Digital News Consumption: Evidence from Smartphone Content in the 2024 US Elections

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Abstract

Using novel smartphone content data, we document that exposure to election-related content for the median American is arguably small. Moreover, exposure rarely comes from news apps and instead mostly occurs through non-traditional sources, such as social media and video apps. While the median was low, we find substantial heterogeneity: individuals in the 90th percentile consume over 50 times the content of those in the 10th percentile. A variance decomposition shows that apps play a role in driving exposure gaps (e.g., X versus Facebook), but individual characteristics (e.g., living in a swing state) are the dominant drivers of election-related exposure.

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Smartphones have become the primary gateway to political information (Newman et al., 2025), yet little is known about the content people consume on them. On the one hand, it is seemingly easier than ever for voters to find information, with relevant news available at their fingertips. Moreover, content sharing through social networks and targeted ads enable even passive voters to encounter election-related information.[1] At the same time, the shift toward smartphones has raised new concerns. First, the prevalence of other content may crowd out digital news consumption (Prior, 2007). Second, individuals may be more likely to encounter information from unvetted sources on their phones, particularly through social media applications (Revealing Reality, 2018; Aral, 2021). Third, platform algorithms can shape exposure by either showing content based on platform priorities or by widening the gap between news seekers and news avoiders (Pariser, 2011; Gillum et al., 2024; Treisman, 2024). Empirically analyzing these issues has been challenging because, until recently, it was not feasible to observe smartphone content.[2]

This paper provides the first analysis of election-related smartphone consumption and answers two main questions: First, how much and from which sources were people exposed to election-related content during the consequential 2024 U.S. election campaign? Second, what drives the substantial variation in exposure to content?

Our data captures the occurrences of pre-specified keywords appearing on a user's smartphone (both text and multimedia content), which we refer to as an encounter, along with the app and timestamp associated with each encounter. By observing *all* applications on the smartphone, we measure previously unobserved consumption, including consumption occurring on communication and social media apps. Our keyword list includes prominent election-related keywords (e.g., "debate", "Republican", "Democrat", "Congress", "election") as well as the names of the president, presidential and vice-presidential candidates, and virtually all congressmembers and governors. Based on a set of concurrent news articles, we argue that the presence of at least one of these keywords on the screen at a given time, which we refer to as an exposure, is highly predictive of an individual consuming election-related content. The sample consists of individuals who downloaded a popular smartphone app and provided permissions to capture the keywords they encounter.[3]

We find that despite campaigns bombarding potential voters with billion-dollar ad spending and the election dominating news coverage, the median individual's consumption of election-related content was arguably small. We describe this result using several benchmarks. First, the me-

[1]Campaigns spent around two billion dollars on digital ads in the 2024 election and more candidates advertise on social media (mostly used on smartphones) compared to television (Fowler et al., 2021; Vandewalker et al., 2025).

[2]Without access to smartphone data, the literature needed to rely on either surveys or browser data. However, self-reported data does not correlate well with actual news consumption, and browsers mostly measure desktop consumption while online consumption is smartphone-led. Furthermore, browsers cannot capture any consumption that occurs within apps, such as social media feeds or search results (Revealing Reality, 2018).

[3]We discuss external validity in Section 1.2 and show that our sample resembles the US population in its phone usage and app composition, and that our results hold when reweighting the sample to match the US population.

dian individual saw the names of the president and presidential candidates (‘Donald Trump’, ‘Joe Biden’, and ‘Kamala Harris’) on their phone for only 3 seconds per day, all congressmembers for only 0.4 seconds, and all our election-related keywords for only 21 seconds. Second, on an average day during the campaign, across all apps, the median individual encountered around half of the number of election-related keywords appearing in a single New York Times article about the election. Third, on most days, the median individual was exposed to no election-related content on communication and search apps that better indicate active interest in the election. Fourth, even during the campaign, the median individual was exposed to 9.6 times more sports and entertainment celebrities than politicians. Finally, the low exposure is remarkably stable throughout the campaign, with little increase in the days leading up to election day and only two exceptions—the presidential debate and election day itself.

Our second finding is that less than 5% of election-related exposures occurred on news apps, where professional journalists and editors curate content. Instead, we document that exposure to election-related content occurred mainly through non-traditional sources: applications with algorithmic curation, such as social media (e.g., Facebook, X) and music & video apps (e.g., YouTube).

While median consumption was arguably low, we find substantial heterogeneity in news consumption across individuals. For example, individuals in the 10th percentile were exposed to only 2 seconds per day of election-related content, compared to 114 seconds for those at the 90th percentile. The Gini coefficient for election-related content consumption is similar in magnitude to that for global income, indicating a large degree of inequality across individuals.

We evaluate two explanations for this heterogeneity: differences in individuals’ propensity to consume news and differences across the applications individuals use. Both explanations play a role. First, individual-level characteristics predict variation in exposure. For example, individuals in swing states have 88% more exposures to election-related content than individuals in non-swing states. Second, there are substantial differences across apps. For example, X has a substantially higher share of election-related content compared to Facebook, which is consistent with reports of X promoting such content and Meta downranking it (Gillum et al., 2024; Treisman, 2024).

To quantify the relative importance of individual and app-level heterogeneity, we conduct a variance decomposition exercise that attributes variance in election-related content exposure to individual-specific effects, application-specific effects, time effects, self-selection of individuals into different apps, and other residual components. We implement this procedure at the market level—treating each application category as a proxy for a “market”—and aggregate across markets to measure the total explained variance. We find that applications matter, as they account for approximately 30% of the explained variation in exposure to election-related content on social media. However, individual-driven variation is still the dominant source of variation for both social media and across all apps.

This paper contributes to a long-standing literature on citizens' exposure to politics by measuring exposure to *content*, providing a *fine-grained* measure of exposure, and by focusing on *smartphones*. We discuss each of these advantages in turn.

First, we contribute to the literature studying news exposure. Studies on digital consumption typically infer exposure from the sources (e.g., domains) that people see or visit (Gentzkow and Shapiro, 2011; Flaxman et al., 2016; Guess, 2021; Levy, 2021). We complement these studies by using the Screenomics methodology (Reeves et al., 2020, 2021) to measure exposure from the *content* appearing on the screen.[4] Our paper provides the first evidence that content about the election is rarely consumed through traditional news sources and occurs much more often through social media and video platforms. Beyond the potential political implications, this means that by focusing on news sources, previous literature could not track or study most of the exposure to election-related content. We also distinguish between different types of content and find that while exposure to national politics is limited, exposure to congressmembers is nearly nonexistent for most individuals. Our results provide evidence that the concerns over the nationalization of politics and reliance on less reliable media sources are warranted.

A second advantage of our data is that it is provided at a *fine-grained* level, allowing us to measure exposure in seconds over time. We find that despite the abundance of easily available content, individuals spend little time exposed to election-related content. This result aligns with earlier work showing limited exposure to political information in other settings (Bennett and Iyengar, 2008; Allen et al., 2020), but takes into account exposure across all apps. We leverage the fine temporal variation to also contribute to the literature on political campaigns (Jacobson, 2015; Chiang and Knight, 2011; Kalla and Broockman, 2018; Di Tella et al., 2021; Le Pennec and Pons, 2023). We find that exposure to election content is remarkably stable (with the exception of the presidential debate), suggesting that campaign events do not seem to affect the exposure of most voters.

The third advantage of our data is that it opens the *smartphone* black box. Smartphones recently surpassed television and became the primary method people come across news (Newman et al., 2025), yet we know little about what people are consuming. While previous studies analyzed the time spent on smartphone applications (Allcott et al., 2022; Aridor, 2025) and the phone's location (e.g., Chen and Rohla, 2018), we provide systematic evidence on exposure to content on smartphones. We find that instead of leveling the playing field, there is substantial heterogeneity in exposure to content on smartphones, perhaps due to different usage patterns or personalized apps. We contribute to the debate on social media algorithms (Bakshy et al., 2015; Guess et al., 2023;

[4]This methodology has been used to study smartphone behaviour (e.g., Brinberg et al., 2021). However, with the exception of Muise et al. (2024), it has not been used to study politics. We extend Muise et al. (2024) by analyzing an order-of-magnitude larger sample over a much longer time period, by studying an election campaign, and by analyzing what drives the variations in exposure.

Aridor et al., 2024) by studying the sources of this variation and providing evidence for the relative importance of individual and application effects.

1 Data

Our primary data consists of observed keyword occurrences across all apps on individuals' smartphones for several thousand Americans. Most of our analysis focuses on the election campaign from September 1st to November 5th (election day).

The data comes from Screenlake, a company that creates and maintains a proprietary database of term-encounters occurring in natural smartphone usage, primarily to serve enterprise businesses in measuring their brands' organic popularity. Screenlake's data is sourced from an SDK (software development kit) that is embedded within a popular smartphone application on Android.[5] An individual who installs this application is informed that the SDK does not collect personal information and asked for explicit additional permission to allow for anonymous on-screen keyword detection during their continuous smartphone usage.[6] Once permission is granted, the SDK passively checks for the presence of specific keywords every three seconds continuously across apps. In addition to observing text rendered visible on-screen, the SDK also detects keywords that arise in the so-called 'alt text', which is text that briefly describes video or image content but is typically not visible. Furthermore, the SDK detects keywords that appear in video captions even when they do not appear on-screen and, for some applications, has access to transcriptions of videos.[7]

The SDK logs the occurrence of any keywords, along with a device identifier, the exact time when the keyword appeared, and the app that was on-screen at the time.[8] We manually classify apps into the following categories: communication, social media, music and video, news, search, browser, and AI assistant, as described in Appendix G.1.

We observe two main groups of election-related terms: 1) *election terms*, which are words related to the elections ("polls", "ballot", "campaign", "debate", "democracy", "Republican", "Democrat", "Congress", "swing", "vote", "election", "electoral", "Mail-In") and 2) *politicians*, which includes current and former presidential and vice-presidential candidates ("Joe Biden","Robert F Kennedy Jr", "Nikki Haley", "Kamala Harris", "Donald Trump", "Tim Walz", "JD Vance",

[5] Similar functionality is not available to third-party developers on iOS.

[6] Users of this app are motivated to enable this permission by free access to directly-related user-facing features, such as short-form video blocking or content blocking. One of these available features is a tool that interrupts smartphone usage whenever excessive political content is on-screen. This particular feature, however, was only enabled by about 1% of the sample at any given time during the sample period.

[7] Alt text is often supplied to the app by humans or AI as part of a general push for accessibility. It is common, but not always available for all images and videos. Transcriptions are common for videos on YouTube, but not, for instance, podcasts on Spotify.

[8] All such content processing is done on the smartphone device itself to avoid the collection of personally identifiable or sensitive information.

"Hillary Clinton", "Bernard Sanders") and virtually all congressmembers and governors.[9] Overall, there are over 500 distinct election-related keywords.[10]

In addition to the election-related keywords, we received data on exposure to several thousand control keywords covering sports, entertainment, commercial brands, and other topics, which we use as benchmarks and to proxy total time spent on each app.

1.1 Primary Outcomes

Our first measure of consumption is election-related *encounters*, defined by the number of occurrences of an election-related keyword that a user encountered. The main benefit of this measure is that it is clearly defined and interpretable. However, this measure is sensitive to the number of words appearing on the screen and the precise keyword subset we use. For example, the number of encounters would be lower for the sentence "I watched the presidential debate last night" compared to "I watched the presidential debate last night between Kamala Harris and Donald Trump", even though they contain similar content. Therefore, our second and primary measure of consumption, termed *exposure*, is the number of observed time periods with at least one keyword occurrence of our election-related keywords. As keywords are generally captured every three seconds, we make a conservative assumption that the keyword was observed for all three seconds, and we multiply the number of exposures by three to measure exposure in seconds.

In Appendix A, we argue that, given our keyword set, an exposure is informative about election-related content, in the sense that an exposure is indicative that an individual consumed such content. Concretely, we treat exposure to our election-related keywords as a classifier to detect consumption of election-related content and, using news articles from the New York Times and Fox News as benchmarks, show that it has very high recall ($\approx 98\%$) and moderate precision. In other words, if someone read an article about the elections by one of these outlets, they would almost surely be exposed to at least one of our keywords. We also use the r/politics subreddit to confirm that our keyword-based metric has high recall in election-related user-generated content.

1.2 The Panel

We include in our analysis active users, defined as those who have at least one keyword captured (not necessarily election-related) on at least fourteen days during the analysis period. This results in an average of 1,081 users per day.

An important concern is how findings from individuals who opt to use the screen management

[9]For political figures with names that are not especially distinct in American English, Screenlake maintains proprietary logic for ascertaining if a reference is indeed in reference to the intended political figure.

[10]Appendix G.2 presents the full set of election-related keywords.

application can be extrapolated to other smartphone users. In Appendix B, we conduct several exercises to assess the generalizability of our results. First, we show that our results are robust to reweighting to a representative sample of U.S. individuals on gender and age inferred from keyword occurrences. Second, the ranking of installed apps in our sample is similar to the ranking in Google Play. Third, we conduct a survey collecting Digital Wellbeing data on time spent on apps and show that our sample resembles a representative sample of U.S. individuals in time spent across apps. Fourth, an additional survey we conducted shows that individuals who use screen management software are at least as likely to consume news. These exercises suggest that the consumption patterns of our sample are unlikely to be substantially different from those of typical U.S. adults.

2 Election-Related Consumption

In this section we characterize the magnitude, timing, and sources of election-related consumption for the median individual in our sample.

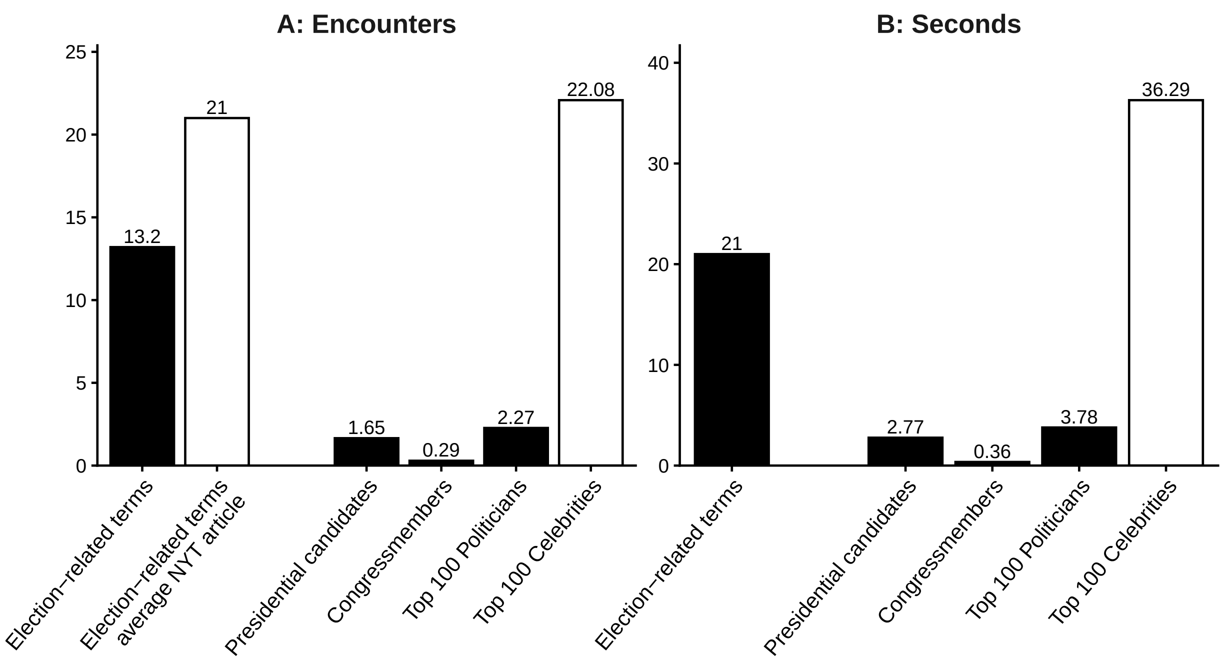
Overall Consumption Our first finding is that consumption of election-related content is arguably low. Figure 1 presents encounters and seconds of exposure to different content per day during the election campaign for the median individual. On an average day between September 1st, 2024 and November 4th, 2024 (the day before election day), the median individual only had 13.2 encounters with our set of election-related keywords, as shown by Panel A. This is the total number of times these election-related words were mentioned in any app, including, for example, social media posts, news articles, or someone mentioning the word 'Trump' in a text message. To benchmark this result, we compare it to the universe of New York Times articles described in Section 1.1 and find that the 13.2 encounters correspond to 57.2% of the terms that appear in an average political article. This means that someone reading a single political article would encounter almost twice as many keywords as the median individual on an average day even without seeing any political ads, political posts on social media, or discussing politics on their phone.[11]

Using our time-based measure, the right panel of Figure 1 shows that the median individual was exposed to approximately 21 seconds of election-related terms on their phone. Recall from Section 1.1 that an exposure in our primary keyword set has high recall and moderate precision, indicating that we can reliably measure consumption of election-related content via this statistic. Overall, the median individual spends on average approximately 5.54 hours a day on their phone suggesting

[11] To calculate this number, we compute the average number of keywords in the article text, multiply the number by 1.1 (as 9% of our keywords appear in other parts of the page, such as section headings), and divide by the median encounters.

that individuals saw election-related terms only 0.1% of the time.[12] In Appendix C.1, we show that our results are robust to reweighting with demographic weights, excluding Spanish speakers, expanding keyword definitions to include political issues, and making alternative measurement assumptions.

Figure 1: Election-Related Content Consumption



NOTES: The figure reports the median encounters (Panel A) and seconds of exposure (Panel B) among active devices on an average day between September 1 and November 4, 2024. From left to right, each panel presents the overall consumption based on the full set of election-related terms, the number of election-related terms in an average New York Times article (only for encounters), names of presidential candidates, congressmembers, top 100 politicians, and top 100 celebrities.

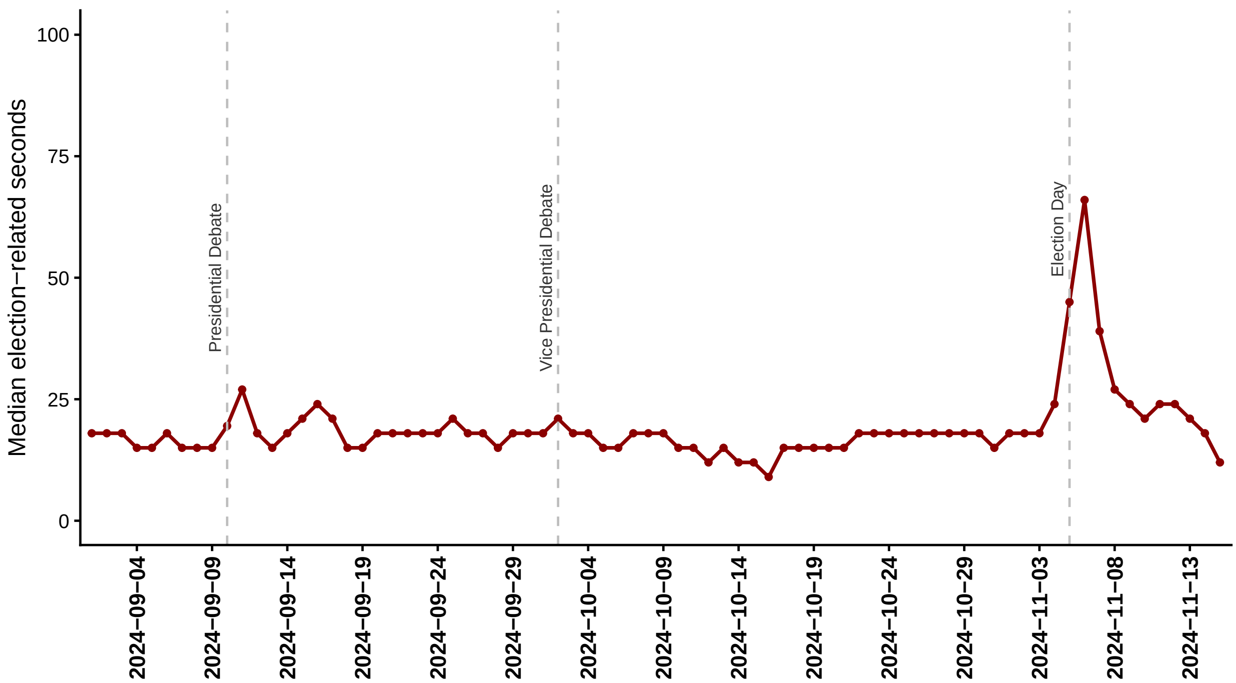
Exposure to Politicians The results so far are based on both election terms and politicians' names. Figure 1 shows that the median individual was exposed to the president and presidential candidates ('Donald Trump,' 'Joe Biden,' and 'Kamala Harris') for less than 3 seconds on an average day. Exposure to the top 100 politicians in our keyword list was slightly higher but still only 3.8 seconds. As a benchmark, we compare politicians to celebrities and find that exposure to the 100 most observed celebrities was 9.6 greater than exposure to the 100 most observed politicians.[13]

[12]We calculate the total amount of time spent on the phone from December 19th, 2024 until January 25th, 2025 since our time use data is accurate for this time period. We find similar results using the industry benchmark of 4.5 hours of average phone use per day (Kemp, 2024)

[13]This stark contrast is consistent with previous work on non-democracies, which finds that people consume online news not for political content, but mainly for entertainment or non-sensitive topics (Chen and Yang, 2019; Simonov and Rao, 2022).

While exposure to presidential candidates was limited, exposure is minuscule when focusing on congressmembers. Surveys have shown that individuals know little about their congressmembers (Mendes, 2013). Therefore, exposure to information about congressmembers is especially important as voters probably have weak priors, and informing them about their representatives may affect their decisions. However, Panel B in Figure 1 shows that the median individual was exposed for only 0.4 seconds per day to *all* congressmembers.[14] Indeed, this number is so low that on an average day only 18% of individuals encountered any congressmembers, as shown in Appendix Table C.2.

Figure 2: Election-Related Exposure in Seconds Over Time



NOTES: The figure displays the median daily number of seconds of exposure to election-related terms per active user between September 1 and November 15, 2024. Vertical dashed lines indicate key political events: the Presidential Debate between Kamala Harris and Donald Trump (September 11), the Vice Presidential Debate (October 2), and Election Day (November 5).

Consumption over Time Given the low consumption of election-related content, a natural question is whether the level of consumption gradually rose closer to the election, or spiked after the many notable events in the campaign, such as the second attempt to assassinate Trump, the presidential and vice presidential debates, and Trump's Madison Square Garden rally. Figure 2 plots the

[14] One limitation is that we observe congressmembers and not candidates. However, in 2024, in approximately 88.7% of districts, a serving congressmember ran in the election and 97% of the incumbents who ran won (Ballotpedia).

median election-related exposures in seconds over time and shows that it is remarkably stable.[15] In 80% of observed days, the median user's daily exposure to political content ranged between 15 and 20 seconds. This confirms that exposure was arguably low throughout the campaign and not only at the beginning of the time period we analyze.

There are two exceptions to this trend: the presidential debate and election day. On the day of the first presidential debate between Kamala Harris and Donald Trump, exposure increased by 44% compared to the previous week. The increase in consumption due to the debate dovetails previous literature showing that debates draw large audiences (Le Pennec and Pons, 2023). On election day, there was a dramatic increase where the median exposure time increased by 287% from the average in September-October to the peak occurring the day after the election. In Appendix Figure C.2 we zoom in on election day and show that most election-related exposures occurred *after* polls closed. This result indicates that most of the increase in exposures around election day is not driven by individuals seeking information before voting, but rather people reading about the results. To summarize, with the sole exception of the presidential debate, there were no large population-level shocks that induced additional information acquisition before voting.[16]

Sources of Information There is concern that individuals today receive less information from editor-curated news sources and instead encounter election-related content in non-traditional channels, such as algorithmically curated social media feeds and music & video apps (Bell et al., 2017; Newman et al., 2025). This shift could affect the *quality* of information, as these environments may surface more polarized or less reliable material (Braghieri et al., 2025; Vosoughi et al., 2018). Our screen-level measure of exposure across all apps (including typically private channels such as communication) allowing us to characterize not only how much election content people see, but also where it comes from.

Figure 3a shows that individuals rarely consume election-related content through news applications. The mean individual-level share of exposures from news applications is only 0.74%, while the median consumer received no election-related content from news applications. One key limitation is that we cannot observe the websites individuals visit through their browsers, and these websites can belong to any category (e.g., facebook.com or nytimes.com). In Appendix C.3.1, we describe two methods for imputing news-site consumption on the browser, and find that the mean share of exposures through news apps and visits to their websites on browsers is still only 0.89%-4.93%.

In Appendix Table C.2, we report consumption by categories at the extensive margin. Through-

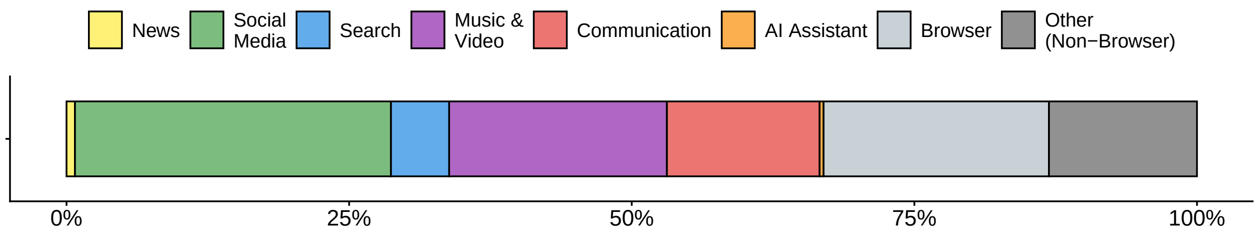
[15] Appendix Figure C.1 presents similar results when plotting encounters instead of exposure.

[16] While this shows that there are limited *population-level* events that increase consumption, in Appendix E we show that Taylor Swift's endorsement led to increased election-related consumption among individuals more likely to follow her. This effect indicates that events can differentially impact exposure across individuals.

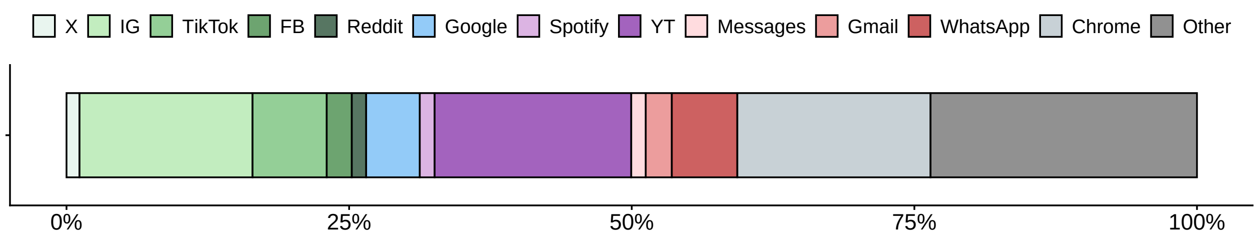
out the entire campaign period, only 9% of individuals encountered election-related content on news apps.

Figure 3: Share of Exposures by App and Category

(a) Categories



(b) Apps



NOTES: The figure shows the overall distribution of election-related exposures across apps and app categories during the period September 1–November 4, 2024. Panel (a) displays the share of exposures by category, and Panel (b) by app. Each bar shows the average share of a user's total election-related exposures occurring in that category or app. The shares are computed in two steps: first, for each user, exposures are summed by category/app and divided by the user's total election-related exposures; second, these user-level shares are averaged across all devices. Abbreviations refer to Instagram (IG), Facebook (FB), and YouTube (YT).

Where do people get election-related content? Exposure via communication and search is important as these channels are more likely to capture active interest. Figure 3a shows that 18.67% of exposure is from communication and search. While this is much higher than news apps, it is relatively low compared to the social media and music & video which make up 47.20% of total exposure. This result suggests that a substantial share of news is consumed passively. Indeed, as Appendix Table C.2 shows, on an average day only about one-third of individuals observe even a single election-related term in their communication apps.

This results in this section highlight the importance of social media platforms (e.g., Instagram), and music & video platforms (e.g., YouTube) in providing election-related content. It also demonstrates the limitations of previous methods that rely on news site visits to measure news consumption, as they only account for a small share of political exposure on smartphones.

3 Drivers of Consumption

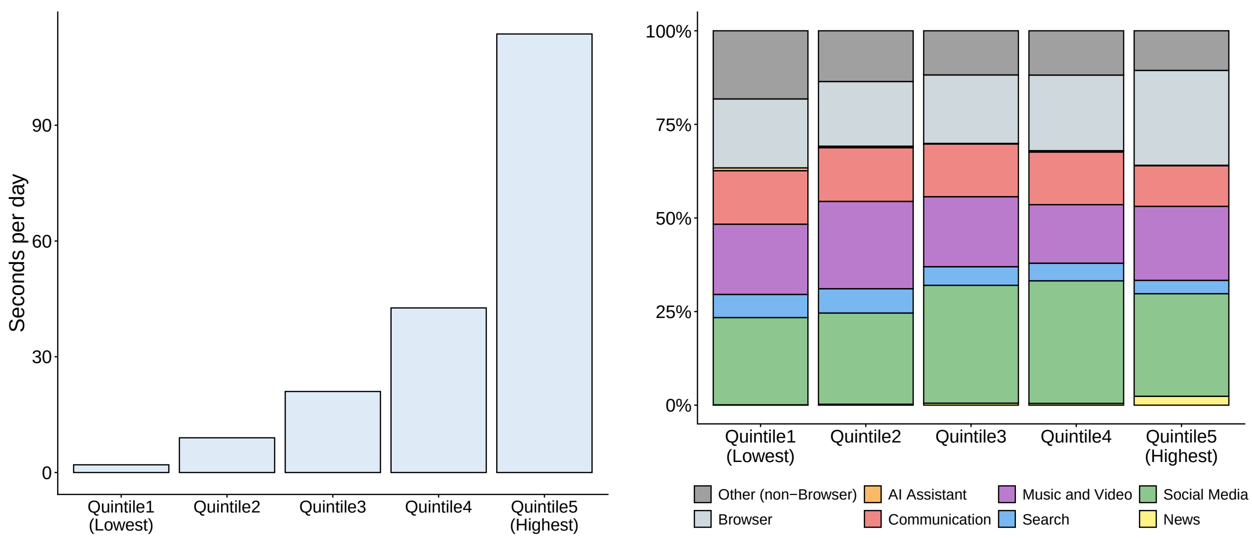
While the median individual consumes a small amount of election-related content, there are intrinsic differences across individuals in their interest in such content, their incentives for acquiring information about the election, and the applications they use. As such, we next turn to characterizing the extent of heterogeneity in and quantifying the potential drivers of these differences in consumption.

3.1 Reduced-Form Evidence

Figure 4: Heterogeneity in Election-Related Content Consumption

(a) Distribution of Seconds

(b) Distribution of Sources of Information



NOTES: Panel (a) shows the distribution of average daily exposure in seconds to election-related content across device quintiles, ranked by overall exposure levels. Exposure for each device is computed as total election-related exposure divided by the number of active days between September 1 and November 4, 2024. Devices are then sorted by this average exposure and divided into five equal-sized quintiles. Panel (b) shows the composition of these exposures by source category (*e.g.*, social media, news, search, communication, browser, and other apps). Category shares are computed at the user level as the fraction of that user's total election-related exposure attributable to each category and then averaged within quintiles. Quintiles are defined as in Panel (a), based on a user's average daily exposure seconds.

Heterogeneity across Individuals Figure 4a shows the average daily exposure to election-related content across quintiles, revealing substantial heterogeneity. The second quintile averages 9 seconds of daily exposure, compared to 43 seconds in the fourth quintile. The gap widens further at the extremes: individuals at the 10th and 90th percentiles have around 2 and 114 seconds of exposure, respectively, corresponding to a 90/10 percentile ratio exceeding 56.8. Journalists, pundits, and politicians are probably overrepresented among the heavy news consumers and thus may have a skewed view of the electorate's news consumption. Appendix Figure D.1 plots the Lorenz Curve of election-related consumption and highlights that the inequality in exposure is dramatic, with a higher Gini coefficient than phone usage and TV watching. This Gini coefficient is also higher than the one for US income (World Bank, 2025) and approximately the same as the one for world income (Chancel et al., 2022).

Importantly, exposure varies across individual characteristics. Because the U.S. relies on the Electoral College for presidential elections, swing states play a pivotal role in determining outcomes. Individuals in swing states likely have greater incentives to seek election-related information or are more heavily targeted by political messaging. Appendix Figure D.2 shows that the median individual in a swing state receives 88% more election-related exposures than other states.

As both the quantity and quality of exposure matter, Figure 4b examines how the composition of election-related content varies across the exposure distribution. While non-traditional sources, which may provide lower-quality content, are the dominant source of information across all groups, individuals with lower overall exposure rely more on these sources and consume virtually no election-related content from news applications. Moreover, Appendix Figure D.2 shows that individuals using news apps are exposed to more election-related content. These patterns suggest that inequality in the quality of election-related exposure may mirror inequality in quantity.

Heterogeneity across Applications The difference between the applications that individuals use, especially within the set of social media applications, likely reflects individual preferences for different content provided across applications (Aridor, 2025). This, paired with possible content prioritization by applications, could lead to different content exposure across applications. In Appendix Figure D.3b we compare the share of election-related content in different social media platforms. We document substantial heterogeneity, with applications such as X and Reddit having considerably higher shares of election-related exposures than Facebook and TikTok. This may imply that individuals' exposure is determined to some extent by the apps they use, but could also simply reflect the differences between the platforms' users. In the next section, we quantify the relative importance of app and individual effects.

3.2 Variance Decomposition

We turn to assessing the relative importance of two dimensions, individuals and applications, on drivers of content consumption. Decomposing these forces is important to characterize what policy interventions can increase or equalize election-related content consumption. If differences across applications are the main driver, policy responses could include algorithmic audits or encouraging individuals to diversify the apps they use (Cowgill, 2019; Agan et al., 2023). If, instead, individual heterogeneity dominates, understanding what motivates political information acquisition becomes central (e.g., changes to the format of news, its price, its perceived relative trustworthiness, or the stakes of being informed (Aral and Dhillon, 2021; Chopra et al., 2025; Ferrali et al., 2023; Campante et al., 2025)).

To disentangle these forces, we leverage the individual-level variation in election-related exposure across applications, and conduct a variance decomposition in the spirit of Abowd et al. (1999)—hereby, AKM.[17] Our key assumption is that individuals have preferences over the share of time devoted to election-related content within each application category (e.g., social media). When the share of election-related consumption is similar across apps, we attribute the variation in consumption as reflecting individual differences; when shares differ systematically across apps, we interpret it as reflecting application-specific factors. These factors can include differentiation in usage across applications (e.g., using X more for election-related content consumption) or systematic prioritization of topics by the platforms (e.g., Meta or X either downranking or upranking political content, respectively).

We estimate the following empirical specification separately for each app category group g:

$$y_{iat}^{g} = \alpha_i^g + \beta_a^g + \gamma_t^g + \varepsilon_{iat}^g, \tag{1}$$

Our main outcome variable, y_{iat}^g, is the share of time user i was exposed to election-related content for app a (within group g) at time t.[18] This measure accounts for usage differences across individuals and applications—allowing us to isolate differences in the *composition* of the content that individuals are exposed to. The parameters α_i^g represent individual fixed effects, and can be interpreted as a combination of (time-invariant) portable individual characteristics that results in equal exposure to election-related content across all apps within the app group. The parameters β_a^g denote app fixed effects, which capture the possibility that some apps over- or under-expose their users systematically to election-related content. Lastly, γ_t^g denote time fixed effects, which allow election-related content to be popular at a given time period—for example, after presidential debates.

We interpret this estimation in descriptive terms, not as a causal analysis. For a causal interpretation, this methodology imposes three main assumptions (Card et al., 2018). First, the error terms ε_{iat}^g are mean-independent from the individual, app, and time-fixed effects. This "exogenous mobility" assumption allows for unrestricted and arbitrarily correlated sorting patterns into apps based on individual and app fixed effects, but rules out sorting based on the error term. Second, an additive separability assumption rules out interactions between individual and app fixed-effects

[17]See Boxell and Conway (2022) and Cagé et al. (2025) for other media applications of the AKM decomposition.

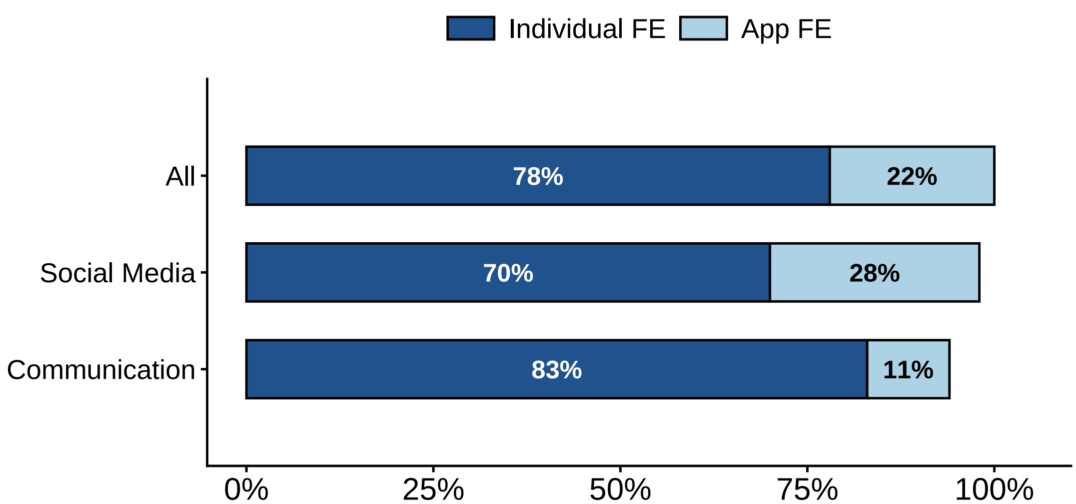
[18]Appendix F.2 explains how we use our set of keywords to calculate the total time spent on each app, the denominator of our outcome variable.

(Bonhomme et al., 2019). This assumption does not rule out the possibility of content personalization. It rather rules out *differential* personalization, such as individuals with a strong preference for election content experiencing relatively more exposures on higher-exposure apps than in lower-exposure apps, within the same category. Third, following Abowd et al. (2002), app effects are identified only within a "connected set" of apps linked by individual "moves". In our setting, this is not an issue as each individual uses many apps. In other words, multi-homing mitigates limited mobility bias (Abowd et al., 2004). Nevertheless, to ensure reliable estimates, we restrict the sample to individuals visiting at least 30 apps and to apps visited by at least 30 such individuals.

As in AKM, we decompose the variance of election-related exposures using Equation (1), within each app group g:

$$\begin{aligned}\text{Var}(y^g_{iat}) =&\text{Var}(\alpha^g_i) + \text{Var}(\beta^g_a) + \text{Var}(\gamma^g_t) + \text{Var}(\varepsilon^g_{iat})\\ &+ 2\text{Cov}(\alpha^g_i, \beta^g_a) + 2\text{Cov}(\alpha^g_i, \gamma^g_t) + 2\text{Cov}(\beta^g_a, \gamma^g_t). \end{aligned} \tag{2}$$

Figure 5: Variance decomposition: Share of variance of share of election exposures



NOTES: The figure shows the share of explained variance in the share of election-related exposures across all apps (excluding those without categorization), social media apps, and communication apps. We decompose the relative importance of the terms in (2) and report the individual and app fixed effects as they are the dominating terms. The values for each of the terms are reported in Table D.1, showing most are negligible apart from the individual and app terms, and summing to 100% when including all of the terms. The adjusted R^2 values are 0.26 (All), 0.27 (Social Media), and 0.21 (Communication). The number of apps included in each category is 285, 10, and 13, respectively, based on a total of 1,469 individuals.

By comparing $\text{Var}(\alpha^g_i)$ and $\text{Var}(\beta^g_a)$, we assess whether individual characteristics or systematic app-specific factors play a larger role in shaping content exposure. The covariance term

$\text{Cov}(\alpha_i^g, \beta_a^g)$ indicates the pattern of individual sorting into apps. For example, if this component is positive, it reflects that individuals with particularly strong exposure to election-related content also tend to use apps that provide a frequent coverage of such content.[19] We estimate the variance decomposition within each app group g. To aggregate across app groups, we weight the share of exposures of each group by the time spent on that group.

Figure 5 shows that individual-specific heterogeneity accounts for 3 times more of the explained variance than app-specific heterogeneity when aggregating across apps. This figure also shows that the relative role of apps is higher in the case of social media—where factors such as algorithmic biases can allow for app-specific systematic effects across individuals. In contrast, as expected, the role of apps is smaller for communication apps where individuals actively decide what to discuss and content curation is less pervasive. Appendix Table D.1 contains the full decomposition results.[20]

How do Apps Affect Exposure? The non-negligible role of social media app effects implies that individuals are using different social media apps in different ways or that the algorithms of different apps prioritize different content. We find evidence suggesting that prioritization plays a role. First, Appendix Figure D.4 presents the estimated coefficients of app fixed effects from Equation (1) and shows that X users are consistently over-exposed to election-related content compared to other platforms, while Facebook users are under-exposed. These results are consistent with reports that Meta reduced political recommendations and with anecdotal evidence of prioritization of political content on X (Gillum et al., 2024; Treisman, 2024). Second, Appendix Figures D.4 and D.5 show that exposure to Elon Musk content is higher on X than on any other social media app, a pattern not observed for comparable CEOs like Mark Zuckerberg. The magnitude of this is substantial with Elon Musk being 20 times more likely to appear on X compared to Facebook.

To further examine these differences in exposure, we conducted a survey asking individuals whether they are *over*- or *under*-exposed to specific content on specific apps. This allows us to measure exposure conditional on preferences in order to isolate platform priorities. We find that 65% of U.S. respondents report feeling overexposed to political content and to Elon Musk on X. This pattern suggests that the increased exposure reflects platform priorities, rather than user preferences for app differentiation. Appendix D.4 provides more details on the survey.

To conclude, this section has two main findings. First, we show that app fixed effects matter and

[19] We conducted a simulation exercise that assumes that the true data-generating process is either entirely determined by (a) applications or (b) individuals and confirm that our procedure correctly identifies which effects dominate.

[20] The overall pattern persists when considering encounters instead of exposures (Appendix Table D.2), daily instead of weekly exposures (Appendix Table D.3), no time fixed effects (Appendix Table D.4), without restricting the sample to apps with fewer than 30 unique users (Appendix Table D.5), and using the leave-one-out bias correction method proposed in Kline et al. (2020) (Appendix Table D.6).

that platform priorities play a role in driving exposure to election-related content, particularly on social media. Second, individual heterogeneity is more important than app heterogeneity, meaning that individuals inclined to consume election-related content tend to be systematically exposed to it across apps, while those inclined to consume less election-related content are generally not exposed to it. This suggests that most exposure is not driven by algorithms generating disparities between individuals based on platform motives, but rather by algorithms mirroring existing gaps between heavy news consumers and news avoiders.[21]

4 Conclusion

In this paper, we characterize the magnitude and drivers of election-related smartphone consumption during the 2024 U.S. election campaign. Exposure to election-related content is arguably small for many individuals and rarely occurs in news apps. Campaigns appear to be adapting by targeting audiences through niche channels (e.g., specific podcasts), but this creates new challenges: individuals receive little exposure to fact-checked, editor-curated news, and congressmembers struggle to reach voters on their phones.

While exposure to election-related content is low for most people, heterogeneity is large and driven mostly by differences across individuals rather than by the apps they use. Our findings suggest that algorithmic ranking plays a role in driving exposure, but that efforts to increase or equalize the consumption of reliable political information should focus on individuals.

[21]Indeed, the Gini coefficient of exposure to election-related content is slightly greater in social media than search and communication, suggesting that social media mirrors or even amplifies differences between individuals.

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Supplementary Appendix

A Keyword Informativeness Benchmarks

In this section, we provide a formulation of our measurement problem as a standard topic classification problem. Our goal is to analyze whether our keywords are predictive of election-related content. Let t denote a time period within a given day and assume that an individual encounters content $\mathbf{w}_t = (w_{t,1}, \ldots, w_{t,N_t})$ in period t (dropping individual subscripts for simplicity). Following standard practice in the natural language processing (NLP) literature (Ash and Hansen, 2023), we represent content as a sequence of tokens, which can represent words but also more general objects such as punctuation or emojis.[22] Let $\mathcal{V}$ denote the universe of tokens that individuals encounter on their phone, and $\mathcal{K} \subset \mathcal{V}$ denote the set of election-related keywords that are tracked. We use the number $k \in \{1, \ldots, |\mathcal{K}|\}$ to refer to keywords in that set.

We define a set of topics $\mathcal{T}$ and denote the set of topics that content $\mathbf{w}_t$ relates to by $topics(\mathbf{w}_t) \subset \mathcal{T}$.[23] Thus, we say that content is election-related when the US 2024 Election is in the set of topics of that content, or $election \in topics(\mathbf{w}_t)$. To ease notation, we define the "ground-truth" indicator of whether the content encountered by an individual on t is election-related:

$$E_t^* = \begin{cases} 1, & \text{if the individual consumed election content in period } t, \\ 0, & \text{otherwise.} \end{cases}$$

We also define our empirical building block: an exposure, defined as an indicator of whether keyword k is displayed in period t, $d_t(k) \in \{0, 1\}$. Our keyword-based proxy of E_t^*, is thus:

$$E_t(\mathcal{K}) = \begin{cases} 1, & \text{if at least one keyword } k \text{ is displayed in period } t, \\ 0, & \text{otherwise.} \end{cases}$$

Because ultimately our goal is to measure E_t^* (true consumption) using $E_t(\mathcal{K})$ (observed keywords), we focus on two performance metrics that are standard in text-based classification: *precision* and *recall*. Precision is the probability that content is election-related given exposure to one of our election-related keywords, $\Pr(E_t^* = 1 | E_t(\mathcal{K}) = 1)$, while recall is the probability that one of our keywords is detected when the content is election-related: $\Pr(E_t(\mathcal{K}) = 1 | E_t^* = 1)$. We

[22] It need not be limited to textual content and can also be textual representations of images or videos (Caprini, 2023).

[23] Topics are canonically defined in the NLP literature as a probability vector over possible tokens (Blei et al., 2003), allowing content to be related to multiple topics. However, the literature also often assumes that content has a single topic (Gentzkow et al., 2019). We can relate our *topics* function to the literature by assuming that it extracts the most likely topics of a given sequence of tokens (e.g., with probability above a certain threshold) or their modal topic.

emphasize that this represents the exposure measure from Section 1.1.

A challenge in our setting is that our keywords had to be pre-specified, preventing us from choosing keywords ex-post based on F1 scores that trade off balance precision and recall. Nevertheless, we pre-specified a set of keywords that we ex-ante believed were predictive of election-related content. Below, we confirm with several metrics using different definitions of ground truth that this is indeed the case. In particular, we collect the universe of articles published by a left-leaning (the New York Times) and a right-leaning (Fox News) news organization during September and October 2024. We then emulate the Screenlake keyword detection algorithm and measure keyword occurrences in the way that they would be logged by the software.

Defining Ground-Truth Topic Labels We rely on the labels that the New York Times and Fox News place on their articles in order to determine whether an article is election related. The assumption is that keywords that are highly likely to be used to discuss the election are present in articles tagged as 'elections' or 'politics' on the New York Times or 'politics' or 'official-polls' on Fox News. To define articles that are *not* election-related, we consider article tags that are probably not related to politics but would be discussed in the news, such as cultural topics, sports, and weather. We then consider the articles within the following set of article tags as our 'non-election' articles: 'Arts' , 'Style', 'Books', 'Movies', 'Food', 'Real Estate', 'Climate', 'Well', 'Technology', 'Science', 'Health', 'Weather' , 'Theater', 'Travel', 'Sports' on the New York Times; and 'Sports', 'Travel', 'Food-Drink', 'Lifestyle', 'Entertainment', 'Tech', 'Health', 'True-Crime', 'Science', 'Family', 'Faith-Values', and 'Weather' on Fox News.[24] We drop articles that do not have any of these tags (as it is ambiguous if they are election-related) or are shorter than 100 words (since they are likely not actual articles but videos instead).

Precision and Recall in News Benchmarks We find that recall is high at 0.98 for both benchmarks. Specifically, 97.74% and 97.89% of articles about the elections in the New York Times and Fox News, respectively, contained at least one of our keywords. If we consider 250-word increments of these articles, a rough approximation to the content visible on the screen at a given time, our recall is 0.87 and 0.88 on the New York Times and Fox News, respectively. This means that if someone saw even part of the article on their screen, one of our keywords would likely be detected.

We then compute the precision statistic for both benchmarks and find that it is 0.58 and 0.70 for the New York Times and Fox News, respectively. Additionally, we find that our keywords cover 7 of the top 10 words with the highest F1 score across both Fox News and New York Times, indicating that, even though we necessarily had to pick our keyword set before the election, it is

[24]Note that any election-related articles that may appear within these topics, for example in climate, will artificially deflate our precision score.

still highly informative ex-post and among the most informative set we could have selected.[25]

Recall in User-Generated Content One concern with using news articles as a benchmark for computing precision and recall is that the language that individuals use to discuss elections may be different than the language written by journalists and edited by news editors. In order to construct a proxy for recall in the context of user-generated content, we pull the full set of posts from the 'r/politics' sub-reddit during September and October 2024. Mirroring full article as the unit of analysis in the news benchmarks, we use the full set of comments under each post and compute our recall statistic over this sample. We find that 90% of the posts have at least one of our keywords in their comment thread, which remains similar once we weight posts by a proxy of their popularity (upvotes on Reddit).

To summarize, we make two main points. First, we provide evidence that our keyword-based metric of exposure achieves a high recall and moderate precision, using labels from New York Times and Fox News articles as ground truth. This means that, while not exhaustive, exposures to our primary keyword set are highly likely to provide an *upper bound* of overall consumption of election-related content from traditional media. Second, we confirm that this set also has high recall of election-related content that is user-generated.

B External Validity

In this appendix, we assess external validity. This is important as our sample is composed of individuals who opt to use the application offered by Screenlake. There are three key concerns for how the results from our sample may not generalize to the broader U.S. population that we address.

1. **Demographic representativeness**: The Screenlake sample may not be demographically representative.

   How we address it: We apply Screenlake-provided demographic weights to match a representative age–gender distribution based on the 2023 U.S. census. We replicate our main figures and results using these weights and find that the results do not qualitatively change. We also conduct a similar exercise, reweighting our sample to match the distribution of red, blue, and swing states.

2. **Different phone usage patterns**: Screenlake users may differ from the typical American in the apps they install and how they use their phones.

[25] The top 10 words with the highest F1 score are: 'trump', 'president', 'harris', 'election', 'campaign', 'former', 'kamala', 'vice', 'biden', 'donald'.

How we address it: We benchmark (i) installed applications against market-level Google Play download data and (ii) time on device and by app category against both industry benchmarks and a U.S.-representative Prolific sample. We find that our sample uses a similar set of applications and has similar overall engagement levels to the representative benchmarks.

3. **Screen-time management motivation**: Individuals installing screen management apps may have different news consumption propensity.

   How we address it: We conduct a survey using Prolific-recruited participants asking whether individuals use screen-time applications and their self-reported propensity to consume news. We find little difference in self-propensity to consume news across this dimension.

We now document the details for each of these exercises that lead us to conclude that our main results are likely robust and generalizable to the broader U.S. population.

B.1 User Demographics

First, we consider the demographic composition of our sample using individual-level weights provided by Screenlake. The data collected by Screenlake is anonymous and disconnected from identifiers. Screenlake infers gender and age post-collection based on the inter-demographic relative likelihood of combinations of app usage and various terms appearing on-screen. Our sample skews male and younger than the general population (over 60% men and over half under the age of 35), and therefore, we analyze how our results change when reweighting the sample. Screenlake provided us with individual-level weights, making our sample representative of the U.S. population on age and gender, according to 2023 U.S. Census data.

We replicate our main results using the reweighted sample. Appendix Figure B.1 replicates Figure 1 and shows that the median exposures and encounters of average daily election-related content consumption increases but remain qualitatively low. For example, we find that the exposure ratio between the top 100 celebrities and politicians remains high at 7.4. Appendix Figure B.2 analyzes exposure over time with the reweighted sample and presents a similar pattern to Figure 2. Finally, we compute the percentage of total election-related content consumption coming from news applications (replicating the main result of the "Sources of Information" subsection of Section 2) and find that it still remains low—0.89% and 0% for the mean and median individual, respectively. Overall, we conclude that our key results on the magnitude, timing, and source of election-related content consumption are qualitatively robust to demographic reweighting.[26]

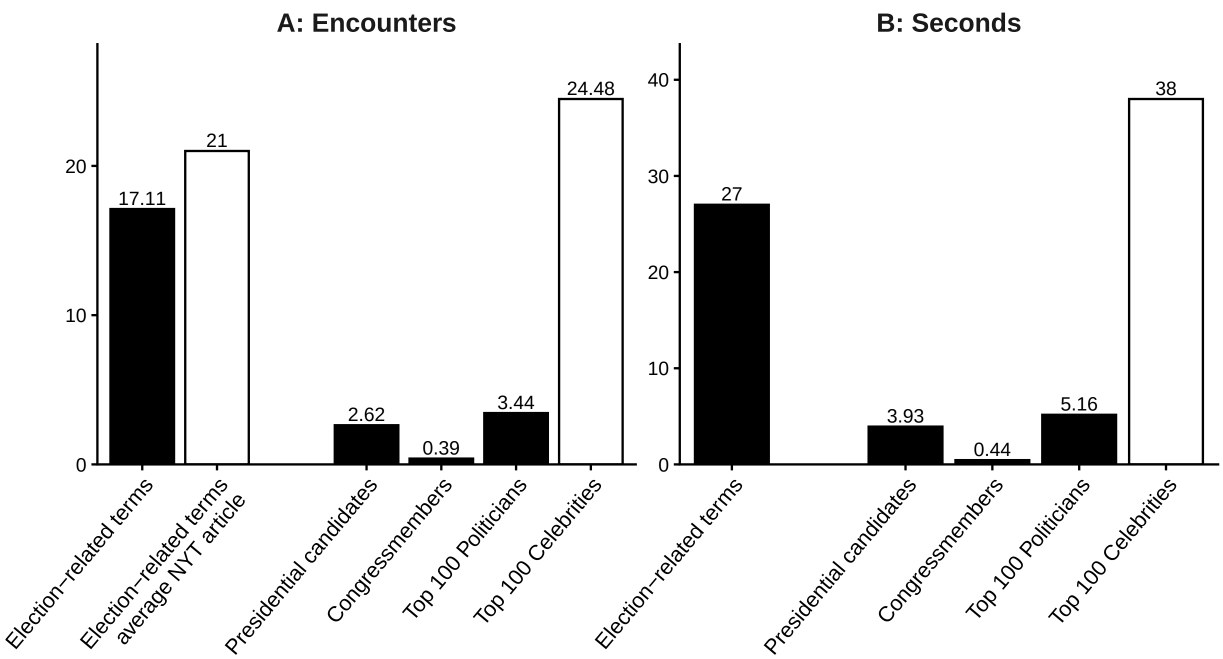
Additionally, we reweight our sample based on the location of individuals to account for potential nonrepresentativeness in location. Specifically, the reweighting is performed at the level of

[26]In Appendix C.1 we present additional robustness exercises for the overall consumption levels.

four political state groups: blue states, red states, swing states, and other states, where we cannot distinguish between two states (e.g., North and South Carolina). We reweight the sample to match the distribution of US population among these states groups based on 2024 U.S. census data. Appendix F.1 discusses the method we use to predict the state for each individual and provides the full list of states in each group. As shown in Table C.1, reweighting based on states results in very similar election-related consumption.

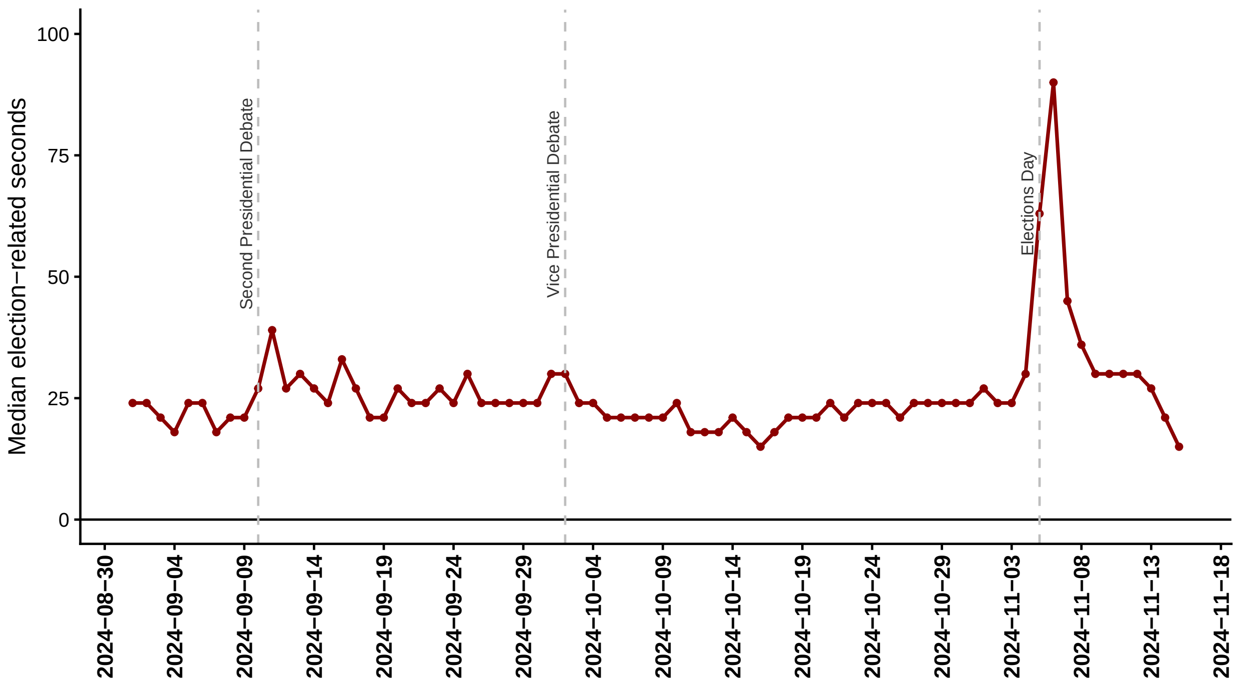
There is still a concern that the sample may differ from the population in unobserved ways. A particularly important concern for our main result is whether people in our sample systematically encounter less political content than the average person in the U.S. To understand selection into the sample, we complement our analysis with additional datasets.

Figure B.1: Election-Related Content Consumption, Reweighted



NOTES: The figure reports the median encounters (panel A) and seconds of exposure (panel B) among active devices on an average day between September 1 and November 4, 2024. From left to right, each panel presents the overall consumption based on the full set of election-related terms, the number of election-related terms in an average New York Times article (only for encounters), names of presidential candidates, congressmembers, top 100 politicians, and top 100 celebrities. This figure uses demographic weights provided by our data provider that reweights our sample to be demographically representative on gender and age based on the 2023 U.S. census.

Figure B.2: Political Exposures Over Time, Reweighted



NOTES: The figure displays the median daily number of seconds of exposure to election-related terms per active user between September 1 and November 15, 2024. Vertical dashed lines indicate key political events: the Presidential Debate between Kamala Harris and Donald Trump (September 11), the Vice Presidential Debate (October 2), and Election Day (November 5). This figure uses demographic weights provided by our data provider that reweights our sample to be demographically representative on gender and age based on the 2023 U.S. census.

B.2 Phone Usage Patterns

Comparison of Installations to Google Play Store Data We now turn to assessing whether the Screenlake users have systematic differences in the types of applications that they have installed on their phones compared to a typical American. To do this, we compared the distribution of apps installed to population-level data available via the Google Play Store – the primary distribution channel for Android applications. We use data on the number of US ratings scraped during October 2024 and January 2025 for all applications with over 1 million downloads, or in the News & Magazines and Social categories.[27] We follow the best practices for using this data and take the number of ratings for an application as an approximation for its overall popularity (Kesler et al., 2020; Kesler, 2023; Affeldt and Kesler, 2021; Janssen et al., 2022).[28] We consider two variants of this: total number of ratings (denoted overall ratings) measuring cumulative popularity and the difference in the number of ratings between the October 2024 and January 2025 data collection

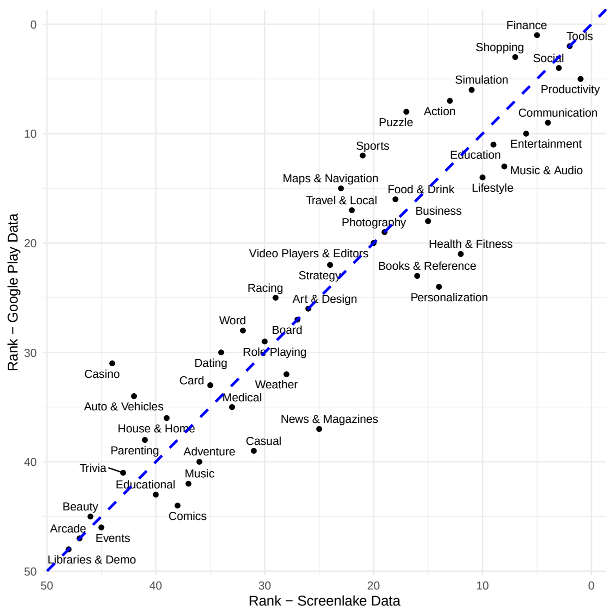
[27]We thank Reinhold Kesler for generously sharing this data with us.

[28]Ratings are typically used since the publicly available range for the number of installations is too wide to provide a meaningful ordering of applications.

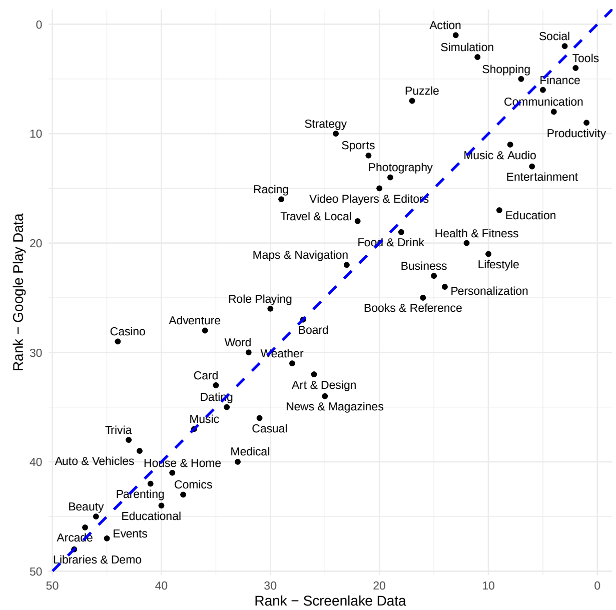
(denoted delta) measuring recent popularity.[29] We compare the overall number of downloads to the overall prevalence of the same applications within our sample. As we do not directly observe installed applications for the individuals in our sample and only observe measures of time usage, we mark an application as being installed for an individual if we ever observe them using the application. Finally, in order to ensure an apples-to-apples comparison, we remove any applications that are pre-installed on Android phones and consider only the set of applications that we observe both in our dataset as well as in the Google Play data.[30]

Figure B.3: Comparison between Screenlake Installed Applications and Google Play

(a) Category Comparison (Delta)



(b) Category Comparison (Overall Ratings)



NOTES: This figure compares the set of applications installed by the Screenlake panelists compared to market-level data from the Google Play Store. For the Google Play Store data, we proxy for total downloads using cumulative number of ratings in (b), and using the difference between the cumulative number of ratings from January 2025 and October 2024 in (a). For the Screenlake data, we mark a user as having an application installed if we ever observe them using it. Panels (a) and (b) provide a rank-rank plot of comparison across downloads aggregated to application categories.

Figures B.3a and B.3b show a remarkably strong correlation between apps used among our sample and the Google Play data, using the delta measure and overall ratings, respectively. Since there is wide heterogeneity in usage within categories across individuals, we compare the relative importance of categories (as defined by Google Play) across the two datasets. For both datasets, we sum across all of the individual applications within the dataset to obtain a total number of instal-

[29] For example, an application such as Among Us was very popular several years ago, and so accumulated a large number of ratings, but is not very popular during our sample period.

[30] Across all individuals in Screenlake data, we observe 26,015 unique applications.

lations or ratings for the category and compare the relative rank across the datasets. These results show strong alignment in the relative set of installed applications across categories, especially according to the more reliable delta measure, indicating that the set of individuals in the sample are reasonably representative in terms of the overall category of applications they use. We compute the Spearman correlation coefficient, a commonly used measure of accordance for ranking data, and find that it is very strong, with 0.928 for the delta measure and 0.888 for the overall rating measures. Notably, according to this analysis, our sample has a *larger* relative importance of news applications compared to the general prevalence of these applications in the population.

We then turn to comparing the ranks of applications within our categories of interest for our primary analyses—news, communication, social, music & audio, and entertainment. The top 10 applications in terms of installations in our sample are: Instagram, Spotify, Facebook, TikTok, Telegram, Snapchat, Discord, Netflix, X, and Reddit. Similarly, the top 10 applications in terms of installations using the delta method in the Google Play sample are: Facebook, Instagram, Truecaller, TikTok, Snapchat, Facebook Lite, WhatsApp, Max, Telegram, and Spotify. This highlights substantial overlap in the top set of applications between our sample and the general population. Beyond the top applications, we consider the full set of applications that we observe across the categories of interest. We compute the weighted Spearman rank correlation coefficient, considering as the weight $\frac{1}{\text{Google Play Rank}}$ in order to place more weight on accordance for higher ranks, relative to those in the long tail. This provides a correlation coefficient of 0.896 for the delta measure and 0.920 for the overall ratings measure, indicating strong agreement in the relative rankings.

Overall, we conclude that the set of apps that the individuals in the sample use is reasonably representative of the app usage of the broader population.

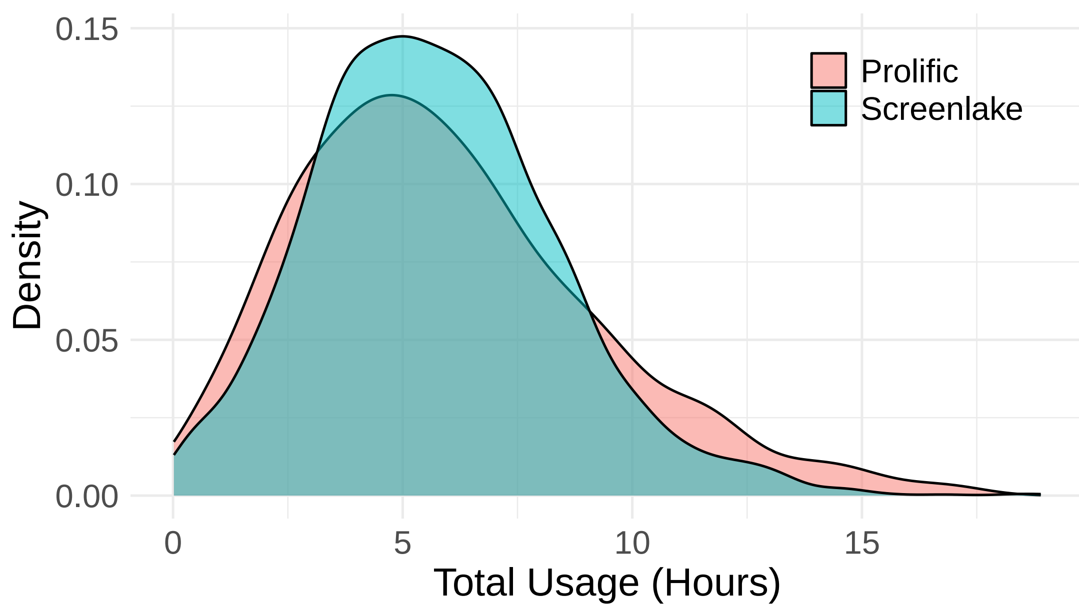
Comparison of Time Usage to Benchmarks and Representative Sample While the set of installed apps among our sample could be reasonably representative, our sample may still differ from the general population in how often each app is used. Therefore, we compare the time usage of Screenlake participants to an industry benchmark and a representative sample of Prolific participants. We consider time usage observed in our dataset from December 19th, 2024 until January 25th, 2025 as this represents the time period where we have the most reliable measurement of application time usage.

We Are Social (Kemp, 2024), which aggregates information from multiple sources, provides a useful industry benchmark. On average, Screenlake individuals spend slightly longer (3.2 hours a day) on a set of communication and social media apps than the average individual (2.5 hours a day).[31]

[31] The set of apps included in this benchmark are Facebook, Discord, Instagram, LinkedIn, Messenger, Pinterest, Reddit, Snapchat, Telegram, Threads, TikTok, WhatsApp, X, and YouTube.

Industry benchmarks may not correspond to the time period of analysis for our sample. To establish a representative baseline of smartphone usage for around the same period and study the time spent on specific apps, we recruited 813 Android individuals on Prolific from October 30 to November 3, 2024. The sample is representative in terms of average age and political affiliation. Participants are asked to complete a demographic survey and upload screenshots of their daily app-level screen time for the past 7 days using Digital Wellbeing, capturing "the entire list of apps that were used for more than 1 minute."[32]

Figure B.4: Distribution Comparison between the Representative Prolific and Screenlake



Dataset	Mean	Median	SD	Q25	Q75	N
Prolific	5.95	5.46	3.27	3.51	7.86	813
ScreenLake	5.71	5.54	2.64	3.84	7.33	2499

NOTES: This table presents the distribution of the average daily hours spent on the phone, per individual, for the representative Prolific sample and for Screenlake data, on which our sample is based. We use Screenlake application usage data from December 19th, 2024 until January 25th, 2025 since it is reliable for this time period.

Figure B.4 shows that the distribution of overall phone usage is similar between our data (based on Screenlake) and the representative Prolific sample.[33] The median individual in both samples spend a strikingly similar amount of time on their phone, 5.46 and 5.54 hours, respectively, in

[32]In order to extract the time usage from the screenshots, we developed an OCR script using the OpenAI API.

[33]We omit usage of Google Chrome from both samples, as Prolific users have a large amount of time on Google Chrome due to completing surveys for their work on Prolific in Chrome.

Table B.1: Comparison of App Usage Between Prolific Data and Screenlake Data

	Average Hours Per Person		Average Hours If Used		Fraction of Nonzero Users		
	Prolific	Screenlake	Prolific	Screenlake	Prolific	Screenlake	Pew
Facebook	0.50	0.20	0.84	0.44	0.60	0.45	0.70
Instagram	0.21	0.63	0.44	0.96	0.47	0.66	0.50
LinkedIn	0.00	0.00	0.05	0.04	0.06	0.11	0.32
Reddit	0.22	0.04	0.50	0.24	0.44	0.17	0.24
Snapchat	0.05	0.07	0.23	0.24	0.20	0.28	0.27
TikTok	0.40	0.55	1.21	1.32	0.33	0.41	0.33
X	0.10	0.04	0.49	0.24	0.21	0.18	0.21
WhatsApp	0.06	0.41	0.38	0.58	0.16	0.70	0.30
Spotify	0.04	0.06	0.15	0.11	0.27	0.52	NA
YouTube	0.60	1.07	0.80	1.18	0.76	0.90	0.85
Fox News	0.00	0.00	0.13	0.00	0.00	0.00	NA
Google News	0.00	0.00	0.03	0.01	0.00	0.02	NA
NYTimes	0.00	0.00	0.25	0.06	0.01	0.01	NA
Netflix	0.04	0.06	0.51	0.27	0.08	0.20	NA

NOTES: This table presents the average daily hours spent on individual applications for the Prolific sample and for the Screenlake sample (on which our data in based). We use Screenlake application usage data from December 18th, 2024 until January 25th, 2025 since it is reliable for this time period. The first two columns present the average number of hours spent on the given application per individual. The next two columns present the average number of hours spent on the given application per individual, conditional on using the application at all. The final three columns present the fraction of individuals who use the application in the Prolific sample, Screenlake sample, and from a PEW survey.

the Prolific representative sample and in our data (a 1% difference). The average individual in the Prolific sample spends 5.95 hours on their phone, while the average individual in our data spends 5.71 hours (a 4% difference). The results suggest that the ScreenLake population (on which our data is based) is reasonably similar in overall phone usage to the representative sample from Prolific.

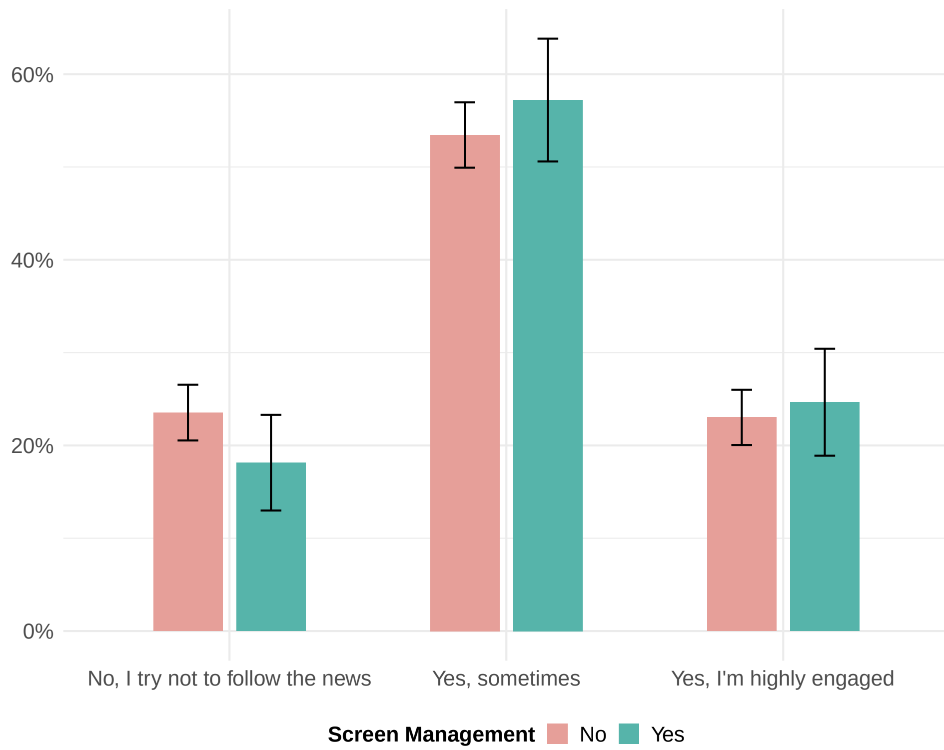
Next, we compare the time spent and usage of top applications – Facebook, Instagram, Netflix, Reddit, Snapchat, Spotify, TikTok, WhatsApp, X, and YouTube – across our data (based on Screenlake), the Prolific sample, and a sample from a Pew Research Center survey.[34] The results are presented in Table B.1. One notable difference between the samples is that the fraction of WhatsApp and Instagram usage for the ScreenLake sample is higher than both the Prolific and Pew samples, while Facebook usage is lower. The Prolific sample has an over-representation of Reddit, both relative to Pew and ScreenLake. Nonetheless, conditional on using the application, the two samples show similar patterns: large time spent on YouTube and TikTok, very similar

[34]The Pew data is available at the extensive margin. See `https://www.pewresearch.org/internet/fact-sheet/social-media/` for details.

time spent on Snapchat and Spotify, and reasonably similar time spent on X and WhatsApp. Their overall time spent on social media is around the same. Importantly, in both Prolific and Screenlake almost no time is spent on news apps, suggesting that the low share of exposure to election-related content from such apps is not due to differences between our sample and the general population. Overall, the Screenlake sample differs on several dimensions from these two benchmarks, but reflects similar engagement patterns across the core applications that individuals spend time on their phones.

B.3 Comparison of Individuals with and without Screen Management Apps

Figure B.5: Screen Management and Level of Political Engagement on Phone



NOTES: This figure presents the distribution of responses, partitioning on whether the respondents use screen management software and the frequency with which they follow the news on their phone. The denoted ranges represent 95% confidence intervals.

Finally, we assess whether there are systematic differences in self-reported news consumption between individuals who use screen management software and those who do not. As part of a news consumption survey,[35] we asked respondents whether they use screen management software and

[35]For more details of the survey, see Appendix D.4.

whether they try not to follow the news, they sometimes follow the news, or are highly politically engaged on their phones. We note that a relatively large fraction of the sample (21.8%) self-reports using screen management software, meaning that we have enough power to study the differences across the groups and that downloading these apps is relatively common.

Figure B.5 presents the distribution of responses, partitioning on whether the respondents use screen management software, and finds little difference in political engagement between these sets of respondents. If anything, individuals with screen management software tend to be slightly more politically engaged. Hence, our results that individuals consumed arguably little news before the election are unlikely to be driven by the characteristics of people who download screen management apps.

C Additional Results for Election-Related Consumption

C.1 Overall Consumption

In this section, we provide additional robustness exercises for our results in Section 2 measuring the median consumption levels of election-related content. Our qualitative conclusion of arguably low consumption does not vary across each of these exercises: reweighting to a representative sample, excluding Spanish speakers, considering an expanded keyword set that includes political issues, and making alternative measurement assumptions. We summarize the change in overall median consumption in Table C.1 and now discuss the details for each.

Reweighting Our data provider provides a set of individual-level weights that allow us to reweight our sample to match the 2023 U.S. census on gender and age. Figure B.1 shows that this consumption slightly increases but does not change dramatically after reweighting. In particular, reweighted median encounters and exposure seconds increase to 17.1 and 27, respectively. While the reweighted data shows slightly elevated levels, it does not change our qualitative conclusion that election-related consumption is small. Additionally, we reweight based on the location of individuals. We find that this reweighting keeps median encounters and exposure seconds almost the same as our main estimate, at 14.0 and 22.3, respectively. The reweighting exercises are described in more detail in Appendix B.1.

Excluding Spanish Speakers Another potential concern is that our keyword set is in English, while in the U.S. there are many individuals whose primary language is Spanish. While we would still be able to detect names, we may not observe some of our election-related keywords for Spanish-speaking individuals. We can identify these individuals by looking for the presence of the application 'Teléfono' or 'Llamar' instead of 'Phone', meaning the individual probably has Spanish set as the default phone language. If we remove these individuals from our data, consumption increases, but still remains low compared to the benchmarks discussed in Section 2.

Table C.1: Median Election-Related Consumption (Robustness)

	Encounters	Seconds
Main analysis	13.2	21
With issues	13.4	21.4
Reweight based on demographics	17.1	27
Reweight based on states	14.0	22.3
Exclude Spanish speakers	18.4	28.5
Exclude non-election context	7.8	12.4
Assume two-second exposure	13.2	14
Exclude first week	13.8	22

NOTES: This table reports the median number of election-related encounters and exposure in seconds across a range of robustness exercises. "Main analysis" corresponds to the baseline estimates reported in Section 2. "With issues" expands the keyword set to include political issue terms (e.g., healthcare, immigration, inflation), counted only when appearing near other election-related words. "Reweight based on demographics" and "Reweight based on states" use weights to align the sample with the 2023 U.S. census distributions by age and gender. "Reweight based on states" use weights to align the sample with the 2024 U.S. census distributions of red, blue, swing, and other states. "Exclude Spanish speakers" excludes users whose device language is set to Spanish. "Exclude non-election context" adjusts consumption using external precision and recall benchmarks from the New York Times benchmark described in Appendix A. "Assume two-second exposure" relaxes the main assumption that each exposure lasts three seconds. "Exclude first week" removes each user's first week of data to address potential behavioral adaptation after the software installation.

Expanded Keyword Set We compute the overall median exposure to an expanded keyword set, with a set of political issues in addition to the election terms and politicians in our primary keyword set.[36] Since many of these terms are typically used in non-political contexts,[37] we only consider them as an election-related exposure if they are mentioned near a much larger set of words that could be related to the election. To provide additional context on the occurrence of a keyword, the SDK records the co-occurrence of a large list of surrounding words. In particular, upon observing the presence of a keyword on the screen, the application scans the ten observed words, excluding stopwords, before and after the identified keyword and logs all of the occurrences of surrounding words within this set. We are able to observe a large set of surrounding words related to the election, with the full list presented in Appendix G.2. This makes it so that these low precision keywords are converted into high precision encounters when paired with these surrounding words.

[36] This list of keywords for the issues includes: "climate", "court", "crime", "economy", "healthcare", "inflation", "women", "Gaza", "West Bank", "immigration", "border", "woke", "DEI", "Roe", "gun", "protest", "recount", "interference", "hoax".

[37] We validated that these keywords have low precision using our New York Times articles discussed in Appendix Section A.

So, for example, in the sentence: ‘the president announced a plan to improve healthcare’, we will consider the word ‘healthcare’ as a political issue keyword, since ‘healthcare’ is surrounded by ‘president’. In contrast, ‘healthcare’ will not be considered a political issue keyword in the sentence ‘are you pleased with your healthcare provider’. The median individual still only consumes approximately 21.4 seconds of election-related content after adding political issues.

Alternative Measurement Assumptions We consider three additional computations of the median consumption that make alternative measurement assumptions.

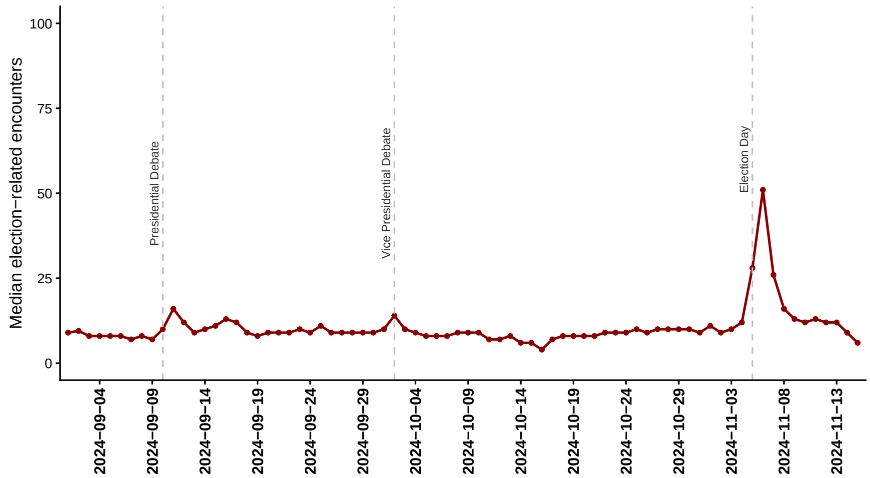
First, we consider excluding non-election context. As noted in Appendix A, our keyword-based classifier has high recall but moderate precision. We can therefore compute a version of overall consumption where we divide by the recall in the New York Times benchmark and then multiply by the New York Times precision. This provides an alternative measure filtering out our false positives. Since we have high recall and moderate precision, this adjustment lowers our estimates for news consumption and results in 7.8 encounters for the median individual and 12.4 seconds of exposure.

Second, in our main analysis we conservatively assume that an exposure is logged as three seconds since we know that software will only capture keywords every three seconds. However, in reality this is an upper bound since most content is likely visible for a fraction of that time. Therefore, we consider a less conservative assumption of exposure seconds where we assume that an exposure corresponds to two, as opposed to three, seconds. This leads the median exposures to reduce to 14 seconds.

Third, as individuals may potentially change their behavior due to the screen management application being installed in the first week of usage, we recompute the same statistics but drop every individual’s first week of usage. This barely affects our estimates and results in 13.8 encounters for the median individual and an exposure of 22 seconds.

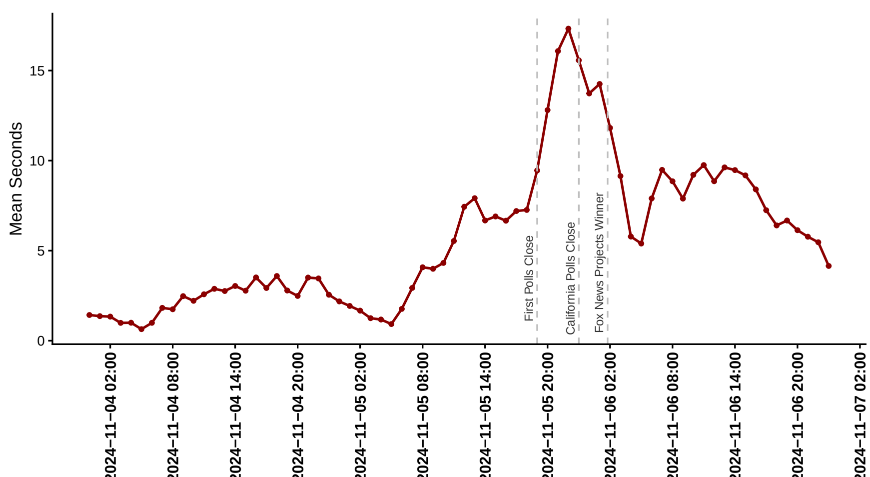
C.2 Consumption over Time

Figure C.1: Median Daily Election-Related Encounters



NOTES: The figure displays the median daily number of election-related encounters per active user between September 1 and November 15, 2024. Vertical dashed lines indicate key political events: the Presidential Debate between Kamala Harris and Donald Trump (September 11), the Vice Presidential Debate (October 2), and Election Day (November 5). See Section 1.1 for the definition of election-related encounters.

Figure C.2: Mean Hourly Election-Related Exposures (EST)



NOTES: The figure plots election-related exposure over time, showing the mean number of election-related seconds of exposure per hour across all active devices during the 48-hour window surrounding Election Day (November 5, 2024). The figure shows that election-related exposures were elevated throughout the day of the election, but that interest peaked around 8 PM when or after polls closed (the vast majority of polls close at 7 or 8PM local time). All timestamps are shown in Eastern Standard Time (EST). Vertical dashed lines indicate key election-night milestones. We use the time zone data provided by Screenlake, which is inferred from the various brands, apps, and/or terms that appear on screen.

C.3 Sources of Information

Table C.2: Share Exposed by Keyword Set and Category

		Share Exposed	
Keyword Set	Category	Average Day	Entire Period
Primary Political Terms	All	0.787	0.986
	News	0.024	0.090
	Social Media	0.403	0.763
	Browser	0.376	0.838
	Music and Video	0.316	0.807
	Communication	0.329	0.801
	Search	0.158	0.567
	AI Assistant	0.007	0.100
Top 100 Politicians	All	0.509	0.948
	News	0.021	0.079
	Social Media	0.192	0.640
	Browser	0.195	0.692
	Music and Video	0.197	0.726
	Communication	0.108	0.511
	Search	0.082	0.444
	AI Assistant	0.001	0.039
Top 100 Celebrities	All	0.857	0.990
	News	0.009	0.048
	Social Media	0.495	0.805
	Browser	0.283	0.806
	Music and Video	0.546	0.927
	Communication	0.233	0.758
	Search	0.138	0.566
	AI Assistant	0.009	0.066
Congressmembers	All	0.177	0.759
	News	0.004	0.037
	Social Media	0.042	0.366
	Browser	0.070	0.480
	Music and Video	0.035	0.355
	Communication	0.025	0.204
	Search	0.021	0.276
	AI Assistant	0.001	0.012

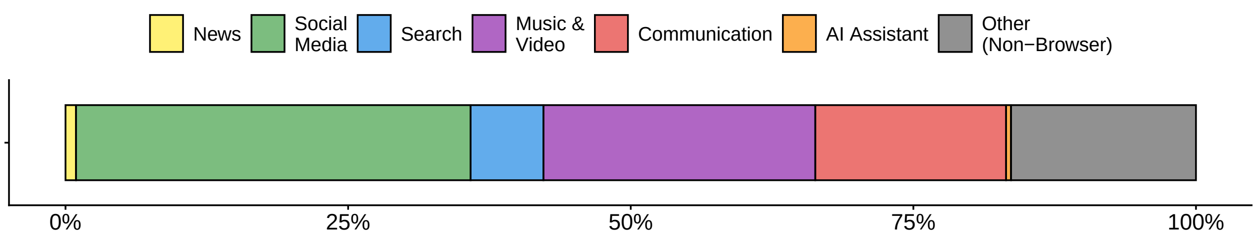
NOTES: The table reports the share of users exposed to each keyword set across app categories. "Average Day" refers to the mean daily share of users exposed on a typical day, while "Entire Period" denotes the share of individuals who encountered at least one term from the corresponding keyword set during the election campaign (September 1 – November 4, 2024). Keyword sets include primary political terms, the top 100 most observed politicians in our dataset, the top 100 most observed celebrities, and all U.S. congressmembers. For example, 0.40 under "Social Media" for the primary political terms indicates that 40% of individuals viewed election-related content on social media on an average day, while 0.99 under "All" for the top 100 celebrities shows that nearly all users encountered celebrity-related content at least once during the campaign period.

C.3.1 Browser-Included News Visits

A key limitation in determining sources of information is that we cannot observe the websites individuals visit through their browsers, and these websites can belong to any category (e.g., facebook.com or nytimes.com). While it is likely that some exposure to news platforms occurs through browsers, based on previous research (Aridor, 2025), most of the time spent browsing on mobile is spent on search (Google), music and video (YouTube), and various social media applications.

In this section, we provide additional estimates of the time spent on news platforms by following two procedures to impute news usage from browser time. The key assumption in each of these is that time spent on the browser is, for the most part, a distribution of time spent on applications on the phone and thus can be informative about what an individual is doing in the browser. The estimates in this section can be interpreted as expanding our measure of time spent on news apps to include time spent on news sites.

Figure C.3: Share of Exposures by Category (Browser Imputation)



NOTES: The figure shows the overall distribution of election-related exposures across app categories during the period September 1–November 4, 2024, where we reallocate the exposures to browsers proportionally into other categories. The bar shows the average share of an individual's total election-related exposures occurring in that category. The shares are computed in two steps: first, for each individual, exposures are summed by category/app and divided by the individual's total election-related exposures; second, these individual-level shares are averaged across all devices. App categories include: News, Social Media, Search, Music and Video, Communication, AI Assistant, and Other (non-browser).

First, for the average individual, we use the time spent on all other application categories and make the assumption that the share of exposures across categories when people use their browser is the same as the overall share of exposures across the other categories. Appendix Figure C.3 presents the distribution of usage across categories under this assumption, which implies that news site usage only increases to 0.89% even accounting for browser time.

Second, we use a model-based imputation that exploits the fact that we not only observe the overall exposure levels across categories, but also the exact keywords across election-related and non-election-related content. In the rest of this section we describe a procedure leveraging that data to ascertain the fraction of news-site exposures in the browser.

There are $I = \{1, \ldots, K\}$ non-Browser categories and $V = \{1, \ldots, V\}$ set of keyword groups.

We define n_{iv} as the total counts of encounters in category i and keyword group v and, consequently, the empirical distribution of encounters across application categories as follows:

$$\phi_{iv} = \frac{n_{iv}}{\sum_{u=1}^{V} n_{iu}}, \quad \sum_{v=1}^{V} \phi_{iv} = 1.$$

where ϕ_{iv} is the share of encounters from keyword group v in category i for the average individual in the sample. We note that these distributions capture the different set of keywords that individuals encounter across different application types. For instance, we would expect (based on Figure D.3a) that this is more heavily skewed towards election-related encounters on news applications and captures other important differences in content across other categories.

Our key assumption is that encounters on the browser are a convex combination of encounter distributions across application categories:

$$b_v(\beta) = \sum_{i=1}^{K} \beta_i \, \phi_{iv}, \quad \sum_{i=1}^{K} \beta_i = 1, \; \beta_i \geq 0.$$

where $b_v(\beta)$ is the share of encounters from keyword group v in the browser category and β is the share of browser encounters generated from each of the $i \in I$ categories. We can write down the log likelihood based on the observed browser counts and the observed distribution of keyword encounters on non-browser applications as follows:

$$\ell(\beta) = \sum_{v=1}^{V} x_v \log\left(\sum_{i=1}^{K} \beta_i \, \phi_{iv}\right)$$

where x_v is the number of observed encounters across keyword group v within the browser for the average individual. We estimate β via maximum likelihood estimation using the expectation-maximization algorithm.

We know from Section F.2 that the density of exposures to any keywords (political and non-political) is higher on news than other categories. As such, to map our encounter estimates to time spent on different categories, we need to adjust for the fact that we will be more likely to capture keywords in some categories (such as news) as opposed to others. We define $\theta_i = \beta_i / m_i$ where m_i is the median fraction of time in category i that is captured by our full bank of keywords.[38] Therefore, θ_i provides us with a measure of the share of browser time spent on each of the categories. We estimate this on the data from September 1st until November 4th and restrict ourselves to $I = \{\text{News}, \text{Other}\}$ and estimate $\theta_{\text{News}} = 0.04$, meaning that approximately 4% of browser time

[38]We normalize θ_i such that $\sum_i \theta_i = 1$.

is spent on news sites.

Our main interest, however, is understanding what fraction of election-related encounters on browsers comes from news platforms. We can compute this fraction using our estimates via the following formulation:

$$P\big(i = \text{News} \mid v = \text{election}\big) = \frac{\theta_{\text{News}}\, \phi_{\text{News, election}}}{\displaystyle\sum_{j \in I} \theta_j\, \phi_{j,\,\text{election}}}$$

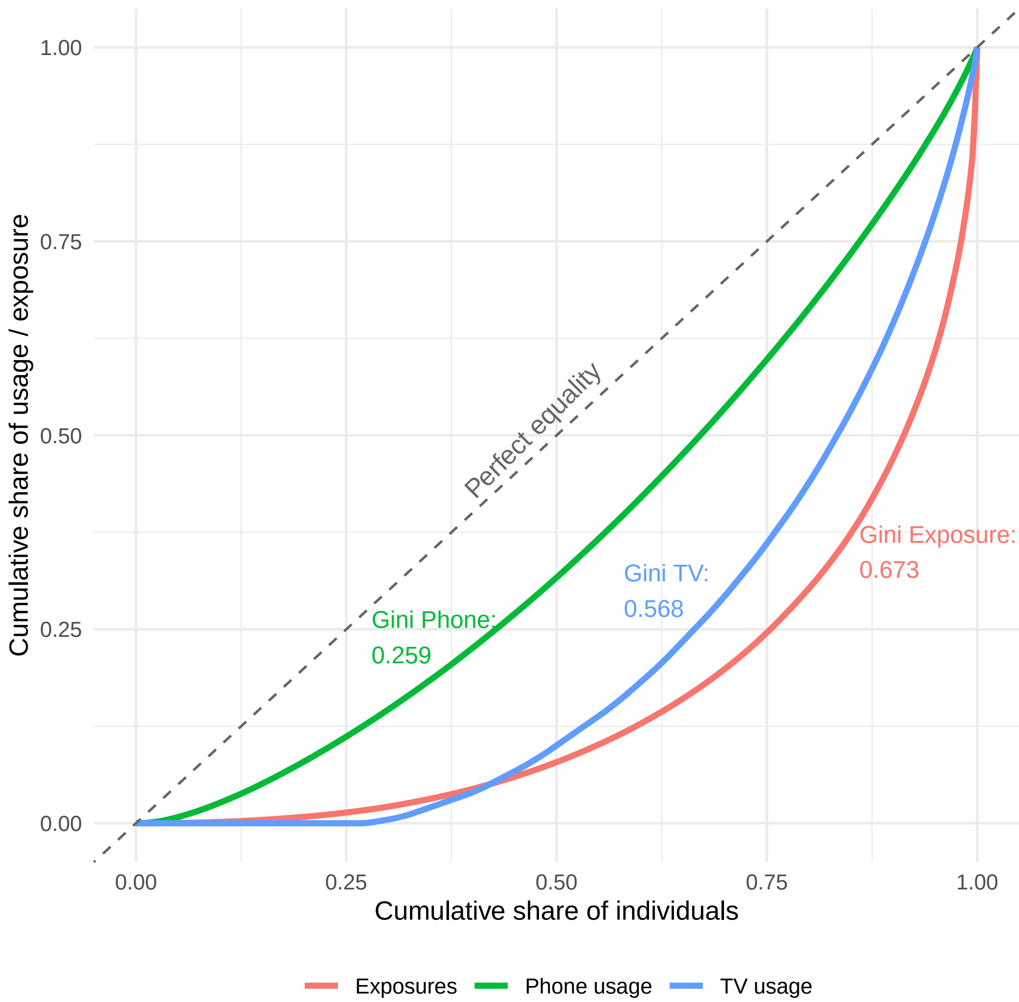
In other words, we divide the time-adjusted share of news encounters in election-related encounters by the total time-adjusted election-related encounters. This provides us with an estimate of $P\big(i = \text{News} \mid v = \text{election}\big) = 0.21$, which tells us that a fraction of 0.21 of election-related exposures that we see in the browser category likely originate from news websites. Finally, we add these imputed news website exposures with the baseline 0.74% exposures in news applications and conclude that 4.93% of election-related exposures originate from either news applications or news websites visited in the browser.

To conclude, using both methods, we find that the mean share of exposures through news platforms increases from 0.74% to 0.89%-4.93%. Thus, this does not change our qualitative conclusion in the main text that consumption on news sites is low.

D Additional Results for Drivers of Consumption

D.1 Heterogeneity Across Individuals

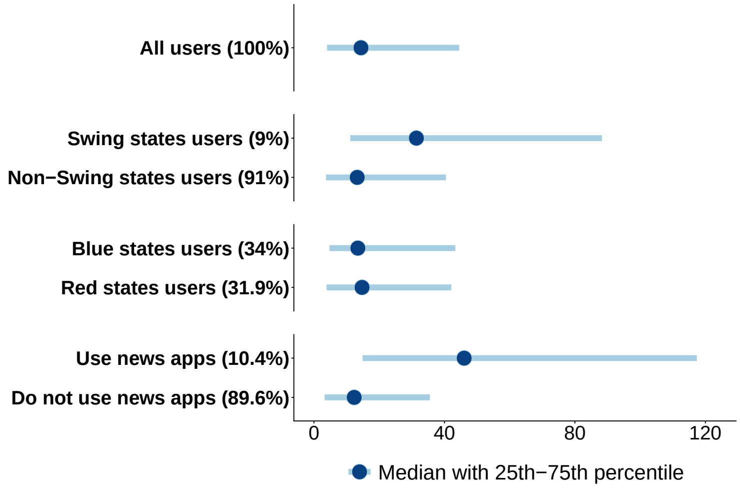
Figure D.1: Lorenz Curve for Exposure



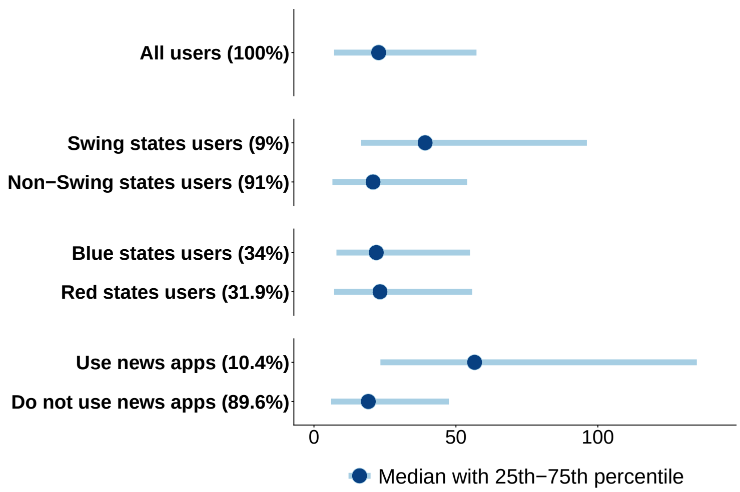
NOTES: This figure plots Lorenz curves for time spent on the phone, time spent consuming TV, and smartphone exposures to election-related content. To calculate time spent on the phone, we use Screenlake application usage data from December 19th, 2024 until January 25th, 2025 since it is reliable for this time period. To calculate time spent consuming TV we use 2024 data from the American Time Use Survey (variable 120303).

Figure D.2: Individual Heterogeneity in Election-Related Encounters and Exposures

(a) Encounters



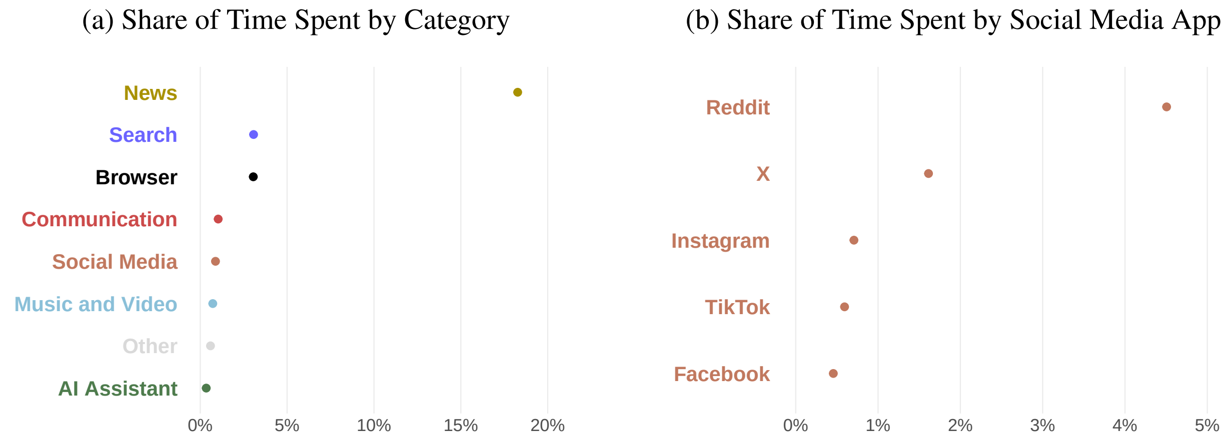
(b) Exposure in Seconds



NOTES: The figure shows the distribution of average daily (a) encounters and (b) exposure in seconds of the median individual to election-related content across subgroups (September 1st–November 4th 2024). Dots represent group medians; bars indicate interquartile ranges (25th–75th percentile). Subgroup labels include the group's share of the total sample in parentheses. Geographic groups were assigned based on the overrepresented state method in encounter data (see Appendix Section F.1).

D.2 Heterogeneity Across Applications

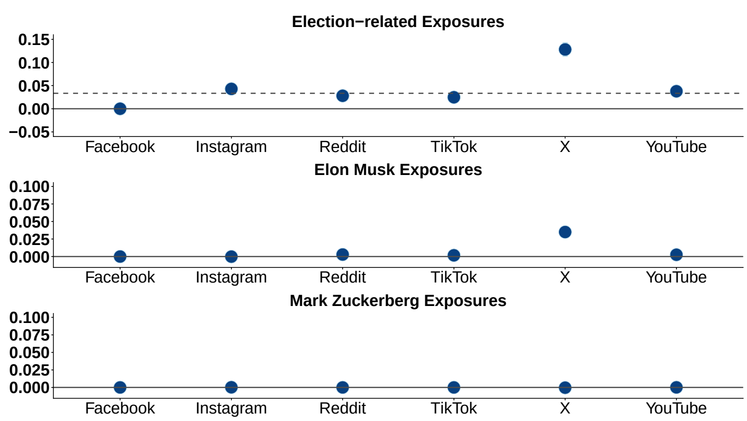
Figure D.3: Heterogeneity in Time Spent on Election-Related Content



NOTES: The figure illustrates variation in the share of time users spent on election-related content across app categories (panel a) and social media apps (panel b). The share is computed by estimated time spent observing election-related content based on exposures divided by estimated time usage on the application. The time usage is based on exposures to the full set of keywords and the imputation in Appendix F.2. Both panels reflect aggregate user behavior between September 1 and November 4, 2024. Panel (b) focuses on social media applications.

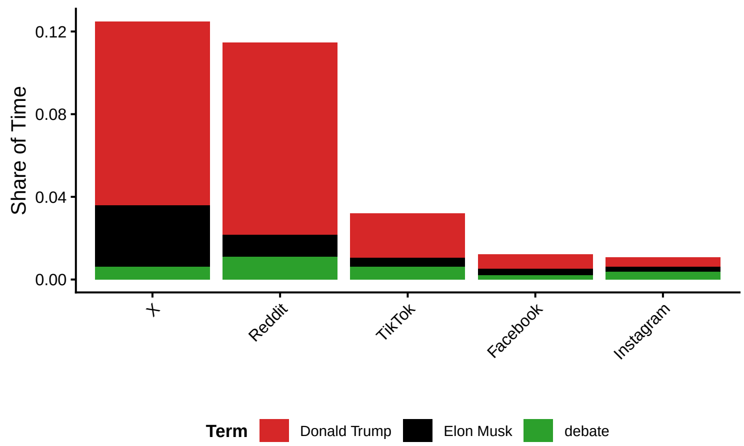
D.3 Additional Variance Decomposition Results

Figure D.4: App Fixed-Effects Across Social Media Apps



NOTES: This figure presents the estimated coefficients of the app fixed effects from Equation (1). We estimate this equation separately for each keyword group (election-related keywords, Elon Musk, and Mark Zuckerberg), restricting the analysis to the social media apps shown in the figure. We use data from September 1st, 2024 until November 4th, 2024. Facebook is the omitted category, serving as the reference group. The (small) 95% confidence intervals are constructed using standard errors clustered at the individual level. The dashed line in the top panel denotes the mean of the Instagram, Reddit, TikTok, and YouTube coefficients.

Figure D.5: Elon Musk and Donald Trump Share



NOTES: This figure presents the share of total encounters, aggregated across individuals, of the terms 'Donald Trump', 'Elon Musk', and 'debate' across each of the presented applications. The figure uses data from September 1st until November 4th.

Table D.1: Variance decomposition (Weekly, election-related keyword exposures

	All apps	Social	Communication
Individual FE	0.78	0.70	0.83
App FE	0.22	0.28	0.11
Time FE	0.03	0.02	0.02
Covariance of ind. & app FE	-0.11	0.02	0.05
Covariance of ind. & time FE	0.00	-0.02	-0.02
Covariance of app & time FE	0.08	0.00	-0.00
Adj. R^2	0.26	0.27	0.21
N apps	285	10	13
N individuals	1469	1469	1469

NOTES: This table presents the share of explained variance corresponding to each component on Equation (2). We estimate this equation separately for each app category. The "All apps" column aggregates across all app categories: AI Assistant, Browser, Communication, Music & Video, News, Search, and Social Media. This aggregation is done by weighting the share of exposures of each group by the time spent on that group, using the category-specific median time frequencies from Table F.1. We exclude apps with fewer than 30 unique users and individuals with fewer than 30 unique apps.

Table D.2: Variance decomposition (Weekly, election-related keyword encounters)

	All apps	Social	Communication
Individual FE	0.86	0.76	0.81
App FE	0.17	0.24	0.13
Time FE	0.04	0.02	0.02
Covariance of ind. & app FE	-0.15	-0.00	0.05
Covariance of ind. & time FE	0.02	-0.02	-0.01
Covariance of app & time FE	0.07	0.00	-0.00
Adj. R^2	0.24	0.26	0.22
N apps	285	10	13
N individuals	1469	1469	1469

NOTES: This table presents the share of explained variance corresponding to each component on Equation (2). We estimate this equation separately for each app category. The "All apps" column aggregates across all app categories: AI Assistant, Browser, Communication, Music & Video, News, Search, and Social Media. This aggregation is done by weighting the share of encounters of each group. We exclude apps with fewer than 30 unique users and individuals with fewer than 30 unique apps.

Table D.3: Variance decomposition (Daily, election-related keyword exposures)

	All apps	Social	Communication
Individual FE	0.81	0.71	0.83
App FE	0.17	0.24	0.10
Time FE	0.03	0.02	0.02
Covariance of ind. & app FE	-0.06	0.04	0.07
Covariance of ind. & time FE	-0.01	-0.01	-0.01
Covariance of app & time FE	0.07	0.00	-0.00
Adj. R^2	0.24	0.26	0.21
N apps	285	10	13
N individuals	1469	1469	1469

NOTES: This table presents the share of explained variance corresponding to each component on Equation (2), with observations at the daily level instead of weekly level. We estimate this equation separately for each app category. The "All apps" column aggregates across all app categories: AI Assistant, Browser, Communication, Music & Video, News, Search, and Social Media. This aggregation is done by weighting the share of exposures of each group by the time spent on that group, using the category-specific median time frequencies from Table F.1. We exclude apps with fewer than 30 unique users and individuals with fewer than 30 unique apps.

Table D.4: Variance decomposition (Aggregated across time, election-related keyword exposures)

	All apps	Social	Communication
Individual FE	0.87	0.74	0.81
App FE	0.24	0.27	0.14
Time FE	0.00	0.00	0.00
Covariance of ind. & app FE	-0.11	-0.02	0.05
Covariance of ind. & time FE	0.00	0.00	0.00
Covariance of app & time FE	0.00	0.00	0.00
Adj. R^2	0.12	0.23	0.17
N apps	285	10	13
N individuals	1469	1469	1469

NOTES: This table presents the share of explained variance corresponding to each component on Equation (2) without time fixed effects. We estimate this equation separately for each app category. The "All apps" column aggregates across all app categories: AI Assistant, Browser, Communication, Music & Video, News, Search, and Social Media. This aggregation is done by weighting the share of exposures of each group by the time spent on that group, using the category-specific median time frequencies from Table F.1. We exclude apps with fewer than 30 unique users and individuals with fewer than 30 unique apps.

Table D.5: Variance decomposition (Weekly, election-related keyword exposures, all apps)

	All apps	Social	Communication
Individual FE	0.70	0.65	0.80
App FE	0.19	0.31	0.13
Time FE	0.02	0.02	0.03
Covariance of ind. & app FE	0.00	0.03	0.06
Covariance of ind. & time FE	0.03	-0.01	-0.01
Covariance of app & time FE	0.06	0.00	-0.00
Adj. R^2	0.25	0.26	0.20
N apps	331	10	14
N individuals	2245	2245	2245

NOTES: This table presents the share of explained variance corresponding to each component on Equation (2). We estimate this equation separately for each app category. The "All apps" column aggregates across all app categories: AI Assistant, Browser, Communication, Music & Video, News, Search, and Social Media. This aggregation is done by weighting the share of exposures of each group by the time spent on that group, using the category-specific median time frequencies from Table F.1. We exclude individuals with less than 30 unique apps.

Table D.6: Variance decomposition (election-related exposures, Kline et al. (2020) correction)

	Social	Communication
Individual FE	0.56	0.65
App FE	0.48	0.25
Covariance of ind. & app FE	-0.03	0.10
Adj. R^2	0.29	0.22
N apps	10	13
N individuals	1469	1469

NOTES: This table presents the share of explained variance corresponding to each component on Equation (2). We estimate this equation separately for each app category. We rely on the implementation of the procedure described in Kline et al. (2020) from `https://github.com/vahid-moghani89/LeaveOutKSS-R`. We consider this for election-related exposures and aggregate across time since this should most closely match our implementation. We only report the category-specific estimates since the library implementation does not compute the covariance terms needed to do our category weighting procedure. We exclude apps with fewer than 30 unique users and individuals with fewer than 30 unique apps.

D.4 Content Consumption Survey

In this section, we present results from a survey designed to provide additional evidence on the drivers of potential under or over exposure to types of content.[39] Recall that in Section 3 we find that individual fixed-effects explain most of the heterogeneity in exposure to election-related content, but app fixed-effects play a non-trivial role in the case of social media. Two channels can explain the role of app fixed-effects: Prior research shows that people use different social media apps for different purposes (Aridor, 2025), but apps may also differ in how they prioritize content. This appendix studies the second channel by analyzing people's exposure, compared to their demand. To do so, we collect self-reported measures of over-exposure to different types of content across applications. We find that users of X consistently report over-exposure to political and Elon Musk–related topics relative to other platforms, while no such pattern emerges for unrelated topics. These findings suggest that platform priorities, rather than differences in user demand alone, play a role in shaping the content individuals encounter.

Our survey was completed by 1,011 respondents that we recruited on August 2025 through Cloud Research, a popular online panel provider (Hartman et al., 2023). We targeted adults in the United States on their mobile phone and respondents who report having an Android device in order to match as closely as possible our primary sample. We filter our final sample to those who passed our three attention checks, including a hidden question for detection of bots, which leaves 986 respondents. The survey asked respondents several blocks of questions, with several goals.

[39]The survey additionally contains questions regarding screen management software, with the analysis of this in Appendix B.

The first block of interest asked participants whether they felt they consumed the right amount of different types of content on various apps, or whether they over- or under-consumed them. The goal of this block was to mimic the exercise that we conduct in Section 3 in order to ascertain whether, for instance, the over-representation of election-related and Elon Musk content on X was purely driven by differences in how people use the different applications. We asked participants about content related to politics and Elon Musk – our primary interest – as well as entertainment, Mark Zuckerberg, Donald Trump, and Kamala Harris. Concretely, we asked:

> Let us know about how you feel about the amount of content related to [topic/person] you receive in your feed on each platform. If you have stopped using any of these platforms, please consider the last time you used them within the past year.

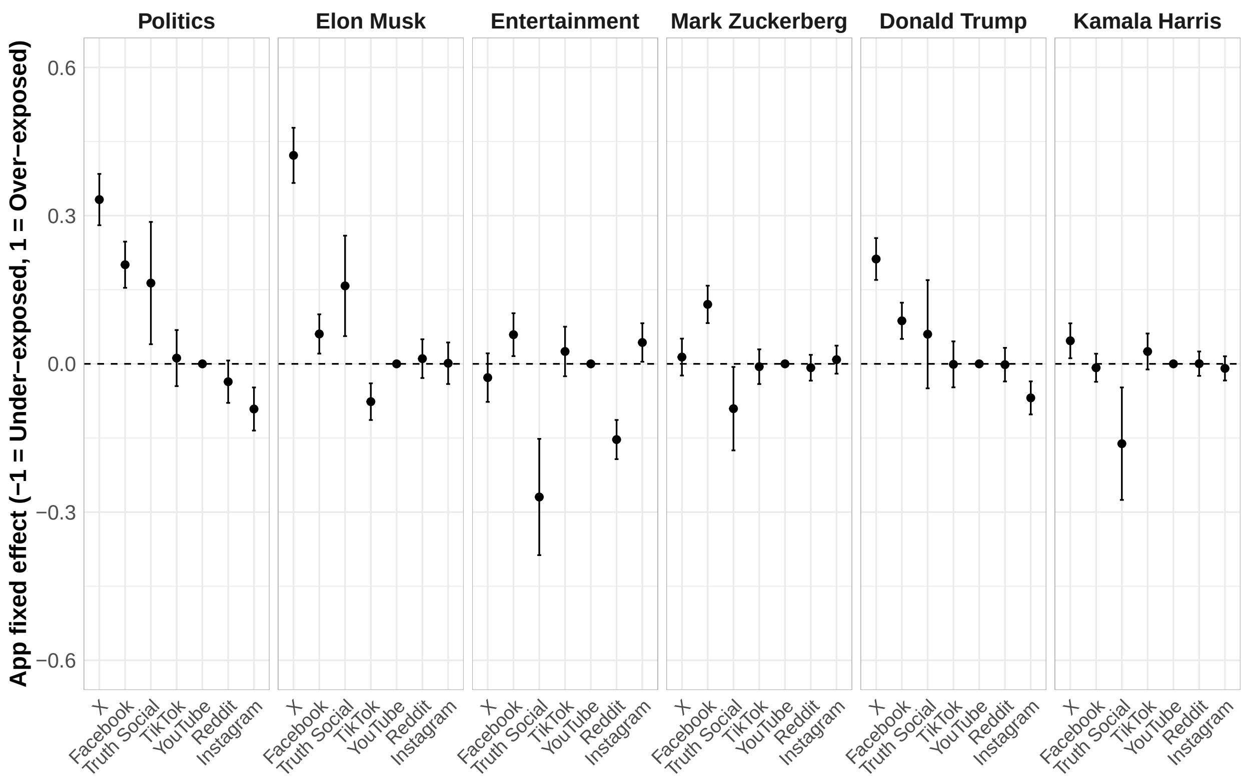
We filtered out responses for respondents who stated that they did not use a given application, leaving a sample of respondents and their perceived content diets on each of these applications. On the remaining sample, we estimated the following regression:

$$y_{ij} = \beta \cdot \text{app}_j + \kappa_i + \epsilon_{ij} \tag{3}$$

where y_{ij} is whether respondent i felt they consumed too little (-1), the right amount (0), or too much (1) of the chosen topic on application j, κ_i indicates respondent fixed effects, and app_j is an indicator for application j. We estimate this on each topic t separately – denoting β_t as the set of estimates across all apps for each topic – and cluster our standard errors at the respondent level.

By controlling for respondent fixed effects, we isolate respondents' sense of exposure to specific content in each app after taking into account their overall sense of over or under-exposure across all applications. This is similar to the regressions in Section 3 that isolate differences in content diets across applications. However, while in Section 3 the differences across applications could be driven by differences in how individuals use the applications, here the differences are in the discrepancy between desired and actual content exposure. Thus, β_t estimates whether, for a given application, they are more exposed to a type of content on a specific application than they would like to be. A positive β_t estimate for a given application indicates perceived over-exposure, relative to the perceived over-exposure levels across all applications. If an application has a non-zero β_t systematically across all topics, it is possible that the application is difficult to personalize. However, if an application has a β_t estimate of zero, relative to other applications, for most topics and only a positive β_t estimate for some then it is possible that it over-prioritizes these types of content.

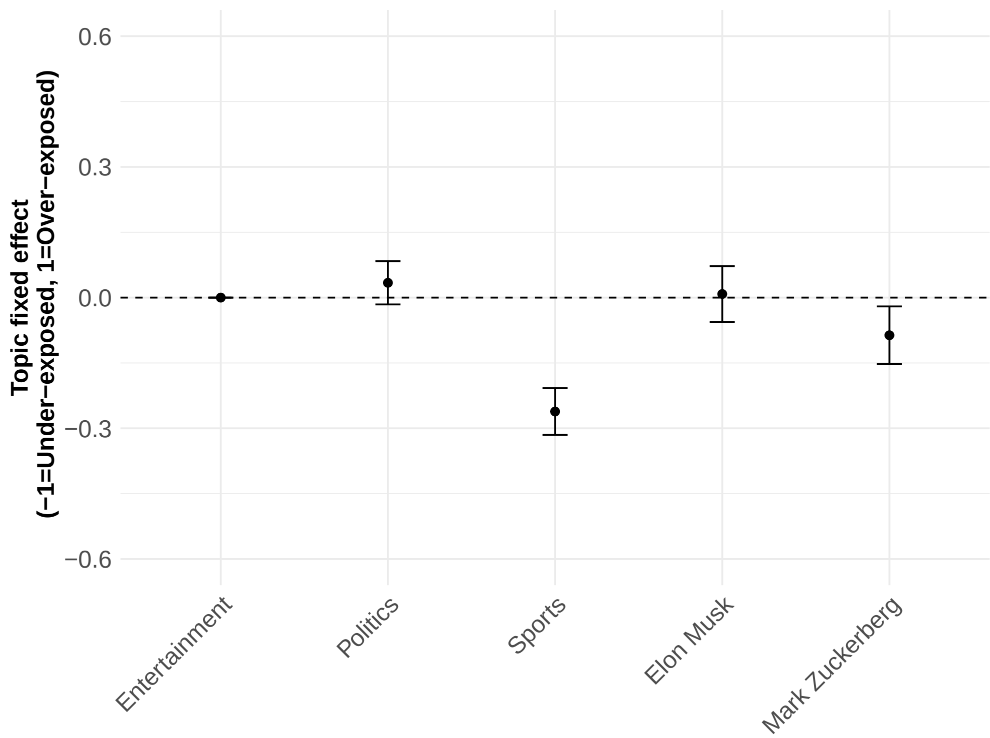
Figure D.6: App Level Over-Exposure to Content



NOTES: This figure presents app fixed effects from equation (3), estimated separately for each topic. YouTube is the omitted category, serving as the reference group. Positive values indicate higher self-reported over-exposure relative to YouTube; negative values indicate under-exposure. The 95% confidence intervals are constructed using standard errors clustered at the respondent level.

Figure D.6 plots the estimated β for Equation (3) estimated for each topic separately with YouTube as the reference application. The results display a striking resemblance to our results from Section 3. Namely, X users report being over-exposed to content about Elon Musk and politics, relative to the other social media applications. Notably, this pattern does not emerge for any of the other topics that we consider, with the exception of a self-reported over-consumption of content related to Donald Trump on X and a small positive effect for Mark Zuckerberg on Facebook. One notable deviation from our results in Section 3 is that Facebook users report over, rather than under, consumption of politics, compared to YouTube, while in Section 3 we found under-consumption of election-related content on Facebook compared to YouTube. This divergence could be due to the self-reported nature of these results or differences in the time period of analysis since our survey was conducted in August 2025. While, based on public reports, there have been no considerable changes to how the other platforms handle political content since the election period, Facebook publicly reverted its earlier downranking of political content and began promoting political content in January 2025.[40]

Figure D.7: Overall Exposure to Content



NOTES: This figure presents app fixed effects from equation (4). Entertainment is the omitted category, serving as the reference group. Positive values indicate higher self-reported over-exposure relative to YouTube; negative values indicate under-exposure. The 95% confidence intervals are constructed using standard errors clustered at the respondent level.

The second block of interest asked respondents whether, across all applications on their phone, they felt they consumed too little (-1), the right amount (0), or too much (1) of a particular topic on their phone. We estimate a similar regression as before:

$$y_{it} = \beta \cdot \text{topic}_t + \kappa_i + \epsilon_{it} \tag{4}$$

where we similarly cluster standard errors at the respondent level. The resulting estimates of β are plotted in Figure D.7. Respondents report similar amounts of over-consumption of politics as

[40]See `https://techcrunch.com/2025/01/07/meta-to-phase-back-in-political-content-on-facebook-instagram-and-threads/` on the reversal on political down-ranking and `https://www.nytimes.com/2025/01/07/technology/meta-facebook-content-moderation.html` on the shift in content moderation to be more similar to X, especially for political content.

they do of entertainment when considering all applications together, in spite of us finding self-reported over-consumption of politics when considering social media applications individually. These results are consistent with our finding in Section 3 that individual fixed effects are the main driver of heterogeneity in consumption, as the content individuals receive in aggregate tends to match their preferences.

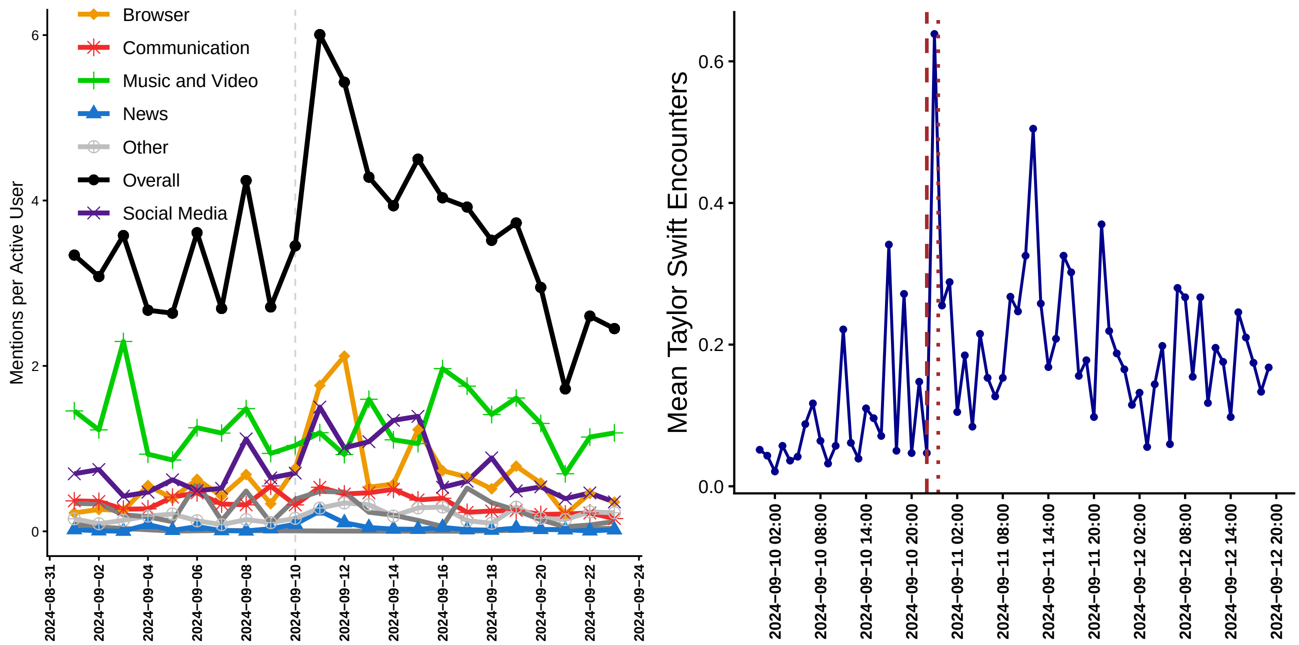
Putting these two results together, they paint a similar picture as Section 3, and suggest possible mechanisms. Given that 1) individuals' satisfaction with the amount of political content varies widely across apps, and 2) many are dissatisfied with their exposure (65% report over-consuming Elon Musk–related content on X), our findings suggest that not all platforms are delivering the content users want, and that over-consumption of political and Elon Musk–related content on X is at least partly driven by platform prioritization choices. At the same time, similarly to our variance decomposition exercise, the magnitudes of consumption aggregated across different applications suggest that, despite these systematic application effects, individuals are still able to curate their full set of applications to produce desired consumption levels of political content.

E Taylor Swift Endorsement Analysis

Figure E.1: Taylor Swift Encounters

(a) Taylor Swift Encounters (Daily)

(b) Taylor Swift Encounters (Hourly)



NOTES: Subfigures (a) and (b) describe the average daily and hourly encounters, respectively, with the term "Taylor Swift" per active individual across different app categories. The dashed vertical line in the first panel marks the timing of Swift's endorsement, while in the second panel the dashed vertical marks the start of debate and the dotted line marks Swift's endorsement.

In this section, we analyze the effect of Taylor Swift's Instagram endorsement of Kamala Harris. The endorsement occurred directly following the highly anticipated presidential debate between Kamala Harris and Donald Trump, which began on September 10th, 2024 at 9:00 PM ET. Taylor Swift's endorsement occurred minutes after the conclusion of the debate at 10:30 PM ET when she posted her endorsement of Kamala Harris on Instagram and directed her followers to register to vote.[41],[42]

To study whether Swift's endorsement could have affected election-related content consumption, we begin by documenting the number of mentions for the term 'Taylor Swift', highlighting

[41]For the endorsement itself, see `https://www.instagram.com/p/C_wtAOKOW1z/?hl=en`. For a discussion of the endorsement, see `https://www.nytimes.com/2024/09/10/us/taylor-swift-endorses-kamala-harris.html`.

[42]Reportedly, the number of visits to 'vote.gov' increased dramatically following the debate and the endorsement. See `https://www.cbsnews.com/news/taylor-swift-kamala-harris-endorsement-vote-gov/`.

that individuals in our sample were exposed to the endorsement event. Figure E.1a shows that overall mentions of Taylor Swift were fairly flat from September 1st until September 10th, while the number of mentions for Taylor Swift dramatically spiked on September 11th, increasing by over 100%. As the endorsement was made late in the evening on September 10th, this is when we expect to see that most individuals would initially be exposed to it. Figure E.1b shows the number of encounters with the term 'Taylor Swift' by hour and confirms the interest spiked exactly when Swift made her endorsement, but was persistently higher for several days afterward. Indeed, the overall mentions of Taylor Swift do not return back to pre-endorsement levels until September 20th, nearly 10 days after the endorsement, suggesting that the event could also have a persistent effect on election-related content consumption. While the spikes for Taylor Swift on news applications only persist for the day following the endorsement, the breakdown by category suggests longer-lasting elevated exposures to Taylor Swift on social media and communication applications.

In order to measure the effect of the endorsement on election-related content consumption, we use a difference-in-differences analysis comparing individuals who were relatively more likely to interact with Taylor Swift-related content. We define 'Swifties' as individuals in our dataset whose share of 'non-political' exposures to the term 'Taylor Swift' (i.e., filtering out instances with a political surrounding word) is above the median.[43] We consider the following regression specification to assess the overall causal effect of the endorsement for a given individual i and time period t:

$$Y_{i,t} = \sum_t \beta_t \Big(\text{Day}_t \times S_i\Big) + \gamma_t + \kappa_i + \epsilon_{it} \tag{5}$$

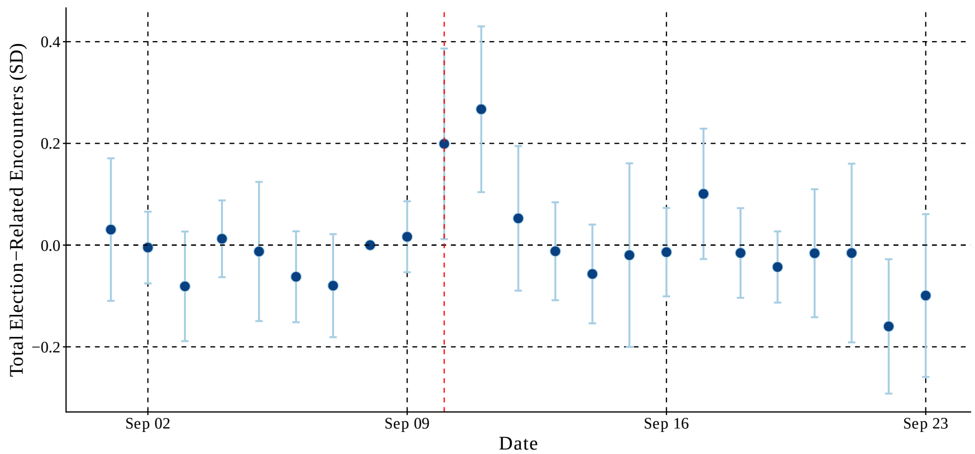
where S_i indicates that individual i is a Swiftie (treated), γ_t is daily fixed effects, and κ_i denotes individual fixed effects. We cluster standard errors at the individual level.

Figure E.2 plots the estimated treatment effects, β_t, derived from estimating specification (5) with normalized election-related encounters and exposures as Y_{it}. Figures E.2a and E.2b show that there was a statistically and economically significant increase in both encounters and exposures, respectively, the two days following the debate. Notably, there is a 0.27 and 0.33 standard deviation increase in election-related encounters and exposures on September 11th, respectively, the day following the debate. The positive effects on election-related content consumption persist for several days and dissipate over time, eventually returning to pre-endorsement levels.

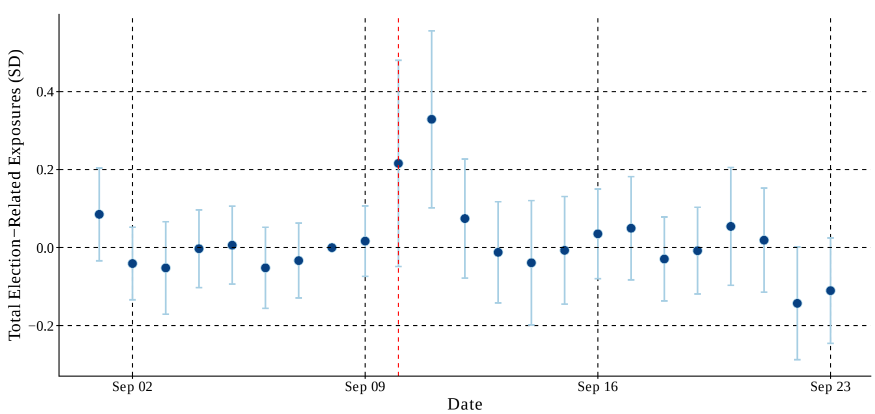
[43]We compute the share for each individual using their total exposures to Taylor Swift divided by the total number of exposures across all terms. Our results are robust to considering an alternative definition of 'Swifties' as individuals with at least one non-political encounter with the term 'Taylor Swift' in a music & video applications such as Spotify and YouTube. Given the popularity of Taylor Swift, this leads to 30.5% of the individuals that we observe being classified as 'Swifties'.

Figure E.2: Effect of Swift Endorsement on Election-Related Content Consumption

(a) Election-Related Encounters



(b) Election-Related Exposures



NOTES: This figure plots the estimated daily effect of Taylor Swift's public endorsement of Kamala Harris on election-related encounters (panel a) and exposures (panel b), using estimates from specification (5). Each point represents the estimated difference in standardized daily election-related exposures or encounters between individuals with above- and below-median pre-endorsement exposure share to the term 'Taylor Swift'. The red dashed line marks the date of the endorsement (September 10, 2024). 95% confidence intervals of the estimated treatment effect are shown, derived from standard errors clustered at the individual level.

We consider an additional robustness specification that controls for the fact that more politically active individuals may differentially respond to the endorsement. We estimate the following regression specification:

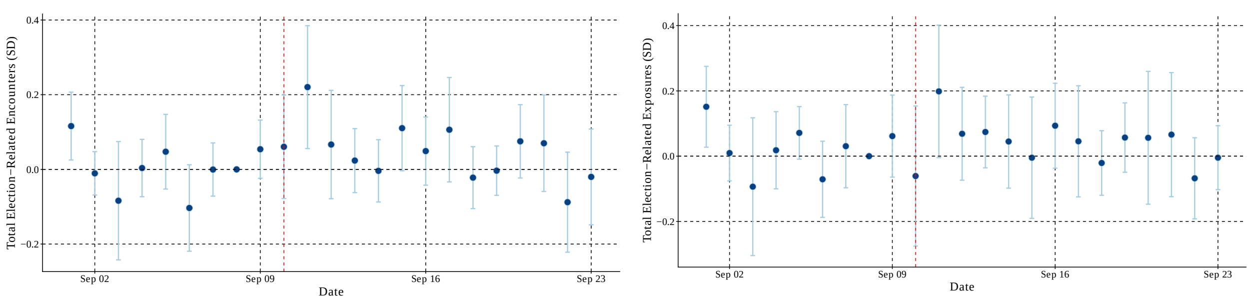
$$Y_{i,t} = \sum_t \beta_t \Big(\text{Day}_t \times S_i\Big) + \alpha_t \Big(\text{Day}_t \times Y_{i,-1}\Big) + \kappa_i + \epsilon_{it} \tag{6}$$

where $Y_{i,-1}$ is the mean value of the outcome variable in the pre-period, which we interact with the date in order to control for differential responsiveness to unrelated time-varying shocks that can influence election-related content consumption. In particular, we proxy and control for political activeness using election-related content consumption in the baseline and interact this with the day fixed effects. Figure E.3 plots the estimated treatment effects, β_t, derived from estimating specification (6) and find similar patterns as our primary specification.

While the results in Section 2 indicate that there are few events that increase election-related content consumption, our results here indicate that endorsements, and more broadly exposure to election-related content via non-political figures, can lead to increases in election-related content consumption among specific segments of the population.

Figure E.3: Effect of Swift Endorsement on Election-Related Content Consumption (Robustness)

(a) Election-Related Encounters (b) Election-Related Exposures



NOTES: This figure plots the estimated daily effect of Taylor Swift's public endorsement of Kamala Harris on election-related encounters (panel a) and exposures (panel b), using estimates from specification (6). Each point represents the estimated difference in standardized daily election-related exposures (encounters) between individuals with above- and below-median pre-endorsement exposure (encounters) share to the term 'Taylor Swift'. The red dashed line marks the date of the endorsement (September 10, 2024). 95% confidence intervals of the estimated treatment effect are shown, derived from standard errors clustered at the individual level.

F Data Imputation Procedures

In this section we provide details for two imputation procedures that we use throughout the text: imputation of the state of an individual and the total time spent on the phone and individual applications.

F.1 State Classification

In this section we discuss our procedure for classifying the state of residence of each individual in our sample. In order to do so, we make use of two aspects of the data: the full set of states as keyword encounters and the timezone set on each individual's device.

To assign each user a likely U.S. state of residence, we implemented a classification procedure based on the overrepresentation of U.S. state mentions in our encounter data. We first identified encounters involving state terms and for each device, we computed the relative share of mentions for each state term and compared it to the corresponding global share of that state's mentions across all devices. This ratio, interpreted as an overrepresentation score, captures how much more frequently a user mentions a specific state compared to the population baseline. We then selected the top three overrepresented states for each device, reflecting the strongest state-level signal based on their appearance on the user's screen.

To improve classification accuracy, we leveraged time zone data provided by Screenlake for each device and cross-referenced it with the local time zones associated with each U.S. state.[44] For example, California and Oregon were mapped to the Pacific Time Zone, while Texas and Illinois corresponded to Central Time. The classification method evaluated the top three overrepresented states for each device in descending order. It first attempted to assign the top-ranked state (i.e., the one most disproportionately mentioned for the user), and verified whether its assigned time zone matched the device's time zone. If the first choice was inconsistent with the device's time zone, we evaluated the second most overrepresented state, and if necessary, the third. If none of the top three states aligned with the device's time zone, the algorithm defaulted to the top-ranked state. This matching process produced a proposed state classification for each device.

Based on this proposed state variable, we assign each individual to one of three political categories: swing states, blue states, and red states.

1. Swing states: Arizona, Georgia, Michigan, Nevada, Pennsylvania, and Wisconsin.

2. Blue states: California, Colorado, Connecticut, Delaware, Hawaii, Illinois, Maine, Maryland, Massachusetts, Minnesota, New Hampshire, New Mexico, New York, Oregon, Rhode Island, Vermont, and Washington.[45]

3. Red states: Alabama, Alaska, Arkansas, Florida, Idaho, Indiana, Iowa, Kansas, Kentucky, Louisiana, Mississippi, Missouri, Montana, Nebraska, North Dakota, Ohio, Oklahoma, South Dakota, Tennessee, Texas, Utah, and Wyoming.

Several states were excluded from the final political classification due to ambiguity in keyword identification. Specifically, references to "Carolina" and "Virginia" could not be reliably disaggregated into North vs. South Carolina or Virginia vs. West Virginia, leading to their exclusion from the swing/blue/red categorization to avoid misclassification. By contrast, the term "Dakota"

[44]Screenlake infers time zone from the various brands, apps, and/or terms that appear on the screen.
[45]Data on New Jersey was not collected due to a technical error.

was not problematic for classification purposes, as both North and South Dakota are consistently categorized as red states.

Our final validation step suggests that this classification method correctly matches the user's time zone in 86% of cases.

F.2 Time Usage Imputation from Encounters Data

Table F.1: Fraction of Time Captured by Exposures

Aggregation	Mean	Min	25th	Median	75th	Max
Total Phone Time	0.0407	0.0012	0.0219	0.0350	0.0528	0.4615
Apps						
Facebook	0.0782	0.0005	0.0246	0.0465	0.0840	0.9730
Gmail	0.1872	0.0016	0.0748	0.1383	0.2418	1.0000
Google	0.1860	0.0013	0.0853	0.1449	0.2384	1.0000
Instagram	0.0364	0.0005	0.0162	0.0264	0.0413	0.5593
Messages	0.1081	0.0010	0.0289	0.0572	0.1121	1.0000
NYTimes	0.1402	0.0032	0.0606	0.0722	0.1288	0.6250
Reddit	0.1001	0.0009	0.0312	0.0587	0.1098	1.0000
Spotify	0.1449	0.0002	0.0498	0.1010	0.1913	1.0000
Threads	0.1363	0.0054	0.0347	0.0887	0.1793	0.9474
TikTok	0.0486	0.0005	0.0192	0.0329	0.0549	0.7178
WhatsApp	0.0486	0.0008	0.0152	0.0305	0.0522	0.8308
X	0.0528	0.0007	0.0110	0.0210	0.0499	0.7500
YouTube	0.0362	0.0002	0.0103	0.0198	0.0393	0.9375
Categories						
AI Assistant	0.1190	0.0009	0.0312	0.0789	0.1558	0.8165
Browser	0.0930	0.0003	0.0328	0.0671	0.1154	1.0000
Communication	0.0509	0.0006	0.0178	0.0352	0.0612	0.8571
Music and Video	0.0501	0.0002	0.0125	0.0253	0.0532	1.0000
News	0.2508	0.0032	0.0736	0.1738	0.3142	1.0000
Other	0.0658	0.0002	0.0237	0.0466	0.0862	1.0000
Search	0.1835	0.0013	0.0824	0.1395	0.2329	1.0000
Social Media	0.0422	0.0003	0.0181	0.0313	0.0487	1.0000

NOTES: This figure presents the fraction of time captured by exposures, using the joined encounter and time usage data between December 19th, 2024 until January 25th, 2025. The first row computes this for overall phone usage, the next set of rows for individual applications, and the final set of rows for application categories.

In this section we describe how we use the encounters data to provide an approximation of the time spent on different applications, application categories, and on the phone in general. The encounters and time usage stream are separate data streams that Screenlake collects from the phone. The permissions that users are required to enable are different for each stream. Unfortunately, during the election campaign, we do not have reliable time usage data. Therefore, for this imputation, we use data from December 18th, 2024 until January 25th, 2025 where we have reliable time usage data and can accurately match it with the encounters data.

We use the following imputation procedure. First, as in the main text, we approximate the time spent using the encounters data by multiplying the number of app-exposure-date observations by three, since the app records the on-screen encounters every three seconds. Then, we compute for each individual their total phone time in which they were exposed to any keyword (based on our full list of thousands of keywords and not just the subset of election-related keywords) according to the unique number of exposures in a given day. We drop the individuals for whom this results in a time estimate higher than the application usage data, since it is likely that these individuals consistently have enabled the encounter permissions and not the time usage permissions. Fortunately, only 44 individuals are dropped based on this criterion. For each of the remaining 1,980 individuals, we aggregate the time spent on each app over the entire time period based on the application data, and aggregate the time spent on each app while exposed to any keyword based on the encounter data. We then compute the fraction of time captured by the full set of keyword encounters overall on the phone, by top applications, and by categories. We use the median of these estimates throughout the text when we approximate time spent using our encounter data. The results are presented in Table F.1.

G Dictionaries

G.1 Classification of Applications into Categories

Applications are classified into the main app categories as follows:

- **News Apps**: CNN, BBC News, CBC News, Washington Post, Fox News, NPR, NBC NEWS, NYTimes, Google News, ABC News, AP News, Samsung News, WSJ, BBC, KSL, Deseret News, NewsBreak, Ground News, Guardian, TVA Nouvelles, Público, La Presse, HuffPost, DailyWire, Epoch Times, The Atlantic, inshorts, Denver Post, CNBC, Yahoo News, SmartNews

- **Communication Apps**: Telegram, WhatsApp, Messages, Messenger, Message+, Email, Gmail, Yahoo Mail, Outlook, WhatsApp Business, Signal, GroupMe, Slack, Discord, Kick, TextNow, Mensajes, WeChat, Viber

- **Social Apps**: Facebook, Instagram, TikTok, X, Threads, Truth Social, Snapchat, LinkedIn, Tumblr, Reddit, Pinterest, Instagram Lite, Facebook Lite, TikTok Lite, Bluesky

- **Browser Apps**: Chrome, Safari, Opera, Brave, Firefox, Edge, Kiwi Browser, Free Adblocker Browser, XBrowser, Samsung Internet, Opera GX, Firefox Nightly, Opera Mini, Silk Browser, Firefox Focus, Chrome Beta, Vivaldi
- **Music & Video Apps**: YouTube, Spotify, YouTube Music, JioSaavn, SoundCloud, Amazon Music, Audify Music Player, Yandex Music, Audible, Spotify Lite, Spotify X, Spotify for Artists, Spotify for Creators, YouTube Music, YouTube Premium, YouTube Pro, YouTube ReVanced, YouTube ReVanced Extended, YouTube Vanced, YouTube.com, Rumble, Podcast Addict, CleanTube, NewPipe, Netflix, Disney+, Hulu, Prime Video
- **Search Apps**: Google, DuckDuckGo, Ecosia, Bing
- **AI Apps**: ChatGPT, Perplexity, Gemini, Claude, Copilot, Character.AI

G.2 Lists of Detected Keywords

In this section, we provide additional documentation of the full set of election-related keywords used in our analyses. Outside of election-related keywords, Screenlake captures a large number of nonpolitical keywords, which we use as a proxy for time spent on the phone (discussed in Section F.2). In total, Screenlake captures 2286 keywords across sports (e.g., Pittsburgh Steelers), entertainment (e.g., NCIS), celebrities (e.g., Gal Gadot), brands (e.g., Sprite), countries (e.g., Israel), and miscellaneous (e.g., weather).

The full set of political figures that Screenlake captures and we include in our definition of election-related keywords are as follows:

- **Presidential Candidates**: Donald Trump, Kamala Harris, J.D. Vance, Tim Walz
- **Notable Political Figures**: Bernard Sanders, Hillary Clinton, Joe Biden, Nancy Pelosi, Nikki Haley, Robert F Kennedy Jr
- **Governors**: Albert Bryan, Andy Beshear, Arnold Palacios, Bill Lee, Brad Little, Brian Kemp, Chris Sununu, Dan McKee, Doug Burgum, Eric Holcomb, Gavin Newsom, Glenn Youngkin, Greg Abbott, Greg Gianforte, Gretchen Whitmer, Henry McMaster, Janet Mills, Jared Polis, Jay Inslee, JB Pritzker, Jim Justice, Jim Pillen, Joe Lombardo, John Carney, Josh Green, Josh Shapiro, Kathy Hochul, Katie Hobbs, Kay Ivey, Kevin Stitt, Kim Reynolds, Kristi Noem, Laura Kelly, Lemanu Peleti, Lou Leon, Mark Gordon, Maura Healey, Michelle Lujan, Mike DeWine, Mike Dunleavy, Mike Parson, Ned Lamont, Pedro Pierluisi, Phil Murphy, Phil Scott, Ron DeSantis, Roy Cooper, Sarah Huckabee, Spencer Cox, Tate Reeves, Tina Kotek, Tony Evers, Wes Moore

- **Congressmembers**: Aaron Bean, Abigail Spanberger, Adam Schiff, Adam Smith, Adrian Smith, Adriano Espaillat, Al Green, Alex Padilla, Alexandria Ocasio-Cortez, Alma Adams, Ami Bera, Amy Klobuchar, André Carson, Andrea Salinas, Andrew Clyde, Andrew Garbarino, Andy Barr, Andy Biggs, Andy Harris, Andy Kim, Andy Ogles, Angie Craig, Angus S. King, Ann Wagner, Anna Eshoo, Anna Paulina Luna, Annie Kuster, Anthony D'Esposito, Ashley Hinson, August Pfluger, Austin Scott, Ayanna Pressley, Barbara Lee, Barry Loudermilk, Barry Moore, Becca Balint, Ben Cline, Ben Ray Luján, Benjamin L. Cardin, Bennie Thompson, Bernard Sanders, Beth Van Duyne, Betty McCollum, Bill Cassidy, Bill Foster, Bill Hagerty, Bill Huizenga, Bill Keating, Bill Pascrell, Bill Posey, Blaine Luetkemeyer, Blake Moore, Bob Good, Bob Latta, Bobby Scott, Bonnie Watson Coleman, Brad Finstad, Brad Schneider, Brad Sherman, Brad Wenstrup, Brandon Williams, Brendan Boyle, Brett Guthrie, Brian Babin, Brian Fitzpatrick, Brian Mast, Brian Schatz, Brittany Pettersen, Bruce Westerman, Bryan Steil, Buddy Carter, Burgess Owens, Byron Donalds, Carlos A. Giménez, Carlos Giménez, Carol Miller, Catherine Cortez Masto, Cathy McMorris Rodgers, Celeste Maloy, Charles E. Schumer, Chip Roy, Chris Deluzio, Chris Pappas, Chris Smith, Chris Van Hollen, Chrissy Houlahan, Christopher A. Coons, Christopher Murphy, Chuck Edwards, Chuck Fleischmann, Chuck Grassley, Chuy García, Cindy Hyde-Smith, Claudia Tenney, Clay Higgins, Cliff Bentz, Colin Allred, Cori Bush, Cory A. Booker, Cory Mills, Cynthia M. Lummis, Dale Strong, Dan Bishop, Dan Crenshaw, Dan Goldman, Dan Kildee, Dan Meuser, Dan Newhouse, Dan Sullivan, Daniel Webster, Danny Davis, Darin LaHood, Darrell Issa, Darren Soto, David Joyce, David Kustoff, David Rouzer, David Schweikert, David Scott, David Trone, David Valadao, Dean Phillips, Deb Fischer, Debbie Dingell, Debbie Lesko, Debbie Stabenow, Debbie Wasserman Schultz, Deborah Ross, Delia Ramirez, Derek Kilmer, Derrick Van Orden, Diana DeGette, Diana Harshbarger, Dina Titus, Don Bacon, Don Beyer, Don Davis, Donald Norcross, Doris Matsui, Doug LaMalfa, Doug Lamborn, Drew Ferguson, Dusty Johnson, Dutch Ruppersberger, Dwight Evans, Ed Case, Edward J. Markey, Eli Crane, Elise Stefanik, Elissa Slotkin, Elizabeth Warren, Emanuel Cleaver, Emilia Sykes, Eric Burlison, Eric Schmitt, Eric Sorensen, Eric Swalwell, Erin Houchin, Frank Lucas, Frank Pallone, Frederica Wilson, French Hill, Gabe Vasquez, Garret Graves, Gary C. Peters, Gary Palmer, Gerry Connolly, Glenn Grothman, Glenn Ivey, Glenn Thompson, Grace Meng, Grace Napolitano, Greg Casar, Greg Landsman, Greg Lopez, Greg Murphy, Greg Pence, Greg Stanton, Greg Steube, Gregory Meeks, Gus Bilirakis, Guy Reschenthaler, Gwen Moore, Hakeem Jeffries, Hal Rogers, Haley Stevens, Hank Johnson, Harriet Hageman, Henry Cuellar, Hillary Scholten, Ilhan Omar, Jack Bergman, Jack Reed, Jacky Rosen, Jahana Hayes, Jake Ellzey, Jamaal Bowman, James Comer, James E. Risch, James Lankford, Jan Schakowsky, Jared Golden, Jared Huffman, Jared Moskowitz, Jasmine Crockett, Jason Crow, Jason Smith, Jay Obernolte, Jeanne Shaheen, Jeff Duncan, Jeff Jackson, Jeff Merkley, Jeff Van Drew, Jen Kiggans, Jennifer McClellan, Jennifer Wexton, Jerry Carl, Jerry Moran, Jerry Nadler, Jill Tokuda, Jim Baird, Jim Banks, Jim Clyburn, Jim Costa, Jim Himes, Jim Jordan, Jim McGovern, Jimmy Gomez, Jimmy Panetta, Joaquin Castro, Jodey Arrington, Joe Courtney, Joe Manchin, Joe Neguse, Joe Wilson, John B. Larson, John Barrasso, John Boozman, John Carter, John Cornyn, John Curtis, John Duarte, John Fetterman, John Garamendi, John Hoeven, John James, John Joyce, John Kennedy, John Moolenaar, John Rose, John Rutherford, John Sarbanes, John Thune, John W. Hickenlooper, Jon Ossoff, Jon Tester, Jonathan Jackson, Joni Ernst, Joseph Morelle, Josh Brecheen, Josh Gottheimer, Josh Harder, Josh Hawley, Joyce Beatty, Juan Ciscomani, Juan Vargas, Judy Chu, Julia Brownley, Julia Letlow, Kat Cammack, Katherine Clark, Kathy Castor, Kathy Manning, Katie Boyd Britt, Katie Porter, Kay Granger, Keith Self, Kelly Armstrong, Ken Calvert, Kevin Cramer, Kevin Hern, Kevin Kiley, Kevin Mullin, Kim Schrier, Kirsten E. Gillibrand, Kyrsten Sinema, Lance Gooden, Laphonza R. Butler, Larry Bucshon, Laurel Lee, Lauren Boebert, Lauren Underwood, Linda Sánchez, Lindsey Graham, Lisa Blunt Rochester, Lisa McClain, Lisa Murkowski, Lizzie Fletcher, Lloyd Doggett, Lloyd Smucker, Lois Frankel, Lori Chavez-DeRemer, Lori Trahan, Lou Correa, Lucy McBath, Madeleine Dean, Marc Molinaro, Marc Veasey, Marco Rubio, Marcy Kaptur, Margaret Wood Hassan, Maria Cantwell, María Elvira Salazar, Mariannette Miller-Meeks, Marie Gluesenkamp Perez, Marilyn Strickland, Marjorie Taylor Greene, Mark Alford, Mark Amodei, Mark DeSaulnier, Mark E. Green, Mark Kelly, Mark Pocan, Mark R. Warner, Mark Takano, Markwayne Mullin, Marsha Blackburn, Martin Heinrich, Mary Gay Scanlon, Mary Miller, Mary Peltola, Matt Cartwright, Matt Gaetz, Matt Rosendale, Max Miller, Maxine Waters, Maxwell Frost, Mazie K. Hirono, Melanie Stansbury, Michael C. Burgess, Michael Cloud, Michael F. Bennet, Michael Guest, Michael McCaul, Michael Rulli, Michael Waltz, Michelle Steel, Mike Bost, Mike Braun, Mike Carey, Mike Crapo, Mike Ezell, Mike Flood, Mike Garcia, Mike Johnson, Mike Kelly, Mike Lawler, Mike Lee, Mike Levin, Mike Quigley, Mike Rogers, Mike Rounds, Mike Simpson, Mike Thompson, Mike Turner, Mikie Sherrill, Mitch McConnell, Mitt Romney, Monica De La Cruz, Morgan Luttrell, Morgan McGarvey, Nancy Mace, Nanette Barragán, Nathaniel Moran, Neal Dunn, Nick LaLota, Nick Langworthy, Nicole Malliotakis, Nikki Budzinski, Norma Torres, Nydia Velázquez, Pat Ryan, Patrick McHenry, Patty Murray, Paul Gosar, Paul Tonko, Pete Aguilar, Pete Ricketts, Pete Sessions, Peter Welch, Pramila Jayapal, Raja Krishnamoorthi, Ralph Norman, Rand Paul, Randy Feenstra, Randy Weber, Raphael G. Warnock, Rashida Tlaib, Raúl Grijalva, Raul Ruiz, Rich McCormick, Richard Blumenthal, Richard Hudson, Richard J. Durbin, Richard Neal, Rick Allen, Rick Crawford, Rick Larsen, Rick Scott, Ritchie Torres, Ro Khanna, Rob Menendez, Robert Aderholt, Robert Garcia, Robert Menendez, Robert P. Casey, Robin Kelly, Roger F. Wicker, Roger Marshall, Roger Williams, Ron Estes, Ron Johnson, Ron Wyden, Ronny Jackson, Rosa DeLauro, Ruben Gallego, Rudy Yakym, Russ Fulcher, Russell Fry, Ryan Zinke, Salud Carbajal, Sam Graves, Sanford Bishop, Sara Jacobs, Scott DesJarlais, Scott Fitzgerald, Scott Franklin, Scott Perry, Scott Peters, Sean Casten, Seth Magaziner, Seth Moulton, Sharice Davids, Sheila Cherfilus-McCormick, Sheldon Whitehouse, Shelley Moore Capito, Sherrod Brown, Shontel Brown, Shri Thanedar, Steny Hoyer, Stephanie Bice, Stephen F. Lynch, Steve Cohen, Steve Daines, Steve Scalise, Steve Womack, Steven Horsford, Summer Lee, Susan M. Collins, Susan Wild, Susie Lee, Suzan DelBene, Suzanne Bonamici, Sydney Kamlager-Dove, Sylvia Garcia, Tammy Baldwin, Tammy Duckworth, Ted Budd, Ted Cruz, Ted Lieu, Teresa Leger Fernandez, Terri Sewell, Thom Tillis, Thomas Kean Jr., Thomas Massie, Thomas R. Carper, Tim Burchett, Tim Kaine, Tim Kennedy, Tim Scott, Tim Walberg, Tina Smith, Todd Young, Tom Cole, Tom Cotton, Tom Emmer, Tom McClintock, Tom Suozzi, Tom Tiffany, Tommy Tuberville, Tony Cárdenas, Tracey Mann, Trent Kelly, Troy Balderson, Troy Carter, Troy Nehls, Val Hoyle, Valerie Foushee, Vern Buchanan, Veronica Escobar, Vicente Gonzalez, Victoria Spartz, Vince Fong, Virginia Foxx, Warren Davidson, Wesley Hunt, Wiley Nickel, William Timmons, Yadira Caraveo, Young Kim, Yvette Clarke, Zach Nunn, Zoe Lofgren

We use the following surrounding keywords as secondary keywords that allow us to ensure that political issues are discussed in a political context:

- Representative, conservative, debate, voters, campaign, liberal, vote, elections, independent, rally, progressive, rights, voting, contribute, debates, election, campaign, republican, fundraising, nomination, candidate, polls, electoral, ballot, reelection, democrat, democracy, suppression, elect, electorate, polling, republicans, nominee, lobbying, constituent, turnout, endorsement, farright, recount, political, recount, absentee, redistricting, populist, progressives, gerrymandering, farleft, president, presidential

We use the following keywords to compare celebrities to politicians. They represent the 100 celebrities with the highest exposure in our data:

- Taylor Swift, Drake, Sabrina Carpenter, Eminem, Billie Eilish, Tyler The Creator, The Weeknd, Lana Del Rey, Travis Scott, Kendrick Lamar, Bruno Mars, Cristiano Ronaldo, Michael Jackson, Justin Bieber, Coldplay, Rihanna, Charli XCX, Kanye West, Linkin Park, Adele, SZA, Katy Perry, Olivia Rodrigo, Doja Cat, Frank Ocean, Shakira, Metro Boomin, Nirvana, Beyoncé, Selena Gomez, Nicki Minaj, Hozier, Imagine Dragons, J Cole, Megan Thee Stallion, Snoop Dogg, Post Malone, Gracie Abrams, Stray Kids, Ed Sheeran, Neymar, Dua Lipa, Chris Brown, Ice Spice, Deftones, Cardi B, Harry Styles, Jennifer Lopez, Gunna, MrBeast, Tate McRae, Kylian Mbappé, Zach Bryan, Fleetwood Mac, Markiplier, Karol G, LeBron James, Morgan Wallen, Benson Boone, Miley Cyrus, Zendaya, Noah Kahan, Logan Paul, Jason Derulo, Jimin, JoJo Siwa, GloRilla, OneRepublic, Virat Kohli, The Kid LAROI, Demi Lovato, Tommy Richman, Jelly Roll, Gordon Ramsay, Alia Bhatt, SIMI, Shraddha Kapoor, Kylie Jenner, Addison Rae, Marques Brownlee, Teddy Swims, Priyanka Chopra, PewDiePie, Bryson Tiller, Mark Rober, Jack Harlow, Cody Johnson, Brandon Lake, Kevin Hart, Jacksepticeye, Jeff Nippard, Dude Perfect, Lionel Messi, Ellen Degeneres, Chris Stapleton, Bailey Zimmerman, JaidenAnimations, El Chapo, James Charles