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A Replication Report on "Political polarization of news media and influencers on Twitter in the 2016 and 2020 US presidential elections" by Flamino et al. 2023

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A Replication Report on “Political polarization of news media and influencers on Twitter in the 2016 and 2020 US presidential elections” by Flamino et al. 2023

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Abstract

Flamino et al. (2023) estimate the levels of ideological polarization and echo chamber behavior for Twitter (now X) users during the 2016 and 2020 U.S. presidential elections using political bias classification and network analysis methods. Using 873 million tweets, they find a decline in the proportion of fake and extremely biased content but identify an increase in echo chamber behaviors and latent ideological polarization among both users and influencers over the investigated period. Using the Twitter data and analysis code provided in the complementary [OSF.io repository](#), we successfully reproduced the results of their analysis with only minor deviations due to small technical adjustments. In general, social media analyses frequently blur the distinction between reproduction and replication due to the dynamic nature of platform data and changing access policies resulting in difficulties retrieving consistent datasets over time. Hence, we conducted a robustness check by querying the Twitter/X Batch Compliance API to evaluate how many tweets from the initial dataset remain accessible today. Our "rehydration" attempts exposed substantial limitations in the Twitter/X API, as data retrieval issues arose across both free and paid access tiers, preventing us from re-collecting the original dataset or obtaining reliable estimates of tweet accessibility from the original study. While the study was largely reproducible with the intermediary and aggregated data provided, its full reproducibility and replicability are constrained by restrictive social media platform data access policies.

1. Introduction

Social media has fundamentally transformed political communication dynamics over the past decades, with platforms like Twitter¹ playing a prominent role in disseminating news and shaping public opinion (see, e.g., Crilley & Gillespie, 2019; Zhuravskaya, Petrova, and Enikolopov, 2020). In light of these changes, research has repeatedly raised concerns about the spread of disinformation (e.g., Aïmeur, Amri, and Brassard, 2023), the creation of echo chambers (e.g., Cinelli et al., 2021), and the deepening of ideological polarization (e.g., Kubin and von Sikorski, 2021). Our replication report focuses on a prominent study from this area. The study by Flamino et al. (2023) investigated polarization dynamics on Twitter during the 2016 and 2020 U.S. presidential elections. More specifically, the study used 873 million tweets to analyze shifts in the political landscape of Twitter, focusing on changes in the dissemination of politically biased and fake news, the role of political influencers, as well as patterns of polarization over time.

The original study by Flamino et al. (2023) was motivated by a growing body of literature documenting increasing polarization in the United States. Researchers have observed both issue polarization among political elites, such as elected representatives and news organizations, and affective polarization among voters, characterized by growing partisan animosity. While traditional survey and roll call voting data have limitations in capturing the temporal and relational dynamics of polarization, the rise of social media offers unprecedented opportunities for tracking the diffusion of political information and misinformation on a large scale. Platforms like Twitter, Facebook, and Reddit provide vast data for analyzing how political messages propagate within (and across) social networks, offering insights into various dynamics, such as the spread of disinformation or the emergence of echo chambers.

The study by Flamino et al. (2023) analyzed data collected during the months leading up to the 2016 and 2020 U.S. elections (June 1 to election day: November 8, 2016, and November 2, 2020). The 2016 dataset consists of 171 million tweets from 11 million users,

¹ Since 23.07.2023, the platform formerly known as Twitter has been renamed to X. In this report, we continue to use the name Twitter, as the data originate from a period when the platform was still known by that name. Accordingly, we will use the term “tweets” when referring to posts on the platform.

whereas the 2020 dataset contains 702 million tweets from 20 million users, reflecting a large increase in participation in political discourse on this platform over the four-year period. Tweets were collected using the names of presidential candidates as keywords. The researchers supplemented the datasets with political bias classifications, extracting the domain names of URLs in tweets linking to news media outlets. Each outlet was classified according to its political bias using the bias classification from allsides.com (AS) for outlets with a documented bias rating in their database, and from mediabiasfactcheck.com (MBFC) for others. These classifications were accessed on January 7, 2021, for the 2020 dataset.

To identify key political influencers—users with the highest potential to spread information—the researchers performed a network analysis. They created a similarity network based on the frequency with which users retweeted influencers, using a cosine similarity matrix to quantify the overlap in retweet patterns. This allowed them to construct an adjacency matrix that revealed the connections between influencers based on shared user interactions. The analysis uncovered two primary communities in both election years: one predominantly composed of influencers linked to fake news and right-leaning outlets, and another associated with center and left-leaning outlets. The division between these communities was assessed using metrics such as modularity and normalized cut, which demonstrated a stronger polarization in the 2020 dataset compared to 2016.

The main findings of the original study are both descriptive and comparative. First, the researchers assessed the proportion of fake and extremely biased news content on Twitter between the two elections. Second, they document an increase in echo chamber behaviors and latent ideological polarization among both all users and influencers, operationalized as the degree of separation between the political alignments of content shared by users. The study further found that new influencers emerging in 2020 were more polarized than those active in 2016. Additionally, there was a notable shift in the composition of influencers with a reported decline in those affiliated with news organizations and a rise in those tied to political organizations.

The present replication report aims to computationally reproduce (Dreber & Johannesson, 2023) and validate these findings. By computationally reproducing the original analyses,

this report seeks to assess the reliability of the original study's conclusions and can, thus, also contribute to broader discussions about transparency and rigor in computational social science research. Due to Twitter/X API restrictions, we are unable to replicate Flamino et al.'s data collection process. Consequently, we are also unable to reproduce their data pre-processing pipeline.

2. Data and material availability

a. Reproduction restrictions

Twitter has implemented various regulatory and technical limitations which, in turn, influence the possibilities of reproduction (see Breuer & Haim, 2024 for a discussion of this issue). Importantly, the raw Twitter data cannot be shared according to the platform's own terms of services. The initial data in 2016 and 2020 was collected via Twitter's so-called Firehose API which has been shut down since.² Moreover, after the acquisition of Twitter by Elon Musk and changes in its policies, Twitter has implemented significant changes in its API access, including pricing and usage restrictions. The Firehose API is no longer available under the same conditions, and access now typically comes through specific commercial partnerships or premium API tiers. However, as has been critically observed in similar public-private collaborations, such partnerships may undermine the independence of academic research (Breuer et al., 2020; Wagner, 2023).

A common way of addressing the data sharing limitations that is also used by Flamino et al. (2023) involves sharing the tweet IDs from the original sample, enabling replicators to selectively re-query these tweets via the API in a process known as rehydration. However, given the current pricing structure of Twitter's API, this approach seems highly impractical: A quick back-of-the-envelope calculation shows that re-querying the original data used by Flamino et al. (2023) via the Twitter API under the new financial and access restrictions would cost approximately: $873.000.000 \text{ tweets} / 1.000.000 \text{ tweets per month (read-limit at the Twitter-API at the "Pro" access tier)}^3 * 5.000 \frac{\$}{\text{month}} = 4.365.000\$$. With the rate limits

² See <https://developer.x.com/en/updates/changelog>.

³ See access level "pro": <https://developer.x.com/en/products/x-api>.

in place at this level of API access, it would also take roughly 72,75 years [(873.000.000 tweets / 1.000.000 tweets per month) / 12 months] to recollect the full data. Even if a team of researchers had such time and financial resources, research has shown that re-collecting tweets often results in a significant loss of the original sample (Pfeffer et al., 2022) — this can amount to even up to 45% of the data (Knöpfle & Schatto-Eckrodt, 2024). This issue is especially pronounced when dealing with datasets that include discussions on sensitive and polarizing topics (Assenmacher et al., 2023; Küpfer, 2024). Given the steep costs, the extensive time required to re-query the data, and the very low likelihood of achieving full rehydration success, this method is unlikely to be a feasible option for replication analyses that involve larger Twitter data sets.

So, on one hand, the inability to share raw materials limits the capacity to re-run analyses, a key aspect of reproduction. On the other hand, relying on rehydration allowed for by the platform's terms of service, leads to systematic data loss, aligning more closely with a conceptual replication. Consequently, while our analysis falls within the scope of systematic replications, we classify our approach as a computational reproduction (see Dreber & Johannesson, 2024).

b. Data and Code Availability in Flamino et al. (2023)

Flamino et al.'s (2023) [OSF.io repository](#) contains all the analysis code necessary to computationally reproduce their analysis and generate the six figures that summarize the central findings of their study. The repository includes 26 Python scripts, 10 R files, as well as C and Cython source files, all of which are essential for reproducing their results. However, due to restrictions on sharing raw Twitter data (as noted above), Flamino et al. (2023) opted to share an anonymized and processed version of their dataset. This dataset contains the following information: tweet ID, user ID, date and time of the tweet, political orientation, and information about whether the tweet came from an official/unofficial source. The unzipped text file containing just the tweet IDs themselves is roughly 16 GB in size. Table 1 provides a summary of the materials provided via the OSF repository.

As their analysis is very computationally intensive, it is important and commendable to note that Flamino et al. (2023) provide intermediary outputs of their calculations when feasible, such as network models, summarized data, and other analysis artifacts. We reproduced Flamino et al.'s (2023) analysis on a Windows desktop computer with the following specifications: Windows 11 Pro 64-Bit, Intel i9-10900 3.7 GHz with 20 cores, and 32GB RAM. The replication took place between July and November 2024. The reproduction was performed with Python (V. 3.12.3) and R (R. 4.3.3).

	Fully	Partial	No
Raw data provided		x	
Processing code provided			x
Analysis data provided		x	
Analysis code provided	x		
Intermediary data output	x		

Table 1 Reproduction material availability

c. Contact with the original authors

The initial OSF repository for this study included almost all necessary materials for reproduction. There only was a minor issue with limited access to the linked 2020 data set. To resolve this issue, we reached out to the original authors via the Institute for Replication and the original authors provided assistance that addressed the specific problem in a timely manner. Shortly after this, the authors also made several updates to the OSF repository, including revisions to the code, data organization, and documentation. These updates resulted in significant improvements in the usability of the repository for our replication/reproduction. Notably, only with the revised materials, we were able to successfully reproduce the study's results as described in the following.

3. Computational reproduction of Flamino et al. (2023)

Flamino et al. (2023) present the majority of their findings through six key figures in their paper. In our reproduction attempt⁴, we successfully replicated five of these figures. Our table 2 summarizes our reproduction process of the figures from Flamino et al. (2023), detailing the data basis, reproduction changes (such as file-path adjustments and encoding modifications), and the success of each reproduction, with corresponding deviations and minor issues noted for figures where this applies.

We present our reproduced versions of these figures in the following. We were unable to reproduce Figure 2, which is a Sankey diagram. The issue appears to stem from compatibility problems with the underlying chart rendering libraries in our computational environment. Additionally, we found minor differences across the news categories for Figure 1. These differences are relatively small and do not affect the conclusions, given the large volume of data involved. Considering the sheer size and computational complexity of the project the reproduction process overall went smoothly, requiring only minor adjustments to account for differences in computing environments and technical

⁴ For code and other materials used in our reproduction, see <https://osf.io/a4uxk/>.

specifications, such as file path modifications, additional library installations, and file renaming.

The most common adjustments involved modifying file paths to adapt from a Unix-based system (used in the original analysis) to a Windows-based system, including converting relative paths to absolute paths. Encoding changes were also required to ensure data compatibility. Beyond these basic adjustments, additional changes were necessary to address library and dependency issues. These included, for example, updating specific dependencies (e.g., updating the floweaver Python library from version 2.0.1 to 2.1.0), resolving widget rendering errors, and correcting minor typos in the OSF folder names (e.g., changing 'ulrs' to 'urls'). In some cases, we needed to rename files for consistency with the provided scripts (e.g., renaming `sim_network_large_2020_anon.pkl` to `sim_network_large_2020.pkl` and similarly for the 2016 file).

We also encountered and resolved a few library-specific conflicts on our machine. For instance, the Python library `python-louvain` required reinstallation to avoid name space conflicts, and the R package `Matrix` had to be installed separately to ensure proper functionality.

Overall, the minor nature of the adjustments we made underscores the robustness of the original analysis, as the majority of the results could be reproduced without substantial changes. This experience also serves as a reminder of the technical challenges that can arise when reproducing complex computational social science research across different computing environments, even when the original materials are well-prepared and publicly available. Some minor lack of information about the original authors' computational environment is also in line with more systematic evaluations of study reproducibility (Artner et al., 2021; Chan et al., 2024).

Figure #	Figure Title	Data basis	Reproduction changes	Reproduction Success?
Figure 1	Distribution of news media links in 2016 and 2020 by news media category.	The authors provide an anonymized and pre-processed version of the data.	File-path adjustments from Unix to Windows system.	Yes, see Figure 1 and Tables A1 and A2 in the appendix for deviations from the author-provided values. Reproduction successful with minor adjustments.
Figure 2	Shifts of users across news media categories from 2016 to 2020.	Intermediary data provided.	File-path adjustments from Unix to Windows system, encoding changes.	No, the Python script for generating the Sankey diagram does not render properly in our computational environment.
Figure 3	Reshuffling distribution of the top 25 influencer types from 2016 to 2020, by news media category.	Intermediary data provided.	File-path adjustments from Unix to Windows system.	Yes, see Figure 2.
Figure 4	Change in influencers' rankings from 2016 to 2020.	Intermediary data provided.	File-path adjustments from Unix to Windows system, encoding changes, update of floweaver dependency from version 2.0.1 to 2.1.0, adjusted widget rendering due to programming environment incompatibilities.	Yes, see Figure 3.
Figure 5	Similarity networks for nodes among the top 25 influencers from each news media category for the two election years.	Intermediary data provided.	Corrected a minor typo in the OSF.io folders (ulrs → urls), file-path adjustments, re-import community library because of naming conflict ("pip install python-lovain"), renamed file from "sim_network_large_2020_anon.pkl" to "sim_network_large_2020.pkl" and "sim_network_large_2016_anon.pkl" to "sim_network_large_2016.pkl".	Yes, see Figure 4.
Figure 6	Latent ideology scale of influencers and their retweeters in 2016 (left) and 2020 (right).	Intermediary data provided.	File-path adjustments, additionally installed R library "Matrix".	Yes, see Figure 5.

Table 2 Reproduction success overview

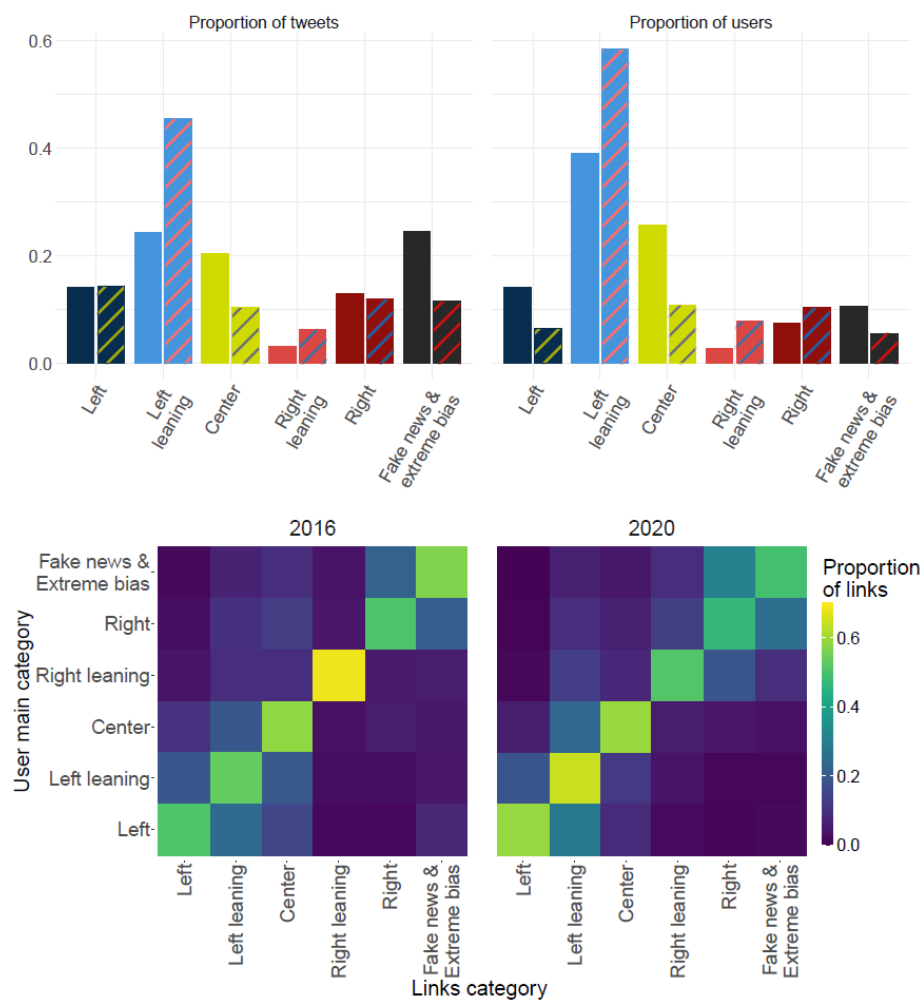


Figure 1 Our reproduction of Figure 1 in Flamino et al. (2023)

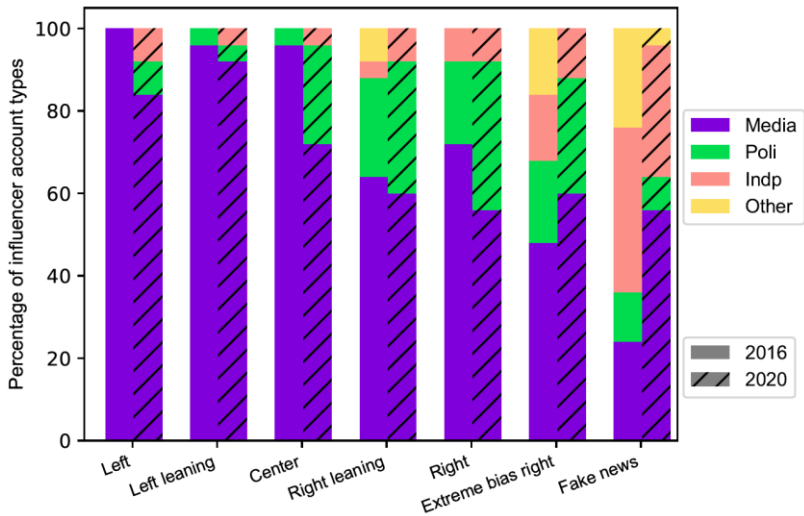


Figure 2 Our reproduction of Figure 3 in Flamino et al. (2023)

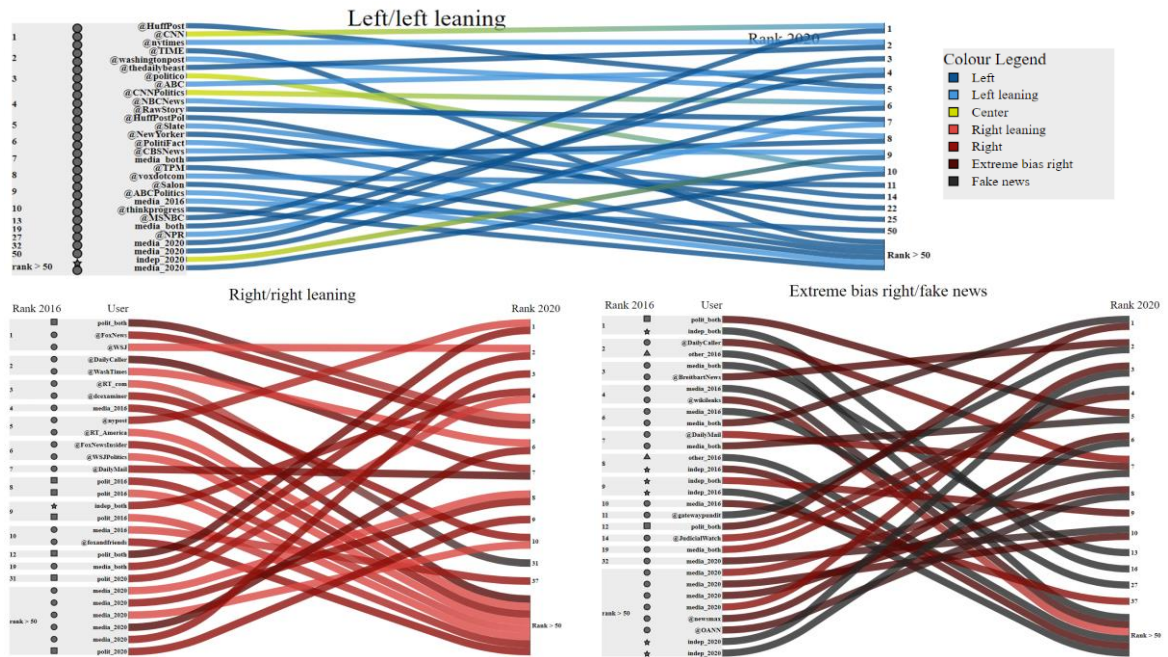


Figure 3 Our reproduction of Figure 4 in Flamino et al. (2023)

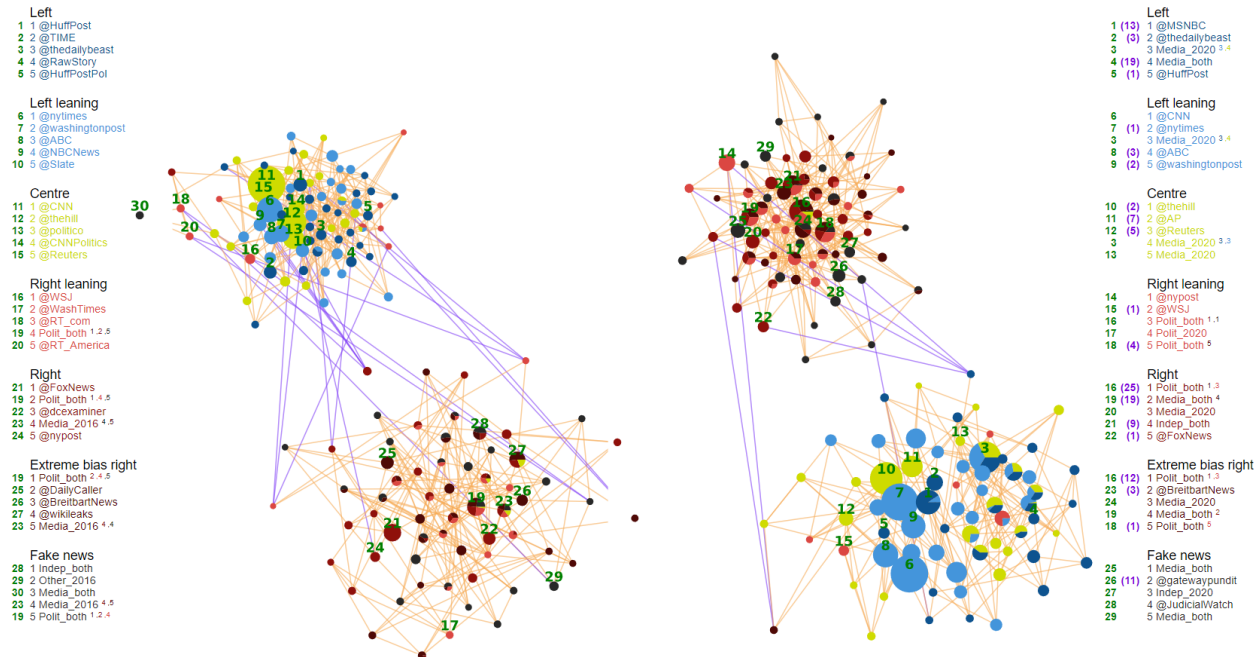


Figure 4 Our reproduction of figure 5 in Flamino et al. (2023)

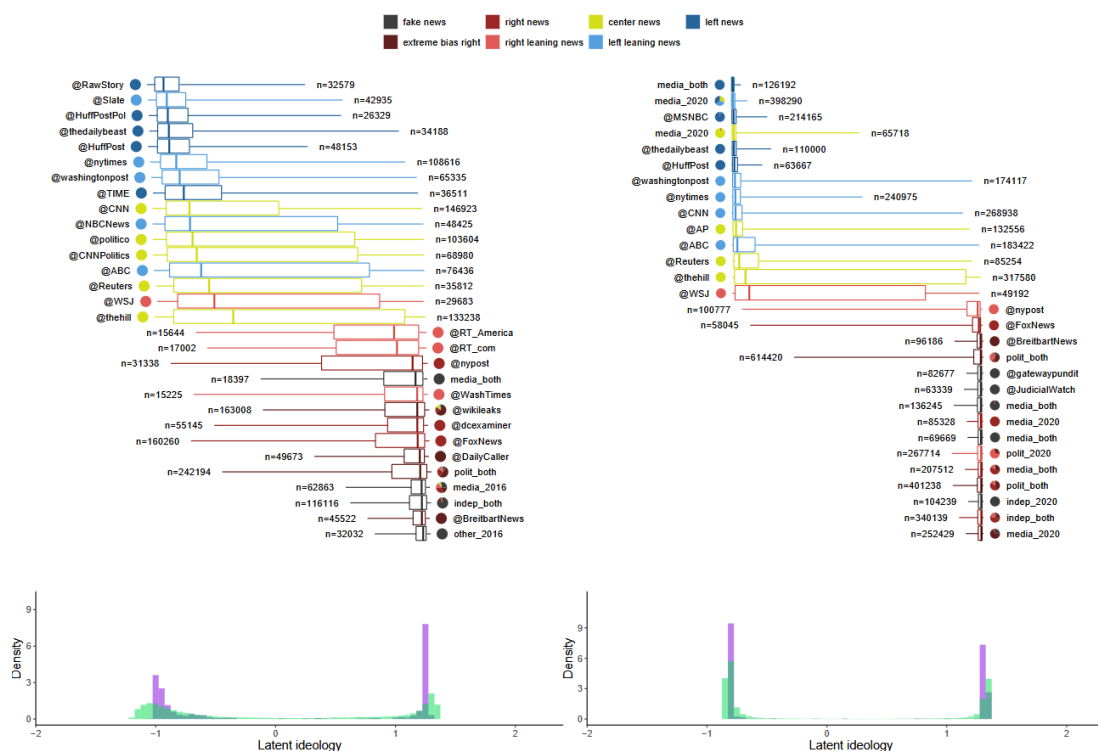


Figure 5 Our reproduction of figure 6 in Flamino et al. (2023)

4. Twitter Rehydration attempt

Performing a complete reproduction or any in-depth replication of Flamino et al.'s analysis requires a re-collection of the original raw data set.⁵ That is, since Twitter/X data cannot be shared for legal reasons, fully replicating each step of their analysis - such as applying the same preprocessing pipeline - requires access to the original data. In the case of Twitter/X data rehydration provides a somewhat cost-efficient approach to achieve this. However, as previously discussed, this is not a feasible option for a research team with moderate resources due to the current restrictions imposed by the Twitter/X API. To demonstrate what a data recollection might yield under today's access conditions, we initially planned to use the Twitter/X Batch Compliance API⁶ to rehydrate a sub-sample of

⁵ For a direct replication, rehydration appears to be the most practical approach, while a conceptual replication would benefit from designing a new data collection strategy.

⁶ See <https://developer.x.com/en/docs/x-api/compliance/batch-compliance/quick-start>. It is important to note that the Twitter Batch Compliance API is not designed for researchers but rather for developers to programmatically ensure datasets remain compliant with Twitter's policies by handling large-scale updates on the status of tweets and user accounts, such as deletions or suspensions.

Flamino et al.'s dataset. The Batch Compliance API allows researchers to evaluate the extent to which their datasets remain intact by identifying tweets or user accounts that have been deleted, made private, or restricted since the original data collection. Researchers submit a batch of tweet or user IDs through the compliance request endpoint of the Twitter/X API. The API then checks each ID against Twitter/X's database to determine its current status—whether it has been deleted, made private, or restricted—and returns a compliance status for each ID, helping researchers assess the availability of the data (Knöpfle & Schatto-Eckrodt, 2024). While this allows us to hypothetically gauge the current accessibility of the data, it does not replace a full re-collection of the dataset.

We attempted to connect to the API under the free access tier in July and December 2024. In July 2024, we were unable to receive any response from the API or submit requests. However, in December 2024, we successfully queried the API, but received empty fields where tweet statuses were expected, a common issue reported with the API⁷. Notably, in December, the API had previously introduced a rate limit across all access tiers, restricting the frequency of queries. We also tested the API under the paid “Basic” access tier⁸. Although we were able to connect and send requests to the API, we still encountered issues with retrieving the expected data. Therefore, under the current access conditions, not only are we unable to actually re-collect the data, but we were also unable to assess the number of tweets that would potentially be re-collectable.

Overall, our attempts to rehydrate the dataset under the current API access conditions highlight the challenges researchers face in reproducing and replicating social media-based studies, underscoring the limitations imposed by evolving platform policies and access restrictions and the assessment made by Davidson et al. (2023) that “Platform-controlled social media APIs threaten open science”.

⁷ See <https://devcommunity.x.com/t/batch-compliance-getting-empty-response/158801>, <https://devcommunity.x.com/t/batch-compliance-endpoint-returning-incomplete-results/225311>, <https://devcommunity.x.com/t/batch-compliance-not-returning-expected-result-for-deleted-tweets/179554>, <https://devcommunity.x.com/t/batch-compliance-results-highly-inconsistent-with-tweet-lookup/171605>, <https://devcommunity.x.com/t/batch-compliance-getting-empty-response/158801>,

⁸ See <https://developer.x.com/en/products/x-api>.

5. Conclusion

We were able to successfully computationally reproduce the findings of Flamino et al. (2023) by recreating five out of six key figures from their analysis of Twitter dynamics during the 2016 and 2020 U.S. presidential elections based on the data, code, and additional materials provided by the authors via their OSF repository. Minor discrepancies in Figure 1 were negligible, while Figure 2, a Sankey diagram, could not be reproduced due to rendering library compatibility issues in our computational environment.

Overall, the reproduction required only minor adjustments, such as modifying file paths, correcting typos, addressing encoding issues, and updating software dependencies. These adjustments were primarily related to differences in computing environments and did not reflect issues with the original materials. The authors' provision of intermediary data outputs and detailed code was instrumental in facilitating the process, offering an effective approach to replicating Twitter/X studies where data sharing is restricted for legal reasons.

The outcomes of our endeavor underscore both the robustness of the original analysis as well as the importance of comprehensive, well-documented materials in computational social science research. It also further highlights ongoing challenges posed by changing data access policies for platform APIs and software dependencies, emphasizing the need for transparent and accessible data access and research practices.

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Appendix

Table A1. Minor reproduction differences for Flamino et al.'s (2023) figure 1, year 2016.

News Category	Replicated unique users 2016 (N_rep)	Unique users 2016 (N)	Absolute difference (N_rep – N)	Relative Difference (%) ((N_rep – N)/N)*100
Fake & extreme bias (N_u)	244986	244971	-15	-0.0061
Right news (N_u)	175445	175519	-74	-0.0422
Right leaning news (N_u)	64055	63903	152	0.2378
Center news (N_u)	596776	596951	-175	-0.0293
Left leaning news	901643	901885	-242	-0.0268
Left news (N_u)	326901	326577	324	0.0992
Fake & extreme bias (p_u)	0.1060635	0.106057	0.0000065	0.0061
Right news (p_u)	0.0759566	0.07598863	-0.00003203	-0.0422
Right leaning news (p_u)	0.02773177	0.02766596	0.00006581	0.2379
Center news (p_u)	0.2583663	0.2584421	-0.0000758	-0.0293
Left leaning news (p_u)	0.3903544	0.3904592	-0.0001048	-0.0268
Left news (p_u)	0.1415275	0.1413872	0.0001403	0.0992
Fake & extreme bias (Nt_Nu)	30.9006	30.90249	-0.00189	-0.0061
Right news (Nt_Nu)	22.98318	22.97349	0.00969	0.0422

Right leaning news (Nt_Nu)	15.7169	15.75428	-0.03738	-0.2373
Center news (Nt_Nu)	10.59402	10.59091	0.00311	0.0294
Left leaning news (Nt_Nu)	8.308548	8.306318	0.00223	0.0268
Left news (Nt_Nu)	13.31901	13.33223	-0.01322	-0.0991
Fake & extreme bias (pu_no)	0.0568808	0.05705573	- 0.00017493	-0.3065
Right news (pu_no)	0.06250962	0.06225537	0.00025425	0.4083
Right leaning news (pu_no)	0.09039107	0.09065302	- 0.00026195	-0.2889
Center news (pu_no)	0.05480951	0.05476999	0.00003952	0.0721
Left leaning news (pu_no)	0.05939269	0.05945104	- 0.00005835	-0.0981
Left news (pu_no)	0.07018945	0.07024377	- 0.00005432	-0.0773
Fake & extreme bias (Ntno_Nuno)	70.91166	70.69858	0.21308	0.3014
Right news (Ntno_Nuno)	39.63217	39.77725	-0.14508	-0.3648
Right leaning news (col 9)	31.78981	31.77335	0.01646	0.0518
Center news (Ntno_Nuno)	38.37378	38.39021	-0.01643	-0.0428
Left leaning news (Ntno_Nuno)	19.2202	19.19618	0.02402	0.1251
Left news (Ntno_Nuno)	26.21368	26.2194	-0.00572	-0.0218

Table A2. Minor reproduction differences for Flamino et al.'s (2023) figure 1, year 2020.

News Category	Replicated unique users 2020 (N_rep)	Unique users 2020 (N)	Absolute difference (N_rep – N)	Relative Difference (%) ((N_rep – N)/N)*100
Fake news (N_u)	99127	99134	-7	-0.0071
Extreme bias right (N_u)	107165	107090	75	0.0701
Right news (N_u)	382251	382704	-453	-0.1184
Right leaning news (N_u)	287938	287895	43	0.0149
Center news (N_u)	398506	398242	264	0.0663
Left leaning news (N_u)	2136945	2136823	122	0.0057
Left news (N_u)	237684	237718	-34	-0.0143
Extreme bias left (N_u)	862	872	-10	-1.1477
Fake news (p_u)	0.02715453	0.02715644	-0.00000191	-0.0070
Extreme bias right (p_u)	0.02935643	0.02933588	0.00002055	0.0700
Right news (p_u)	0.1047126	0.1048367	-0.0001241	-0.1184
Right leaning news (p_u)	0.07887679	0.07886501	0.00001178	0.0149
Center news (p_u)	0.1091654	0.1090931	0.0000723	0.0663
Left leaning news (p_u)	0.5853877	0.5853543	0.0000334	0.0057
Left news (p_u)	0.06511038	0.06511969	-0.00000931	-0.0143
Extreme bias left (p_u)	0.0002361335	0.0002388728	-0.0000027393	-1.1477

Fake news (Nt_Nu)	43.87046	43.86736	0.0031	0.0071
Extreme bias right (Nt_Nu)	37.93048	37.95705	-0.02657	-0.0700
Right news (Nt_Nu)	22.73873	22.71181	0.02692	0.1185
Right leaning news (Nt_Nu)	16.14236	16.14478	-0.00242	-0.0150
Center news (Nt_Nu)	18.99212	19.00471	-0.01259	-0.0663
Left leaning news (Nt_Nu)	15.48625	15.48714	-0.00089	-0.0057
Left news (Nt_Nu)	44.23228	44.22596	0.00632	0.0143
Extreme bias left (Nt_Nu)	46.23782	45.70757	0.53025	1.1601
Fake news (pu_no)	0.006547157	0.006597131	-0.000049974	-0.7575
Extreme bias right (pu_no)	0.008752858	0.008787002	-0.000034144	-0.3884
Right news (pu_no)	0.00777238	0.00776318	0.0000092	0.1185
Right leaning news (pu_no)	0.01196785	0.01185849	0.00010936	0.9222
Center news (pU_no)	0.01743261	0.01740399	0.00002862	0.1644
Left leaning news (pU_no)	0.01709403	0.01713993	-0.0000459	-0.2677
Left news (pU_no)	0.01658925	0.01644806	0.00014119	0.8584
Extreme bias left (pU_no)	0.02436195	0.02522936	-0.00086741	-3.4388
Fake news (Ntno_Nuno)	84.03544	83.39297	0.64247	0.7703

Extreme bias right (Ntno_Nuno)	72.75586	72.52391	0.23195	0.3199
Right leaning news (Ntno_Nuno)	23.23999	23.45782	-0.21783	-0.9285
Center news (Ntno_Nuno)	33.81474	33.8928	-0.07806	-0.2303
Left leaning news (Ntno_Nuno)	22.88401	22.82403	0.05998	0.2628
Left news (Ntno_Nuno)	74.27974	74.90665	-0.62691	-0.8367
Extreme bias left (Ntno_Nuno)	86.52381	82.59091	3.9329	4.7645