated flows theory (Bandy & Diakopoulos, 2021; Thorson et al., 2019; Barnidge, 2021). Selective exposure theory (Lazarsfeld et al., 1968) suggests individuals are drawn to content which is consistent with their currently held beliefs and attitudes. Curated flows theory (Thorson & Wells, 2016) recognizes that the content curating power of individuals exists among four other

curating agents: social networks, journalists, strategic communicators, and algorithms. These theories present two different approaches to understanding how online information environments are created. The first difference relates to agency. Selective exposure theory positions individuals as the foremost responsible agent in determining the content they receive online, while curated flows theory leaves more room for other actors to play a (perhaps even more primary) role in the process. The second difference relates to treating algorithms across all platforms as acting the same in all cases. That different curating actors (of concern here are individuals and algorithms) deserve equal consideration concerning filter bubbles online is appealing as it is accurate. An algorithm can be very involved in the curation process of content online, or it may take a back seat to other curating actors (just like a person). Like people, algorithms are not a monolith, we cannot assert that because one algorithm does not create a filter bubble, that the filter bubble does not exist.

By utilizing curated flows theory for this research, I aim to quantitatively explore the case for the filter bubble on Facebook. Doing so will demonstrate the value of recognizing multiple content curating actors. There is evidence that Facebook in particular is vulnerable to the identified problems of filter bubbles and misinformation (Fletcher & Nielsen, 2018; Dutt & Ferrara, 2019; Jamison et al., 2020; Del Vicario et al., 2016). Therefore, I examine whether news consumers who use Facebook to seek out news will have a less ideologically balanced news repertoire compared to news consumers who utilize other platforms.

Furthermore, I explore the implications of the presence of filter bubbles on our society in the relation Facebook use for news gathering has to misinformation. On Facebook, climate change misinformation in particular has been identified as problematic by even CEO Mark Zuckerberg (C-SPAN, 2021). Previous research has shown that individuals who believe climate

change is a serious, anthropogenic issue (which misinformation on the subject seeks to refute) tend to cite information from more sources than those who deny these beliefs (Jasny et al., 2015). This finding would logically suggest individuals who deny the seriousness of climate change are likely in a filter bubble. It is further suggested that a filter bubble can amplify the refutations of climate change seriousness (Jasny et al., 2015). The nature of these kinds of bubbles leads to resharing these denials of climate seriousness to the point where these few refutations appear numerous (Jasny et al., 2015). Given Facebook's connection to both filter bubbles and misinformation, I examine whether news consumers who use Facebook to seek out news will be more likely to deny the seriousness of climate change than news consumers who utilize other platforms. Exposure to misinformation also has been linked to distrust in the media (Ognyanova et al., 2020). I then further hypothesize that news consumers who use Facebook to seek out news will be less likely to believe the news media is effectively providing accurate information on climate change than those who use other platforms.

LITERATURE REVIEW

Selective Exposure and Curated Flows

In order to examine the academic discussion of bubbles online, I identify two groupings of theoretical concepts. The use of the first of these groupings is more likely to result in the denial of the concept of an algorithmically created bubble online because of its prioritizing of the agency of the individual internet user. This first group of concepts contains selective exposure theory, the echo chamber model, and the term personalization. The other group—which I argue suggests a more holistic accounting of just how much control any one individual has online among other agents—consists of curated flows theory, the filter bubble model, and the term curation. Selective exposure theory places the individual as the foremost curating agent, while curated flows theory ascribes no such primacy. For example, Bakshy, Messing, and Adamic's (2015) research into Facebook and the filter bubble utilizes selective exposure. The conclusion that the user is primarily responsible for the news content they receive (Bakshy et al., 2015) is entirely in line with selective exposure theory's foundational core: that individuals are drawn to content which is consistent with their currently held beliefs and attitudes (Lazarsfeld et al., 1968). Since the conception of selective exposure theory in 1968, conceptions of the agency of individuals in the process of curation of news have become complicated by algorithms. Selective exposure theory research has expanded in that there is a new attention to algorithmic personalization and systemic biases which are reflected in the choices of media producers (Bryant et al., 2020). In practice, this means selective exposure research does not entirely ignore other curating agents that are not the individual news consumer. However, this selective

exposure research situates these agents of curation as reflections of user preference (Bryant et al., 2020).

Curated flows theory (Thorson & Wells, 2016) is not a rote negation of selective exposure theory (Lazarsfeld et al., 1968). The agency of the individual to curate the news content they encounter is not completely denied in a deterministic or nihilistic fashion. Instead, curated flows theory complicates this agency by suggesting that other curating agents also play a role in this curation process. Five distinct curating actors are identified in the theory: "journalists, strategic communicators, individual media users (personal curators), social contacts, and algorithmic filters" (Thorson & Wells, 2016, p. 314). In common parlance, "getting out of your bubble" places the most importance in the flow of curation on personal curators. Neither this research, nor curated flows theory, intends to deny the phenomenon of cognitive dissonance or the notion that people self-select attitude-consistent messages. However, curated flows theory (and accordingly this research) does attend to the reality that individuals' own curation does not occur absent of other flows of content (Thorson & Wells, 2016). No innate hierarchy of these actors is suggested in the theory (Thorson & Wells, 2016). Of particular concern for this research is the power of algorithms as curating agents.

Echo Chambers and Filter Bubbles

To further develop this theoretical contrast I am drawing, I align the concepts of echo chambers to selective exposure and filter bubbles to curated flows. Filter bubbles and echo chambers may appear interchangeable in the phenomena they describe and in conversation, but here I will examine their origins to establish them as distinct. Both models can be understood as a response to the development of internet content curation at the time of their founding. The echo chamber model (Sunstein, 2002) comes about with an age where the innovation of the internet is

an explosion of available content for consumers. This sense of an explosion of infinite and specialized content as a commodity can be seen manifested in the rampant, unscrupulous investment of the dot-com boom. Echo chambers are understood to form with the freedom of choice and the availability of many niches of content on the internet (Sunstein, 2002). In this model, members of political groups are described as choosing spaces which reinforce their beliefs (Sunstein, 2002). This focus on the choices of the individual as a limiting factor in content curation is in line with selective exposure theory.

In contrast, the innovation the internet contributed to content curation in 2009 was the development of Google's Personalized Search (which algorithmically curates the order of and which results to show to users, based on various deliberately opaque criteria) (Pariser, 2011). This is the concern addressed in the filter bubble model (Pariser, 2011). Similarly to curated flows, the model recognizes a number of factors that contribute to the delivery of a particular piece of content to an individual consumer. Technology companies design algorithms which take into account a piece of content's popularity, the calculated likelihood a user will interact with that content, and if there is profit to be made from displaying that content (Pariser, 2011). In summary, selective exposure and echo chambers place the individual as having primary (if not absolute) agency in the process of curation, whereas curated flows and filter bubbles describe an interaction between the curation of different agents.

The Case Against Filter Bubbles

The existence of filter bubbles is sometimes presented as dubious in academic research (Bakshy et al., 2015; Fletcher and Nielson, 2018). In a widely cited article, Bakshy, Messing, and Adamic (2015) suggest "that individuals are exposed to more cross-cutting discourse … [on Facebook] than they would be under the digital reality envisioned by some" (p. 1131). However,

it is not entirely clear that the data presented in this research supports this conclusion. Indeed, researchers Allcott and Gentzkow (2017) cite Bakshy, Messing, and Adamic to suggest the opposite: that Facebook is an ideologically separated platform. Bakshy, Messing, and Adamic report the chance of a Facebook user clicking on cross-cutting content is less likely than clicking on ideologically consistent content. This is indeed better than "the [ideologically separated] digital reality envisioned by some" (Bakshy et al., 2015, p. 1131), but only if this reality is one in which no content a user clicks on is cross-cutting.

Bakshy, Messing, and Adamic (2015) go on to conclude "individual choices … more than algorithms … limit exposure to attitude challenging content in the context of Facebook" (p. 1131). Whether this conclusion is supported by the research presented is also worth examining. To justify this claim, the trio demonstrate that content gathered at random on Facebook is more politically cross-cutting than content which may have been shown in an individual's network before the News Feed algorithm filters this content (Bakshy et al., 2015). One limitation in using this comparison to demonstrate the effect an individual has on their own news cultivation is admitted in the paper: that this random condition being compared against does not exist in the world (Bakshy et al., 2015). So it is not as if one's network is limiting one from cross-cutting content available in this hypothetical selection of content, because no such condition actually exists. Something else to consider is Facebook constantly, algorithmically suggests new people to add as friends. In other words, one's network on Facebook *is itself the result of algorithmic sorting.* So, taking the comparison of the content in one's network to a random selection of content as valid, one might also say it is still Facebook's algorithms which curates the flow of news from this random selection of news. There are perils of attempting to create an experimental Facebook use control condition where algorithms are absent. What I instead

implement in this research is a comparison of the conditions created by Facebook's algorithm against the average conditions created by other platforms online. Other online use is separated into two comparison groups of algorithmic and non-algorithmic. This comparison should clearly demonstrate if Facebook's algorithmic curation is acting in a way which is significantly different from other platforms' curation online.

Research which has utilized a methodology comparing platforms has also rejected the concept of the filter bubble, however (Fletcher & Nielson, 2017; Fletcher & Nielsen 2018). Fletcher and Nielson (2017) suggest incidental exposure to news on social media for users correlates to a greater diversity of news sources for those users than that of individuals gathering news online directly. Considering Facebook use in particular, the effect of incidental news exposure on news diversity loses significance when controls for additional Twitter and YouTube use are introduced (Fletcher & Nielsen, 2017). This finding further supports investigating Facebook specifically as I do in this paper. News diversity in this (Fletcher & Nielsen, 2017). research is measured by the number of news sources an individual is exposed to, without regard for diversity of political leaning. The pair acknowledge, "incidental exposure via social media may indeed result in an echo-chamber effect if all additional sources are highly similar to what is already being used" (2017, p. 2461). Therefore, the following hypothesis utilizes a later operationalization of the filter bubble by Fletcher and Nielson (2018). When the pair find that using Google News search for news-gathering leads to a relatively more balanced news repertoire, this measure attends to the balance of left-leaning and right-leaning sources (Fletcher & Nielsen, 2018). This measurement seems to be conceptually aligned with the concern of the filter bubble, and so the term *balanced news repertoire* will be adopted and operationalized in the following hypothesis and methods.

Personalization and Curation

The contrast I make between these groupings of concepts culminates in the contrast between the terms *personalization* and *curation*. These are terms used to describe the actions of algorithms. I align personalization with selective exposure and echo chambers, and curation with curated flows theory and filter bubbles. Indeed, previous selective exposure research adopts the language of personalization. In one such instance of selective exposure research, the filter bubble model is said to describe "algorithmic filtering which personalizes content presented on social media" (Zimmer et al., 2019, p. 50). This focus on personalization leads to the conclusion that "algorithms (as, for instance, Facebook's ranking algorithm)" are said to "only amplify users' information behavior" (Zimmer et al., 2019, p. 50). Similarly, another study which finds Facebook to be associated with a more varied news diet (Scharkow et al., 2019) defines the filter bubble as "positing that search and recommendation algorithms bias news diets toward users' preferences and, thus, decrease content diversity" (Scharkow et al., 2019, p. 117). These definitions of the filter bubble are mostly accurate, but do not contend with the later wrinkle introduced in Pariser's (2011) book on the filter bubble. Although Pariser often does refer to algorithms as serving personalization, in the seventh chapter entitled What You Want, Whether You Want It or Not, this is complicated as he notes "You don't get to create your world on your own. You live in an equilibrium between your own desires and what the market will bear" (p. 118). Algorithm filtering is not a reflection of users' own interests in the filter bubble thesis, but also serves to curate media in the service of other interests, such as revenue generation.

In research utilizing curated flows theory, that the terminology of curation (rather than personalization) is adopted impacts how algorithms are represented. In curated flows theory, algorithms are situated as a distinct curating agent (Bandy & Diakopoulos, 2021; Thorson et al.,

2019; Barnidge, 2021). Twitter offers an obvious test case for this, as users have the option to scroll through a purely chronological timeline with content from their followed accounts, or an algorithmically filtered timeline. Investigating this as a case of algorithmic curation, it was found that algorithmic timelines reduced users' exposure to external links by half in comparison to the chronological timeline (Bandy & Diakopoulos, 2021). This discrepancy demonstrates plainly that algorithmic filters do act as independent curating agents. Facebook's News Feed algorithm exhibits similar curating behavior, distinct from the desires of individual users. Regardless of an individual's self-reported interest in politics, the News Feed algorithm interprets digital trace data (data which records user behavior) to determine if news and political content should be shown in their feed (Thorson et al., 2019). The flagging of an individual as interested in news and political content, regardless of their behaviorally expressed interest in such content, can be observed in user's flagged ad topics (Thorson et al., 2019). Another way this relationship between user and algorithm can be observed on Facebook is in the temporal order of interaction with content and content appearing in users' feeds. In a conceptualization of algorithms as a personalizing agent, it would be expected that this ordered relationship would manifest in the user sharing news, and then the News Feed algorithm displaying more news content (resulting in incidental news exposure). In a temporal order analysis, results indicate that incidental news exposure is predicted by news sharing, but that the reverse-ordered relationship also is significant (Barnidge, 2021). This suggests that there is indeed interaction between the curating agents of the individual and the algorithmic filter, but the curation of one does not necessarily precede the other.

I make no claim as to the superiority of either grouping in the contrast I draw between selective exposure, echo chambers, and personalization to curated flows, filter bubbles, and

curation. The purpose for this comparison is to implore researchers to carefully consider the theories, concepts, and language they are using to examine algorithms in content curation. If one were to design research which investigates specifically the decisions users are making, then indeed selective exposure, echo chambers, and personalization are appropriate to use. What I do argue is inappropriate is the assertion of the absolute superiority of this grouping of concepts, and thus a general assertion of the supremacy of the agency of the individual. As the curated flows research reviewed suggests, algorithms are not in all cases entirely subservient to the agency of the individual (Bandy & Diakopoulos, 2021; Thorson et al., 2019; Barnidge, 2021).

The Filter Bubble and Facebook

The Facebook News Feed provides a unique opportunity to investigate the filter bubble. The News Feed was introduced in 2006, which was essentially a list of Facebook activity (Luckerson, 2015). Prior to this, the content of Facebook users existed on their own pages, with no feed to speak of (Luckerson, 2015). If users wanted to see a picture of someone, they would have to go to that person's page (Luckerson, 2015). There was a kind of crude algorithm curating the content on the initially released News Feed, but in 2011, the machine-learning algorithm that curates content in the feed (as we know Facebook to today) was released (Luckerson, 2015). Many understand this machine-learning algorithm to be filtering content with respect to users' own desires, but this is not entirely accurate. The customers of Facebook are not its users, but rather other businesses that use its platform to distribute their content. Thus, it is more coherent to consider the News Feed algorithm a service for these customers rather than Facebook's users. In promotional material for media and publisher business partners, Facebook promises these partners "effective audience growth drivers, when it comes to average traffic and engagement per piece of content" (Harman, 2021, para. 1). Note here, Facebook is not promising an audience

who is cognitively aligned to this content, but an engaged and larger audience. We may logically infer, then, the design of the News Feed algorithm is not primarily concerned with serving users media content which aligns with users' preexisting beliefs, but rather it is designed to drive user engagement. These two design philosophies may often coincide, but they are distinct. Indeed, curated flows theory asks us to consider that algorithmic curation, such as the Facebook news feed, is designed by technology experts of corporations rather than simply the mirroring of personal curation (Thorson & Wells, 2016). For example, the elderly on Facebook may receive ads for will-writing services, or people who have miscarried may receive ads for maternity products after their miscarriage (Murgia, 2021). Furthermore, recently leaked internal documents from Facebook whistleblower Frances Haugen show Facebook has known and ignored that its "recommendation systems can very quickly lead users down the path to conspiracy theories and groups" (Mac & Frenkel, 2021). Individuals could hardly be said to desire to seek content concerning their own impending death, recent tragedy, or radicalization. It is instead Facebook's desire for engagement with content that drives these recommendations from the News Feed algorithm. Considering the established ideological radicalization and algorithmic agency on Facebook—as well as a body of research suggesting an absence of specifically an ideological filter bubble (Eady et al., 2019; Zimmer et al., 2019; Bakshy et al., 2015; Fletcher & Nielson, 2018)—the following hypothesis is proposed:

> **Hypothesis 1 (H1):** Individuals who use Facebook to seek out news will have a less balanced repertoire of left-leaning and right-leaning news sources than individuals who use other platforms.

Misinformation

The extent to which the filter bubble one finds themself in is ideologically unbalanced is related to the likelihood of encountering misinformation (Bessi et al., 2015). Previous research has established a link between partisanship and susceptibility to misinformation (Weeks, 2015; Nelson & Lewis, 2021). Additionally, social media is implicated in the spread of misinformation (Naeem et. al, 2020; Valenzuela et al., 2019). Unfortunately for the ideals of a deliberative democracy and an informed public, those who are misinformed resist accurate information under the impression they are correct, and thus form policy preferences based on this misinformation (Kuklinski et al., 2000).

Facebook specifically creates an environment which facilitates the spread of misinformation through a combination of its policies and the functioning of its News Feed algorithm. Both in the case of the 2016 election and 2019 (measles outbreak related) anti-vaccine movements, Facebook did not strictly enforce disclosure requirements for advertisers (Dutt & Ferrara, 2019; Jamison et al., 2020). This led to Russian misinformation and vaccine misinformation being spread on Facebook, without any clear indication that it was from an unreliable source (Dutt & Ferrara, 2019; Jamison et al., 2020). Exacerbating this issue, Facebook promises advertisers increased engagement (Harman, 2021), so this insufficient initial vetting of advertisements leads to prioritization of misinformation by the News Feed algorithm. Furthermore, analysis of scientific and conspiracy news suggests polarized groups built around these two opposing categories were being created on Facebook (Del Vicario et al., 2016). This system certainly drives engagement, as like-minded users share information (or misinformation) that reinforces their beliefs, but this means efforts to debunk misinformation are rendered ineffective (Del Vicario et al., 2016). These findings, taken together, suggest Facebook has

prioritized engagement at the expense of moderating and limiting the spread of misinformation regardless of the potential societal damages misinformation exposure has at the scale of Facebook's user base.

The implications of the reviewed misinformation literature are especially damning in the face of the necessity for an informed society which can agree to enact policy which addresses existential threats to humanity. Climate change is one such existential threat to humanity (Tabari, 2020; Raza et al., 2019; Ouhamdouch & Bahir 2017), and also happens to be the subject of misinformation spread on Facebook. CEO Mark Zuckerberg admitted in a March House Hearing, "climate misinformation … is a big issue" (C-SPAN, 2021). Research from not-for-profit organization Stop Funding Heat (2021) suggests there are anywhere from 818,000 to 1.36 million daily views of climate misinformation on the platform. Research from NGO Center for Countering Digital Hate (2021) identifies far-right outlet Breitbart as primarily responsible for climate change misinformation on Facebook. If, indeed, an ideological filter bubble effect on Facebook is supported with analysis for H1, then based upon previous research (Jasny et al., 2015) we should be able to expect the presence of climate change misinformation. With the established connections between filter bubbles, Facebook, and climate change misinformation, two hypotheses concerning misinformation have been developed. Due to previous difficulties finding direct, empirical evidence of the prevalence or consumption of misinformation, measuring news consumer awareness and understandings of news is advantageous in understanding the influence of misinformation (Watts et al., 2021). It is a combination of noted limitations of self-reported exposure to misinformation (Buchanan, 2020), a desire to explore the impact of filter bubbles, and evidence for specifically climate change misinformation which logically lead to the following hypothesis:

Hypothesis 2 (H2): Individuals who use Facebook to seek out news are more likely to deny the seriousness of climate change than those who use other platforms.

Furthermore, exposure to misinformation also has been linked to distrust in the media (Ognyanova et al., 2020). Given that previous literature has linked misinformation to social media, as well as the presence of specifically climate change misinformation on Facebook, we should then expect some amount of distrust in the media with regard to climate change reporting. With exploring the effects of misinformation in a filter bubble environment on Facebook in mind, this third hypothesis is proposed:

Hypothesis 3 (H3): Individuals who use Facebook to seek out news are less likely to believe the news media is effectively providing accurate information on climate change than those who use other platforms.

METHODOLOGY

Sample

Based on the above literature, I hypothesize that individuals who use Facebook to seek out news (H1) will have a less balanced repertoire of left-leaning and right-leaning news sources (H2) are more likely to deny the seriousness of climate change, and (H3) are less likely to believe the news media is effectively providing accurate information on climate change than those who use other platforms. To test these hypotheses I utilize data from the 2020 Reuters Institute Digital News Report survey (Newman et al.).

The survey data used was gathered by YouGov in partnership with the Reuters Institute for the Study of Journalism at the University of Oxford in late January and early February of 2020. Over 80,000 people were surveyed online across 40 countries. Roughly 3% of respondents were removed, as they reported having not consumed news in the last month (the report is concerned with news users). This paper is specifically concerned with United States respondents among this set, so the following analysis uses data from 2,055 United States news users. These respondents are weighted to reflect the demographics of the United States. Respondents were 48.7% male and 51.3% female. Respondents aged in range from 18 to 91 (M = 47.47, SD = 17.679). The mean of household income of respondents is roughly middle-class, represented as 2 (as opposed to lower or upper represented as 1 and 3, respectively) (M = 1.99, SD = .716). The mean political ideological affiliation is roughly center, represented as 2 (as opposed to left or right represented as 1 and 3, respectively) (M = 1.98, SD = .734). Regarding highest education level completed, 1.9% of respondents did not complete any formal education, .7 % completed an

early childhood education, .5% completed primary education, 1.6% completed lower secondary education, 40.9% completed upper secondary education, 9.6% completed post-secondary education, 13.1% completed short-cycle tertiary education, 19.7% completed a Bachelor's or equivalent degree, 9.1% completed a Master's or equivalent degree, and 2.7% completed a Doctoral or equivalent degree. In terms of preference for attitude-consistent news sources most respondents prefer sources that don't have a particular point of view, represented as a 2 (as opposed to sources that share or challenge their point of view, represented by a 1 or 3, respectively) (M = 1.80, SD = .599).

Measures

News Platform

The independent variable (IV) for this research is the choice of platform to seek out news, operationalized similarly as it is in Fletcher and Nielson's (2017) work. To that end, three groups of news users will be identified: *Facebook users*, *other algorithmic users*, and *non-algorithmic users*. The group, *Facebook users*, is ascertained through an item which asks, "Which, if any, of the following have you used for finding, reading, watching, sharing or discussing news in the last week? Please select all that apply" (Newman et al., 2020). Answers include various social media and messaging services such as Facebook, Facebook Messenger, Twitter, and WhatsApp. Other online sources implement sophisticated algorithms, such as Google, the original concern of the filter bubble (Pariser, 2011). Users of these other sources can be identified using another item. This item asks, "Thinking about how you got news online (via computer, mobile or any device) in the last week, which were the ways in which you came across news stories? Please select all that apply." (Newman et al., 2020). Examples of other algorithmic sources identified in this response are search engines, newsreader sites (like Apple News), or mobile phone alerts (which

can be from the previously listed categories). Respondents who answer Facebook or Facebook Messenger (or both), and not any other algorithmic sources, can thus be identified as *Facebook users*. Therefore, the remaining respondents who indicated they use any other algorithmic sources for news gathering that are not part of *Facebook users* are *other algorithmic users*. *Non-algorithmic users* will be all of the other remaining users in the data set, such as users who go directly to news websites

To address the weakness created by narrowing down a relatively small group of *Facebook users*, I performed two propensity score matchings using a logistic model and nearest neighbor matching. Propensity score matching procedures utilize statistical techniques to select similarly sized groups of respondents (from a larger available respondents) based on similar predictive characteristics. Two propensity score matches were performed based on the predicted variable selected for its apparent relevance to the hypotheses. I performed one to match groups with consideration for the desire of individuals to seek attitude-consistent content for H1, as this predictive variable is clearly relevant to filter bubbles. To match groups with consideration for H2 and H3, individuals' ideological leaning is used as the predictive variable due to its relevance to climate change seriousness denial. Using these differing criteria, the IV group sizes are slightly different for testing H1 or H2 and H3. For H1, these are *Facebook users* (N = 185), *other algorithmic users* (N = 167), and *non-algorithmic users* (N = 162). For H2 and H3, these are *Facebook users* (N = 185), *other algorithmic users* (N = 173), and *non-algorithmic users* (N = 169).

Balance of News Repertoire

The dependent variable (DV) for H1 is the balance of news repertoire. News repertoires of individual members of groups were identified using the response to two questions. These

questions ask “Which of the following brands have you used to access news online in the last week (via websites, apps, social media, and other forms of Internet access)? Please select all that apply.” and “Which, if any, of the following have you used to access news in the last week? Please select all that apply.” (Newman et al., 2020), respectively. The first question offers 29 popular online news outlets such as BBC News, CNN, or the *New York Times* as answers. The second question offers 10 online hyperpartisan sources such as Breitbart, Infowars, or Occupy Democrats as answers. Seven of these sources in the second question are used because ideological lean is not available in the data used to code the excluded 3 sources. In all of these questions, responses like “other” or “don’t know” (Newman et al., 2020) were ignored, as they do not help establish the ideological leaning of each individual’s news repertoire. In previous research (Fletcher & Nielsen, 2018), the ideological leaning of each of the sources was determined using the mean of self-reported ideological leaning of its consumers among this survey. This was purported to be accurate and comparable to methodologies which use content analysis to determine ideological leaning (Fletcher & Nielsen, 2018). When attempting to utilize self-reported ideological leaning with a 7-point scale from very left-wing, fairly left-wing, slightly left-of-centre, centre, and then the same scale of right-wing measurements, irregularities were observed. For example, the mean of ideological leaning of InfoWars users placed the outlet as the most centrally ideologically aligned outlet. This is in contrast to other content analysis methodologies which place InfoWars as one of the most extremely ideologically conservative outlets (AllSides, 2016; Muller, 2021). Therefore, the Ad Fontes ideological bias ratings (utilizing content analysis) for each news outlet are adopted to ascertain balance of news repertoire. Ad Fontes uses a process to code each ideological bias rating wherein a panel of three coders (a self-reported right, centrist, and left leaning coder) rate content from outlets (Otero,

2021). This rating is on a scale from -42 being the most left, 0 being exactly center, and 42 being the most right (Otero, 2021). The mean of these scores among the sources of each respondent is used to ascertain the ideological lean of their news repertoire (M = 7.607, SD = 5.771). The absolute value of this ideological lean of a news repertoire can then be taken to ascertain the balance of a news repertoire. The measure of news repertoire balance will then be compared across each grouping of news users identified in the IV.

Denial of the Seriousness of Climate Change

The DV of denial of the seriousness of climate change for H2 will be ascertained using the scale present in the survey item regarding it. This question asks "How serious a problem, if at all, do you think climate change is?" (Newman et al., 2020). The answers available are on a 5-point scale from (1) "extremely serious" to (5) "not serious at all" (Newman et al., 2020) (M = 2.352, SD = 1.445). Responses of "don't know" (Newman et al., 2020) will be ignored, as this response is not an indication of denial of the seriousness of climate change but rather a lack of an opinion of its seriousness altogether. This measure of denial of the seriousness of climate change will then be compared across each grouping of news users identified in the IV.

Belief the News Media is Providing Accurate Information on Climate Change

The DV of belief the news media is providing accurate information on climate change for H3 will be ascertained via responses to the question "To what extent do you think the news media does a good or bad job at the following?: - Giving me accurate information about climate change" (Newman et al., 2020). The answers available are on a 5-point scale from "very bad" to "very good" (Newman et al., 2020). Responses of "don't know" (Newman et al., 2020) will be ignored. Belief the news media is providing accurate information on climate change is operationalized on a scale from 1 to 5, 1 viewing the media as doing a very poor job providing

accurate information and 5 viewing the media as doing a very good job providing accurate information (Newman et al., 2020) (M = 2.935, SD = 1.358). This measure of belief the news media is providing accurate information on climate change will then be compared across each grouping of news users identified in the IV.

Data Analysis

All analyses were carried out using SPSS 12. Three analyses of covariance (*ANCOVA*) tests were conducted, one for each hypothesis. Bootstrapping procedures, which enable parametric statistical analyses on non-normally distributed data sets, were used to address limitations of the data set regarding normality. These procedures estimate statistical parameters using a large number of random samples (with replacement) from an original data set. Bootstrapped z-statistic and p values (bias corrected, accelerated with 5000 replications) were calculated. Age, gender, household income level, ideological leaning, and desire to seek out attitude-consistent news were all included as covariates in the three *ANCOVA* tests. Desire to seek out attitude-consistent news is important to control for as it is essentially the desire to self-select a bubble, and the effect of algorithms rather than self-selection is of concern. The remaining covariates are standard demographic factors which may in some way contribute to individual behavior as identified by previous research (Fletcher & Nielson, 2017; Fletcher & Nielson, 2018). The independent variable, news use type, included three categories: Facebook users, algorithmic users, and non-algorithmic users.

The bootstrapped *ANCOVA* comparing the news repertoire balance among the identified groups of the independent variable was statistically significant ($F_{2,323}$ = 6.695, p = 0.001, effect size [partial eta squared $\eta 2_p$] = 0.041). Preference for attitude-consistent news ($F_{1,323}$ = 34.900, p < 0.001, $\eta 2_p$ = 0.099), was a significant covariate. Bootstrapped parameter estimates indicated

Facebook users (M_{-} = 9.001, *SD* = 6.164) have significantly less balanced news repertoires than other algorithmic users (M_{-} = 6.7325, SD = 5.341). The difference in balance of news repertoires between Facebook users (M_{-} = 9.001, SD = 6.164) and non-algorithmic users (M = 10.448, SD = 5.878) was non-significant. Given the significant findings of this *ANCOVA*, hypothesis 1 is partially supported.

The bootstrapped *ANCOVA* comparing the denial of the seriousness of climate change among the identified groups of the independent variable was not statistically significant ($F_{2,375}$ = 2.023, p = 0.134, $\eta 2_p$ = 0.011). Preference for attitude-consistent news ($F_{1,375}$ = 339.651, p < 0.001, $\eta 2_p$ = 0.480), ideological lean ($F_{1,375}$ = 11.797, p < 0.001, $\eta 2_p$ = 0.031), and gender ($F_{1,375}$ = 12.021, p = 0.002, $\eta 2_p$ = 0.025) were significant covariates. Given the non-significant findings of this *ANCOVA*, hypothesis 2 is not supported.

The bootstrapped *ANCOVA* comparing the belief the news media is providing accurate information on climate change among the identified groups of the independent variable was not statistically significant ($F_{2,375}$ = 3.406, p = 0.111, $\eta 2_p$ = 0.012). Ideological lean ($F_{1,375}$ = 130.763, p < 0.001, $\eta 2_p$ = 0.262), household income level ($F_{1,375}$ = 6.302, p = 0.012, $\eta 2_p$ = 0.017), and gender ($F_{1,375}$ = 9.829, p = 0.002, $\eta 2_p$ = 0.026), were significant covariates. Given the non-significant findings of this *ANCOVA*, hypothesis 3 is not supported.

DISCUSSION, LIMIATIONS, AND CONCLUSION

Discussion

The analysis shows users of only Facebook's algorithm and no other algorithm have significantly less balanced news repertoires than those who use any other algorithm. This is even when controlling for an individual's preference for attitude-consistent news. Noting this control is significant, as previously it has been argued that it is this self-selection that is the foremost determinant factor in news repertoire balance beyond that of the curation of algorithms (Bakshy et al., 2015; Scharkow et al., 2019; Zimmer et al., 2019). Therefore, the data suggests there is a filter bubble that is being created by Facebook's News Feed algorithm.

The selective exposure research reviewed (Bakshy et al., 2015; Scharkow et al., 2019; Zimmer et al., 2019) argues that the content an individual receives from an algorithmically curated feed is primarily the result of individual agency; that the algorithms at work are simply *personalizing* rather than *curating.* In contrast, if an algorithm is curating it is doing so according to some set of rules set by the policy makers of a tech company. A curating algorithm is one with an agency separate from that of the individual news consumer. Facebook's (and Zuckerberg's) decisions following a meeting with conservatives in 2016 reflect this. Upon fielding the complaints of right-wing content being in some way unfairly not receiving a wide enough audience, Facebook responded by removing humans from the process that determines trending news topics (Akhtar, 2016). Of course, this decision does not actually remove the potential for bias in the process of determining these trending news topics, it just moves where that human bias may enter to the engineers responsible for determining the algorithm's selection criteria. One can see just the extent to which this is true by viewing the top performing links on Facebook today. At the time of writing, these are the sources of those most seen links on Facebook: Ben

Shapiro, TMZ, Fox, NPR, Dan Bongino (a right-wing pundit recently banned from Youtube partially due to COVID misinformation), Franklin Graham, ComicBook.com, and Charlie Kirk (Roose & Giglietto, 2022). At a glance, you can easily see the impact of that 2016 meeting as well as the naivete of claiming the News Feed algorithm is a mere reflection of users' views.

What is being attempted by Facebook and other companies in maneuvers such as this trending topic algorithm change, is a minimizing of the agency of algorithms to curate content. Even if the effect on news repertoires that algorithm agency has is ceded, however, the data analysis failed to show evidence of undesirable consequences of a filter bubble (in this case, climate change denial and misinformation). Does this mean the debate about the existence of filter bubbles is entirely pointless? Logically, if groups of people debating approaches to humanity's most pressing issues from their own bubble are both saying we could find the correct solution if we simply get out of our own bubble, both of these groups cannot be correct in this assertion. Regardless, something compels us to discuss the filter bubble issue. However long it may take to gather and reproduce enough empirical support for the harm of filter bubbles, it is clear they are undesirable. If they were not undesirable, there would not be such an interest in *disproving* their existence. Surely, there wouldn’t be thousands of citations of the Bakshy, Messing, and Adamic (2015) article refuting the existence of filter bubbles on Facebook if filter bubbles truly didn’t matter. Additionally, there is evidence outside of this research that does suggest significant impacts for misinformation exposure for those in filter bubbles (Bessi et al., 2015; Jasny et al., 2015) (surely an undesirable outcome). Whether or not filter bubbles matter, it is clear algorithms matter, as different algorithms having observable effects on news consumption would suggest. The partial support for the first hypothesis serves to further demonstrate that algorithmic design matters. It is not the difference between news repertoires

resulting from non-algorithmic news gathering platform use and Facebook use that is found to be significant, but instead the news repertoires of different algorithmic users than Facebook users are found to be significantly more balanced. The reasons for this significant difference are not within the scope of the hypotheses of this paper, nor are they readily discernable behind the black-boxed design of the algorithms. Technology companies have a legitimate interest in keeping these design philosophies secret, as transparency could result in abuse from bad actors looking to illegitimately boost their engagement from these companies' sites (especially if this boosting is toward nefarious ends like the spread of misinformation). Perhaps Fletcher and Nielson's (2018) work regarding the news repertoire balance of Google news search users offers some reasonable speculation as to the reason for a filter bubble effect on Facebook. Where Google search users were found to have relatively balanced and homogeneous news repertoires (Fletcher & Nielson, 2018), perhaps it is an idiosyncratic nature of Facebook News Feeds that is to blame for a filter bubble effect. We might extrapolate further from this and say it is a design philosophy which drives engagement *longer* on Facebook which is to blame, rather a philosophy of getting users results *fast* on platforms like Google. Again, the limited access given to researchers about the functionality of these algorithms means that we can only speculate as to the reasons for algorithmic behavior. This leaves us with this: an algorithm does not perform an infallible calculation which, upon request, delivers us what we truly desire like a magical mirror on a wall. Instead, the significant finding giving partial support for hypothesis 1 provides support for the curated flows model. There are different curating actors, and when controlling for important actors like the self, we can observe the difference a curating actor like an algorithm can make. In the case of Facebook, the News Feed algorithm has agency as a curating actor which can create a filter bubble effect.

Limitations

This research is, of course, not without limitations. First, the Reuters Digital News Survey (2020) reported NBC and MSNBC usage for respondents together in one item. This was significant, as the slant of the tv programs from these sources is different. This prevented using non-online news to measure news repertoire balance. Thus, news repertoire balance refers to the balance of only online news of the respondents. This comparison is still worthwhile, and does not impact the conclusions and implications discussed significantly, as it still allows comparison between behavior of algorithms. Demonstrating that Facebook's algorithm behaves differently than other algorithms is sufficient to arrive at the conclusions that were reached. Secondly, the nature of survey data is that it is self-reported, which leaves the data open to some inaccuracies from inaccurate self-reporting. This had a significant impact on the original line of news source lean measurement method which was originally attempted being facially inaccurate. An alternate method was adopted, and the research proceeded without further issue.

Conclusion

An algorithm is a tool designed by humans; a tool which serves the interests of the company of the humans that designed it. An algorithm is one curating actor among many, in line with curating flows theory. Their curation may vary from one another according to their designers' interests just like individuals (another curating actor) do according to their own interests. Acknowledging this, we should recognize that perhaps broader societal interests should be considered in the design of these algorithms, interests like an accurately informed public. These are interests which must be incentivized and protected by some other entity that is not a profit-driven company, because clearly these interests do not always align if a filter bubble effect is undesirable, yet is detectable on Facebook. Furthermore, the solution cannot be to simply rely

on the agency of individuals. A majority of Americans recognize social media platforms have issues with misinformation and filter bubbles (Auxier, 2020), but their own agency to choose a more balanced news repertoire is in competition with the agency of other actors (such as algorithms) recognized in curated flows theory. As researchers, we should be cautious when encountering or making claims of the absolute primacy of curating actors' agency. As the behavior of the News Feed algorithm shows when taken in comparison to Google's search algorithm in Fletcher and Nielson's (2018) filter bubble research, curating actors have differing levels of power in the curation process in different contexts. More research on filter bubbles (whether supporting or denying their existence) would do well to adopt this kind of comparative framework used for this research which the curated flows model supports. Expanding on the value of a comparative framework, perhaps a comparison utilizing regression of many platforms to one another (rather than one to many as is used in this research) would be of value. What would be especially useful is if future research could explore why these algorithms are acting in certain ways to promote or counter filter bubble effects. This will require either greater cooperation from tech companies, or sophisticated experimental research design.

REFERENCES

Allcott, H., & Gentzkow, M. (2017). Social Media and Fake News in the 2016 Election. *Journal of Economic Perspectives*, *31*(2), 211–236. https://doi.org/10.1257/jep.31.2.211

AllSides. (2016, April 11). *InfoWars Media Bias Rating*. https://www.allsides.com/news-source/infowars

Akhtar, A. (2016, August 27). *Facebook removes human-written descriptions on Trending topics*. USA TODAY; USA TODAY. https://www.usatoday.com/story/tech/news/2016/08/26/facebook-removes-human-written-descriptions-trending-topics/89440416/

Auxier, B. (2020, October 15). *64% of Americans say social media have a mostly negative effect on the way things are going in the U.S. today*. https://www.pewresearch.org/fact-tank/2020/10/15/64-of-americans-say-social-media-have-a-mostly-negative-effect-on-the-way-things-are-going-in-the-u-s-today/

Bandy, J., & Diakopoulos, N. (2021). Curating quality? How Twitter's timeline algorithm treats different types of news. *Social Media + Society*. https://doi.org/10.1177/20563051211041648

Bakshy, E., Messing, S., & Adamic, L. A. (2015). Exposure to ideologically diverse news and opinion on Facebook. *Science*, *348*(6239), 1130–1132. https://doi.org/10.1126/science.aaa1160

Barnidge, M. (2021). Incidental Exposure and News Engagement: Testing Temporal Order and the Role of Political Interest. *Digital Journalism*, 1-19. https://doi.org/10.1080/21670811.2021.1906290

Bessi, A., Coletto, M., Davidescu, G. A., Scala, A., Caldarelli, G., & Quattrociocchi, W. (2015). Science vs conspiracy: Collective narratives in the age of misinformation. *PloS one*, *10*(2), e0118093. https://doi.org/10.1371/journal.pone.0118093

Bryant, J., Oliver, M. B., Raney, A. A., Knobloch-Westerwick, S., Westerwick, A., & Sude, D. J. (2020). Media Choice and Selective Exposure. *Media effects: Advances in theory and research* (4th ed., pp. 146–162). essay, Routledge.

Buchanan, T. (2020). Why do people spread false information online? The effects of message and viewer characteristics on self-reported likelihood of sharing social media disinformation. *PLOS ONE*, 15(10), e0239666. https://doi.org/10.1371/journal.pone.0239666

C-SPAN. (2021, March). *House Hearing on Combating Online Misinformation and Disinformation*. https://www.c-span.org/video/?510053-1%2Fhouse-hearing-combating-online-misinformation-disinformation.

Center for Countering Digital Hate. (2021). *The Toxic Ten*. https://252f2edd-1c8b-49f5-9bb2-cb57bb47e4ba.filesusr.com/ugd/f4d9b9_277d4dc5f1f84858a6a2dc149f00b759.pdf

Del Vicario, M., Bessi, A., Zollo, F., Petroni, F., Scala, A., Caldarelli, G., ... & Quattrociocchi, W. (2016). The spreading of misinformation online. *Proceedings of the National Academy of Sciences, 113*(3), 554-559. https://doi.org/10.1073/pnas.1517441113

Dimok, M. (2020, February 19). *How Americans view trust, facts, and democracy today*. Retrieved October 6, 2021, from https://www.pewtrusts.org/en/trust/archive/winter-2020/how-americans-view-trust-facts-and-democracy-today

Dutt, R., Deb, A., & Ferrara, E. (2018, December). "Senator, We Sell Ads": Analysis of the 2016 Russian Facebook Ads Campaign. *International conference on intelligent information technologies* (pp. 151-168). Springer, Singapore. https://doi.org/10.1007/978-981-13-3582-2_12

Eady, G., Nagler, J., Guess, A., Zilinsky, J., & Tucker, J. A. (2019). How Many People Live in Political Bubbles on Social Media? Evidence From Linked Survey and Twitter Data. *SAGE Open*, 9(1), 215824401983270. https://doi.org/10.1177/2158244019832705

Fletcher, R., & Nielsen, R. K. (2017). Are people incidentally exposed to news on social media? A comparative analysis. *New Media & Society, 20*(7), 2450–2468. https://doi.org/10.1177/1461444817724170

Fletcher, R., & Nielsen, R. K. (2018). Automated serendipity. *Digital Journalism, 6*(8), 976–989. https://doi.org/10.1080/21670811.2018.1502045

Harman, C. (2021, September 18). *Reuters leverages Instant Articles to support commercial and audience growth*. Retrieved October 6, 2021, from https://www.facebook.com/journalismproject/reuters-leverages-instant-articles-to-support-commercial-and-audience-growth

Jasny, L., Waggle, J., & Fisher, D. R. (2015). An empirical examination of echo chambers in US climate policy networks. *Nature Climate Change, 5*(8), 782–786. https://doi.org/10.1038/nclimate2666

Jamison, A. M., Broniatowski, D. A., Dredze, M., Wood-Doughty, Z., Khan, D., & Quinn, S. C. (2020). Vaccine-related advertising in the Facebook ad archive. *Vaccine, 38*(3), 512-520. https://doi.org/10.1016/j.vaccine.2019.10.066

Kuklinski, J. H., Quirk, P. J., Jerit, J., Schwieder, D., & Rich, R. F. (2000). Misinformation and the currency of democratic citizenship. *The Journal of Politics, 62*(3), 790-816. https://doi.org/10.1111/0022-3816.00033

Lazarsfeld, P. F., Berelson, B., & Gaudet, H. (1968). *The people's choice*. Columbia University Press.

Luckerson, V. (2015, July 9). *Here's how Facebook's News Feed actually works*. Retrieved November 19, 2021, from https://time.com/collection-post/3950525/facebook-news-feed-algorithm/.

Mac, R., &Frenkel, S. (2021, October 22). *Internal Alarm, public shrugs: Facebook's employees dissect its election role*. Retrieved October 30, 2021, from https://www.nytimes.com/2021/10/22/technology/facebook-election-misinformation.html

Muller, B. (2021, December 2). *Interactive Media Bias Chart Public - Ad Fontes Media*. Ad Fontes Media. https://adfontesmedia.com/interactive-media-bias-chart/

Murgia, M. (2021, September 28). *Time to turn off Facebook's digital fire hose*. Retrieved October 30, 2021, from https://www.ft.com/content/d5dcfece-4e3c-4937-81ac-20dc736c4c27

Naeem, S. B., Bhatti, R., & Khan, A. (2021). An exploration of how fake news is taking over social media and putting public health at risk. *Health Information & Libraries Journal, 38*(2), 143-149. https://doi.org/10.1111/hir.12320

Nelson, J. L., & Lewis, S. C. (2021). Only "sheep" trust journalists? How citizens' self-perceptions shape their approach to news. *New Media & Society*. https://doi.org/10.1177/14614448211018160

Newman, N., Fletcher, R., Kalogeropoulos, A., Levy, D., & Nielsen, R. K. (2020). *Reuters Institute digital news report 2020*.

Roose, K., & Giglietto, F., (2022). Twitter. https://twitter.com/FacebooksTop10/status/1491804200484802563?cxt=HHwWhsCoxYaB-rMpAAAA

Ognyanova, K., Lazer, D., Robertson, R. E., & Wilson, C. (2020). Misinformation in action: Fake news exposure is linked to lower trust in media, higher trust in government when your side is in power. *Harvard Kennedy School Misinformation Review.*

Otero, V. (2021, September 6). *White Paper: Multi-Analyst Content Analysis Methodology September 2021*. Ad Fontes Media. https://adfontesmedia.com/white-paper-2021/

Ouhamdouch, S., & Bahir, M. (2017). Climate change impact on future rainfall and temperature in semi-arid areas (Essaouira Basin, Morocco). *Environmental Processes, 4*(4), 975-990. https://doi.org/10.1007/s40710-017-0265-4

Pariser, E. (2012). The filter bubble: what the internet is hiding from you. *Penguin Books*.

Raza, A., Razzaq, A., Mehmood, S. S., Zou, X., Zhang, X., Lv, Y., & Xu, J. (2019). Impact of climate change on crops adaptation and strategies to tackle its outcome: A review. *Plants, 8*(2), 34. https://doi.org/10.3390/plants8020034

Scharkow, M., Mangold, F., Stier, S., & Breuer, J. (2020). How social network sites and other online intermediaries increase exposure to news. *Proceedings of the National Academy of Sciences, 117*(6), 2761-2763. https://doi.org/10.1073/pnas.1918279117

Stop Funding Heat. (2021, November 11). *#InDenial - Facebook's Growing Friendship with Climate Misinformation.* https://stopfundingheat.info/facebook-in-denial/.

Sunstein, Cass. (2002). The law of group polarization. *The Journal of Political Philosophy, 10*(2), 175–195

Tabari, H. (2020). Climate change impact on flood and extreme precipitation increases with water availability. *Scientific reports, 10*(1), 1-10. https://doi.org/10.1038/s41598-020-70816-2

Thorson, K., Cotter, K., Medeiros, M., & Pak, C. (2021). Algorithmic inference, political interest, and exposure to news and politics on Facebook. *Information, Communication & Society, 24*(2), 183-200. https://doi.org/10.1080/1369118X.2019.1642934

Thorson, K., & Wells, C. (2015). Curated Flows: A Framework for Mapping Media Exposure in the Digital Age. *Communication Theory, 26*(3), 309–328. https://doi.org/10.1111/comt.12087

Valenzuela, S., Halpern, D., Katz, J. E., & Miranda, J. P. (2019). The paradox of participation versus misinformation: Social media, political engagement, and the spread of misinformation. *Digital Journalism, 7*(6), 802-823. https://doi.org/10.1080/21670811.2019.1623701

Watts, D. J., Rothschild, D. M., & Mobius, M. (2021). Measuring the news and its impact on democracy. *Proceedings of the National Academy of Sciences, 118*(15), e1912443118. https://doi.org/10.1073/pnas.1912443118

Weeks, B. E. (2015). Emotions, partisanship, and misperceptions: How anger and anxiety moderate the effect of partisan bias on susceptibility to political misinformation. *Journal of communication, 65*(4), 699-719. https://doi.org/10.1111/jcom.12164

Zimmer, F., Scheibe, K., Stock, M., & Stock, W. G. (2019). Fake news in social media: Bad algorithms or biased users?. *Journal of Information Science Theory and Practice, 7*(2), 40-53. https://doi.org/10.1633/JISTaP.2019.7.2.4

APPENDIX

Table 1

H1 Tests of Between-Subjects Effects, Dependent Variable: News Repertoire Balance

Source	Type III Sum of Squares	*df*	Mean Square	*F*	Sig.	Partial Eta Squared
Corrected Model	2059.214[a]	7	294.173	9.865	<.001	.179
Intercept	121.809	1	121.809	4.085	.044	.013
Desire To Seek Attitude-consistent News	29.063	1	29.063	.975	.324	.003
Gender	18.527	1	18.527	.621	.431	.002
Age	10.816	1	10.816	.363	.547	.001
Income	8.458	1	8.458	.284	.595	.001
Ideological Affiliation	1040.720	1	1040.720	34.900	<.001	.099
News Platform	399.284	2	199.642	6.695	.001	.041
Error	9423.218	316	29.820			
Total	35051.443	324				
Corrected Total	11482.432	323				

a. R Squared = .179 (Adjusted R Squared = .161)

Table 2

H1 Parameter Estimates, Dependent Variable: News Repertoire Balance

Parameter	*B*	Std. error	*t*	Sig.	Lower Bound 95% Confidence Interval	Upper Bound 95% Confidence Interval	Partial Eta Squared
Intercept	5.274	2.361	2.234	.026	.629	9.918	.016
Desire To Seek Attitude-consistent News	-.531	.538	-.987	.324	-1.589	.527	.003
Gender	-.496	.629	-.788	.431	-1.733	.742	.002
Age	.014	.024	.602	.547	-.033	.061	.001
Income	-.253	.474	-.533	.595	-1.185	.680	.001
Ideological Affiliation	2.421	.410	5.908	<.001	1.615	3.228	.099
Non-Facebook user	.708	.809	.875	.382	-.884	2.300	.002
Other Algorithmic User	-1.976	.750	-2.637	.009	-3.451	-.502	.022
Facebook User	0_a	.	.	.	.	.	.

a. This parameter is set to zero because it is redundant

Table 3

H2 Tests of Between-Subjects Effects, Dependent Variable: Denial of the Seriousness of Climate Change

Source	Type III Sum of Squares	*df*	Mean Square	*F*	Sig.	Partial Eta Squared
Corrected Model	534.908[a]	7	76.415	60.991	<.001	.537
Intercept	.579	1	.579	.462	.497	.001
Desire To Seek Attitude-consistent News	14.781	1	14.781	11.797	<.001	.031
Gender	12.021	1	12.021	9.594	.002	.025
Age	.447	1	.447	.357	.551	.001
Income	1.352	1	1.352	1.079	.300	.003
Ideological Affiliation	425.549	1	425.549	339.651	<.001	.480
News Platform	5.070	2	2.535	2.023	.134	.011
Error	461.068	368	1.253			
Total	3823.000	376				
Corrected Total	995.976	375				

a. R Squared = .537 (Adjusted R Squared = .528)

Table 4

H2 Parameter Estimates, Dependent Variable: Denial of the Seriousness of Climate Change

Parameter	*B*	Std. error	*t*	Sig.	Lower Bound 95% Confidence Interval	Upper Bound 95% Confidence Interval	Partial Eta Squared
Intercept	.326	.456	.715	.475	-.571	1.223	.001
Desire To Seek Attitude-consistent News	-.357	.104	-3.435	<.001	-.562	-.153	.031
Gender	-.368	.119	-3.097	.002	-.601	-.134	.025
Age	.003	.004	.597	.551	-.006	.011	.001
Income	.094	.091	1.039	.300	-.084	.272	.003
Ideological Affiliation	1.495	.081	18.430	<.001	1.335	1.654	.480
Non-Facebook user	.128	.150	.851	.395	-.168	.423	.002
Other Algorithmic User	-.163	.146	-1.120	.263	-.450	.123	.003
Facebook User	0_a	.	.	.	.	.	.

a. This parameter is set to zero because it is redundant

Table 5

H3 Tests of Between-Subjects Effects, Dependent Variable: Belief the News Media is Providing Accurate Information on Climate Change

Source	Type III Sum of Squares	*df*	Mean Square	*F*	Sig.	Partial Eta Squared
Corrected Model	259.112[a]	7	37.016	24.053	<.001	.314
Intercept	101.936	1	101.936	66.237	<.001	.153
Desire To Seek Attitude-consistent News	3.520	1	3.520	2.287	.131	.006
Gender	15.127	1	15.127	9.829	.002	.026
Age	1.918	1	1.918	1.246	.265	.003
Income	9.698	1	9.698	6.302	.012	.017
Ideological Affiliation	201.237	1	201.237	130.763	<.001	.262
News Platform	6.812	2	3.406	2.213	.111	.012
Error	566.332	368	1.539			
Total	3501.000	376				
Corrected Total	825.444	375				

a. R Squared = .314 (Adjusted R Squared = .301)

Table 6

H3 Parameter Estimates, Dependent Variable: Belief the News Media is Providing Accurate Information on Climate Change

Parameter	*B*	Std. error	*t*	Sig.	Lower Bound 95% Confidence Interval	Upper Bound 95% Confidence Interval	Partial Eta Squared
Intercept	4.399	.509	8.649	<.001	3.399	5.399	.169
Desire To Seek Attitude-consistent News	.175	.116	1.512	.131	-.053	.402	.006
Gender	.412	.131	3.135	.002	.154	.671	.026
Age	.006	.005	1.116	.265	-.004	.015	.003
Income	-.250	.100	-2.510	.012	-.447	-.054	.017
Ideological Affiliation	-1.027	.090	-11.435	<.001	-1.203	-.850	.262
Non-Facebook user	-.315	.166	-1.897	.059	-.642	.012	.010
Other Algorithmic User	-.288	.163	-1.774	.077	-.608	.031	.008
Facebook User	0_a	.	.	.	.	.	.

a. This parameter is set to zero because it is redundant