Social Media and Division in America: Unraveling the Ties Between Curation Algorithms and Political Polarization

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Rylie Jackson Gentile
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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

Advisors
William F. Stafford, Jr., Department of Engineering and Society

Introduction

The enigmatic nature of the algorithms powering social media platforms remains a puzzle for the majority of Americans, fueling skepticism about their influence on their politics. These fears are compounded by observable data indicating an unprecedented level of polarization within American politics (Desilver, 2020). Many attribute this growing divide to the subtle, yet impactful, influence of recommendation algorithms.

During his congressional testimony, Robert Epstein, a renowned behavioral research psychologist, discussed the issues of algorithmic bias. Epstein presented evidence suggesting that Google's content curation displayed a partisan tilt, favoring one political party over another (Epstein & Williams, 2019). He emphasized the importance of a “system built to keep an eye on Big Tech because if these companies all support the same candidate – and that’s likely – they will be able to shift upwards of 15 million votes to that candidate without leaving a paper trail.” He worries that such large-scale manipulation of this sort “would make democracy meaningless, even if your chosen candidate prevailed.” To back up his claims, he preserved more than 47,000 election-related searches in 2018 on Google, Bing, and Yahoo which showcased that Google’s search results may have shifted an upwards of 78.2 million votes.

Over the last 6 years, recommendation algorithms have expanded into more engaging spaces than just search engines. Social media has become an integral part of society with 314.76 million active Americans, averaging 2.18 hours of screen time in 2023 (Statista, 2023). A huge reason that people spend a significant portion of their day scrolling on their phone can be attributed to the algorithm that curates this content for them. Alongside increased user-time, an algorithm’s “successful curation” creates filter bubbles, echo chambers, confirmation bias, and trend amplification which can taint a user's perception of reality and opinion. This paper will focus on if and how these phenomena contribute to polarization in American politics? The largest study in this matter, conducted by Meta, researched these questions in the most robust methods to date. I will review their report, methodologies, and findings about recommendation algorithms. I question Meta’s methodologies in assessing polarization. A main limitation in the study stems from their decisions to focus through solely an individual lens, not societal. Meta also chose unfriendly conditions for any opinions to be reshaped. While critiquing their methods, which represent reason for more considerate research and design in the future, I do not believe we currently have enough reason to blame algorithm curation for political polarization. Despite no immediate threat, I raise possible concerns from the recent acceleration of machine learning.

Discussion of Literature

How does one go about testing if these algorithms contribute to political-polarization in the United States? The first step in addressing a seemingly intractable question is to understand the phenomenon of political polarization and why, in extreme doses, it is bad for society. Political polarization happens when different groups within a population start to have markedly different views about political parties, their members, ideologies, and policies. In a low-polarization scenario, the majority of individuals back a variety of liberal and conservative positions on various issues and can favor one political party without harboring negative feelings towards the others. This can be healthy for a country and promote a wide range of policy options that lead to constructive debates which, in turn create a stable government with widely-supported policies that address big issues. However, in an environment of extreme polarization, distinct and large segments of the population adopt uniform ideological positions on all matters, showing strong allegiance to their chosen party and intense disdain for the opposing one. (Hetzel et. al, 2020). On the negative side, extreme polarization in a two-party system can lead to ineffective, often-revised policies and impede democratic consensus by discouraging engagement with opposing viewpoints (Carothers, 2019).

Utilizing data from the American National Election Studies and national exit polls, there was compelling evidence of a significant rise in ideological polarization among both the general public and political elites since the 1970s (Abramowitz et al., 2015). More than ever, Americans endorse their party's stance across all issues. Key metrics used to gauge this shift include analyses of responses to issue-based questions, correlations among these issue positions, and levels of political engagement. This study reveals, not only, the prevalence of political ideologization across the electorate but also the positive correlation between political engagement and polarization.

Recommendation Algorithms and Human Psychology

Determining whether recommendation algorithms contribute to this phenomenon described above cannot be resolved through clear methodology. A good first step is in the direction of its effects on the human psyche. It is evident that there are many inherent psychological human tendencies that alone breed polarization. So, it is important to understand how humans behave when very little-to-no curation is applied or when they can behave autonomously. A great deal of research suggests that citizens enabled by a high degree of user control, tend to selectively seek information and maintain communication networks consistent with their political orientations, which eventually reinforces the partisan divide in society (Gentzkow & Shapiro, 2011). Paradoxically, evidence also suggests that if presented with an increasing choice of opportunities, citizens often "expose themselves to a range of ideas that cut across partisan or ideological lines" (Song, Cho, & Benefield, 2020). This research points out that information consumption and political discussion online are perhaps more complicated than suggested.

There are two motivations behind information-seeking behavior: directional and accuracy motivation (Kunda, 1990 and Hart et al., 2009). Directional motivation leads people to seek information that aligns with their pre-existing beliefs, while accuracy motivation drives them to look for information that is highly informative, regardless of ideological lines. The interaction between these motivations contributes to complex patterns of information consumption, where individuals may not strictly adhere to partisan lines but might also engage with opposing viewpoints, especially in the fragmented online information environments. The Human's directional tendency to seek out information that aligns with our pre-existing political beliefs can lead to affective polarization, especially those with strong partisan identities. Exposure to opposing viewpoints could potentially mitigate this polarization by introducing ambivalence (Huckfeldt et al., 2004); however, the personalized nature of digital information, shaped by algorithms that cater to our preferences, often limits such exposure, thereby reinforcing our existing biases and deepening the divide between 'us' and 'them'.

Recommendation algorithms operate by analyzing inputs such as search terms or user preferences, utilizing techniques like content-based and collaborative filtering. This interaction allows platforms to gather valuable user data, revealing interests and preferences, which in turn enhances the personalization of future searches and recommendations. This cycle can be described as the duality of digital media, which Webster (2011) defines as the "process through which agents and structures mutually reproduce the social world". The more insights that a user provides, the more accurate the algorithm becomes to tailor suggestions. This synthesizes a more efficient and relevant user experience but also raises concerns about creating "filter bubbles," where users are increasingly exposed to information that aligns with their existing views. Parser (2016) states that "Your filter bubble is your own personal, unique universe of information that you live in online. What's in your filter bubble depends on who you are, and it depends on what you do. But you don't decide what gets in - and more importantly, you don't see what gets edited out." These recommendation algorithms are naturally designed to operate with, not against, human tendencies, one of which is that people feel more comfortable with consistency and confirmation (Kunda,1990). This means that tailoring search outcomes in such a way is key for economic success.

Recommendation Algorithms and Polarization

The concept that our emotions and attitudes, especially in politics, are deeply intertwined with our long standing beliefs, such as our ideological leanings, has been well acknowledged. Essentially, our political feelings are often a reflection of our established ideological positions, leading us to favor ideas and entities that align with our views and to dislike those that oppose them. This affective alignment with our ideology can be further solidified when we consume information that supports our existing beliefs, thereby reinforcing our ideological perspectives through additional supporting details, and intensifying our emotional responses towards politically charged subjects.

So, would an algorithm that effectively chooses a citizen's consumption of politics on media continuously reaffirm their beliefs enough to induce political polarization? In a study featured in the Journal of Broadcasting and Electronic Media, researchers tested just that. The methodology involved manipulating YouTube's algorithm with personalized search terms related to the 2016 U.S. presidential candidates, derived from participants' interests (Cho et al., 2020). Emotional responses towards the candidates were gauged using a pre- and post-exposure questionnaire, employing a 5-point scale for five primary emotions and a "feeling thermometer" for overall sentiment. The study aimed to understand ideological reinforcement, measured by the alignment of emotional responses with participants' political ideologies, and affective polarization, assessed by the variance in emotional reactions towards preferred and opposed candidates. The findings revealed a significant correlation between anger and political ideology in the personalized recommendation condition, with liberals exhibiting less anger towards Clinton in comparison to Trump. This condition showed a stronger alignment of political emotion with ideology, especially for negative emotions, suggesting that personalized content might reinforce ideological biases. Despite these findings, the study found no significant increase in polarization for specific emotions across different conditions. However, a trend indicated that recommendations based on social connections, or recommendations based on general societal trends, might marginally reduce overall polarization. The "social" group showed the lowest levels of polarization, as measured by the feeling thermometer, compared to the "self" and control groups. This nuanced result suggests that algorithmic recommendations can intensify ideological biases when suggestions are based on one's own negative emotions. On the other hand, recommendations may even slightly diminish it when based on social preferences.

Discussion of the Case

Until recently, no comprehensive, large-scale study had been conducted on the impact of a major social media company, Meta (formerly Facebook), on political news exposure. In collaboration with U.S. university academics, Meta investigated the effects of its algorithms on American democracy, allowing unprecedented access to its algorithms. The research, aimed at being unbiased, was independently designed by a diverse academic team without direct Meta funding, though Meta could veto designs for legal or privacy reasons. The team, specializing in political polarization, misinformation, and democratic norms, worked with Meta to design experiments integrated with its platforms, using consenting users' data to understand algorithm-driven content personalization. Meta provided access to aggregate data on U.S. adult users on its platforms, ensuring individual privacy.

The team investigated 2 relevant hypotheses, publishing each as their own paper: “How Do Social Media Feed Algorithms Affect Attitudes and Behavior in an Election Campaign?” and “Like-minded sources on Facebook Are Prevalent but not Polarizing”. Each experiment was run for 3 months during one of the most critical times in American democracy: the 2020 presidential election.

"How do social media feed algorithms affect attitudes and behavior in an election campaign?"

The intersection of social media algorithms with democratic processes has become a critical area of inquiry, especially in light of the 2020 US election. The Public has been concerned about how these algorithms fostering "filter bubbles," exacerbating polarization, and facilitating disinformation have prompted a need for comprehensive study. Leaders of this project admit that this is a challenging task to answer, even with direct access to proprietary code. The personalization of factors like a user's past behavior, predictions arising from other users leads to complex and mixed results on how the content is ranked for curation. When studying algorithmic effects, generally discrete measurements like the number of posts are of focus. But here, the target interest is the aggregate impact of an algorithm.

A randomly selected treatment group received feed's presented in reverse-chronological order. While this is still technically an algorithm, it serves as the control because it has essentially no curation processes. It also displays the same content for each user. Many previous studies on social media have bundled all of its features together, including algorithms, repeated interactions, and content resharing. Replacing Meta's current algorithm with the control enables research to study effects on specifically the *ranking* of a user's feed. Researchers believe this method minimizes the applications personalization features. Compared against the control, Meta's status quo algorithm aims to maximize user-engagement by learning and adapting to the user.

All users in the case study were those more active than the average monthly active user. Each user was assigned to five different surveys spread out before and after election Day, shared their on-platform activity, and participated in passive tracking of off-platform internet activity. Each participant was randomly assigned to the chronological or the most updated ranking algorithm. Each group experienced about 80% of their usual feed was manipulated. The main estimator of interest tested was the population average treatment effect (PATE), which considers a user's predicted ideology, friend count, number of political pages followed, number of days active, and a few other factors.

Using the metrics of Engagement, user satisfaction, and news originality, results found that the chronological feed group engaged significantly less with Facebook and Instagram. While the average participant exceeded the US monthly active user's time on these platforms, those in the Algorithmic Feed group spent significantly more time: 73% more on Facebook and 107% more on Instagram. In contrast, the increase for the Chronological Feed group was lower, at 37% for Facebook and 84% for Instagram.

Algorithmic Feed groups on Facebook and Instagram engaged more with content, liking an average of 6.7% and 3.1% respectively, compared to those in the Chronological Feed group. The Chronological Feed significantly reduced the proportion of content users saw from friends on Facebook by 24 percentage points and from mutual followers on Instagram by 5 percentage points. Additionally, the Chronological Feed led to a decrease in the diversity of users' networks, including friends, Pages, and Groups on Facebook, and mutual followers on Instagram, affecting the overall content exposure.

Next, the study investigated how chronological ranking affected the mix of content in users' feeds. The shift to Chronological Feeds led to a decrease in content from both ideologically opposing ("cross-cutting") and similar ("like-minded") sources on Facebook, with reductions of 18.7% from cross-cutting and 48.1% from like-minded sources, compared to 20.7% and 53.7% respectively in Algorithmic Feeds. Interestingly, this reduction was balanced by an increase in content from moderate or ideologically mixed sources, suggesting that Algorithmic Feeds might contribute more to creating echo chambers or filter bubbles by promoting like-minded content over cross-cutting or moderate viewpoints.

Researchers came up with three big claims at the end of their study. Tests across both Facebook and Instagram revealed no significant differences between algorithm groups in affective or issue polarization. Second, there were no significant differences in election or news knowledge, indicating a lack of support for the hypotheses. Lastly, chronological Feed on Facebook had almost no impact on participation nor was there a difference reported in election voting between the two groups. Although, measurement from on-platform behavior suggested that chronological ordering significantly reduced political engagement like posting/liking political content.

"Like-minded sources on Facebook Are Prevalent but not Polarizing"

The study investigated the impact of 'echo chambers' on Facebook, focusing on whether exposure to like-minded content contributes to political polarization. The researchers analyzed the entire population of active adult Facebook users in the USA in 2020, revealing that the majority of content seen by users came from like-minded sources, even though political information and news constituted a minor fraction of total exposure.

To address the issue of echo chambers, a multi-wave field experiment was conducted with 23,377 Facebook users during the 2020 US presidential election. The experiment reduced exposure to like-minded content by about one-third to assess its effects on users' political attitudes. The intervention successfully increased exposure to cross-cutting sources and reduced exposure to uncivil language. However, it had no measurable impact on a range of attitudinal measures, including affective polarization, ideological extremity, candidate evaluations, and belief in false claims.

The methodology for measuring these attitudinal changes was comprehensive. Attitudinal measures were assessed using a combination of on-platform behavioral data from Facebook and survey data collected before and after the 2020 US presidential election. The survey component included questions designed to gauge affective polarization (emotional responses to opposing political parties), ideological extremity (strength of adherence to liberal or conservative ideologies), and belief in false claims (acceptance of misinformation related to the election). These attitudinal measures were pre-registered, meaning they were identified and documented before the data analysis began, ensuring transparency and reducing the risk of bias in data interpretation.

Statistically, the intervention led to a notable decrease in exposure to like-minded content (from 53.7% to 36.2% for the treatment group) and a slight increase in exposure to cross-cutting content. Despite these changes, the precisely estimated results showed no significant effects on the pre-registered attitudinal measures. For instance, the study confidently ruled out effects of ± 0.12 standard deviations or more on these outcomes, indicating that the manipulation of like-minded content exposure did not significantly influence users' political attitudes.

The findings suggest that while like-minded content exposure on social media is common, simply reducing it during a politically charged event like the 2020 US presidential election does not necessarily reduce polarization in beliefs or attitudes. This challenges the prevailing narrative that echo chambers on social media are a primary driver of political polarization, highlighting the complexity of the relationship between social media content consumption and political attitudes.

Analysis

This Meta study is unprecedented on many levels and the right step in the direction for better understanding the major socio-political consequences from curation algorithms. The collaboration between academia and private industry in conducting this research sets a valuable standard for future endeavors. Having the cooperation of the algorithm's creator, Meta, brings insights we previously were not able to gather. Access to their data is the only way to graduate from theoretical cases like the ones discussed in the literature review. Meta's cooperation also brings algorithmic transparency and ethical oversight from those unaffiliated with the company. The incorporation of leading academics not only keep Meta accountable for their impactful products and provide validation for policy and implementation changes if needed.[1]

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[1] Please note that Meta's involvement in the case study can act as a double-edged sword. The costs associated with the research (such as participant fees, recruitment, and data collection) were paid by Meta. Meta did not have the right to pre-publication approval, yet I still hesitate to say that there are no conflicting stakeholders involved which could affect the bias of the results. While none of the academic researchers nor their institutions received financial or any other compensation from Meta, fifteen of the researchers each had one or many of the following relations with Meta or a related social media company: Current employee, Past employee, Own individual stocks, Paid consulting work, Direct research funding as private investigator, received an honorarium/fee, attended an event where food,

Given this, there are still a number of issues in how the study conceptualizes the link between technology and the social dynamics of polarization. I will walk through a series of considerations: the length of the study, individual vs. societal perspective, user demographics, and autonomous behavior. First, the longevity of the study was only 3 months long. Psychology points out that changing one's opinion is no easy feat and everyone's resistivity operates at different rates due to many different factors. Clear, compelling information is easy to digest but complex information, such as a candidate's policies given the state of our country, require time to process. A user's relationship to a polarizing source could also take time as trust in credibility needs to be established. The speed of this change can depend on the individual's tolerance for dissonance and their motivation to resolve it. I do not believe the Meta study gave participants ample time to allow the algorithm to provoke polarization, if it were to occur. In fact, the study states that it "is possible such downstream effects require a more sustained intervention period".

The Meta study only focused on users who were more active than the average; this is a poor design that leads to biased results and discards an opportunity to learn about algorithmic impacts at different engagement levels. Active users may already be influenced by the algorithms, potentially skewing results by not accounting for pre-existing exposure and behavioral biases. Active users might be entrenched in echo-chambers, amplifying the feedback loop of engagement and polarization. The algorithm may have already taken into effect, making it hard to capture its full impact. A more robust approach would involve a baseline comparison group of less active or new users, offering a clearer picture of the algorithms' initial impact. Once an algorithm learns a user's behavior, it tends to select the same content type. A longitudinal study could track changes over time, providing insights into the development of polarization of a new user.

Additionally, exploring polarization solely through an individual lens may overlook its profound societal implications. Life's inherent unpredictability, where minor events can ignite a cascade of changes in behavior and action, complicates tracing these effects back to a single cause. This unpredictability might also extend to the nuanced ways algorithms influence societal polarization. Studies show that while recommendation algorithms tend to expose individuals to like-minded content, this doesn't necessarily polarize them directly. However, the cumulative effect of continuous exposure to such content could incite discussions, content sharing, and behaviors that, collectively, might amplify societal polarization. This raises the question of whether algorithms could be subtly molding societal polarization in ways that are challenging to measure directly. Adding to this complexity, current research designs may not adequately capture the broader societal impact of social media. They can pinpoint direct effects on individuals but

travel, or lodging was paid, own individual stocks. These are not violations to a research study, nor evidence to invalidate the study by any means, however it would not be convenient for Meta if their algorithms did significantly increase polarizing behavior.

struggle to assess how social media reshapes societal norms or influences the behavior of other users and entities like civic organizations and content producers. The overlooked dynamics, such as how changes in ranking algorithms might shift content demand and create feedback loops within the algorithmic ecosystem, further blur our understanding. The studies' limitations, particularly in not allowing an individual's algorithmic experience to affect their network and including posts from non-participant users subjected to standard algorithmic sorting, hinder a comprehensive grasp of "general equilibrium" effects. If the interventions studied were applied universally, their impact could diverge due to the intricate interplay of networked systems, underscoring the need for a more integrated approach to discerning the complex relationship between algorithms and societal polarization.

While it's tempting to attribute polarization solely to recommendation algorithms, research suggests their impact might be more nuanced than initially believed. The selective exposure theory, as (Stroud, 2011) outlines, posits that individuals gravitate towards political information that aligns with their pre-existing beliefs, potentially amplifying polarization. However, the effectiveness of algorithms in facilitating this selective exposure is under scrutiny. The key lies in the act of selection itself; polarization is thought to stem not just from encountering content that echoes one's views but from actively choosing such content. This is where the distinction between forced and self-selected exposure becomes crucial. If content is imposed rather than chosen, it could provoke resistance rather than reinforcement of existing attitudes.

This perspective gains further complexity when considering user interaction with algorithmically curated content. Users might feel in control as they navigate through content with a simple swipe, but their choices are constrained by the algorithm, limiting their exposure to a predefined selection. This echoes Parser's (2016) observation that users lack control over what is presented to them and remain unaware of what is omitted. This scenario raises questions about the nature of exposure: Is it truly self-selected if the options are algorithmically constrained? Research by Hobden & Olson (1994) and later discussions by Gaines & Kuklinski (2011) highlight that the impact of exposure on attitude formation and polarization is most potent when it is self-selected. This suggests that the potential polarizing effect of ideological media might be mitigated if the exposure is perceived as forced, challenging the assumption that algorithm-driven exposure inherently leads to greater polarization.

Conclusion

As social media increasingly shapes our lives, it's crucial to delve deeper into how its algorithms might drive political polarization, especially with rapid advancements in machine learning enhancing their sophistication. These algorithms could become so adept at aligning with user preferences that their recommendations might be mistaken for personal choices. Recognizing the limitations of recent studies in the United States, there's a pressing need to refine our approaches, pursue long-term data collection, and thoroughly dissect this intricate issue. Proactively developing strategies to counteract the potential polarizing effects of recommendation algorithms is essential, even if their impact isn't immediately evident. Given their transformative influence on the consumer market, these algorithms are here to stay. To mitigate the risk of significant polarization, social media platforms should consider measures such as diversifying content exposure, enhancing transparency, offering user-customizable filters, implementing stringent fact-checking and content moderation, fostering constructive interactions, conducting regular algorithm audits, promoting collaborations for ongoing research, and emphasizing media literacy among users. These initiatives can help balance the diverse viewpoints, contributing to a less polarized online environment.

References

Abramowitz, A., & Saunders, K. (2015, February). *Is polarization a myth? | The Journal of Politics: Vol 70, no 2*. Chicago Journals. https://www.journals.uchicago.edu/doi/10.1017/S0022381608080493

Carothers, T., & O'Donohue, A. (2019). *Democracies divided: The Global Challenge of Political Polarization*. Brookings Institution Press.

Cho, J., Ahmed, S., Hilbert, M., Liu, B., & Luu, J. (2020). Do search algorithms endanger democracy? an experimental investigation of algorithm effects on political polarization. *Journal of Broadcasting & Electronic Media*, *64*(2), 150–172. https://doi.org/10.1080/08838151.2020.1757365

DeSilver, D. (2022, March 10). *The polarization in today's Congress has roots that go back decades*. Pew Research Center. https://www.pewresearch.org/short-reads/2022/03/10/the-polarization-in-todays-congress-has-roots-that-go-back-decades/

Dixon, S. J. (2024, January 30). *U.S.: Social media users 2020-2029*. Statista. https://www.statista.com/statistics/278409/number-of-social-network-users-in-the-united-states/

Epstein, R., & Williams, R. (2024, April 2). *Why google poses a serious threat to democracy and how to end that threat*. Mercator. https://www.mercatornet.com/why-google-poses-a-serious-threat-to-democracy-and-how-to-end-that-threat

Gaines, B. J., & Kuklinski, J. H. (2011). Experimental estimation of heterogeneous treatment effects related to self-selection. *American Journal of Political Science*, *55*(3), 724–736. https://doi.org/10.1111/j.1540-5907.2011.00518.x

Gentzkow, M., & Shapiro, J. (2011). Ideological segregation online and offline. *The Quarterly Journal of Economics*, *126*(4), 1799–1839. https://doi.org/10.3386/w15916

Guess, A. M., Malhotra, N., Pan, J., Barberá, P., Allcott, H., Brown, T., Crespo-Tenorio, A., Dimmery, D., Freelon, D., Gentzkow, M., González-Bailón, S., Kennedy, E., Kim, Y.

M., Lazer, D., Moehler, D., Nyhan, B., Rivera, C. V., Settle, J., Thomas, D. R., … Tucker, J. A. (2023). How do social media feed algorithms affect attitudes and behavior in an election campaign? *Science*, *381*(6656), 398–404. https://doi.org/10.1126/science.abp9364

Guttmann, A. (2024, March 11). *U.S. average daily media use 2023*. Statista. https://www.statista.com/statistics/1289938/daily-media-usage-us/

Heltzel, G., & Laurin, K. (2020, August). *Polarization in America: Two possible futures*. Current opinion in behavioral sciences. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7201237/

Hobden, K. L., & Olson, J. M. (1994a). From jest to antipathy: Disparagement humor as a source of dissonance-motivated Attitude Change. *Basic and Applied Social Psychology*, *15*(3), 239–249. https://doi.org/10.1207/s15324834basp1503_2

Hobden, K. L., & Olson, J. M. (1994b). From jest to antipathy: Disparagement humor as a source of dissonance-motivated Attitude Change. *Basic and Applied Social Psychology*, *15*(3), 239–249. https://doi.org/10.1207/s15324834basp1503_2

Huckfeldt, R., Mendez, J. M., & Osborn, T. (2004). Disagreement, ambivalence, and Engagement: The political consequences of heterogeneous networks. *Political Psychology*, *25*(1), 65–95. https://doi.org/10.1111/j.1467-9221.2004.00357.x

Kunda, Z. (1990, March). *The case for motivated reasoning*. American Psychological Association. https://psycnet.apa.org/record/1991-06436-001?doi=1

Nyhan, B., Settle, J., Thorson, E., Wojcieszak, M., Barberá, P., Chen, A. Y., Allcott, H., Brown, T., Crespo-Tenorio, A., Dimmery, D., Freelon, D., Gentzkow, M., González-Bailón, S., Guess, A. M., Kennedy, E., Kim, Y. M., Lazer, D., Malhotra, N., Moehler, D., … Tucker, J. A. (2023). Author correction: Like-minded sources on Facebook are prevalent but not polarizing. *Nature*, *623*(7987). https://doi.org/10.1038/s41586-023-06795-x

Parser, E., & Raz, G. (2016, December 16). How Can We Look Past (or See Beyond) Our Digital Filters? *TED Radio Hour*. other. Retrieved February 17, 2024, from https://www.npr.org/transcripts/505586856.

Romm, T. (2017, June 27). *Europe has fined Google $2.7 billion for manipulating search results*. Vox. https://www.vox.com/2017/6/27/15878980/europe-fine-google-antitrust-search

Song, H., & Cho, J. (2018, August 1). *The dynamics of message selection in online political ...* SageJournals. https://journals.sagepub.com/doi/10.1177/0093650218790144

Stroud, N. (2011a). Niche news: The politics of news choice. *Political Science Quarterly*, *127*(2), 335–336. https://doi.org/10.1002/j.1538-165x.2012.tb02263.x