Auditing Political Exposure Bias: Algorithmic Amplification on Twitter/X During the 2024 U.S. Presidential Election

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Abstract

Approximately 50% of tweets in 𝕏's user timelines are personalized recommendations from accounts they do not follow. This raises a critical question: What political content are users exposed to beyond their established networks, and what implications does this have for democratic discourse online? In this paper, we present a six-week audit of 𝕏's algorithmic content recommendations during the 2024 U.S. Presidential Election by deploying 120 sock-puppet monitoring accounts to capture tweets from their personalized "For You" timelines. Our objective is to quantify *out-of-network* content exposure for right- and left-leaning account profiles and assess any potential inequalities and biases in political exposure. Our findings indicate that 𝕏's algorithm skews exposure toward a few high-popularity users across all monitoring accounts, with right-leaning accounts experiencing the highest level of exposure inequality. Both left- and right-leaning accounts encounter amplified exposure to users aligned with their own political views and reduced exposure to opposing viewpoints. Additionally, we observe that new accounts experience a right-leaning bias in exposure within their default timelines. Our work contributes to understanding how content recommendation systems may induce and reinforce biases while exacerbating vulnerabilities among politically polarized user groups. We underscore the importance of transparency-aware algorithms in addressing critical issues such as safeguarding election integrity and fostering a more informed digital public sphere.

CCS Concepts

• **Human-centered computing → Collaborative and social computing design and evaluation methods**; **Empirical studies in collaborative and social computing**.

Keywords

Algorithmic bias, Social media auditing, Content recommendation systems, Politics, U.S. Presidential Election, Twitter, X

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1 Introduction

During the 2024 U.S. Presidential Election, social media platforms like 𝕏 (formerly Twitter) play a pivotal role as hubs for political information and public discourse. However, the information users encounter on 𝕏 is increasingly curated by algorithmic recommendation systems that personalize content in their "For You" timelines. As of this writing, 𝕏's "For You" timeline typically consists of 50% *in-network* tweets (i.e., from accounts a given user follows) and 50% *out-of-network* tweets (i.e., from accounts that user does not directly follow)—an increase from the 37% *out-of-network* tweets in 2023 [8].

How does 𝕏's algorithm select relevant tweets from outside a user's network? In 2023, Twitter partially open-sourced its recommendation algorithm, revealing that out-of-network recommendations are sourced through engagement and follow graphs, ranked by a neural network, and refined with heuristics and filters [28]. Despite the increasing prominence of out-of-network tweets in user timelines, much remains unknown about their composition and nature. While prior research has demonstrated amplification of certain political groups and media sources within users' *in-network* tweets, the extent to which such biases extend to *out-of-network* recommendations is unclear. In contexts like the 2024 U.S. Election, examining this issue is essential to understanding how algorithms shape the consumption of online political content and influence users' perspectives.

Research on 𝕏's algorithmic auditing faces a critical challenge in analyzing out-of-network content: While many studies assess amplification by comparing personalized timelines with reverse-chronological timelines as a baseline—where tweets appear in the order they were posted without algorithmic effects [6–8, 20, 29], out-of-network tweets lack a reverse-chronological baseline as users do not follow the authors of those tweets, making it challenging to quantitatively measure exposure bias. To address this limitation, we utilize a "sock-puppet audit," a study design that deploys artificial user accounts with controlled features to systematically capture and analyze platform recommendations [4, 6, 9, 19]. Specifically, we introduce a self-constructed baseline using accounts that follow a politically balanced social media diet, enabling direct comparisons with other manually-created partisan user accounts. This approach is particularly well-suited to studying out-of-network exposure patterns because it allows us to observe algorithmic behavior without the interference of the variations of user behaviors or connections. Furthermore, previous sock-puppet audits on 𝕏 are often constrained by small sample sizes (fewer than 10 accounts) and restricted tweet collection in terms of both quantity and frequency [4, 6, 9], limiting the generalization and robustness of their findings. Our audit aim to implement a more comprehensive data collection strategy, enabling us to systematically observe and analyze algorithmic behaviors on a much larger scale.

Contribution of this work. In this study, we deploy 120 sock-puppet accounts distributed into four groups across the political spectrum[1]—left-leaning, right-leaning, balanced, and neutral—collecting a robust dataset of over 9 million tweets over six weeks from October to November 2024. Within this framework, we systematically evaluate potential exposure biases, such as popularity bias and algorithmic (de-)amplification across account groups.

The contributions of this work can be summarized as follows:

- **We quantify algorithmic exposure to out-of-network content** for accounts with varying political alignments during the 2024 U.S. Election through a sock-puppet audit of 𝕏's personalized timelines.
- **We propose a methodology for evaluating out-of-network (political) exposure biases** by creating a baseline using politically balanced accounts.

We find that 𝕏 skews exposure toward a few high-popularity users for all monitoring accounts, with right-leaning accounts experiencing the most inequality. Both left- and right-leaning accounts encounter amplified exposure to users aligned with their own political stance and reduced exposure to opposing viewpoints. Additionally, neutral accounts who do not follow anybody (akin to a newly-registered user account) show a default right-leaning bias in content exposure. Our findings reveal how content recommendation systems can influence and amplify biases, potentially increasing vulnerabilities within politically polarized user groups. This work underscores the urgent need for transparent algorithms to safeguard the integrity of online discourse and the sovereignty of elections.

2 Background & Research Questions

2.1 Related Work

The impact of algorithmic content curation on political discourse in social media and search engines [24, 26] has been a major focus of research and public debate. Previous studies consistently show that 𝕏's algorithm amplifies political biases and prioritizes high-engagement content, including emotionally charged, toxic, and low-credibility information [4, 6, 8–10, 20]. Researchers have used methods including randomized experiments, sock-puppet audits, crowdsourced audits, and observational data to study 𝕏's algorithmic effects. Some have found that Twitter's algorithms tend to amplify content from right-leaning media sources and politicians more than their left-leaning counterparts [15, 20]. Other studies report increased exposure to ideologically aligned friends [4, 8], but decreased exposure to external links [4, 29]. Studies also observe increased low-credibility content in algorithmic timelines [10], with right-leaning users experiencing higher exposure to such content [9]. Although algorithms are often flagged for promoting ideological bias and political polarization [5], as observed on platforms like YouTube [18, 27], other analyses of 𝕏 and YouTube suggest that its algorithm tends to push centrist content to partisan users [9, 19] and displays a more diverse political mix overall [8, 29].

Despite these insights, the existing literature has a key limitation. Algorithmic timelines consist of two distinct components: the reordering and filtering of in-network tweets and the rendering of out-of-network recommendations. While most studies treat the timeline as a unified entity, making it difficult to disentangle biases between these components, our study focuses explicitly on the latter—out-of-network recommendations—which has received little attention in prior research. Our focus is particularly relevant after Elon Musk's takeover of the platform, as subsequent changes to content moderation and algorithmic priorities [28] may have heightened the impact of out-of-network recommendations on user experiences. In what follows, we outline the algorithmic biases under investigation and introduce our research questions (RQs).

2.2 Exposure Inequality

One significant aspect of algorithmic biases on social media is popularity bias [25]. Algorithms often tend to amplify content from certain users over others, creating inequalities in exposure [7]. For instance, Twitter's ranking algorithm employs a ~48M parameter neural network, which uses thousands of features to score each tweet based on engagement probabilities, prioritizing content with higher likelihoods of interaction in users' feeds [28]. Previous research has shown that popularity biases can lead to a skew in the visibility of tweets when comparing personalized feeds with reverse-chronological ones, and that users are disproportionately exposed to friends' tweets [6, 7]. Yet, it remains unclear whether exposure inequalities extend beyond friends to include a broader set of recommended users. Specifically, we pose the following RQ:

> ***RQ1:*** *To what extent do personalized recommendations in 𝕏 exhibit exposure inequality among our sock-puppet accounts, and how do these inequalities differ based on political leanings?*

2.3 Out-of-Network (De-)Amplification

Another key dimension of bias is ideological bias, particularly its relationship with algorithmic (de-)amplification and selective exposure to political content. Selective exposure is a psychological concept that refers to the tendency of individuals to prefer information that aligns with their pre-existing beliefs, attitudes, or preferences, while avoiding information that contradicts them [16]. Algorithms on social media platforms can amplify this effect by recommending content similar to what users already prefer or agree with, reinforcing selective exposure through personalization [22]. Existing research has produced mixed findings on this issue. On one hand, Bakshy et al. [2] report considerable cross-cutting exposure on Facebook, and Wang et al. [29] find that Twitter/𝕏 provides higher-quality and less ideologically congruent news curation. On the other hand, Haroon et al. [18] trained sock puppets to represent five ideological positions ranging from left to right, and found that YouTube's algorithm consistently promotes ideologically aligned content to partisan users. Given the inconsistency in findings and our focus on algorithmic recommendations, we seek to address the following RQ:

> ***RQ2:*** *Which out-of-network users are (de-)amplified in the timelines of left- and right-leaning accounts compared to balanced accounts?*

[1]Here "left-leaning" and "right-leaning" are used relative to the U.S. political context (Democrats as center-left, Republicans as center-right).

In the next sections, we outline our experimental setup, data collection process, and methodology designed to address our RQs.

3 Methods

3.1 Experimental Setup

We create 120 sock-puppet accounts on 𝕏 divided into four groups based on their political leaning: 30 neutral accounts (default setting, following no one), 30 left-leaning accounts, 30 right-leaning accounts, and 30 balanced accounts. One general concern about sock-puppet audits is ecological validity—whether artificial accounts accurately represent real user behavior and interactions [3, 4, 29]. However, since we are auditing political biases in algorithmic recommendations, which can be influenced by user engagement and community affiliation, it is crucial to control user behavior as much as possible. Previous studies often deploy bots that mimic real-world content consumption by replicating real user follows as "preset" [4, 19]. However, real users often follow diverse, non-political accounts, which could confound our focus on political contents. To address this, we limit our sock-puppet accounts to follow exclusively media, political figures, and entities.

We define the orientation of these sock-puppets based on the accounts they follow. To categorize the political alignment of accounts to follow, we use the AllSides Media Bias Chart,[2] which rates news sources on a spectrum from left to right based on their political bias. Each left-leaning and right-leaning account follows 10 media outlets, including seven outlets with a moderate (center-left or center-right) bias and three with a stronger (left or right) bias, as defined by the AllSides' chart. This selection ensures that these accounts represent a realistic mix of moderately and strongly aligned sources, enhancing the accuracy of our analysis of political exposure. Additionally, left-leaning accounts follow key Democratic figures and entities (Kamala Harris, Tim Walz, House Democrats, and Senate Democrats), while right-leaning accounts follow their Republican counterparts (Donald Trump, JD Vance, House Republicans, and Senate Republicans). Balanced accounts, designed to reflect a centrist perspective, follow five center-left and center-right media outlets and both presidential candidates from each major party. All media follows are randomly selected from the respective groups in the media bias chart, ensuring consistency with each group's intended alignment.

While some studies, particularly on YouTube, allow bots to interact with algorithms (e.g., following recommendations to study radicalization [18, 19]), we refrain from inducing interactions in the current study for several reasons. First, interactions can create feedback loops that distort the algorithm's outputs, making it difficult to isolate baseline biases. Second, interaction-based designs complicate comparisons across accounts, as partisan accounts might engage differently with recommendations, introducing variability that is hard to standardize. Third, our focus is on measuring how algorithms recommend political content based on baseline configurations, such as predefined follows. Unlike radicalization studies, which examine user-algorithm feedback, our goal is to capture inherent biases in the recommendation system, best analyzed without user interactions.

[2] *AllSides Media Bias Chart* https://www.allsides.com/media-bias/media-bias-chart

We also take efforts to mitigate bias in the design of sock-puppet accounts. According to the 𝕏 platform, each account was required to select at least three interests at the time of creation. We use a program to select these interest randomly, alongside random birthdates between 1990 and 1999. To further randomize account attributes and mitigate location-based biases in recommendations, a VPN was used during data collection. These steps ensured consistent and relatively unbiased data capture while adhering to platform constraints.

3.2 Data Collection

We develop a timeline crawler to systematically collect tweets recommended to different types of account profiles in 𝕏's "For You" timeline. The timelines for each account are collected four times daily, yielding approximately 500–700 tweets per session, or about 2,000–3,000 tweets per account per day, within the limits that 𝕏's terms of service impose on new, non-premium accounts. The choice of four daily scraping sessions was made to capture the variability in recommendations throughout the day, as the content recommended by 𝕏's algorithm can shift based on temporal factors like recent events or trending topics. It provides a more comprehensive picture of the algorithmic exposure that users might experience. Data collection spanned from October 2, 2024, one month before the election, to November 19, 2024, two weeks after the election, yielding a dataset of 9.79 million tweets. Figure 5 in the Appendix display the number of active accounts and the total tweets collected daily.

Table 1 provides an overview of the statistics for the collected tweet dataset across different account types. It shows the average proportion of out-of-network tweets that each account type encounters, with neutral accounts seeing exclusively out-of-network content, while the other accounts have 55%-63% of their timelines composed of out-of-network tweets. Additionally, it details the average proportions of retweets, quoted tweets, and promoted tweets observed by each account type.

3.3 Exposure Evaluation Metric

To measure a user's exposure within a timeline, we introduce a metric called "weighted occurrence per 1,000 tweets," defined as the number of times a user's tweets appear per 1,000 tweets in the timeline, weighted by each tweet's visibility according to its rank. This adjustment gives more weight to tweets that appear earlier in one's timeline, as those tweets are also the more likely to be seen by a user and are known to generate more engagements [21]. For each 𝕏 user whose tweet appears in the personalized timelines of our monitoring accounts, the "weighted occurrence per 1,000 tweets" metric is mathematically expressed as:

$$\text{Weighted Occurrence Per 1K Tweets} = \frac{1}{N}\sum_{i=1}^{n} p_i \cdot 1000,$$

where p_i is the probability of exposure related to a specific tweet, n denotes the total number of times the user's tweets appear in the monitoring account's timeline, and N is the aggregate count of tweets in all timelines collected for the monitoring account.

The probability of exposure, p_i, represents the estimated likelihood that a tweet is seen by a real user. Items near the top of a

Table 1: Statistics of the collected dataset (mean values with standard deviations)

Statistic	Neutral	Left	Right	Balanced
Out-of-network tweet	100%	59.23% (7.45)	55.88% (6.66)	62.27% (5.70)
Retweet	0.15% (0.66)	2.93% (1.07)	2.54% (1.35)	2.41% (1.62)
Quoted tweet	1.37% (2.32)	8.67% (2.33)	12.65% (2.90)	11.98% (2.00)
Promoted tweet	1.36% (1.65)	7.43% (0.60)	7.21% (0.68)	7.84% (1.39)

user's social media feed are more visible and thus more likely to be viewed. Following prior work on modeling collective attention on social media [23, 30], we employ an exponential decay function, $p(r) = A \cdot e^{-\lambda r}$, to approximate the probability that a tweet at a given rank r in a timeline will be seen. Each tweet in the sequence is assigned a weight that decreases gradually from 1 towards 0, representing the declining probability of user exposure as the tweet's position moves further down the timeline.

The parameters of the exponential decay function are informed by findings from studies on platforms like TikTok and YouTube [17], which indicate that the top 20% of an account's videos receive more than 70% of the views. Using this as a reference, we assume that the top 20% of tweets in a timeline similarly capture the majority (70%) of user attention, and we calibrate our decay model accordingly. For instance, for a neutral account with an average timeline length of 500, the exponential decay function is defined as:

$$p_{\text{neutral}}(r) = 1.009 \cdot e^{-0.0120 \cdot r}.$$

3.4 Inequality Measure

Gini Coefficient. To measure whether exposure is evenly distributed among users or dominated by a few users, we employ the Gini coefficient, a widely used measure to quantify inequality [7, 13]. The Gini coefficient ranges from 0 to 1, where 0 indicates perfect equality (all users have the same exposure) and 1 signifies maximum inequality (exposure is concentrated among a few accounts). In our specific case, the Gini coefficient G is calculated as:

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |E_i - E_j|}{2n^2 \bar{E}},$$

where E_i and E_j represent the exposure metrics—weighted occurrence per 1,000 tweets—of users i and j in a monitoring account's timeline, n is the total number of users, and $\bar{E}$ is the mean exposure metric across all users. A higher Gini coefficient indicates greater inequality in exposure distribution, suggesting that a small number of users dominate exposure in the timeline, while a lower coefficient suggests a more even distribution among users. To complement this analysis, we use the Lorenz curve [14] as a visual representation of exposure inequality.

3.5 Amplification Measure

To assess the (de-)amplification of specific users in relation to left- and right-leaning monitoring accounts compared to a baseline constructed from balanced accounts, we introduce the "mean amplification ratio," inspired by the work of Huszár et al. [20] on algorithmic amplification.

The mean amplification ratio a_u for a user u, take the example of left-leaning monitoring accounts, is defined by the formula:

$$a_u = \left(\frac{\bar{E}_u^{\text{left}} + 1}{\bar{E}_u^{\text{balanced}} + 1} - 1 \right) \times 100\%,$$

where:

$$\bar{E}_u^{\text{left}} = \frac{1}{|V_{\text{left}}|} \sum_{v \in V_{\text{left}}} E_{v,u},$$

$$\bar{E}_u^{\text{balanced}} = \frac{1}{|V_{\text{balanced}}|} \sum_{v \in V_{\text{balanced}}} E_{v,u}.$$

Here, V_{left} is the set of left-leaning accounts, and V_{balanced} is the set of balanced accounts. $E_{v,u}$ denotes the weighted occurrence per 1,000 tweets of account u in the timelines of account v. This amplification ratio quantifies the extent to which a user's exposure is increased or decreased when viewed by left-leaning monitoring accounts compared to the balanced baseline. A positive *mean amplification ratio* indicates amplification, while a negative ratio indicates de-amplification. The calculation for right-leaning monitoring accounts follows a similar approach.

4 Results

4.1 Out-of-Network Exposure Inequality Among Different Political Profiles (RQ1)

RQ1 explores the extent to which personalized recommendations in 𝕏 exhibit exposure inequality among users and how these inequalities vary between partisan accounts. To address this question, we use the Gini coefficient, a standard measure of inequality that quantifies disparities in exposure by calculating how concentrated exposure is across a set of users. Detailed descriptions of the Gini coefficient calculation and the exposure metric are provided in the Methods section. For each sock-puppet monitoring account, we compute its Gini coefficient with respect to all recommended users in that account's timelines.

Figure 1 presents the distribution of Gini coefficients across different account groups: Left-Leaning, Right-Leaning, Balanced, and Neutral. The average Gini coefficient across all groups exceeds 0.45, which suggests a moderate to high level of inequality in exposure on the 𝕏 platform. Similarly, as shown in Figure 2, the Lorenz curves for all account groups deviate substantially from the line of equality (dashed black line). The greater the curvature of the Lorenz curve, the higher the inequality in exposure. This indicates that algorithmic exposure is concentrated among certain users rather than evenly distributed.

Notably, right-leaning accounts experience the highest exposure inequality, followed by balanced and left-leaning users. The

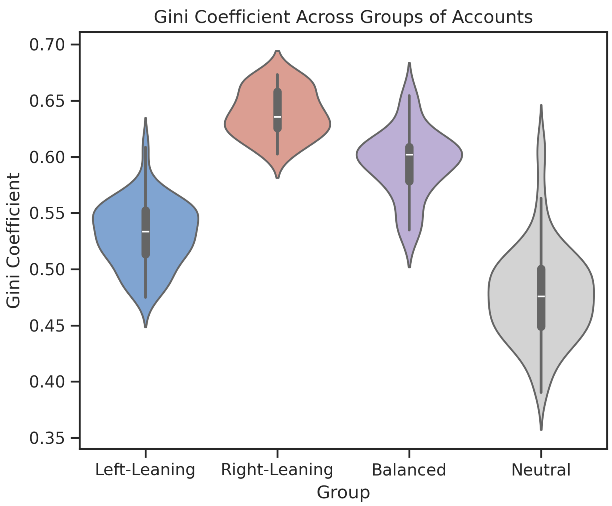

Figure 1: Distribution of Gini coefficient across different groups of accounts. Significant disparities are found in all pairwise comparisons (Mann-Whitney U test: $p < 0.001$), with right-leaning users experiencing the highest out-of-network exposure inequality.

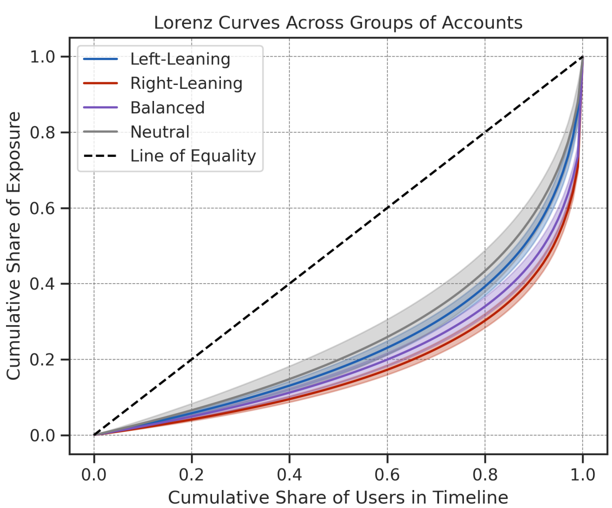

Figure 2: Lorenz curves for different groups of accounts. Each curve represents the average Lorenz curve for all accounts in the group, with error bars indicating the standard deviations at each cumulative point.

Mann-Whitney U test reveals that the differences in Gini coefficients between all pairs of groups are significant at the 0.001 level, underscoring meaningful disparities in exposure inequality across these groups. This suggests that the algorithm's out-of-network tweet recommendations for right-leaning accounts are more centralized, reflecting a stronger popularity bias, where a few users dominate exposure. In contrast, neutral accounts—who do not follow anyone—receive the most diverse recommendations, potentially due to *algorithmic cold start*, i.e., the absence of information about user preferences that typically informs recommendations [31].

Our findings are significant when compared to previous studies that report Gini coefficients of approximately 0.6–0.7 for inequality in exposure to friends' tweets [6]. This suggests that even beyond the friend network, exposure inequality remains at a similar level, indicating that the platform's algorithm amplifies certain accounts both within and outside of users' direct networks.

Now that we understand that out-of-network exposures are skewed toward certain users, an important question arises: *Who are these users?* Here, we are particularly interested in neutral accounts, which provide an unbiased look at the algorithm's default behavior. Since neutral accounts are critical for detecting bias, we took particular care in their setup to ensure neutrality. Neutral accounts follow no other accounts and, therefore, receive exclusively out-of-network recommendations. This configuration limits any bias that could arise from following choices, aiming to capture a baseline view of how the algorithm behaves when no user preferences are specified. However, it is worth noting that certain factors, such as 𝕏's default settings or trending topics, could still introduce slight biases into these recommendations.

Figure 3 displays the top 20 recommended users for *neutral* accounts, ranked by their weighted occurrence per 1,000 tweets. Each box in the boxplot represents the distribution of this exposure metric across all neutral accounts. Boxes are colored red or blue to indicate whether the user is right- or left-leaning, based on publicly available data, including 𝕏 user profile descriptions and external sources such as Wikipedia. A user's political stance is classified as left- or right-leaning if they are affiliated with a political party or a media outlet with a recognized ideological alignment. A qualitative inspection reveals that right-leaning users appear more frequently among the top recommendations than left-leaning users. To quantify this difference, we use the "weighted occurrences per 1,000 tweets" metric: among the top 20 recommended users, right-leaning users make up 30.16% of exposure, compared to 12.92% for left-leaning users. This disparity persists as we expand the pool, with right-leaning users making up 35.26% of exposure in the top 50 (versus 22.34% for left-leaning users) and 31.39% in the top 100 (versus 20.83% for left-leaning users).

Notably, *balanced* accounts receive a roughly even mix of left- and right-leaning recommendations, whereas left- and right-leaning accounts predominantly receive recommendations from ideologically aligned users. In the Appendix, interested readers can find the top 20 recommendations for left-leaning, right-leaning, and balanced account groups, highlighting the most amplified users within each account category. A detailed table describing these users' public information is also provided in the Appendix.

4.2 Differential (De-)Amplification of Political Content Among Partisan Accounts (RQ2)

To address RQ2 and evaluate the amplification of certain users in partisan accounts' timelines, we introduce the "mean amplification ratio" metric inspired by Huszár et al. [20], as detailed in the Methods section. Figure 4 shows the amplification ratio of the top

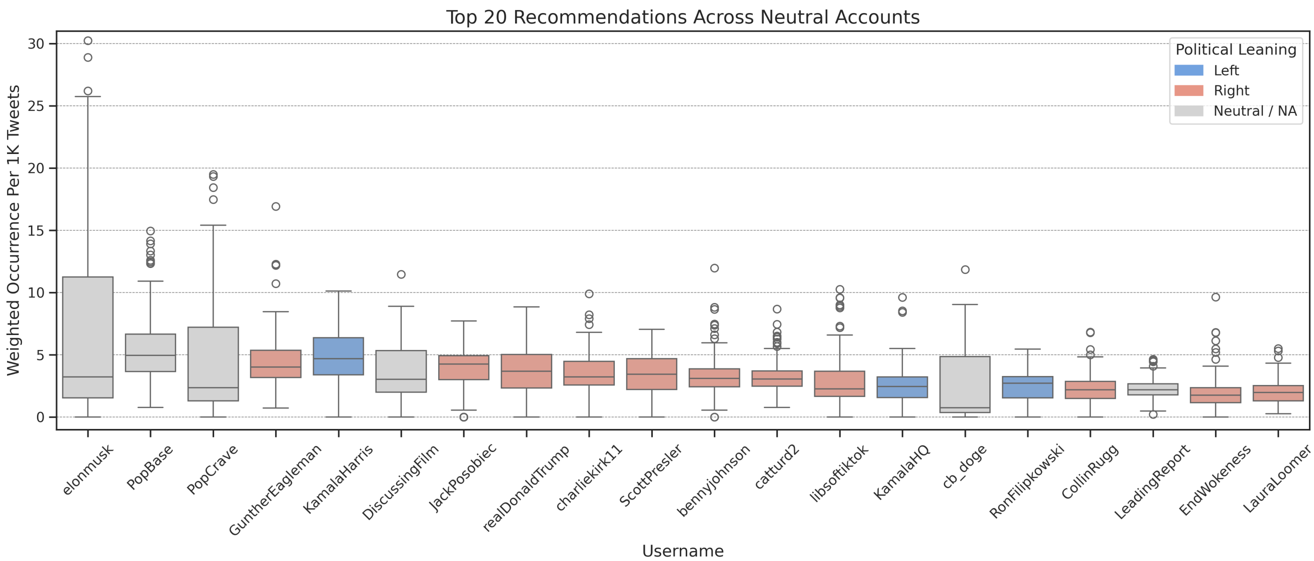

Figure 3: Top 20 recommended users for neutral accounts, ranked by their average weighted occurrence per 1,000 tweets. Each box in the boxplot shows the distribution of exposure across all neutral accounts, with red and blue colors indicating right- and left-leaning users, respectively. The figure suggests that right-leaning users are more frequently recommended than left-leaning users in the algorithm's out-of-network recommendations for neutral accounts.

50 recommended users in left-leaning and right-leaning accounts, compared to a baseline observed in politically balanced accounts' timelines. Colored bars indicate a significant difference in exposure metrics (weighted occurrence per 1,000 tweets) between groups at the 0.05 significance level (using the Mann-Whitney U test), while gray bars indicate no significant difference.

A qualitative inspection reveals that left-leaning sock-puppet accounts tend to see left-leaning users amplified, and right-leaning users de-amplified, with the opposite pattern observed for right-leaning accounts. For instance, in left-leaning accounts, the top three amplified users are *Ron Filipkowski* (a former federal prosecutor known for his criticisms of conservative figures), *Mueller, She Wrote* (a political commentary and investigative journalism account with a liberal stance), and *George Takei* (an American actor, author and Democrat activist). In contrast, the most de-amplified accounts are *Elon Musk* (CEO of Twitter/𝕏, who has recently shared conservative viewpoints), *Charlie Kirk* (a conservative political activist), and *Jack Posobiec* (a right-wing media personality and political activist). This suggests that left-leaning timelines prioritize left-aligned figures while downplaying right-leaning accounts.

On the contrary, for right-leaning accounts, the top three accounts with the highest amplification in right-leaning timelines are *catturd2* (a right-wing influencer known for political satire), *atensnut* (a conservative commentator), and *DC_Draino* (Rogan O'Handley, a right-wing political commentator). Conversely, the most de-amplified accounts are *JoJoFromJerz* (a left-leaning political influencer), *acnewsitics* (a liberal-leaning news commentator), and *Tristan Snell* (a pro-democrat lawyer and legal commentator). This pattern highlights the algorithm's tendency to amplify conservative figures more heavily in right-leaning timelines while reducing exposure to left-leaning accounts.

To further illustrate this trend, usernames are displayed in blue (left-leaning) or red (right-leaning) based on their political stance, which is inferred from publicly available data (may be subject to inaccuracies or changes over time). As shown in Figure 4, top liberal and conservative voices are amplified more than 50% above baseline for left- and right-leaning users, respectively. Given that our sock-puppet accounts only follow a few moderately partisan media and politicians, it suggests that once a new user begins following a few partisan accounts, their algorithmic recommendations quickly become filled with like-minded voices.

Interestingly, we observe that amplified users in left-leaning group experience a slightly higher magnitude of amplification compared to those in right-leaning group (M_{left} = 36.76%, M_{right} = 30.29%, Mann-Whitney U $p < 0.05$). However, there are no significant differences in the extent of de-amplification between the two groups.

5 Discussion & Conclusions

In this study, we present a six-week audit of algorithmic recommendations on 𝕏's "For You" timelines during the course of the 2024 U.S. Election. Using 120 sock-puppet accounts with left-leaning, right-leaning, balanced, and neutral political orientations, we observe that 𝕏 skews exposure toward a select few high-popularity users for all accounts, with right-leaning accounts experiencing the highest level of inequality. Both left- and right-leaning accounts see amplified exposure to users aligned with their political stance, while exposure to opposing viewpoints is reduced. Additionally,

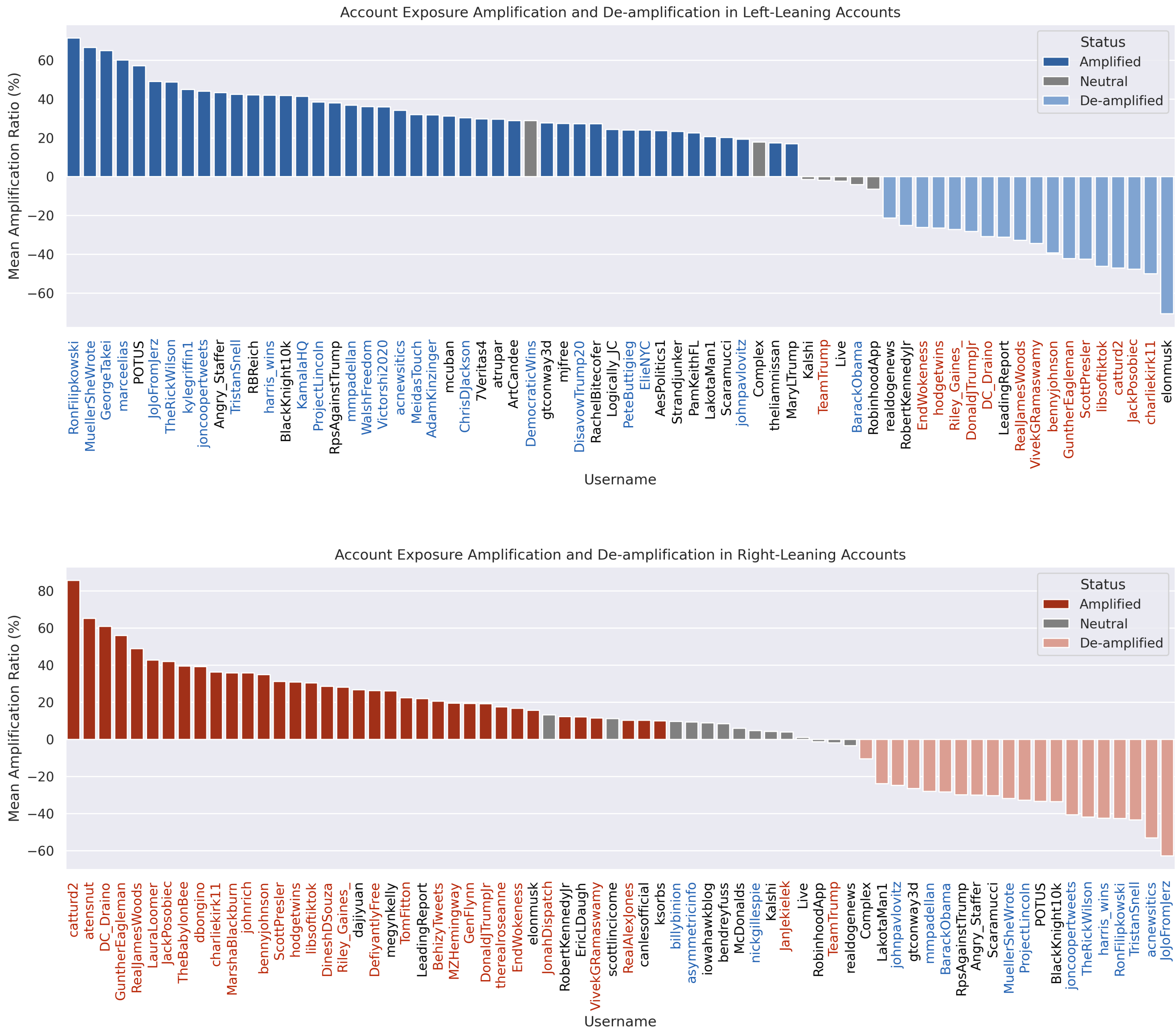

Figure 4: Amplification ratio of the top 50 recommended users in left-leaning (top) and right-leaning (bottom) accounts, compared to the baseline of balanced accounts. Colored bars indicate a significant difference in exposure metrics (weighted occurrence per 1,000 tweets) between the groups at the 0.05 significance level (using the Mann-Whitney U test), while gray bars indicate no significant difference. Usernames are displayed in blue (left-leaning) or red (right-leaning) based on their political stance, according to publicly available data.

analysis of neutral accounts with no follow activity reveals a default right-leaning bias in the platform's recommendations.

Our analysis of exposure inequality aligns with previous studies on algorithmic bias, which have reported similar amplification patterns within users' in-network content [7]. However, our findings diverge from earlier research suggesting that personalized recommendations tend to be more centrist in political stance [8, 9, 29]. This discrepancy perhaps highlights a shift in 𝕏's algorithmic behavior, which might have moved away from promoting moderate content to reinforcing users' existing preferences more explicitly, especially in out-of-network recommendations. The results also add to the growing body of literature indicating that right-leaning accounts are often more prominently featured in algorithmic curation [15], a trend seen here in the default bias toward right-leaning content for new or neutral accounts.

Another noteworthy observation is that, unlike prior research, which has primarily examined the amplification of tweets from media outlets [29] and political figures—especially elected legislators from major political parties [20]—our findings reveal that 𝕏's algorithm now also amplifies political commentators and influencers. This trend is most pronounced in the recommendations for neutral accounts, suggesting a shift in the algorithm's prioritization toward these types of voices. This shift could be influenced by recent claims that 𝕏 prioritizes verified and paid subscription accounts[3], potentially amplifying influencers who invest in these platform features. The prominence of these non-institutional voices in political content raises questions about the influence of individual commentators on public opinion, as their perspectives may carry a more personal or sensational tone compared to traditional media sources. Adding to the concerns, recent investigations uncovered state-sponsored foreign interference operations with financial backing of prominent political influencers.[4] This underscores the need for further examination into how the recommendation algorithm's priorities may shape political engagement and public discourse, especially during critical periods like an election year.

Implications and Future Research. Our research findings offer both theoretical and practical implications regarding the algorithm's influence on echo chambers and the design of transparency-aware content recommendation algorithms. The 𝕏 algorithm's amplification of ideologically aligned out-of-network accounts, along with the reduced exposure to opposing viewpoints, suggests that algorithmic recommendations can reinforce echo chambers not just in the composition of social networks [12] but also in the ideological framing of content circulating in the network. The increased prominence of non-institutional voices, such as verified political commentators and influencers, further exacerbates this issue by potentially introducing sensationalism and misinformation into these echo chambers [11]. Additionally, the default right-leaning bias observed for neutral accounts suggests that new users are likely to encounter partisan content early in their engagement with the platform. This raises concerns about how early algorithmic shaping of timelines might influence political perspectives and preferences. Future research could address these concerns by 1) systematically comparing in-network and out-of-network exposure biases and 2) conducting user studies to investigate how algorithmically curated timelines influence political attitudes over time (see "sociotechnical audit" [29]).

The study also provides practical considerations for designing fair and transparent algorithms. Current recommendation systems appear to disproportionately amplify high-popularity accounts, creating inequality in exposure that may result in less personalized and miscalibrated recommendations for certain user groups [1]. Fairness algorithms could address this by factoring in diversity constraints that balance the exposure of popular and less popular accounts. Platforms should enhance transparency around how algorithms prioritize specific users, particularly verified and paid subscription accounts for the Twitter/𝕏 scenario. Future research should focus on monitoring algorithmic shifts and developing transparency standards during high-stakes periods such as elections, public health crises, and social unrest, where equitable and informed public discourse is critical.

Limitations. We acknowledge several limitations in our research. First, the study is conducted during a six-week period leading up to the 2024 U.S. elections, a politically charged time that may differ from other contexts. This temporal limitation could affect the reproducibility of our results in less politically sensitive periods. Second, we deliberately avoid inducing interactions between sock-puppet accounts and algorithmic recommendations to isolate baseline biases in the recommendation system. Although our sock-puppet auditing method ensures precise control over account behaviors, it does not account for personalization or the dynamics of user activity. Since the sock-puppet accounts do not engage with tweets (e.g., clicking, responding, or retweeting), our study does not capture the effects of user-algorithm interactions on political exposure bias. Third, potential confounding factors, such as pre-selected interests, age, and location, may influence algorithmic recommendations for neutral accounts. While we took care to randomize these settings, their residual effects cannot be entirely ruled out. Forth, the use of balanced accounts as a baseline for measuring exposure biases may not fully capture the platform's broader algorithmic behavior across diverse user demographics or global political contexts, potentially limiting the generalizability of our findings.

Ethical Statement. Throughout our research process, we have adhered to stringent ethical standards to ensure the integrity and societal responsibility of our work. Our sock-puppet accounts were designed solely to follow media and public figures, observe, and collect data, without engaging in any interactions with real users on the 𝕏 platform, thereby avoiding disruptions to other users' experiences. All personal-identifiable information utilized in this study pertains exclusively to public figures and is derived from publicly available data. Additionally, we have carefully considered the societal impacts of our research. To mitigate risks of overgeneralization or misinterpretation, we provide thorough contextual information and openly address the limitations of our findings. While acknowledging these potential risks, we posit that our work could contribute to the development of algorithmic transparency standards and inform platform responsibilities during politically sensitive periods in the long term.

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https://x.com/elonmusk/status/1650731557164818437?lang=en

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A Data Collection Details

Figure 5 display the number of active accounts and the total tweets collected daily. Data collection for neutral monitoring accounts began around October 2, 2024, and reached a stable deployment of approximately 30 active neutral accounts per day on October 11. Left-leaning, right-leaning, and balanced accounts began appearing consistently in the dataset around October 7, with each group reaching a stable count of about 30 active accounts per day shortly thereafter. Each neutral account receives approximately 500 tweets per session, while each left-leaning, right-leaning, and balanced account receives around 700 tweets per session.

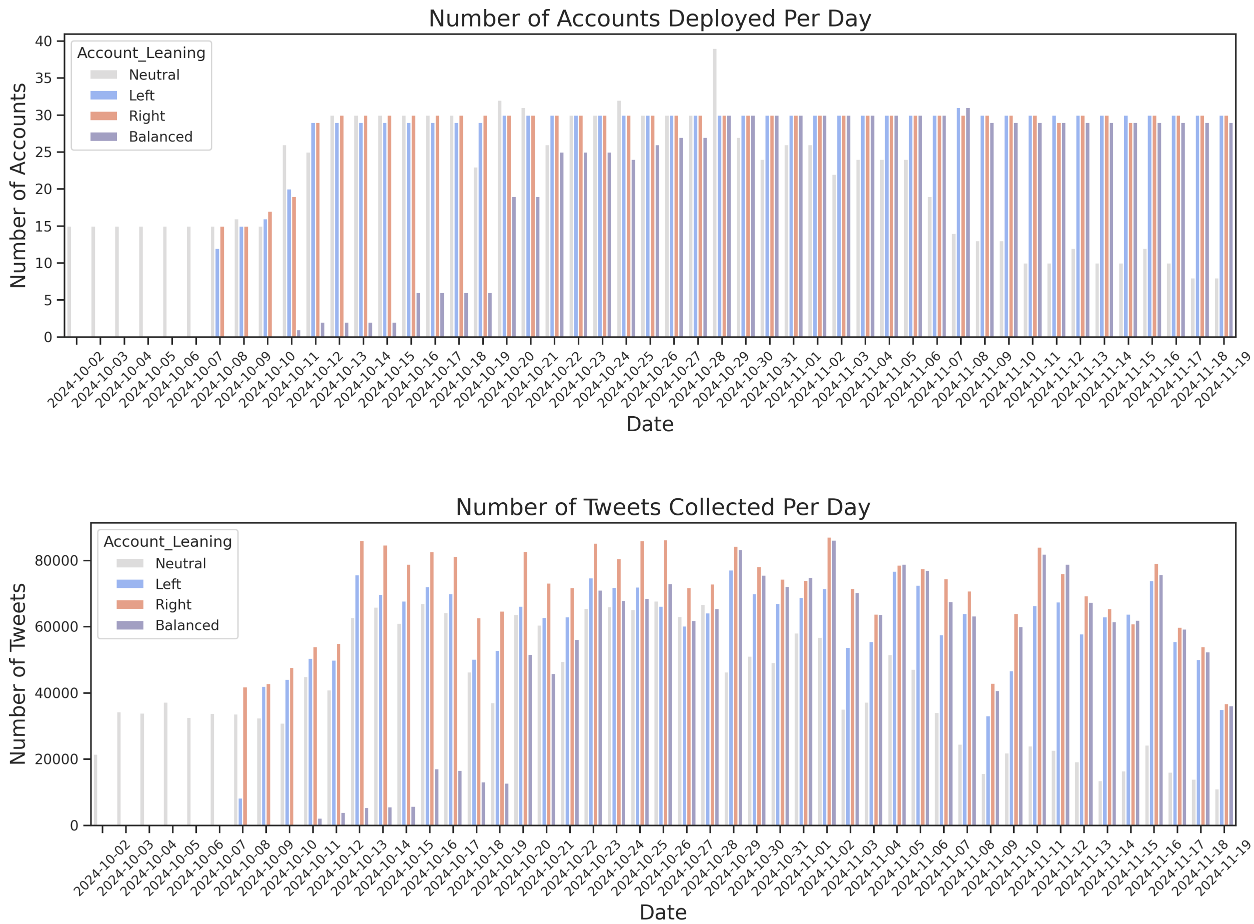

Figure 5: Overview of data collection: (a) Number of active accounts per day, and (b) Number of tweets collected per day.

Technical Considerations for Neutral Accounts. Managing neutral accounts presented several challenges during data collection. For accounts that followed no users, 𝕏 disabled the timeline after 7 days, requiring us to create additional neutral bots to maintain at least 30 active accounts daily. However, during the election period, the platform temporarily modified this restriction, disabling the timeline immediately after account creation for accounts that followed no users. Consequently, data collection was limited to approximately 10 older neutral accounts after November 5.

B Top Recommended Users in Left-Leaning, Right-Leaning, and Balanced Accounts

Figure 6, figure 7 and figure 8 display the top 20 recommended users in left-leaning, right-leaning, and balanced accounts, ranked by their average weighted occurrence per 1,000 tweets. Each box in the boxplot represents the distribution of exposure across all accounts in each group, with red indicating right-leaning users and blue indicating left-leaning users. Political leanings of users are inferred based on publicly available data, which may be subject to inaccuracies or changes over time. Notably, balanced accounts receive a roughly even mix of left- and right-leaning recommendations, whereas left- and right-leaning accounts predominantly receive recommendations from ideologically aligned users.

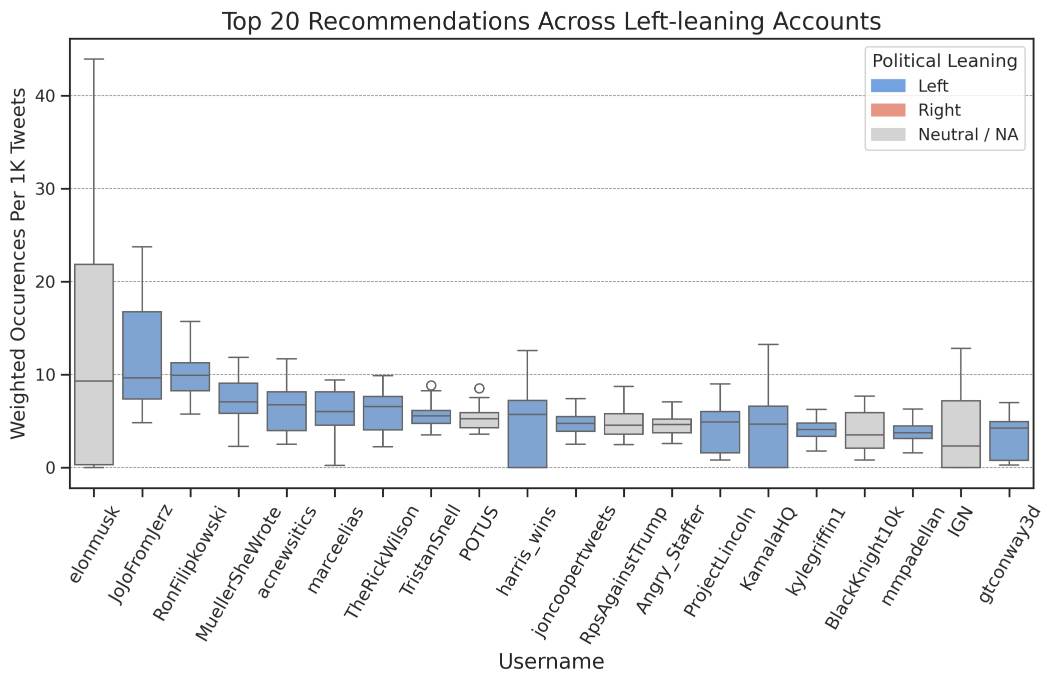

Figure 6: Top 20 recommended users in left-leaning accounts.

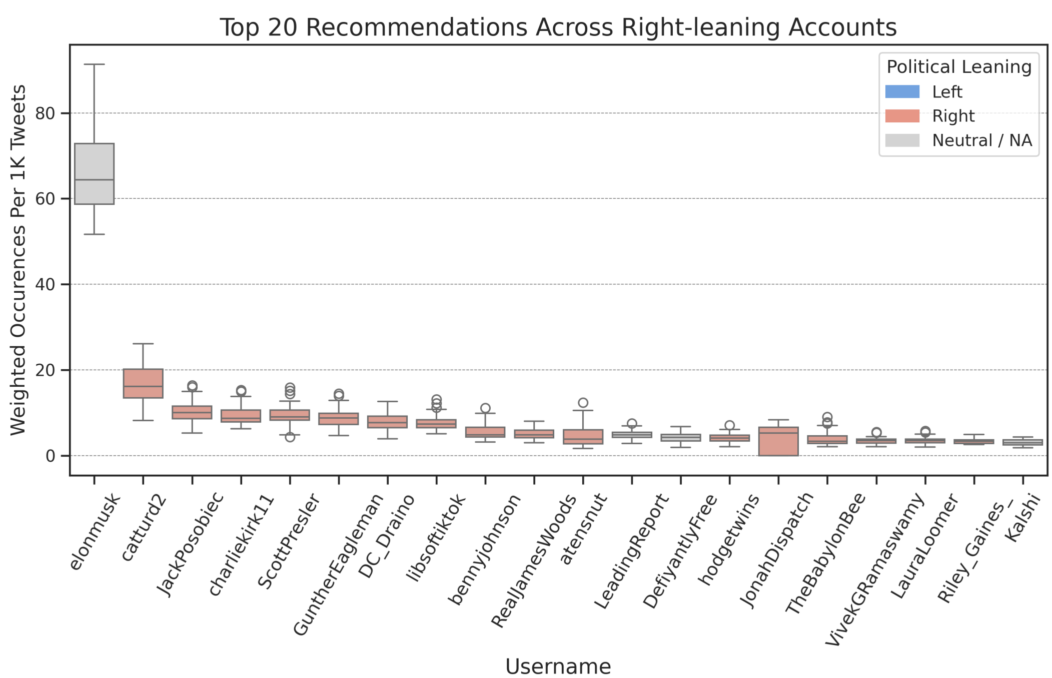

Figure 7: Top 20 recommended users in right-leaning accounts.

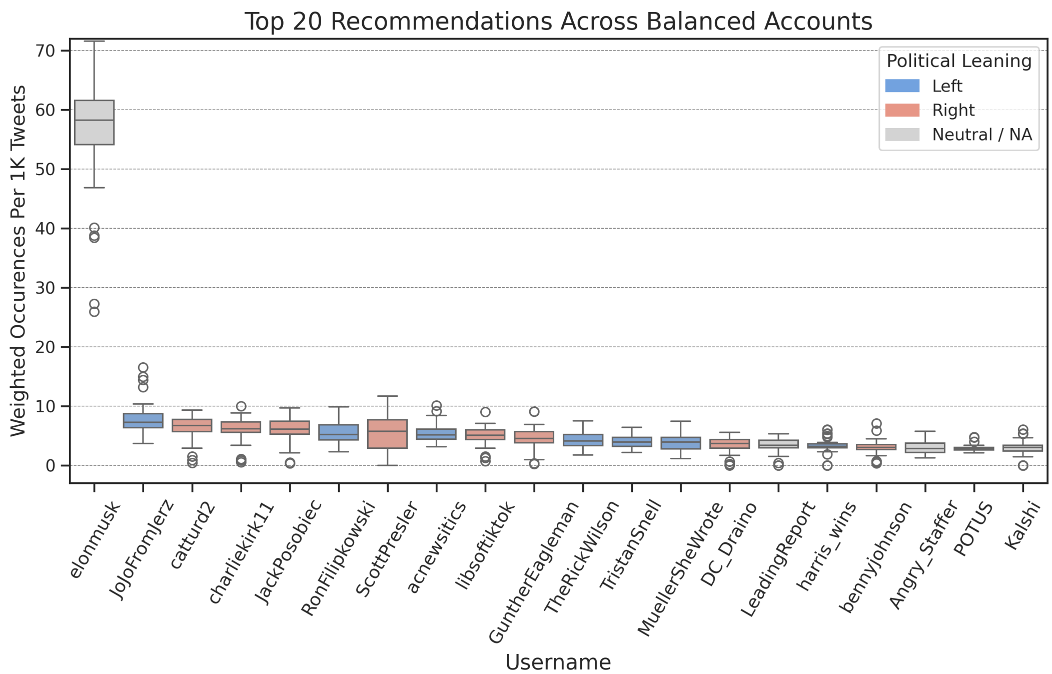

Figure 8: Top 20 recommended users in balanced accounts.

C Profile Information of the Top Recommended Users

Table 2 presents the profile information of the top 30 out-of-network recommendations across all account groups combined, sorted in descending order by the number of followers for each user. Note that, for left-leaning, right-leaning, and balanced accounts, top recommendations exclude media and politician accounts they already follow.

Table 2: Profile information of top out-of-network recommendations across all groups of accounts

Index	Username	Screenname	Profile Description on 𝕏	# of Followers
1	elonmusk	Elon Musk	Read @America to understand why I'm supporting Trump for President	202742780
2	BarackObama	Barack Obama	Dad, husband, President, citizen.	132026578
3	realDonaldTrump	Donald J. Trump	45th President of the United States of America	92023938
4	POTUS	President Biden	46th President of the United States, husband to @FLOTUS, proud dad & pop.	36825725
5	KamalaHarris	Kamala Harris	Fighting for the people. Wife, Momala, Auntie. She/her. Official account is @VP.	21259465
6	AdamSchefter	Adam Schefter	ESPN Senior NFL Insider. Interview & Podcast Requests: ESPNPR@espn.com Host of the Adam Schefter Podcast https://t.co/oz43ix5jZU	11319193
7	Live	Live		9024660
8	mcuban	Mark Cuban	Dunking on the pharma industry with @costplusdrugs.com, the lowest prices on meds anywhere. check it out !	8959820
9	dbongino	Dan Bongino	Public Enemy #1	5881895
10	historyinmemes	Historic Vids	Daily history lessons. Education through memes!	5451424
11	AMAZlNGNATURE	Nature is Amazing	Animals Nature Discovery	4496570
12	RealJamesWoods	James Woods	Please enjoy our inaugural YouTube video about the creation of my album with Shooter Jennings, right here: https://t.co/N1RReBLopn	4271926
13	TheBabylonBee	The Babylon Bee	Fake news you can trust. January 6: The Most Deadliest Day— now streaming!	4217074
14	RobertKennedyJr	Robert F. Kennedy Jr		4110129

Index	Username	Screenname	Profile Description on 𝕏	# of Followers
15	PeteButtigieg	Pete Buttigieg	Personal account. For official updates, follow @SecretaryPete. Husband, father, veteran, writer, South Bend's former Mayor Pete. (he/him)	3876190
16	charliekirk11	Charlie Kirk	Founder & CEO: @TPUSA • @TPAction_ • Host: The Charlie Kirk Show • Click the link below to subscribe	3689713
17	libsoftiktok	Libs of TikTok	News you can't see anywhere else. submissions@libsoftiktok.com. DM submissions. Bookings: Partnerships@libsoftiktok.com. Subscribe to our newsletter	3619947
18	InternetH0F	internet hall of fame	the internet just wouldn't be the same without these iconic posts.	3360230
19	megynkelly	Megyn Kelly	Happily married to Doug, crazy in love with my children Yates, Yardley, and Thatcher, journalist.	3278907
20	catturd2	Catturd ™	The turd you can't flush.	3054117
21	ProjectLincoln	The Lincoln Project	"You cannot escape the responsibility of tomorrow by evading it today." – Abraham Lincoln | Home of #TheBreakdown and LP Podcast	2994780
22	hodgetwins	Hodgetwins	Merch & Giveaways at: https://t.co/kxb8qjGCDW —— PODCAST: @thetwinspod	2993141
23	bennyjohnson	Benny Johnson	i make internet	2937906
24	JackPosobiec	Jack Posobiec	Sr Editor, @HumanEvents. Veteran Navy intel officer. Catholic. NYT Bestselling Author	2809915
25	gtconway3d	George Conway	President and Executive Director of @PsychoPAC24, the Anti-Psychopath Political Action Committee. President, @chkbal. Contributor, @TheAtlantic.	2396447
26	unusual_whales	unusual_whales	Stocks/Options/Crypto/Market News + Tools. Not advice Get $50-$5000 to trade: https://t.co/wGf2ZdlXpw Discord: https://t.co/0xJ9e0ZYYG More: https://t.co/nsxZlPV0pC	1901961
27	PopCrave	Pop Crave	Craving Pop Culture.	1884374
28	DC_Draino	DC_Draino	Rogan O'Handley	1855070
29	DiscussingFilm	DiscussingFilm	Your leading source for quick reliable news. Home for healthy and liberating discussion on all things pop culture. (Amazon links shared may earn us commissions)	1835626
30	ScottPresler	ThePersistence	I helped defeat Hillary, Cheney, & organized the Baltimore cleanup. My goal is to re-elect President Trump. Check out @EarlyVoteAction MAGA MAHA	1776345
31	TheRickWilson	Rick Wilson	Lincoln Project. Award-winning ad-maker. Writer. Instrument-rated pilot. NYT #1 best-seller. Still got the shovel. Writing: https://t.co/e04n749N5H	1698059
32	PopBase	Pop Base	Pop Base is your best source for all pop culture related entertainment, news, award show coverage, chart updates, statistics and more. | email@popbase.tv	1683990
33	CollinRugg	Collin Rugg	Co-Owner of Trending Politics | Investor | American	1561596
34	atensnut	Juanita Broaddrick	Author, "You'd Better Put Some Ice On That" retired RN & business owner, Speaker.	1455919
35	KamalaHQ	Kamala HQ	Providing context.	1416761
36	kylegriffin1	Kyle Griffin	Executive Producer @TheWeekendMSNBC. Opinions mine. Do not congratulate. THREADS @griffinkyle	1409244
37	joncoopertweets	Jon Cooper	Ex: LI Campaign Chair for Barack Obama; National Finance Chair of Draft Biden; Majority Leader of Suffolk County Legislature. Gay dad of 5 kids. #YesWeKam	1391095
38	LauraLoomer	Laura Loomer	Investigative Journalist Free Spirit Founder of LOOMERED. Host of @LoomerUnleashed Former @Project_Veritas operative. America First Feisty Jewess	1364113
39	Tim_Walz	Tim Walz	Running to win this thing with @KamalaHarris.	1311484
40	Riley_Gaines_	Riley Gaines	Host of Gaines for Girls podcast | Author of Swimming Against the current | TPUSA contributor | Director of the Riley Gaines Center	1283591
41	MeidasTouch	MeidasTouch	The official account of the MeidasTouch Network. Unapologetically pro-democracy.	1239469
42	RexChapman	Rex Chapman	It's Hard For Me to Live With Me is available now. For speaking inquiries please contact Jornstein@wmeagency.com	1221843
43	AdamKinzinger	Adam Kinzinger	Proud RINO, dad, Husband, Lt. Col in @AirNatlGuard, CNN Senior Political Commentator, former Congressman, founder @thecountryfirst	1082499
44	Scaramucci	Anthony Scaramucci	Entrepreneur @SkyBridge. Host, Open Book and @RestPoliticsUS. https://t.co/t4SOzQjxuy	1077632
45	JoJoFromJerz	Jo	mom. jersey. dem. news junkie. Lebanese. hothead.views are my own.https://t.co/zueo7YDFWx https://t.co/q4qgmwRLzt. https://t.co/9Fp1kdOX6w	1029714
46	RonFilipkowski	Ron Filipkowski	Editor-in Chief https://t.co/HLS0hEHY1C, Co-host Uncovered, Attorney, Marine, Former Federal and State Prosecutor, Republican Party Insane Asylum Escapee	1021928

Index	Username	Screenname	Profile Description on 𝕏	# of Followers
47	GuntherEagleman	Gunther Eagleman™	Political Commentator - America First - MAGA - Trump 2024 - Unfiltered	1011785
48	atrupar	Aaron Rupar	journalist. sign up for my newsletter, Public Notice (link below). Powered by @SnapStream (more info: https://t.co/2oHPuuFBnN).	987623
49	Dexerto	Dexerto	The leading source for influencer, streamer, gaming, and viral content	980351
50	cb_doge	DogeDesigner	UX/UI & Graphic Designer at Dogecoin & MyDoge Inc./ Citizen Journalist	935600
51	marceelias	Marc E. Elias	Founder @DemocracyDocket. Chair @EliasLawGroup. My dog's name is Bode.	899982
52	RpsAgainstTrump	Republicans against Trump	Pro-democracy conservatives Republicans fighting Trump & Trumpism. Please support our work: https://t.co/FkmisNic4X	821564
53	MuellerSheWrote	Mueller, She Wrote	DONATE to Kamala Harris: https://t.co/gOvFmy1bYN Subscribe to my FREE newsletter	803719
54	harris_wins	Kamala's Wins	Keeping Score of Kamala Harris' wins. The largest online community supporting soon to be President Kamala Harris	790310
55	LeadingReport	Leading Report	Leading source for breaking news.	630544
56	Angry_Staffer	Angry Staffer	Not a WH Staffer | Politics, NatSec, and Snark - Your Mileage May Vary | Subscribe to my Patreon newsletter for free: https://t.co/Kj4zTIcPyk |	609103
57	TristanSnell	Tristan Snell	Lawyer, legal commentator, fighter for democracy. Prosecuted Trump University @ NY AG. Commentator, MSNBC. Creator of book/podcast/newsletter TAKING DOWN TRUMP.	583266
58	7Veritas4	Jack E. Smith	"Whatever you are, be a good one". Here for people, politics and PARODY. alt @jackesmith22	543575
59	Victorshi2020	Victor Shi	Now—Working on Team Harris-Walz. Writer. Fmr—Host @iGenPolitics_, @JoeBiden, @WhiteHouse, @Precisionstrat, @SKDK. @UCLA 24 English alum. Chicagoan. Views mine.	328827
60	acnewsitics	Alex Cole	Software Engineer & Pilot | Progressive Follow @newsitics & https://t.co/Retehye9rD	286475
61	Logically_JC	John Collins	Dad Husband Low-Key Nerd EdD / JD	225758
62	scottlincicome	Scott Lincicome	@CatoInstitute Vice President (Econ/Trade), @DukeLaw adjunct, @TheDispatch newsletter-er. CH RTS. You didn't read the article, did you? Go @Rangers.	78894
63	EpochTimesChina	The Epoch Times - China Insider	China content of The Epoch Times. Sign up for our China newsletter Read on App: https://t.co/wGG3L4uBaT	63943
64	Kalshi	Kalshi	The first legal way to bet on the election in America.	50930
65	GanJingWorld	Gan Jing World	Video and movie streaming. Join #KindnessIsCool contest & win awards. Connect with friends & family.	32626
66	canlesofficial	Canles	Engineered for walking | Comfy & versatile footwear for life's adventures | Breathable, lightweight designs	7407
67	janicehisle	Janice Hisle Epoch Times	Assigned to report on President Trump's 2024 campaign and related topics. Supporter of free speech. Email tips to janice.hisle@epochtimes.us.	2846