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

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**Abstract**

Smartphones, personalized from applications to notifications, are now a dominant source of political information, yet little is known about the content people consume on them. We provide the first systematic analysis of the magnitude and drivers of election-related smartphone consumption, using novel data on the content people observed on their phones during the 2024 U.S. election campaign. Despite a highly contentious campaign, the median American consumed limited election content on their phones, and consumption remained stable over time. Consumption primarily came from applications with personalized content (social media and music & videos apps), with less than 10% from dedicated news applications. To understand the drivers of this pattern, we examine heterogeneity across both applications and individuals. We find that across applications, individuals consumed more election content on X and Reddit than on Facebook or Instagram. Across individuals, consumption was positively skewed, with higher consumption among swing-state residents, news app users, and even fans of a non-political figure (Taylor Swift) following her endorsement. Using a variance decomposition exercise, we find that differences across individuals, rather than differences between the applications they use, drive the observed heterogeneity. These findings suggest that policies altering voter incentives to consume news – rather than regulating platform algorithms – may be more effective for increasing political engagement.

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# 1 Introduction

Models of democratic accountability typically assume that citizens are better off when voters make informed choices (Downs, 1957; Persson and Tabellini, 1994; Larreguy and Raffler, 2025). As smartphones have become a dominant source of news consumption, it is seemingly easier than ever for the electorate to stay informed.[1] At the same time, the shift toward digital consumption, and specifically smartphones, has raised new concerns. First, the prevalence of other content may crowd-out digital news consumption among less politically-engaged individuals (Prior, 2007). Second, individuals may be more likely to encounter information from biased or unvetted sources on their phones, particularly through social media applications and similar platforms (Aral, 2021). Relatedly, platform algorithms can generate disparities in exposure to political content by either showing content based on platform priorities or by widening the gap between news seekers and news avoiders (Pariser, 2011; Schiffer and Newton, 2023). Empirically analyzing these issues has been challenging because, until recently, it was not feasible to observe smartphone content.

In this paper, we overcome this limitation and measure the amount of election-related content consumption during the consequential 2024 U.S. elections, along with the factors driving heterogeneity in individuals' exposure. We do so using novel data on smartphone-mediated content consumption that allows us to objectively measure consumption at fine temporal granularity. 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 and stable throughout the election period.[2] At the same time, we find substantial heterogeneity in consumption, which is mostly driven by systematic differences across individuals and not the apps they use.

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. The sample consists of individuals who downloaded a popular smartphone app and provided permissions to capture the keywords they encounter.[3] A unique feature of this dataset is its coverage of *all* applications on the smartphone. This data allows us to measure previously unobserved consumption, such as on communication apps, the relative importance of different types of applications, and the total consumption across apps.

[1] In 2025, for example, a plurality of Americans reported that smartphones are the first way they come across news in the morning, surpassing televisions and computers, which were more common in 2016 (Newman et al., 2025).

[2] Campaigns spent over a billion dollars on digital ads, with most of the spending occurring after September 1, see: `https://www.brennancenter.org/our-work/analysis-opinion/online-ad-spending-2024-election-topped-135-billion`. Election-related coverage was so dominant that a majority of Americans say they were worn out by it. `https://www.pewresearch.org/journalism/2024/10/10/how-americans-feel-about-election-coverage/`

[3] We discuss external validity in section 2.2 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.

Our keyword list includes prominent election-related keywords, as well as the names of the president, presidential and vice-presidential candidates, and virtually all congressmembers and governors. 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. We formalize this argument as a topic classification problem and use the universe of Fox News and New York Times articles and their publisher-assigned tags during the election campaign as ground-truth labels for election-related content to measure the performance of our keyword-based classifier. We find that our classifier does well, with over 97% of articles about the election in both the New York Times and Fox News containing at least one of our keywords.

We use these data to address two main questions. First, we examine total exposure to election-related content. Smartphones allow us to observe content that was difficult to capture in earlier media (e.g., private discussions about political candidates) and have also become a primary source of news consumption. Therefore, we ask how much election-related content people are exposed to during the campaign, and where this content comes from. Second, we analyze heterogeneity in exposure. Smartphones may introduce greater variation in information consumption than previous technologies given the vast array of available apps and content, as well as algorithms that personalize content based both on user interests and platform incentives. We ask what drives the variation in exposure to election-related content.

Our first finding is that despite the highly contested nature of the election, most individuals in our sample had limited consumption of election-related content on their smartphones. Overall, on a given day, the median individual was exposed to fewer than 10 instances of our keywords, which include, for example, all mentions of a presidential candidate (and many other words) on a social media post, search engine ad, news article, email, or any other app.

Compared with several benchmarks, this level of exposure is arguably small. First, our estimates suggest that on an average day from September 1st until the day before the election, across all apps, the median individual encountered around half of the number of election-related keywords appearing in a single New York Times election-related article about the election. Second, we find that the total amount of time that people are exposed to election-related content is minuscule. For example, on an average day, the median individual saw the terms 'Donald Trump', 'Joe Biden', and 'Kamala Harris' on their phone for only 3 seconds. Third, exposure to congressmembers is almost non-existent, with only 18% of individuals encountering *any* congressmembers on their phone on an average day. Fourth, we find that the median individual was exposed to less than one instance of election-related content per day on communication and search apps – platforms that better indicate active interest in the election, unlike other exposures that may be incidental or driven by ads. Finally, even during the election campaign, the median individual is eight times more likely to encounter sports and entertainment celebrities than politicians.

With limited consumption of election-related content, it is especially important to determine the source of such content. We find that less than 10% of election-related exposures are on news apps, where professional journalists and editors curate content, and instead individuals are exposed to election-related content mainly on applications with algorithmic curation, such as social media (e.g., Facebook, X, TikTok) and music & video (e.g., YouTube) apps, where concerns have been raised over the proliferation of biased, low-quality information.

The overall low amount of consumption begs the question: when, if ever, does election-related content consumption increase over the election cycle? In the lead-up to the election, numerous events could have increased consumption of election-related content: scandals, endorsements, debates, politically-charged rallies, and assassination attempts. Yet, we find that the low levels of consumption for the median individual are remarkably stable throughout the campaign. The only two exceptions are the day following the first presidential debate between Kamala Harris and Donald Trump (which was followed by Taylor Swift's endorsement), and election day itself, which led to a 44% and 287% increase in exposures, respectively, compared to the week before these events. Most of the increase on election day occurred after the polls closed, suggesting that this is not driven by individuals acquiring actionable information on how they should vote.

While median consumption is arguably low, we find substantial heterogeneity in news consumption across individuals. The mean individual is exposed to 51 seconds of election-related content per day (based on our set of keywords), compared to 21 seconds per day for the median individual, indicating that the distribution of exposures is positively skewed. The dramatic inequality is demonstrated in the gap between individuals in the 5th percentile, who are exposed to only 1 second of election-related content, and those at the 95th percentile, who are exposed to 179 seconds per day.

We then turn to understanding what factors can explain the observed inequality in election-related exposures. There are two main plausible explanations that we evaluate: differences in individuals' propensity to consume news or the applications individuals use may limit or amplify exposure to election-related content. To unpack this question, we begin by studying heterogeneity based on individual characteristics and applications.

We document several important dimensions that predict variation in exposure. First, using imputed state information from keyword occurrences, we find that individuals in swing states – who likely have greater incentives to seek election-related information or are more heavily targeted by political messaging – have 88% more exposures than individuals in non-swing states.[4] Second, individuals who use news applications, and are probably more interested in the elections, experience 195% more election-related exposures than individuals who do not use news applications.

[4] Appendix Section F.1 provides details for our imputation method, which relies on which US state is more disproportionately commonly seen on-screen, relative to the rest of the sample.

Third, in the modern media environment, the nonpolitical interests of individuals can influence consumption since, on many non-news applications, election-related content is mixed with entertainment and social updates. Consistent with this idea, we show with a difference-in-differences design that Taylor Swift's endorsement of Kamala Harris led to a 0.33 standard deviation increase in election-related exposures the following day among individuals with above-median likelihood of being exposed to Taylor Swift content, compared to those below the median. This effect remained positive, though diminished, over the subsequent days.

Our analysis also reveals substantial heterogeneity across applications and application categories. While unsurprisingly news applications have the highest share of election-related content, there is heterogeneity across social media and communication applications. X, Truth Social, and Reddit have a substantially higher share of election-related content compared to Facebook, Instagram, and TikTok. While these patterns could be due to differences in how consumers use these applications, the low share of election-related content is consistent with Meta reportedly limiting the distribution of such content right before the election and consistent with X promoting specific political content, including posts by Elon Musk himself.[5] Indeed, we find that, once we control for individual and time fixed effects, Facebook and X continue to have a persistently lower and higher share of exposure to election-related content, respectively, while the other platforms are more similar. Furthermore, the term 'Elon Musk' had a 4 percentage points higher share of total exposures on X than on Facebook, making it 43 times more likely to appear. These results suggest that the differences we observe across social media applications are not only driven by individuals' propensity to consume, but also partly reflect platforms' choices in prioritizing certain types of content.

We quantitatively evaluate the relative importance of individual and app-level heterogeneity in driving inequality in election-related content consumption by conducting a variance decomposition exercise that attributes variance in election-related content exposure to individual-specific effects, application-specific effects, time-fixed 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. The intuition for the procedure is that we observe consumption across all applications within a given market and consider application effects as dominating when shares are relatively similar across individuals for a given application. Concretely, if individuals who use X have systematically higher shares of election-related content on X compared to Facebook, then

[5] See https://www.npr.org/2024/03/26/1240737627/meta-limit-political-content-instagram-facebook-opt-out for discussion of Instagram political downranking, https://about.fb.com/news/2021/02/reducing-political-content-in-news-feed/ for discussion of Facebook political downranking, and https://www.nbcnews.com/tech/social-media/elon-musk-turned-x-trump-echo-chamber-rcna174321 for discussion of political upranking on X.

we would attribute this to application effects. We find that individual-driven variation accounts for over 8 times more of the explained variance than app-driven variation across all applications. App effects are more important when studying social media applications but still explain less than 30% of the explained variation in election-related consumption.[6]

Overall, we find evidence that news consumption in the most important US political setting—the presidential elections—is limited and often based on potentially less reliable sources than traditional media. Our results provide more nuance to the discussion on social media algorithms. On the one hand, despite concerns that algorithms increase or decrease exposure to political content, the apps people use are not the main driver of variation in election-related exposure. At the same time, the personalization enabled by these algorithms results in substantial inequality in exposure across individuals. Instead of these platforms systematically prioritizing or deprioritizing election-related content, they seem to be reflecting existing divisions in content consumption across individuals. Thus, policy interventions aiming to increase consumption of political information may be more effective if they focus on changing individual incentives to consume news, rather than primarily regulating platform algorithms or content prioritization practices.

Our paper builds on a long-standing literature on citizens' exposure to politics, dating back to Lazarsfeld et al. (1944). We contribute to this debate by measuring exposure to *content*, providing a *fine-grained* measure of exposure, and by focusing on *smartphones*. We believe that each of these advantages provides a unique contribution, which we discuss in turn.

First, we contribute to a rich literature studying exposure to news, recently focusing on exposure to like-minded information (Gentzkow and Shapiro, 2011; Stroud, 2011; Flaxman et al., 2016; Guess, 2021), misinformation (Guess et al., 2020; Allcott and Gentzkow, 2017; Allen et al., 2020), or "soft news" and opinion programs (Baum and Jamison, 2006; Bursztyn et al., 2023). This literature typically relies on self-reported survey answers or infers exposure from the sources (e.g., domains) that people visit (see Capozza et al. (2022) for an overview of measurement techniques). We complement these studies by using the *screenomics* methodology (Reeves et al., 2020, 2021), to measure exposure directly from content people see on their screen.[7] Our results align with earlier work showing limited exposure to political information (Bennett and Iyengar, 2008; Allen et al., 2020), but also reveal new stylized facts. First, most encounters with politics occur outside traditional news outlets, but rather through other apps, including social media and music & video

[6]Our procedure cannot disentangle whether the app component reflects differences in how consumers use the applications or systematic algorithmic prioritization of content. Survey evidence in Appendix H shows that many individuals feel over-exposed to political and Elon Musk–related content on X, closely mirroring our exposure estimates. This suggests that differences in app usage alone do not fully explain the patterns we observe.

[7]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 offering evidence on political consumption during an election, and by analyzing its drivers.

apps. Second, on most days, most people do not discuss politics on their phones.[8] Third, we distinguish between different types of exposure and find that while exposure to national politics is limited, exposure to congressmembers is nearly nonexistent for most individuals. Thus, our results are consistent with recent concerns about the nationalization of politics, news avoidance, and reliance on potentially less reliable media sources.

A second advantage of our data is that it is provided at a *fine-grained* level: We observe content every three seconds across all apps and keywords. This granularity allows us to contribute to the literature on political campaigns and specific events, such as debates, endorsements, and other "October surprises" (Wald and Lupfer, 1978; Fridkin et al., 2007; Jacobson, 2015; Brierley et al., 2020; Chiang and Knight, 2011; Di Tella et al., 2021; Le Pennec and Pons, 2023). We find that, besides debates, exposure to election news is remarkably stable, suggesting that campaign events do not seem to affect the exposure of most voters.[9] At the same time, we show that endorsements from non-political celebrities, like Taylor Swift, shift the consumption behavior of their followers, illustrating how non-traditional political actors can shape political exposure.

The third advantage of our data is that it opens the *smartphone* black box. Smartphones have become a dominant source of political content, and there are concerns that they are changing the way news is consumed, yet we have not been able to observe the content people see on their phones. While previous studies analyzed the time spent on different applications (Allcott et al., 2022; Aridor, 2025) or the phone's location (e,g, Chen and Rohla, 2018), we provide the first systematic evidence on exposure to election-related content on smartphones. We find that instead of leveling the playing field, there is substantial heterogeneity in exposure to content on smartphones.[10] This could be due to increased media options (Prior, 2007; Bennett and Iyengar, 2008) or due to personalization algorithms (Sunstein, 2017). Studying new media phenomena (personalized apps), requires new methods; we contribute to the debate on social media algorithms (Bakshy et al., 2015; Guess et al., 2023; Aridor et al., 2024) by conducting a variance decomposition to separate out the explanatory role of systematic individual effects from the role of application-specific choices.

This paper proceeds as follows: Section 2 describes our data sources, Section 3 presents new evidence on patterns of election-related consumption and Section 4 presents new evidence on the drivers of these patterns.

[8]Previous studies on political conversation relied on surveys (e.g., Wojcieszak and Mutz, 2009) or on public online discussions (e.g., Barberá et al., 2015). We analyze mentions of election-related keywords in digital conversations, including emails and instant messages.

[9]A related literature finds that campaign contact has minimal persuasive effects (Kalla and Broockman, 2018).

[10]The heterogeneity in exposure to news is consistent with substantial variation in voters' information (Carpini and Keeter, 1996; Angelucci and Prat, 2024).

## 2 Data

Our primary data consists of observed keyword occurrences across all apps on individuals' smartphones for several thousand Americans between September 1st, 2024 and November 30th, 2024. Most of our analysis focuses on the election campaign, defined as September 1st to November 5th (election day).

The data we use comes from Screenlake, a company that creates and maintains a proprietary database of term-encounters occurring in natural smartphone usage around the world, primarily to serve enterprise businesses in measuring their brands' organic popularity over time across apps. Screenlake's data is sourced from an SDK (software development kit) that is embedded within a popular smartphone application. An individual who installs this application on their personal device 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.[11] Once permission is granted, the SDK passively checks for the presence of specific keywords every three seconds continuously across apps. The SDK logs the occurrence of any keywords, along with an installation identifier, the exact time when the keyword appeared, and the app that was on-screen at the time.[12] We manually classify apps into the following categories: communication (e.g., Gmail, WhatsApp), social media (e.g., Facebook, X), music and video (e.g., YouTube, Spotify), news (e.g., New York Times, Fox News), search (e.g., Google, Bing), browser (e.g., Samsung Browser, Google Chrome) and AI (e.g., ChatGPT, Claude).[13] 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 rendered visibly on the screen. Additionally, the SDK detects keywords that appear in video captions and, for some applications, has access to transcriptions of videos.[14]

We observe two main groups of election-related terms: 1) *election terms* are words related to the elections ("polls", "ballot", "campaign", "debate", "democracy", "Republican", "Democrat", "Congress", "swing", "vote", "election", "electoral", "Mail-In") and 2) *politicians*, are the presidential and vice-presidential candidates ("Joe Biden","Robert F Kennedy Jr", "Nikki Haley", "Ka-

[11] 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.

[12] All such content processing is done on the smartphone device itself to avoid the collection of personally identifiable or sensitive information. The resulting anonymous term exposure logs are uploaded to the cloud periodically, to be automatically cleaned, sorted, and combined with other such data streams.

[13] See Appendix J for the list and classification of apps.

[14] 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.

mala Harris", "Donald Trump", "Tim Walz", "JD Vance") and virtually all congressmembers and governors.[15] Overall, there are 532 distinct election-related keywords.[16] In addition, we received data on exposure to several thousand control keywords covering sports, entertainment, commercial brands, and other topics. These terms are mostly used as a proxy for the time spent by each user on each app as we document in Appendix Section F.2.

In the rest of this section, we discuss our main outcomes and our sample.

## 2.1 Primary Outcomes

The first natural measure of consumption to consider is election-related *encounters*, defined by the number of occurrences of an election-related keyword. This measure can be computed most directly from our observed keyword-stream data and allows us to measure the exact number of keywords individuals were exposed to. 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. To fix ideas, imagine two pieces of election-related content: "I watched the presidential debate last night" versus "I watched the presidential debate last night between Kamala Harris and Donald Trump." The former has one encounter (debate), whereas the latter has three encounters (debate, Harris, Trump). It is not clear that the latter statement has more election-related content than the former and we would want to count them both as a single moment of election-related content consumption.

Motivated by this, we utilize a second measure of content consumption, which we term election-related *exposure*, defined as the number of observed time periods with at least one keyword occurrence of our election-related keywords. This measure is more robust to our underlying keyword set, as it treats the multiple simultaneous encounters as a single instance of election-related content consumption. As keywords are generally captured every three seconds, we multiply the number of exposures by three to determine an upper bound for the number of seconds in which any election-related terms appeared on the screen. We typically provide our main results using either encounters or exposures with the version for the other outcome measure in Appendix A.

### 2.1.1 Keyword Informativeness

The two primary keyword-based measures above capture different dimensions of consumption of election-related content, but all rely on the underlying assumption that the pre-specified keywords are informative of the topics of interest. We want our keywords to be strongly indicative of a piece

[15] 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 or not, and preferentially does not include references that do not meet that criteria.

[16] The full set of keywords is shown in Appendix Section I.

of content being about the election as well as ensure that they are able to capture instances of election-related content consumption.

In Appendix C we formulate the measurement problem as a classification problem where the presence of at least one of our keywords (an "exposure") indicates that an individual is consuming election-related content at a given observation period. We primarily rely on two supply-side benchmarks – the set of articles from the New York Times and Fox News during the election period – to benchmark the performance of our keyword-based classifier. These supply-side benchmarks provide us with ground-truth labels for whether content is election-related since they provide article-related tags, which allows us to differentiate between articles that are about the election versus other topics. Using these ground-truth labels we then measure the performance of our keyword-based classifier at correctly detecting election-related content.

We demonstrate that our keywords perform reasonably well, achieving high recall with 97.74% and 97.89% of election-related articles on the New York Times and Fox News, respectively, including at least one of our keywords.[17] Furthermore, we demonstrate that the keyword-based classifier has a moderately high precision statistic of 0.58 and 0.70 for the New York Times and Fox News, respectively.[18] Combined, these statistics suggest that our keyword-based classifier can accurately measure the extent of election-related content consumption. If anything, the moderate precision suggests that our results may be an upper-bound on the magnitude of consumption.[19]

## 2.2 The Panel

We include in our analysis active users, defined as those who have at least one keyword captured on at least fourteen days during the analysis period. On an average day, 1,170 users appear in our final dataset. Figure B.1 documents the number of individuals observed over time, showing that the panel grew substantially during the observation period. Screenlake did not substantially change its marketing strategy for the application during our sample period, ensuring a consistent degree of selection into the application.

[17] We additionally compute this statistic using 250-word increments – an approximation for how many words would be on an individual's screen at a single point in time. Using these 250-word increments, we still find a high recall of 0.87 and 0.88 on the New York Times and Fox News, respectively. In other words, if someone has just one random segment from a New York Times or Fox News article on their smartphone screen, we are highly likely to record an exposure to election-related content.

[18] These results demonstrate that our keywords are highly informative about classifying election-related content written by journalists and curated by editors. We additionally compute recall on a benchmark dataset of user-generated content by measuring its performance over the full set of comments on the sub-reddit 'r/politics'. We find that 90% of the posts have at least one of our keywords in their comment thread.

[19] Selecting a keyword subset from our available bank corresponds to choosing a point on the precision-recall curve. While, in principle, we could prioritize a smaller set of keywords with higher precision and lower recall, in our context the cost of false negatives is higher than that of false positives. We therefore selected a set that lies toward the high-recall region of the curve, accepting more false positives in exchange for fewer cases where we miss a relevant keyword.

Naturally, there is panel churn and individuals are not consistently observed throughout the sample period. Figure B.2 plots the histogram of the number of observed active days during our sample period and finds that 56.67% of individuals are observed for at least two weeks. Despite the panel growth and attrition, Figure B.3 shows that the overall usage of different application categories remains consistent across the sample period of interest. Therefore, we primarily focus on aggregated daily statistics for our analyses.

**Representativeness** Our sample is composed of individuals who opt to use the application offered by Screenlake. An important concern is how findings from this group can be extrapolated to the broader U.S. population. We conduct several exercises, including collecting app time use from a representative sample during the same time period, to assess the generalizability of our results.

Using gender and age inferred from keyword occurrences, we find that demographic composition of our sample does not change much over time and our main results on election-related content consumption are robust to reweighting to match a representative sample of U.S. individuals on these dimensions. However, the sample may still differ from the population in unobserved ways. A particularly important concern for our main result is whether they systematically encounter less political content than the average person in the U.S.

To address this, we complement our analysis with additional datasets to understand selection into the sample. First, we compare the app composition and phone usage of our sample to market-level Google Play application downloads data and industry benchmarks, and show that our sample is similar to the population at the extensive margin. Second, we compare our sample to a representative sample on their app and total phone usage at the intensive margin. As neither population-level nor existing representative sample estimates are available for this period, we recruited a sample of Prolific participants representative of the US population in the week before election day. We find that the average Screenlake user has similar phone usage, spends more time on social media applications, and is more likely to have news apps installed than the average American. Third, the primary reason users install the application is to manage their screen time. We conducted an additional survey with mobile users and found no evidence that users of screen management software are less politically engaged; in fact, individuals who actively manage their screen time may be slightly more politically engaged. These patterns suggest that our results around limited election-related consumption are not due to low phone usage or lack of news interest, compared to the US population. If anything, this suggests our sample may be more exposed to election-related content than the typical U.S. adult, and our estimates likely represent upper-bounds. We document the details of these exercises in Appendices D and H.

# 3 Election-Related Content Consumption

## 3.1 Magnitude of Consumption

A functioning democracy relies on individuals receiving high-quality information about topics and candidates, deliberating with their social networks, adjusting their beliefs, and making choices accordingly. Indeed, this is the basic structure of most political economy models (e.g., Persson and Tabellini (1994)). However, in the modern media environment, this basic model might not hold for at least two reasons. First, surveys have revealed a sharp decline in the demand for news (Newman et al., 2023). Second, individuals may be exposed to biased or low-quality information. Until recently, it was almost impossible to observe the political information people were exposed to and discussed, and empirically test these claims.

Figure 1 shows that the consumption for the median individual of election-related content is arguably low. We computed encounters with and exposures to election-related content per day during the election campaign. The first column of Figure 1 shows that 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 keywords.[20] 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. As shown in the second bar of Figure 1, the 13.2 encounters comes from 7.0 unique exposures.[21] Recall from Section 2.1 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. Since we can measure the content appearing on the phone at least once every three seconds, that implies that the median individual are exposed to approximately 21 seconds of election-related terms on their phone. Overall, the median individual spends on average approximately 5.54 hours on their phone suggesting that individuals saw election-related terms only 0.11% of the time.[22]

Another way to test whether individuals consumed election-related content is to define a *session* as whether there was any encounter occurring within a fixed time window. This measure captures the density of exposure. For example, encountering 10 keywords within a ten-minute span likely reflects more active consumption (e.g., reading a news article), whereas the same number spread throughout the day may reflect more passive exposure (e.g., scrolling past headlines in

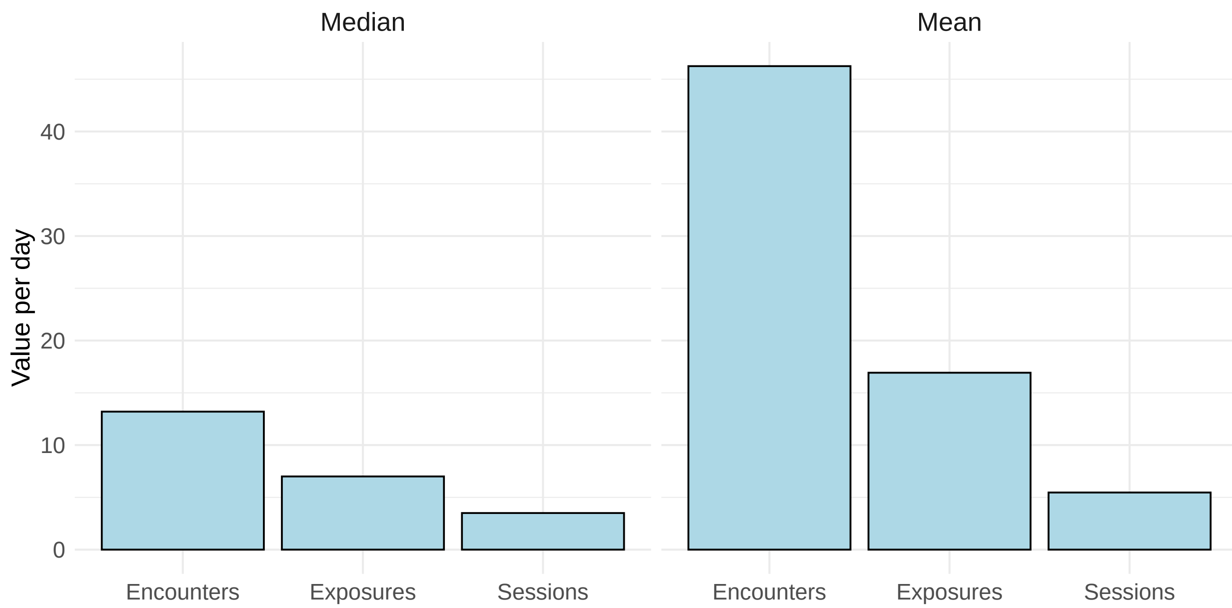
[20] Figure D.1 shows that this consumption slightly increases but does not change dramatically when weighting individuals using our demographic weights to match a representative sample based on age and gender.

[21] The median number of exposures after re-weighting to a demographically representative sample is 9.0.

[22] We calculate the total amount of time spent on the phone based on data from December 19th, 2024 until January 25th, 2025 since our time use data is accurate for this time period. We can also use the total time the average American spends on their phone (4.5 hours) from industry benchmarks as the denominator: the individuals saw political terms only 0.13% of the time.

a social media feed). Using a ten-minute time window, the third bar of Figure 1 shows that the 7.0 exposures to election-related content (21 seconds) typically result from 3.5 sessions.[23] This indicates not only that election-related content consumption is low, but also that it is likely spread throughout the day given that the number of sessions is half the number of exposures.

Figure 1: Election-Related Content Consumption




NOTES: The figure reports the median number of primary election-related encounters, exposures, and sessions among active devices for the median (left) and mean (right) user on an average day from September 1 to November 4th, 2024. We consider only the sample of devices where we observe data for at least 14 days during September-November 2024.

While election-related content consumption for the median individual is low and spread throughout the day, the right panel of Figure 1 shows that the mean encounters, exposures, and sessions are considerably higher than the median, indicating that the distribution of consumption of election-related content is positively skewed. Appendix Figure A.2 plots the histogram of the total number of election-related exposures across individuals in September and October 2024. While many individuals have between 5 and 20 exposures (15 seconds to 1 minute), 41.20% individuals have less than 5 exposures (15 seconds) per day and 21.34% individuals have more than 20 exposures (1 minute) per day. Furthermore, the figure shows that about 13.18% of individuals have less than 1 exposure (3 seconds) per day and another 1.96% are heavy news consumers and have at least 100 election-related exposures (5 minutes) per day.

[23]The median number of sessions after re-weighting to a demographically representative sample is 6.4.

**Benchmarks** We provide several benchmarks to provide additional context on its magnitude, which suggest that individuals are exposed to relatively little election-related content. First, we compare it to the New York Times articles described in Section 2.1. We find that the median individual encounters about 51.8% of the terms that appear in an average political article. This means that someone reading a single political article would encounter twice as many keywords as the median individual even without seeing any political ads, political posts on social media, or discussing politics on their phone.[24]

Second, as an additional benchmark, we compare politicians to celebrities and find that encounters with politicians on one's phone are vastly outnumbered by encounters with celebrities, even during the peak political season—the election campaign. The median daily encounter rate for the top 100 most observed celebrities in our data is about 8.45 times higher than that for the top 100 most observed politicians.[25] Even when focusing on the president and presidential candidates ('Donald Trump', 'Joe Biden', and 'Kamala Harris'), on an average day the median individual was exposed to these figures for only 3 seconds.

Third, we study whether individuals actively seek or discuss content and not just encounter it passively, for example, through campaign ads. As a simple proxy for active interest (in addition to the sessions we previously defined), we define *active* exposure as a political encounter that originates from a communication (e.g., Gmail or WhatsApp) or search (e.g., Google) application. We find that the median individual has less than one election-related active encounters per day. In fact, on the vast majority of days, most individuals do not discuss any election-related keywords in communication apps. We discuss additional sources of information in Section 3.3.

**Robustness** In Appendix Figure A.1a we show that our results are robust to different definitions of the keyword set by adding a set of political issues in addition to the election terms and politicians in our primary keyword set.[26] Since many of these terms are typically used in non-political contexts,[27] we only consider them as an election-related exposure if they are mentioned near a much

[24] To calculate this number, we first calculate the number of average number of keywords in the text across the New York Times election articles discussed in Section 2.1.1. We then multiply the number by 1.1 since we found that about 9% of our keywords appear outside the text or title, for example, in captions or section headings. Finally, we divide the median number of encounters by this number.

[25] Since most of the celebrities in the data are artists, we also run the comparison without Spotify to ensure that listening to music does not drive the difference in encounters. We still find that the median person encountered the 100 most observed celebrities about 7.39 times for each encounter with the 100 most observed politicians.

[26] 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".

[27] We validated that these keywords have low precision using our New York Times articles discussed in Section 2.1.

larger set of words that could be related to the election.[28] The median individual is still exposed to only approximately 7.1 instances of our keywords after adding political issues. 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 and so would not observe some of our election-related keywords. 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, the numbers do not change dramatically with the median exposures increasing to 9.5.

**Congressmembers** While exposure to election-related content is limited, exposure is minuscule when focusing specifically on congressmembers. Previous papers and surveys have shown that individuals have limited information on their congressmembers (Balles et al., 2023). In fact, 65% cannot even name their congressmembers.[29] Therefore, exposure to information about congressmembers is especially important as voters probably have weak priors and informing them about their representatives can affect their decisions. However, Appendix Figure A.1b shows that the median individual is only exposed to an average of 0.15 encounters and 0.12 exposures per day on *all* congressmembers.[30] Indeed, this number is so low that on an average day only 18% encounter any congressmembers. Appendix Figure A.1b focuses on all congressmembers since we do not know the individuals' districts. In order to get a measure of exposure with local congressmembers, we conservatively assume that individuals' most encountered congressmember is their local house representative (which provides an upper bound). The median individual only has 0.08 encounters per day of their local representative or a single mention approximately every thirteen days. This low exposure confirms that most individuals are getting little information on their congressmembers on their phones before casting their votes.

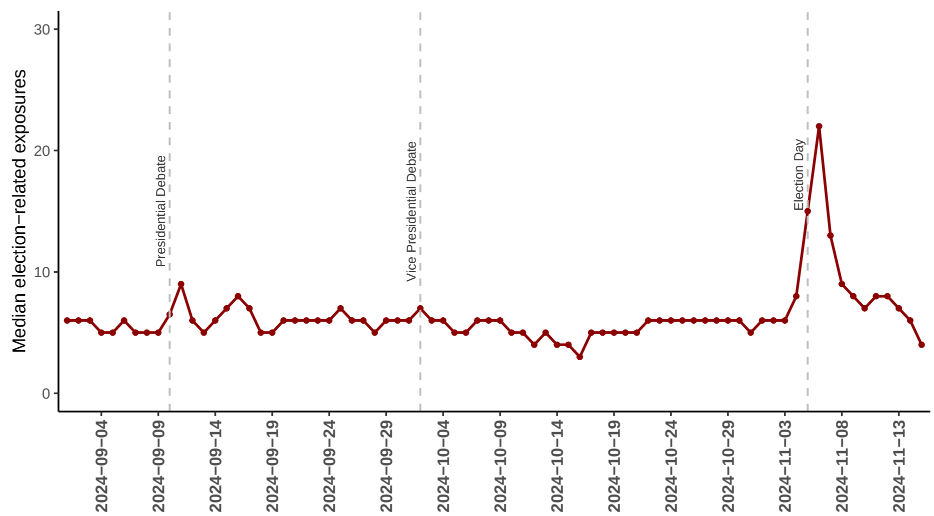
[28] To provide additional context on the occurrence of a keyword, the SDK records the co-occurrence of a large list of surrounding words. In particular, upon observing the presence of a keyword on the screen, the application scans the ten observed words, excluding stopwords, before and after the identified 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 I. This makes it so that these low precision keywords are converted into high precision encounters when paired with these surrounding words. 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'.

[29] https://news.gallup.com/poll/162362/americans-down-congress-own-representative.aspx

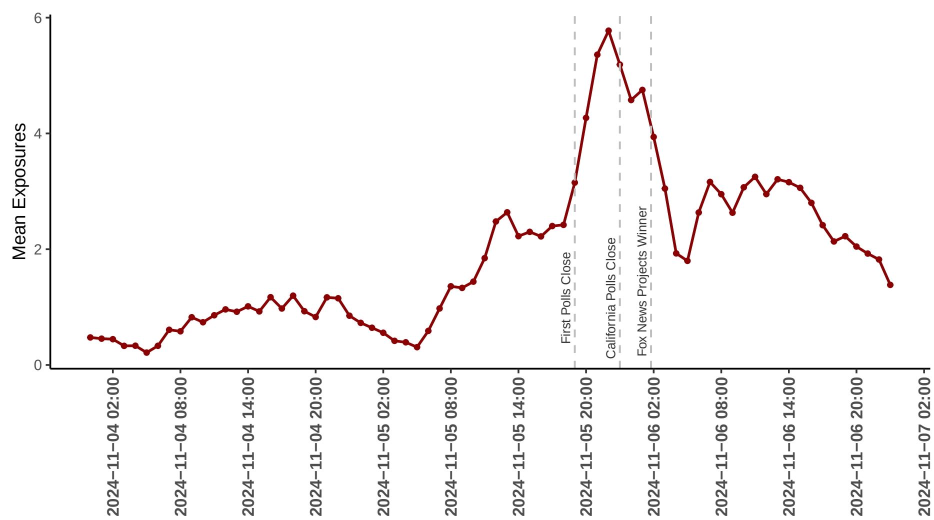
[30] One limitation is that we observe congressmembers and not candidates. However, in 2024, in approximately 88.7% a serving congressmember ran in the election and 97% of the incumbents who ran won (https://ballotpedia.org/United_States_House_of_Representatives_elections%2C_202). More generally, races for congress are often considered referendums on the incumbent (Jacobson and Carson, 2019).

Figure 2: Election-Related Exposures Over Time

(a) Median Daily Election-Related Exposures




(b) Mean Hourly Election-Related Exposures (EST)




NOTES: The figure displays election-related exposures over time. Panel (a) shows the median daily number of exposures per active user between September 1 and November 15, 2024. Panel (b) presents mean hourly exposures across all active devices for the 48-hour window around Election Day (November 5, 2024), in Eastern Standard Time (EST). In Panel (a), 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). In Panel (b), additional annotations mark important election-night milestones, including the First Polls Close, California Polls Close, and the moment Fox News Projects Winner. See Section 2.1 for the definition of election-related exposures.

## 3.2 Changes in Median Exposure over Time

Given the median individual's election-related content consumption is arguably low, our goal is to unpack what drives consumption that does occur. The first natural question is whether the many notable events in the campaign changed election-related content consumption, such as the second attempt to assassinate Trump, the presidential and vice presidential debates, the Washington Post deciding not to endorse a candidate, Musk's increased involvement in the campaign, Joe Rogan's Trump endorsement and the Madison Square Garden rally where Puerto Ricans were called garbage.[31] Each of these, in principle, may increase consumption.

Figure 2a plots the median election-related exposures over time and shows that it is remarkably stable. There are two exceptions to this trend: the debates and election day. On the day of the first presidential debate between Kamala Harris and Donald Trump, individuals had 9 election-related exposures, an increase of 44% compared to the previous week. The increase in consumption we find as a result of the debates dovetails previous literature showing that debates draw large audiences (Le Pennec and Pons, 2023).

However, the increase was much more dramatic around election day where the median number of exposures increased by 287% from the average number of exposures in September-October to the peak occurring the day after the election. This interest could be due to people encountering information only after they voted, but could also be consistent with individuals searching for relevant information before going to the polls. To better understand the peak interest around election day, we analyze hourly election-related exposures.

Figure 2b shows that most election-related exposures occurred *after* polls closed.[32] The figure plots the mean hourly election-related exposures in the days before and after the election.[33] It 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.[34] Finding increased interest when polls close is not surprising. People probably want to read about the results and find out who won the election. At the same time, this result indicates that the majority of the increase in election-related exposures around election day is not due to people searching for relevant information before they vote.

These figures strengthen our conclusion that individuals were exposed to limited information before election day, and that the dramatic increase in consumption around election day is due to people reading about the results rather than gathering information to make a more informed decision. Thus, we conclude that, with the sole exception of the presidential debate, there were no

[31] See `https://www.ft.com/content/1010cf62-932e-4a19-9510-f5033c1c7fa5` for an extended discussion and timeline.

[32] We use the time zone data provided by Screenlake, which is inferred from the various brands, apps, and/or terms that appear on screen.

[33] We plot the mean rather than the median because this figure is at the hourly rather than daily level, and variation over the day is harder to detect using the median.

[34] The vast majority of polls close at 7 or 8PM local time. Of course election results are available beforehand for people not living in the eastern time zone. For example, participants in California might have encountered election-related news at 4 PM local time just by checking election results. In Appendix Figure A.5 we present the election-related encounters broken out by time zone and find the same pattern.

large population-level shocks that induced additional information acquisition before voting.

## 3.3 Sources of Information

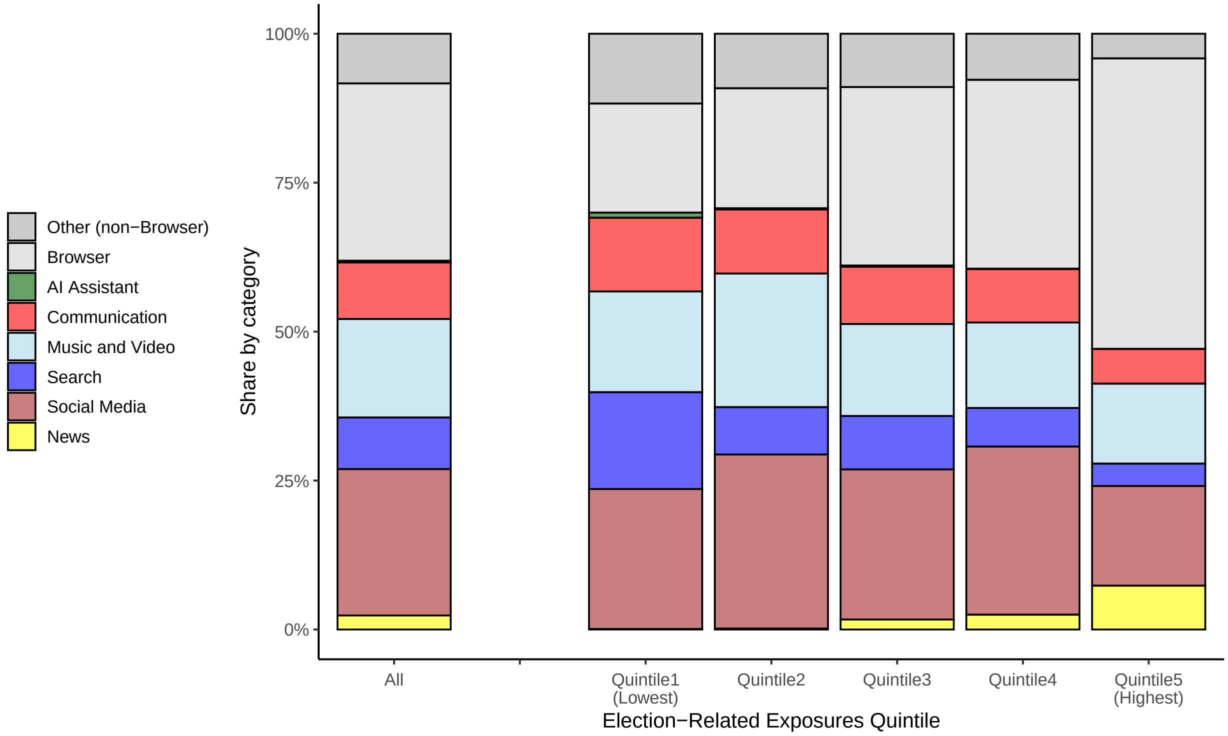
We now turn to characterizing the applications where individuals consume election-related content. This is important as there are growing concerns that individuals may be getting more news on non-traditional sources where news may be less accurate and more polarized. Thus, the applications that individuals are exposed to this content could provide meaningful evidence on differences in the *quality* of information that individuals receive.

Figure 3 shows that individuals get a plurality of election-related content from social media and almost no content from news applications.[35] The figure presents the share of election-related exposures overall as well as broken down by quintile. We define the quintiles by the share of an individual's total exposures that include election-related keywords. The left panel of Figure 3 shows the share of exposures across all individuals and all categories. One key observation is that a sizeable portion of exposure comes from non-traditional sources, indicating that it could potentially include more polarized content (Braghieri et al., 2024) or information that is less reliable (Vosoughi et al., 2018). 41.08% of election-related exposures occur in categories with personalized algorithmic curation: social media and music & video. Appendix Figure A.6 plots the same figure, except by top applications as opposed to categories. It shows that TikTok, Reddit, YouTube, and Instagram are the largest aggregate source of election-related encounters. Notably, only 2.36% of election-related consumption comes from news apps.[36] This implies that people have shifted from primarily consuming content curated directly by editors to content that is downstream of such sources or unrelated altogether, raising concerns that some of what they now encounter may lack fact-checking or relevant context.

[35] Interestingly, many of the exposures in the 'Other' category come from widgets and notifications. This highlights a unique aspect of content consumption on smartphones, which is that a non-negligible portion of exposures comes passively through these summarizations of information and not directly on the applications itself.

[36] 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). 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. We use two different assumptions to impute categories when individuals use mobile browsers. First, in Appendix Figure A.7, we assume that the share of exposures across categories when people use their browser is similar to the overall share of exposures across categories. Second, in Appendix F.3, we use a model-based imputation. We assume that exposure on the browser is a convex combination of exposure distributions across application categories. We then estimate which share of browser activity dedicated to each category would best fit the distribution of keywords in browsers that is similar to the actual observed distribution. Using both methods, we find that the share of exposures through news apps and their website only increases from 2.36% to 4.15%-8.62%.

Figure 3: Share of Exposures by App Category




NOTES: The figure shows the distribution of election-related exposures by app category across quintiles of each user's share of exposures to election-related content. For each device, we calculate the proportion of total exposures that were election-related, then assign the device to a quintile of this proportion (Quintile1 = lowest share, Quintile5 = highest). Within each quintile, each bar shows the average across devices of the share of exposures occurring in a given app category, calculated over the period September 1–November 4, 2024. App categories include: News, Social Media, Search, Music and Video, Communication, AI Assistant, Browser, and Other (non-browser). The leftmost bar ("All") shows the overall distribution, computed as the average across all devices regardless of quintile.

We next characterize whether there are considerable differences across individuals in terms of their sources of information. This is important to examine as Figure 1 documents that there is heterogeneity across individuals in their total amount of consumption. Thus, the aggregated results could mask important differences in sources of information between individuals with limited and high election-related exposures. The right panel of Figure 3 highlights that the dominance of non-traditional sources is highest for individuals in the bottom two quintiles with these individuals having virtually no election-related exposures in news applications, while the highest quintile has 7.36% of exposures coming from news applications. This indicates that the lower quintiles of individuals may not just be receiving less election-related content, but also lower quality content. Figure 3 also highlights the prevalence of election-related exposures from non-traditional sources is high across all quintiles with social media making up 23.47% and 16.72% of election-related exposures for the first and fifth quintiles, respectively.[37]

Given the differences across individuals and application categories, we next explore the main drivers of consumption of election-related content.

# 4 Drivers of Consumption

Our primary results thus far indicate that the median individual had limited exposure to election-related content and that a large share of these exposures occur on applications with personalized algorithmic curation such as social media and music & video applications. At the same time, we find substantial heterogeneity in exposure to election-related content. In this section, we study whether individual characteristics or app-specific factors are the more important drivers of election-related content consumption. We begin by characterizing heterogeneity in consumption of election-related content, at the application and individual level, and then decompose the variation in consumption to assess whether systematic differences across individuals or across apps play a larger role.

## 4.1 Heterogeneity in Content Exposure

### 4.1.1 Heterogeneity across Applications

There are two key components that can explain differences in election-related content exposure across applications: the time that individuals spend on applications and the prevalence of election-related content per unit of time. While Figure 3 shows heterogeneity in the total number of election-related encounters, in this section we focus mainly on the latter by measuring the *share* of time spent on election-related content across applications.[38]

Figure 4a documents the share of time spent on election-related content consumption across application categories. It shows, unsurprisingly, that news applications have the largest share (18.27%) since the supply of content on these applications is predominantly political content. Apart from news applications, Figure 4a shows that election-related content makes up 3.07% of the time on search applications.[39] In application categories with considerable personalized algorithmic curation, such as music & video and social media, election-related consumption represents only 0.72% and 0.88% of time, respectively. This is in contrast to Figure 3 which shows that music &

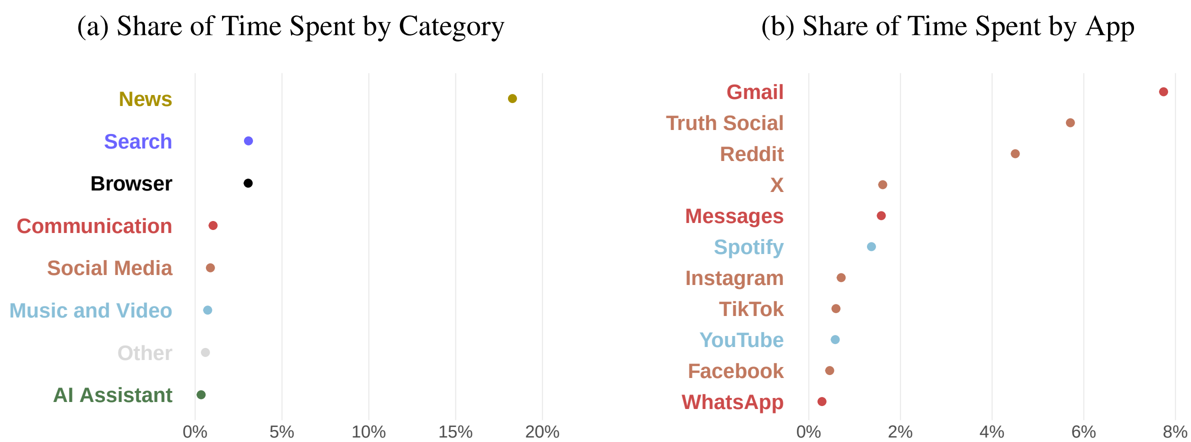
[37] The different quintiles have unequal browser time, which prevents easy comparisons. In Appendix Figure A.7 we plot the same figure, except imputing browser time across categories within quintile and find similar conclusions.

[38] We construct the share of time spent using a combination of the full set of keywords and reliable time usage data after the election. We provide additional details for this procedure in Appendix Section F.2.

[39] Consistent with the discussions in Section 3.3 the fact that the browser share is much closer to search and social media, as opposed to news, provides further evidence that news websites make up a small portion of time on the browser.

video and social media applications make up a larger fraction of overall election-related content exposures, largely because individuals spend substantially more time on them compared to news and search applications.

Figure 4: Heterogeneity in Time Spent on Election-Related Content

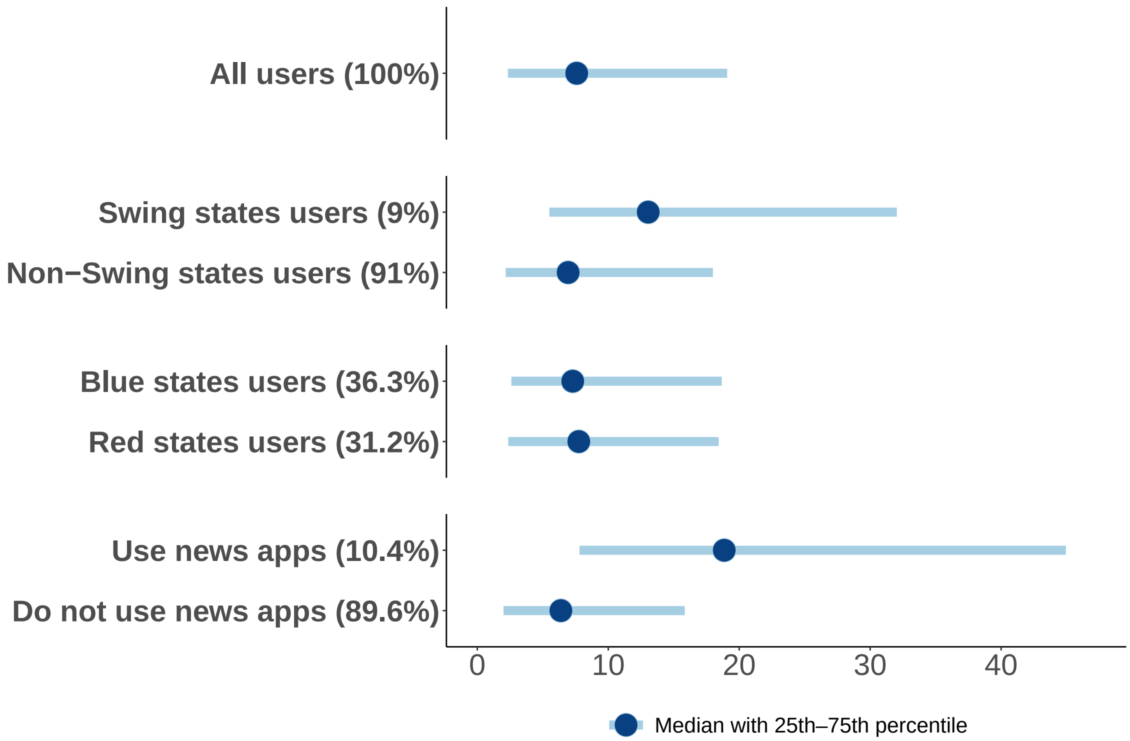



NOTES: The figure illustrates variation in the share of time users spent on election-related content across app categories (panel a) and apps (panel b). The share is computed by estimated time spent observing election-related content based on exposures divided by estimated time usage on the application,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

We next consider differences across applications within the same category for social media, communication, and music & video apps. Figure 4b presents the share across popular applications from each of the different categories. We find little differentiation between different music & video apps, but do find differentiation within the communication and social media categories. Within communication applications, there is a large discrepancy between email (Gmail) and messaging applications (Messages, WhatsApp). One likely explanation is that individuals receive emails with election-related content from politicians directly or newsletters, but spend little time messaging about politics with their friends and family, suggesting limited active engagement through personal conversations. Within social media applications there is considerable heterogeneity, with Truth Social, the social media application run by Donald Trump, having nearly the highest share of election-related content. X and Reddit also have higher shares of election-related content per unit time, whereas Meta-owned Facebook and Instagram, as well as TikTok, each have less than half the share compared to other social media platforms. These results align with media reports of Meta downranking and X upranking political content, and with users of X and Reddit being more likely to primarily seek information rather than entertainment or social connection.[40,41]

### 4.1.2 Heterogeneity across Individuals

Figure 5: Individual Heterogeneity in Election-Related Exposures




NOTES: The figure shows the distribution of average daily exposure of the median user to election-related content across subgroups (September–November 4th 2024). Dots represent group medians; bars indicate interquintile 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) while news users were defined by app usage data.

Another important possible determinant of differences in election-related content consumption is simply that there are intrinsic differences across individuals in their interest in election-related content, their incentives for acquiring information about the election, and the supply of such content available to them. Figure 5 plots the 25th, 50th, and 75th percentiles of election-related exposures across several dimensions of individual level heterogeneity.

[40]The latter has been found via survey-based results from Aridor (2025) and `https://www.pewresearch.org/journalism/2024/06/12/how-americans-get-news-on-tiktok-x-facebook-and-instagram/`, but our analysis provides objective evidence for this differentiation.

[41]As discussed in footnote 5, Meta downranked political content across all of its applications, but it has been implemented more aggressively on Facebook since 2022, whereas on Instagram it has been implemented since 2024. This is one possible explanation for the discrepancy between Facebook and Instagram election-related content shares.

The first dimension that we consider is whether there are differences in consumption based on where individuals live. Due to the United States' reliance on the electoral college for presidential elections, many elections are determined by several "swing states" whose vote ends up being pivotal in determining the winner.[42] Figure 5 shows that the median individual in a swing state gets around 88% more election-related exposures compared to the median individual not in a swing state. This difference could result from "rational inattention" (Maćkowiak et al., 2023) as voters in non-swing states have a small incentive to acquire information, and due to a larger supply of election-related content (advertising and campaign events) in swing states. Interestingly, Figure 5 finds limited differences in the level of consumption between red and blue states, which indicates that partisan differences are not a large driver of overall election-related content consumption.

The second dimension that we consider is differences based on intrinsic demand for election-related content. We use as a proxy for this whether or not an individual uses news applications at all. Figure 5 shows that this can result in a substantial difference, with the median individual who uses news applications seeing 195% more election-related exposures than the median individual who does not.[43] While this measure is clearly endogenous, it does indicate that the low amount of exposure to election-related content could largely be demand-driven.

The final dimension that we consider is differences in the non-political interests of individuals. Given that each individual curates the set of individuals they follow and the content they engage with on social media and music & video applications, differences in election-related consumption can occur when a non-political figure posts election-related content. This is a major difference in the news consumption environment on smartphones, relative to traditional media, since political content is mixed with entertainment and social updates on these types of applications. As such, differences in election-related encounters across individuals can result from differences in the non-political figures they follow.

To test whether non-political figures affect exposure, we use a difference-in-differences strategy to measure the impact of a prominent celebrity endorsement on election-related exposures – Taylor Swift's Instagram endorsement of Kamala Harris.[44] We show in Figure 6 that individuals who had above median pre-endorsement share of exposures to the term 'Taylor Swift' – a proxy of the likelihood of being exposed to Taylor Swift content in general – had a 0.33 standard deviation increase in election-related exposures the day following the endorsement with positive, but declining, estimates for the following several days.[45] Given the results in Section 3.2, which show

[42] We define swing states as Arizona, Georgia, Michigan, Nevada, Pennsylvania, and Wisconsin. In Appendix Section F.1 we discuss the classification method that we use to determine an individual's state, as well as the definition of swing, blue, and red states.

[43] The difference is not mechanical (fully driven by exposures through news apps). Individuals who use news apps have 14.0 election-related exposures per day even when excluding exposures in news applications.

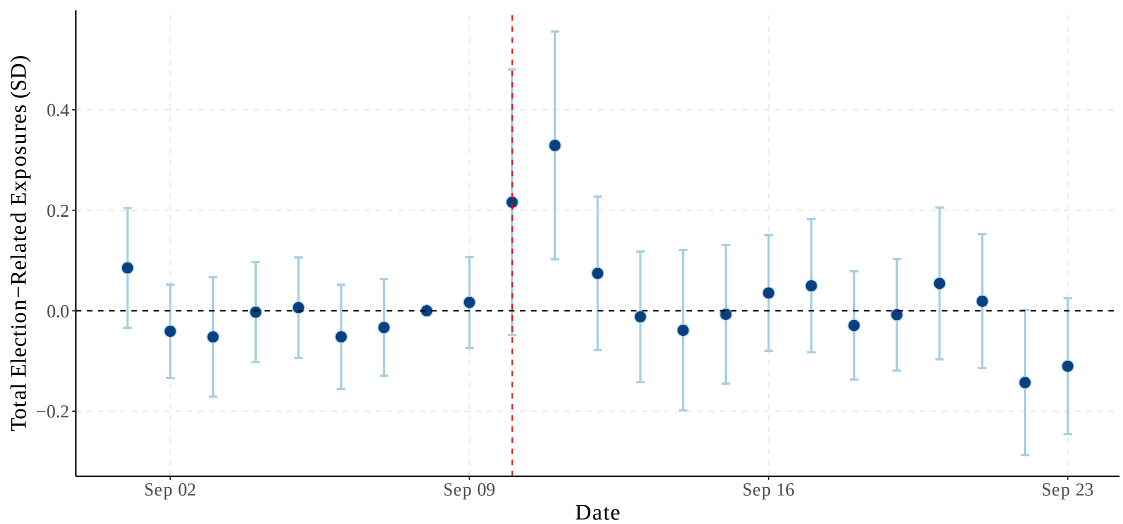
[44] We thank Melanie Monastirsky for the suggestion to add Taylor Swift as a keyword.

[45] We provide a more in-depth analysis for the effects of the endorsement in Appendix E.

the limited effect of major campaign events on increasing election-related consumption for the median individual, this result highlights that individual's non-political interests can influence their election-related content consumption in the modern media environment.

These results show that there is considerable individual-level heterogeneity that is consistent with different intrinsic demand for election-related content across individuals, but also due to less obvious factors such as the set of non-political celebrities that individuals are interested in. These findings are consistent with Le Pennec and Pons (2023), who argue that information from third parties—whom voters may perceive as more credible than the candidates themselves—could play an influential role in determining vote choice.

Figure 6: Effect of Taylor Swift Endorsement on Election-Related Content Consumption




NOTES: The figure plots the estimated difference in standardized daily election-related exposures 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). Estimates are derived from estimation of specification (3), with 95% confidence intervals of the treatment effect shown, derived from standard errors clustered at the individual level.

## 4.2 Unpacking the role of applications vs. individuals

We now turn to answering the question of which of the two forces – applications or individuals – is more important in driving the observed variation in exposure to election-related content. This characterization is important since we have documented that there is heterogeneity across both applications (Section 4.1.1) and individuals (Section 4.1.2). If the main reason for low exposure to election-related content comes from systematic differences across applications, then we need to understand which apps are systematically under/over exposing individuals to election-related content, and the potentially relevant policy tools are algorithmic audits, increasing competition on social media, and encouraging individuals not to depend only on specific applications for their information. If, on the other hand, individual heterogeneity is the dominant driver, then we need to understand what motivates individuals to acquire political information and why some lack such incentives.

The idea of our approach is to exploit that we observe, for each individual, the shares of election-related exposure across different applications and across application categories. We begin by fixing an application category, which we take as a proxy for a market (e.g., Facebook and X for social media, New York Times and Fox News for news). The key assumption is that, through a combination of individual preferences and available supply on each platform, individuals have a share of time on the application consuming election-related content that they would prefer within each of these markets. Individuals can achieve this either through personalization (e.g., on social media via directly following news outlets or indirectly by engaging more with election-related content) or by choice (e.g., by choosing to message friends about the election). When each individual consumed a similar share of election-related content across different applications within a given market, we interpret this as suggesting that the heterogeneity in the shares observed across individuals are driven purely by *individual* differences. If there are systematic differences in the shares across applications within a given market, then we consider the heterogeneity as being driven by *application* differences. We note that application differences can arise either due to individuals' perceived differentiation in usage across applications (e.g., using X more for election-related content consumption) or systematic prioritization of topics (e.g., Meta or X either downranking or upranking political content, respectively).

Our goal in this section is to empirically characterize the relative magnitude of each of these forces in driving exposures to election-related content. We focus on the share of election-related exposures as our main outcome of interest because it accounts for usage differences across individuals and applications. By conditioning on total exposures, we can better understand the differences in the *composition* of the content that individuals are exposed to.[46] Formally, we conduct a variance decomposition in the spirit of Abowd et al. (1999)—hereby, AKM.[47] Our main estimation uses weekly data from September 1 to November 4.

**Empirical Specification.** Concretely, we consider the following empirical specification that we estimate separately for each app category group $g$:

$$y^g_{iat} = \alpha^g_i + \beta^g_a + \gamma^g_t + \varepsilon^g_{iat}, \tag{1}$$

[46] The logic for using this measure is conceptually similar to the reason why the literature on echo chambers focuses on the *percent* of content of different political affiliations that individuals are exposed to (Bakshy et al., 2015).

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

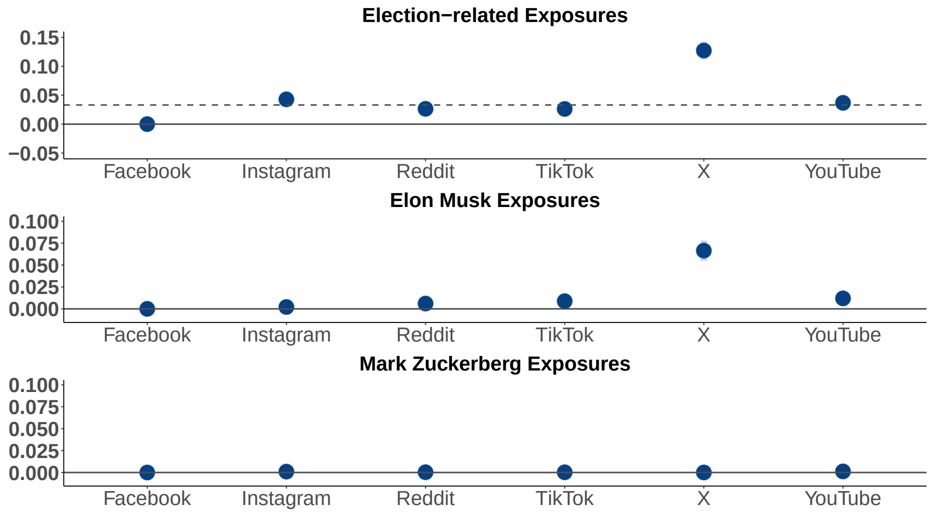
where $i$ indexes individuals, $a$ indexes apps within group $g$ and $t$ indexes time periods. Our main outcome $y^g_{iat}$ is given by the number of election-related exposures as a fraction of the total number of exposures of an individual on a given app and period. We also consider different outcomes, such as the share of election-related encounters, or the share of exposures to or encounters with other keywords.

The parameter $\alpha^g_i$ represents 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. For example, it may be the result of different apps serving a given share of exposures to an individual due to their personalized algorithms or due to the individuals choosing to read specific articles or posts within the app. The parameter $\beta^g_a$ denotes app fixed effects, which captures the possibility that some apps expose their individuals systematically to election-related content. For example, this parameter will capture any algorithmic prioritization or systematic differentiation that is uniform across individuals. Lastly, the parameter $\gamma^g_t$ denotes time fixed effects, which allows election-related content to be particularly popular across all individuals and apps on a given time period—for example, after presidential debates.

This methodology imposes three main assumptions (Card et al., 2018). First, we assume that the error terms $\varepsilon^g_{iat}$ are mean-independent from the individual, app, and time-fixed effects. While this "exogenous mobility" assumption rules out that individuals sort into apps and keywords based on the shocks, it allows for unrestricted sorting patterns of individuals into apps based on any function of their own and the app fixed-effects—these can be arbitrarily correlated. Second, we impose an additive separability assumption, which rules out interactions between individual and app fixed-effects—and thereby, complementarity between these two forces (Bonhomme et al., 2019).[48] Third, as explained in Abowd et al. (2002), the app effects are only identified up to a constant within a "connected set" of apps—indirectly or directly connected via individual "moves." In our context, the largest connected set encompasses over 99.9% of the individuals and of the apps. Moreover, due to multi-homing, our setting differs from the standard labor context and is unlikely to suffer from the limited mobility bias caused in settings with a limited amount of mobility (Abowd et al., 2004). Nevertheless, to ensure that fixed effects are computed with enough observations, we restrict our sample to individuals who visit at least 30 different apps and, subsequently, to apps visited by at least 30 of these individuals.

[48]This assumption does not rule out the possibility of content personalization, since individuals with a high taste for election-related content can still be systematically more exposed to it across all apps. 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.

Figure 7: 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. We exclude apps with fewer than 30 unique users and users with fewer than 30 unique apps.

**Case Studies.** We primarily use this specification for the variance decomposition, documented in more detail below. As a prior step, we investigate a series of case studies to understand whether there are still persistent differences across applications in the social media category, even after controlling for individual and time fixed effects.

First, the top panel of Figure 7 shows that, even after controlling for the rate of content observed across social media applications at an individual level, X has persistently higher exposure to election-related content relative to Facebook and to other social media platforms. We use Facebook as the reference category in light of Meta's decision in early 2024 to stop actively recommending political content (see footnote 5). To the extent that Meta claims that this change enables individuals to have more agency in their exposure to political content, it is a useful reference point. Thus, the X coefficient in Figure 7 can be interpreted as indicating that an individual receives a 12.7 pp higher share of election-related exposures when using X rather than Facebook during a given week in this period. Similarly, Figure G.2 estimates the same regression at the category level and finds that news applications result in persistently higher exposure to election-related content.

A natural question is whether the effects we find are due to application differentiation or systematic prioritization of different types of content. To provide some evidence for the latter, we assess the media claim of bias on X towards content about Elon Musk by estimating the same regression using the share of Elon Musk mentions. The middle panel of Figure 7 shows that the shares of encounters containing the term Elon Musk were 4 pp—43 times—higher on X than on Facebook.[49] This pattern did not apply to other apps or to CEOs of other applications—that were not subject to anecdotal reports of bias (see, for instance, the coefficients corresponding to Mark Zuckerberg on the bottom panel of Figure 7 or those of other CEOs on Figure G.3). While not definitive evidence for systematic prioritization, it seems unlikely that the prioritization of Elon Musk was entirely demand-driven. Thus, while we cannot decompose these two channels, this exercise paired with the systematically low election-related content on Meta provides suggestive evidence that the differences across applications are not entirely due to differentiation in how individuals use them.[50]

Thus, our results suggest that, even once we control for individual and time fixed effects, some of the effects documented in Section 4.1 still persist and are large. This pattern suggests that it is possible that applications themselves played a big role in determining the content that individuals were exposed to. We therefore turn to investigating how much of the observed variation in exposures can be explained by individual preferences versus application effects, providing a more rigorous and holistic measurement of the overall influence of both in determining the political content diets of individuals.

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

$$\begin{aligned}\text{Var}(y_{iat}^g) =&\text{Var}(\alpha_i^g) + \text{Var}(\beta_a^g) + \text{Var}(\gamma_t^g) + \text{Var}(\varepsilon_{iat}^g) \\ &+ 2\text{Cov}(\alpha_i^g, \beta_a^g) + 2\text{Cov}(\alpha_i^g, \gamma_t^g) + 2\text{Cov}(\beta_a^g, \gamma_t^g).\end{aligned} \tag{2}$$

By comparing $\text{Var}(\alpha_i^g)$ and $\text{Var}(\beta_a^g)$, we assess whether individual characteristics or behaviors 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 a particularly strong exposure to election-related content also tend to use apps that provide a frequent coverage of such content.[51]

[49] We plot the raw encounter shares across applications for 'Elon Musk', 'Donald Trump' and 'debate' in Appendix Figure G.1.

[50] Additionally, Appendix H presents survey evidence from 1,000 U.S. respondents showing that 65% of them self-report over-consuming Elon-Musk content on X. This pattern persists after controlling for individual and app fixed effects and closely matches our exposure results, suggesting that endogenous app differentiation alone does not fully explain the over-exposure we document.

[51] We conducted a simulation exercise that assumes that the true data generating process for keywords is either (a) entirely determined by applications or (b) entirely determined by individuals and confirm that our variance decomposition correctly identifies that application-specific effects dominate in (a), while individual-specific effects dominate in (b).

Table 1 contains the variance decomposition results, showing the share of explained variance that is attributed to each of the main components on Equation (2). We estimate the variance decomposition within each app group and present results aggregated across all app groups and separately for social apps and communication apps. To aggregate across app groups, we weight the share of exposures of each group by the time spent on that group.

Table 1: Variance decomposition of the weekly share of election-related exposures

| | All apps | Social | Communication |
|---|---|---|---|
| Individual FE | 0.94 | 0.70 | 0.82 |
| App FE | 0.10 | 0.27 | 0.12 |
| Time FE | 0.04 | 0.03 | 0.03 |
| Covariance of ind. & app FE | -0.09 | 0.02 | 0.05 |
| Covariance of ind. & time FE | -0.04 | -0.02 | -0.02 |
| Covariance of app & time FE | 0.04 | 0.00 | -0.00 |
| Adj. $R^2$ | 0.22 | 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, Social Media, and Other. 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 users with fewer than 30 unique apps.

Our estimates show that individual-specific heterogeneity account for 8 times more of the explained variance than app-specific heterogeneity when aggregating across apps. This table 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—compared to communication apps, where content curation is more scarce. Moreover, it shows a limited role for sorting effects, given that the covariances between fixed effects are small.[52]

These results underscore that individual heterogeneity is more important than app heterogeneity in driving exposure to election-related content. Intuitively, smartphone apps are highly personalized and content curation is pervasive. These results do not rule out the existence of algorithmic biases increasing or decreasing the exposure to election-related content, as app effects still explain a fraction of the variation in news exposure. Still, these results reveal that individuals inclined to consume election-related content tend to be systematically exposed to it across apps (e.g., even

[52]Appendix G presents several robustness checks and additional findings, showing that this pattern persists when considering encounters instead of exposures (Table G.1), daily exposures (Table G.2), no time fixed effects (Table G.3), and without restricting the sample to apps with fewer than 30 unique users (Table G.4).

on Facebook, where such content is relatively scarce). Conversely, those inclined to consume less election-related content are generally not exposed to it across apps (e.g., even on X, where such content is more common). In other words, instead of generating disparities between individuals based on app-specific strategies or platform motives, algorithms appear to be mirroring existing gaps between individuals.

# 5 Conclusion

In this paper, we characterized the magnitude and drivers of election-related content consumption in the final two months of the 2024 U.S. election campaign. We find that overall consumption was both limited and stable, punctuated only by brief spikes occurring around the presidential debate and election day, with social media and video apps accounting for a sizable portion of the consumption that did occur. We also uncover substantial heterogeneity in election-related content consumption across both apps and individuals. A variance decomposition exercise reveals that differences across individuals are more important drivers of election-related exposure on smartphones than difference across apps.

We note several limitations in our analysis. First, our panel is not representative of all smartphone users. While Appendix Section D describes the extensive steps taken to assuage concerns over external validity, we cannot rule out all degrees of selection. Second, while we use our supply-side benchmarks to quantify how our limited keyword set impacts our estimates as discussed in Appendix Section C, we only observe the occurrence of pre-specified keywords at a three-second interval. Third, while our study opens the smartphone blackbox, it does not account for news consumption on other media.

Despite these limitations, this paper establishes new facts with clear implications. First, smartphone exposure to election-related content is arguably small for many individuals. Campaigns seem to have already started adapting by targeting audiences in niche channels, such as specific podcasts. However, this creates new challenges: individuals get little exposure to news that have been directly fact-checked and curated by editors, and congressmembers seem to have a harder time reaching voters on their phones. Second, our results cast doubt on the notion that the algorithmic down-ranking of news is a big concern, since individuals who typically receive election-related content still access it across apps. Therefore, attempts to increase or equalize news consumption should focus on individuals, such as changing the incentives to seek information.

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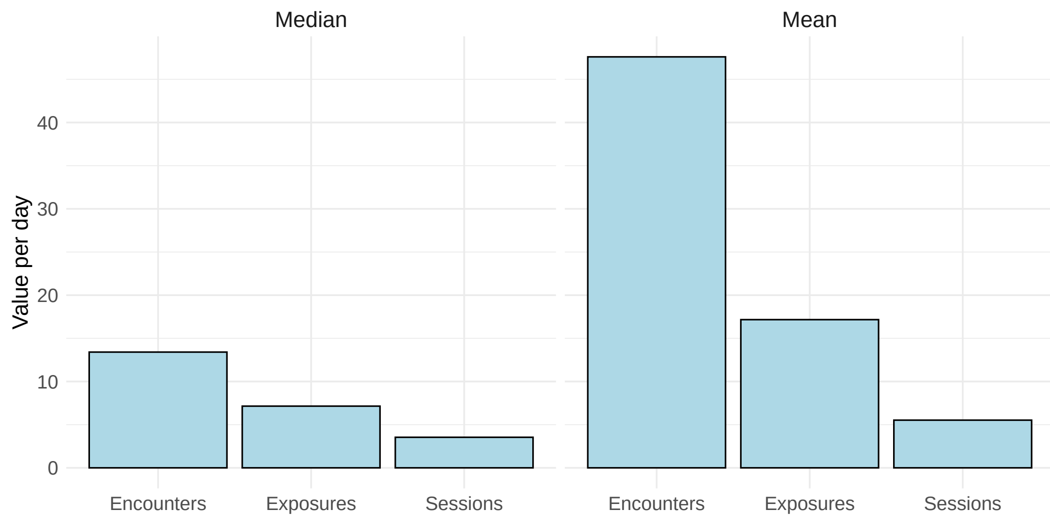
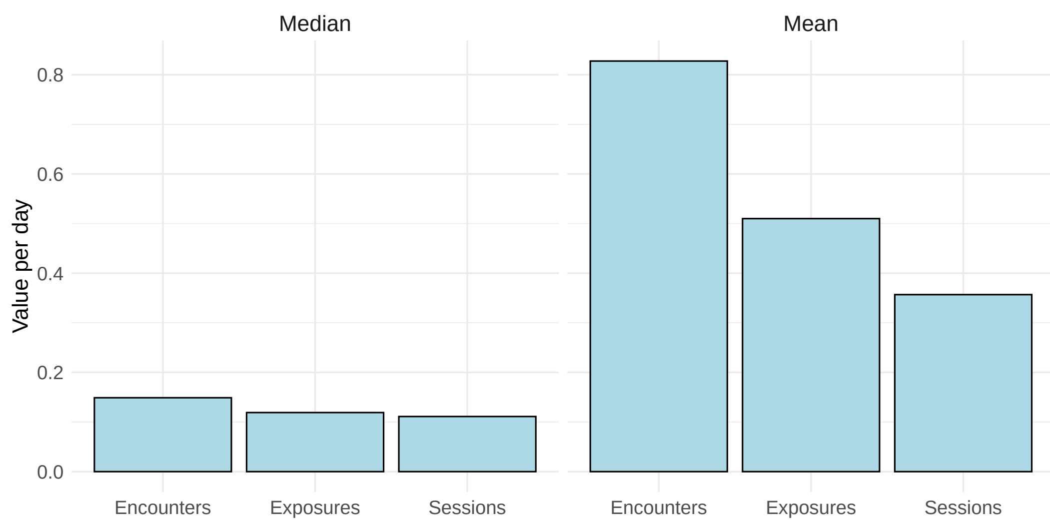
# Appendix

## A Additional Figures and Tables

Figure A.1: Additional Measures of Election-Related Consumption




(a) Election-Related Consumption (Including Issues)

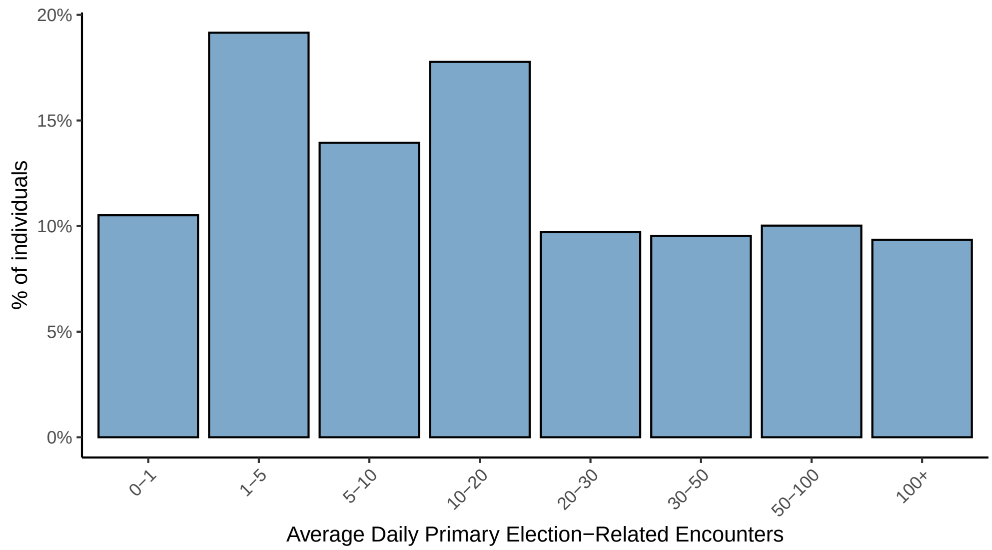



(b) Consumption Related to Congressmembers

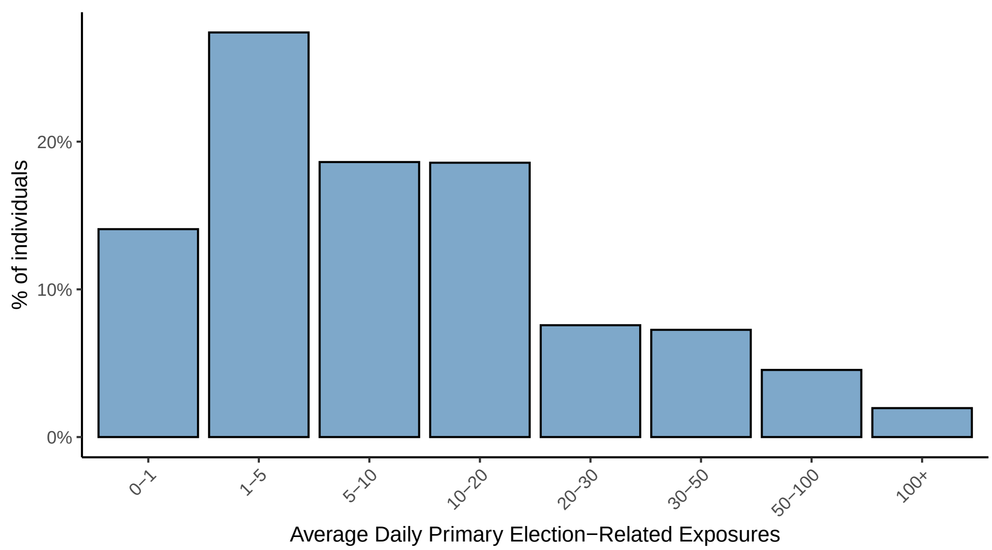
NOTES: The figures report the median number of election-related encounters, exposures, and sessions among active devices for the median (left) and mean (right) user on an average day from September 1 to November 4, 2024. Figure A.1a includes all election-related content, including issue-related keywords. Figure A.1b focuses specifically on exposure to members of Congress. We consider only the sample of devices where we observe data for at least 14 days during September–November 2024.

Figure A.2: Distribution of Election-Related Consumption

(a) Election-Related Encounters



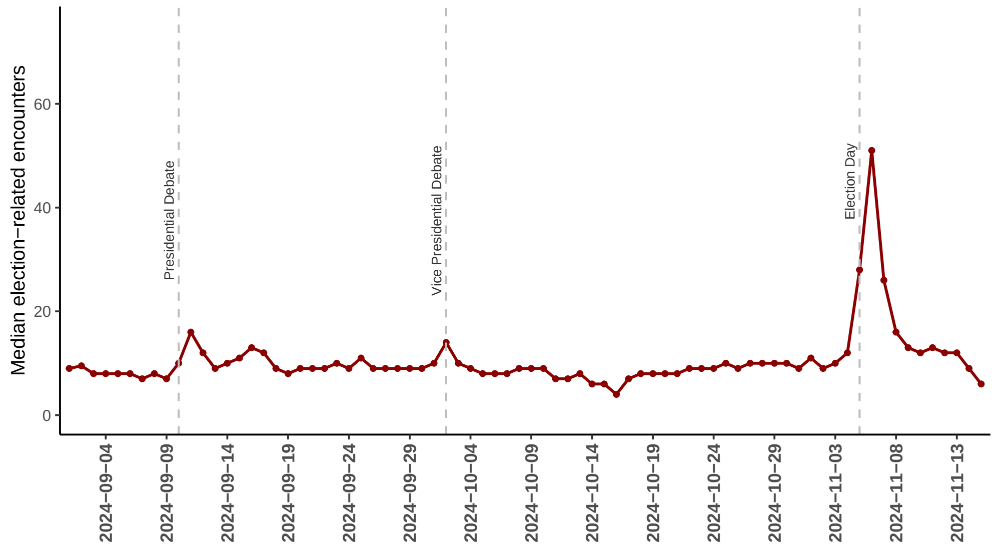

(b) Election-Related Exposures



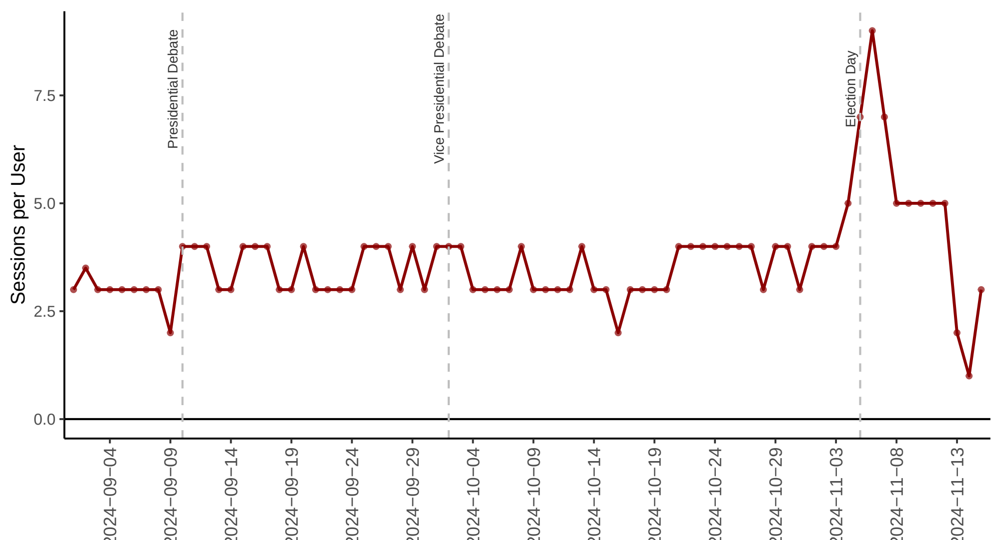

NOTES: The figure shows the distribution of users by their average daily consumption of election-related content, measured between September 1 and November 4, 2024. Panel (a) presents the distribution of election-related encounters, and Panel (b) presents the distribution of election-related exposures. Each bar reflects the share of individuals falling into a given range of average daily values. Only devices with at least 14 days of observed activity during September - November 2024 are included.

Figure A.3: Election-Related Encounters Over Time (Robustness)

(a) Median Daily Election-Related Encounters

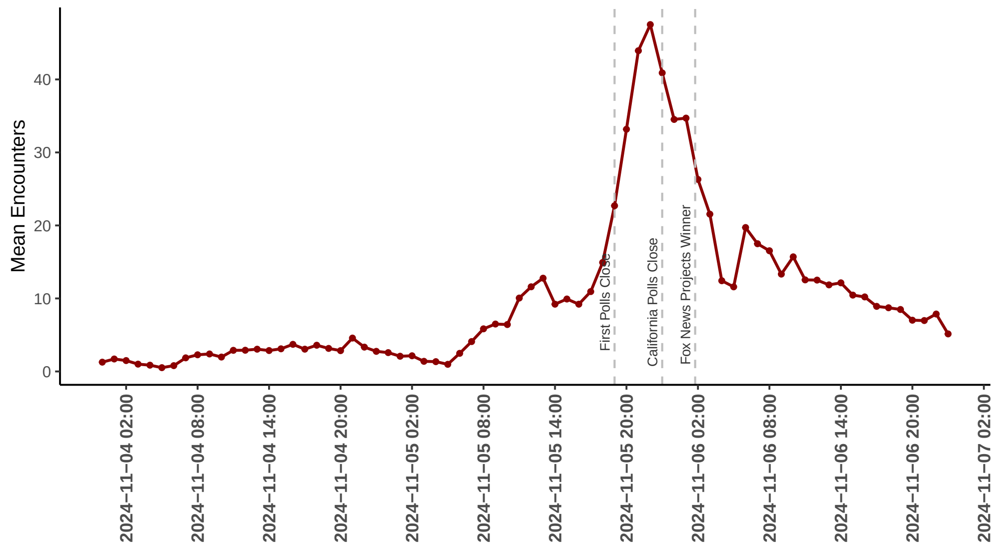



(b) Median Daily Election-Related Sessions



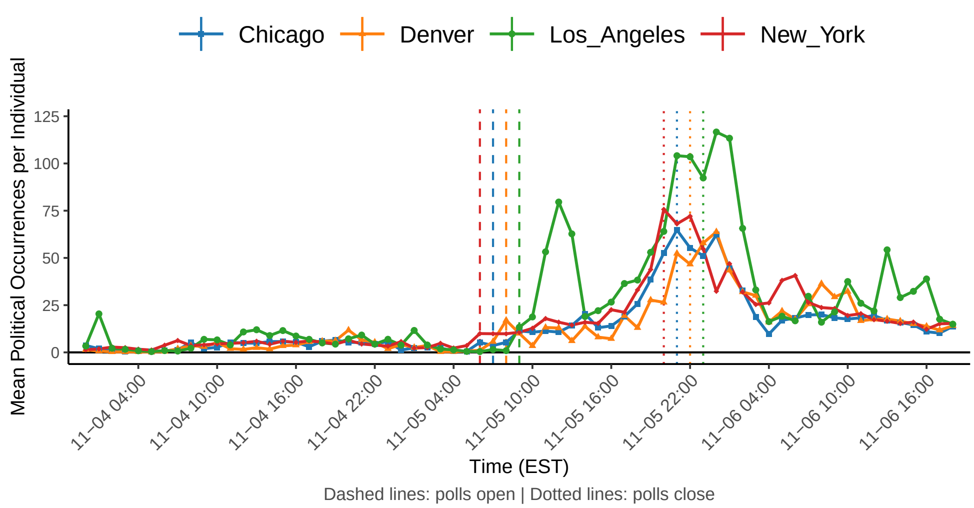

NOTES: The figure displays election-related (a) encounters and (b) sessions over time. Both figures show the median daily number of encounters and sessions per active user between September 1 and November 15, 2024. Vertical dashed lines indicate key political events: the Second Presidential Debate (September 11), the Vice Presidential Debate (October 2), and Election Day (November 5). See Section 2.1 for the definition of election-related encounters and sessions.

Figure A.4: Mean Hourly Election-Related Encounters (EST)



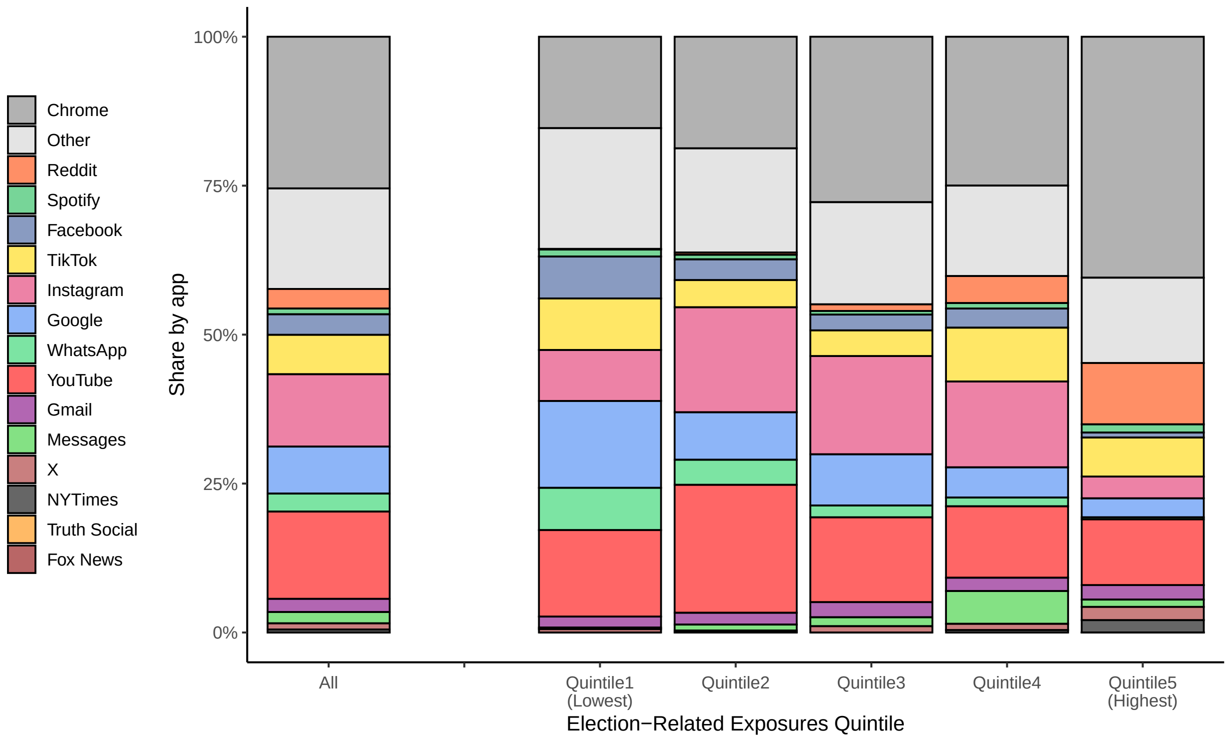

NOTES: The figure displays election-related encounters over time. It presents mean hourly encounters across all active devices for the 48-hour window around Election Day (November 5, 2024), in Eastern Standard Time (EST). Vertical dashed lines indicate key election-night milestones, including the First Polls Close, California Polls Close, and the moment Fox News projects the winner. See Section 2.1 for the definition of election-related encounters.

Figure A.5: Mean Hourly Election-Related Encounters (By Time Zone)



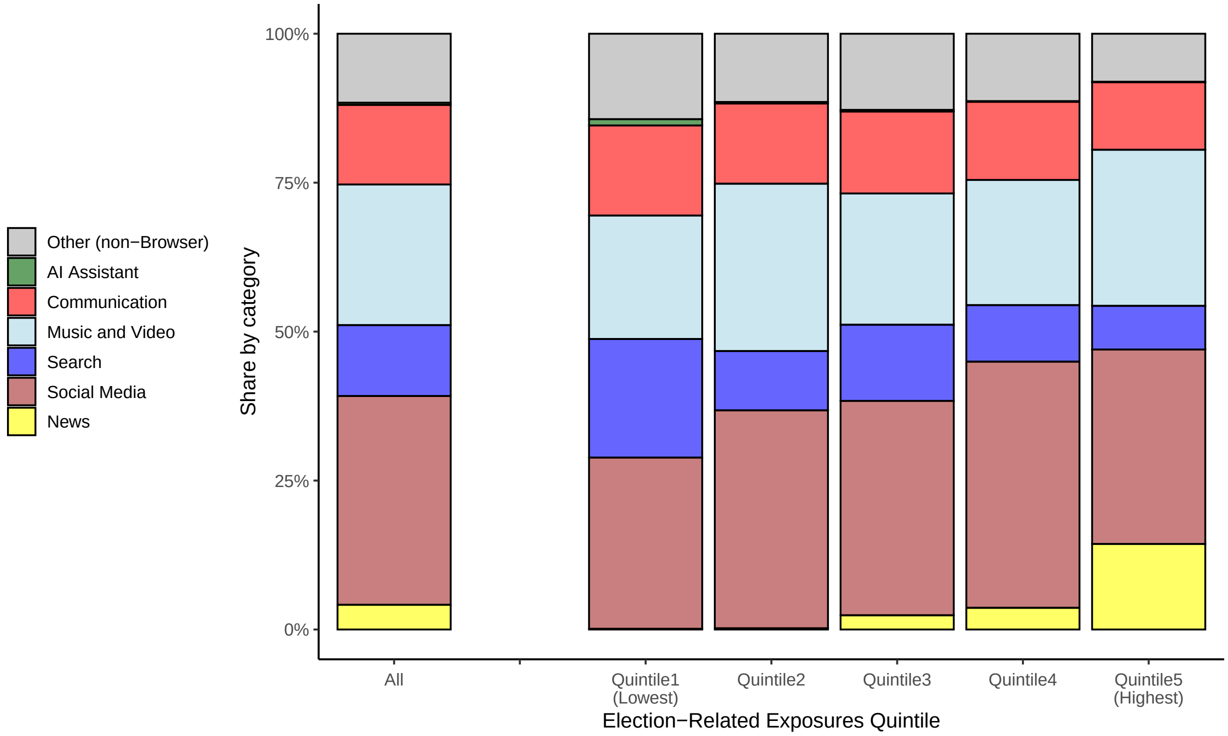

NOTES: The figure shows the mean number of hourly election-related encounters per individual across the four main U.S. time zones - Eastern (New York), Central (Chicago), Mountain (Denver), and Pacific (Los Angeles) - for the 48-hour window surrounding Election Day (November 5, 2024). All times are shown in Eastern Standard Time (EST). Dashed vertical lines indicate poll opening times, and dotted lines indicate poll closing times in each time zone.

Figure A.6: Share of Exposures by Popular Apps




NOTES: The figure shows the distribution of election-related exposures by app across quintiles of each user's share of exposures to election-related content. For each device, we calculate the proportion of total exposures that were election-related, then assign the device to a quintile of this proportion (Quintile1 = lowest share, Quintile5 = highest). Within each quintile, each bar shows the average across devices of the share of exposures occurring in a given app, calculated over the period September 1–November 4, 2024. Apps include: Chrome, Reddit, Spotify, Facebook, TikTok, Instagram, Google, WhatsApp, YouTube, Gmail, Messages, X, NYTimes, Truth Social, and Fox News; all other apps are grouped as "Other." The leftmost bar ("All") shows the overall distribution, computed as the average across all devices regardless of quintile.

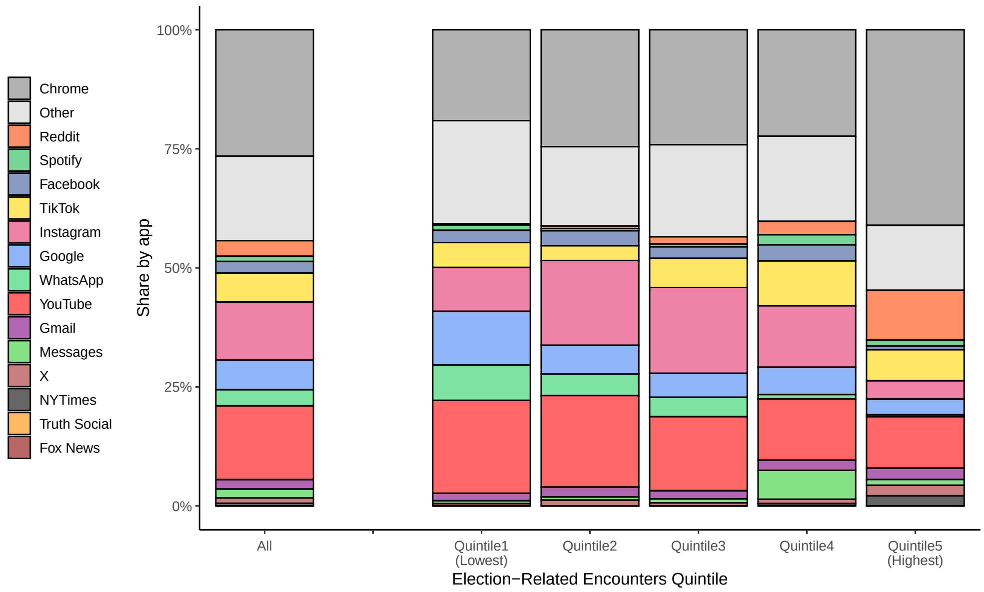
Figure A.7: Share of Exposures by Category (Browser Imputation)



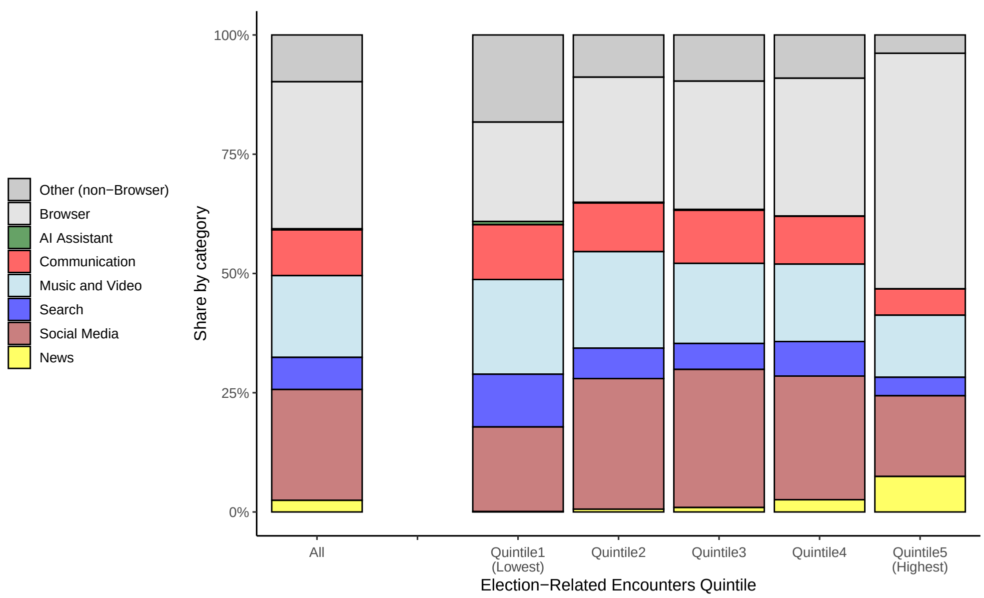

NOTES: The figure shows the distribution of election-related exposures by app category across quintiles of each user's share of exposures to election-related content. For each device, we calculate the proportion of total exposures that were election-related, then assign the device to a quintile of this proportion (Quintile1 = lowest share, Quintile5 = highest). Within each quintile, each bar shows the average across devices of the share of exposures occurring in a given app category, calculated over the period September 1–November 4, 2024. We reallocate the encounters allocated to browsers proportionally into other categories. App categories include: News, Social Media, Search, Music and Video, Communication, AI Assistant, and Other (non-browser). The leftmost bar ("All") shows the overall distribution, computed as the average across all devices regardless of quintile.

Figure A.8: Share of Encounters by Popular Apps and Category

(a) Popular Applications




(b) Application Category

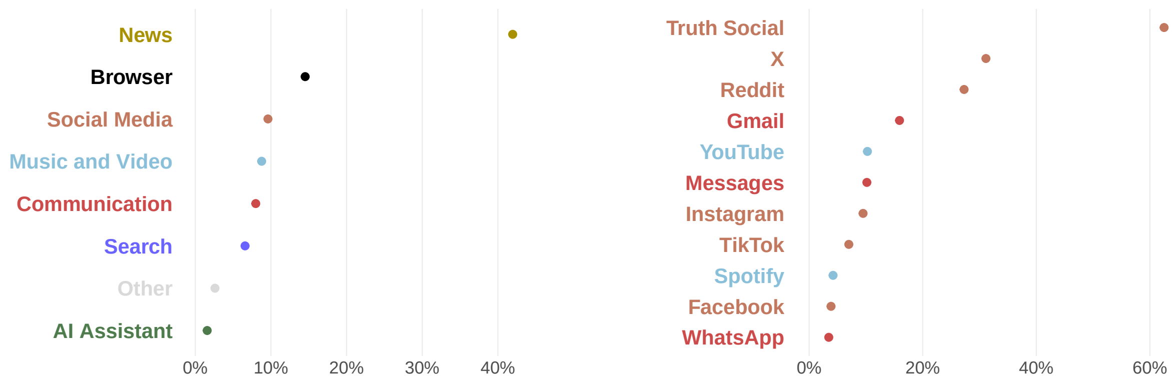



NOTES: The figure shows the distribution of election-related encounters by app category in panel (a) and by individual applications in panel (b) across quintiles of each user's share of encounters with election-related content. For each device, we calculate the proportion of total encounters that were election-related, then assign the device to a quintile of this proportion (Quintile1 = lowest share, Quintile5 = highest). Within each quintile, each bar shows the average across devices of the share of encounters occurring in a given app category or app, calculated over the period September 1–November 4, 2024. The leftmost bar ("All") shows the overall distribution, computed as the average across all devices regardless of quintile.

Figure A.9: Heterogeneity in Encounters with Election-Related Content (Robustness)

(a) Share of Encounters by Category

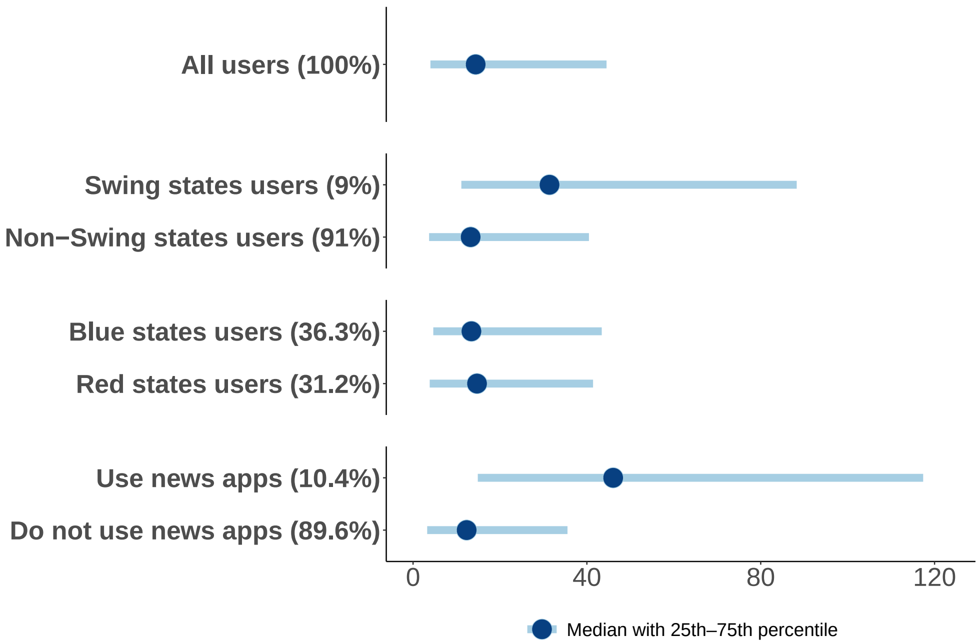
(b) Share of Encounters by App



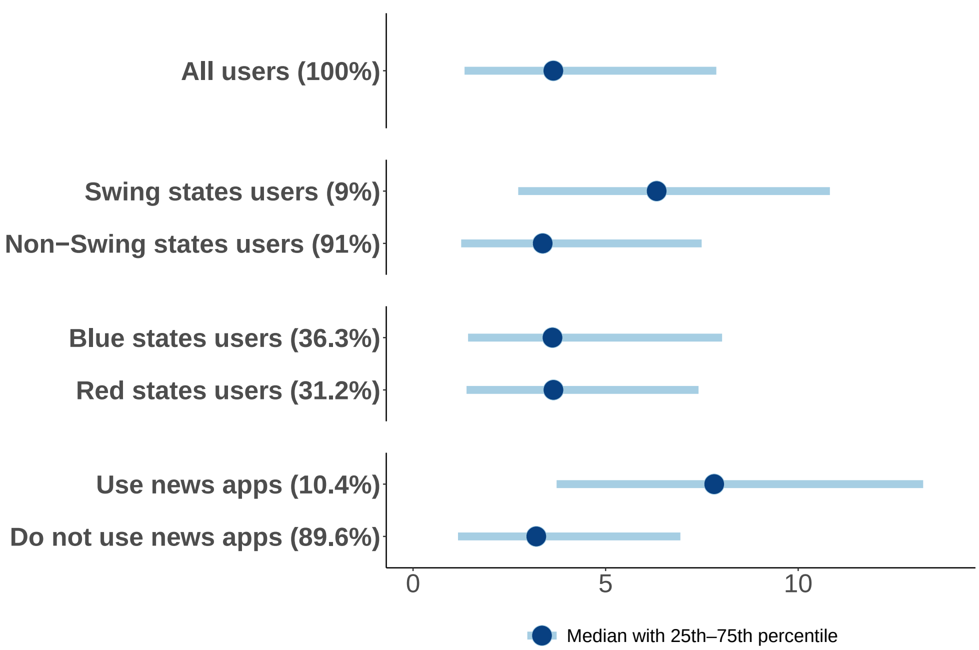

NOTES: The figure illustrates variation in the share of encounters of election-related content across app categories (panel a) and apps (panel b). Importantly, the figure focuses on encounters with election-related content, relative to all other topical categories in our dataset, which include sports, celebrities, entertainment, and others. Both panels reflect aggregate user behavior between September 1 and November 4, 2024. Unlike Figures 4a and 4b, we rely on encounter shares and do not rely on time imputation from Appendix Section F.2.

Figure A.10: Individual Heterogeneity in Election-Related Encounters and Sessions

(a) Encounters



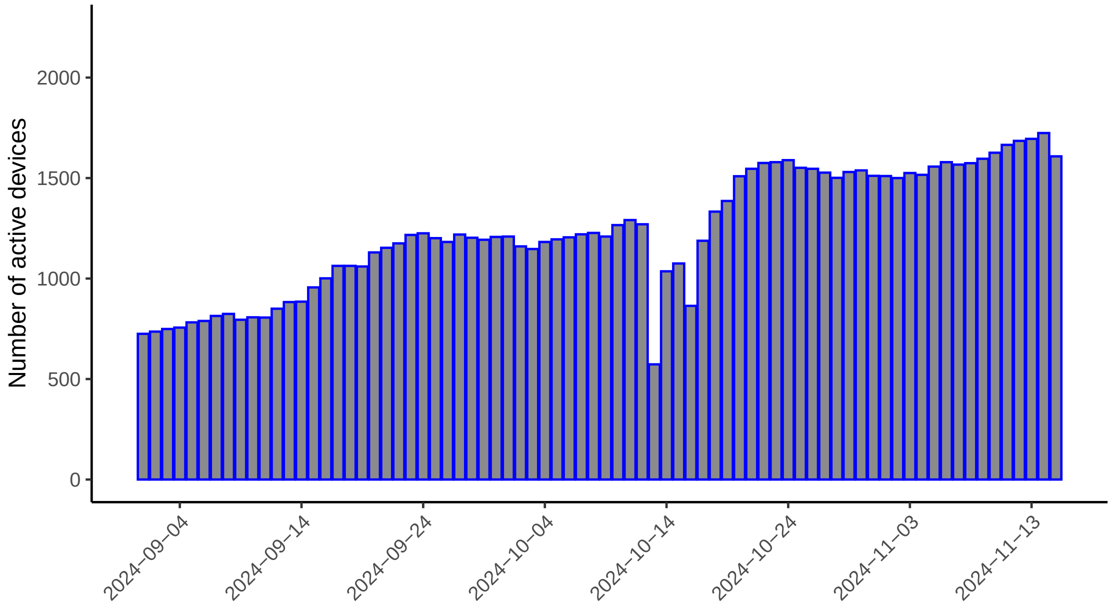

(b) Sessions




NOTES: The figures show the distribution of average daily encounters (panel a) and sessions (panel b) of the median user to election-related content across subgroups (September–November 15th 2024). Dots represent group medians; bars indicate interquintile 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) and news users were defined by app usage data.

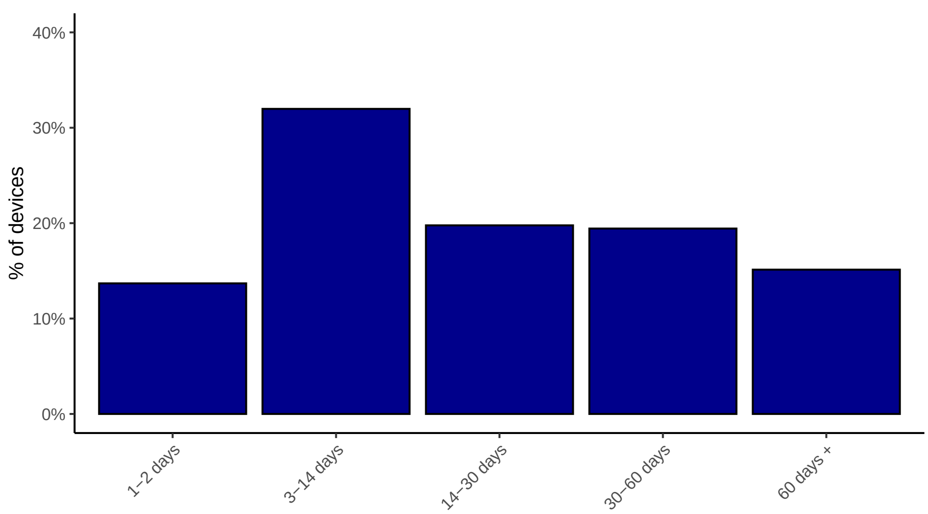
# B Screenlake Panel over Time

Figure B.1: Total number of users across time



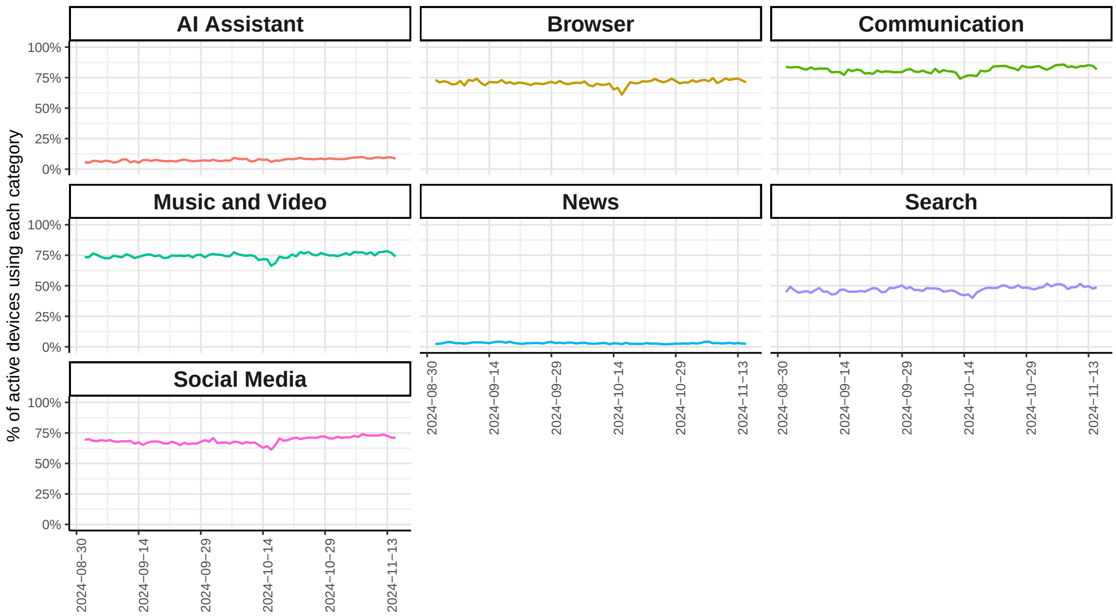

NOTES: This figure provides the number of active devices throughout the sample period from September 1st until November 15th. We define a user as being active on a given day if they have at least one encounter across the entire set of keywords.

Figure B.2: Number of days users are active




NOTES: This figure plots the distribution of active devices throughout the sample period from September 1st until November 15th. We define a user as being active on a given day if they have at least one encounter across the entire set of keywords.

Figure B.3: Application category encounters across time




NOTES: This figure provides the number of active devices throughout the sample period from September 1st until November 15th that use a given application category on each day. We define an active device in a category on a given day if it has at least one encounter from our full set of keywords in an application in that category.

# C Keyword Informativeness Benchmarks

In this section we provide a formulation of our measurement problem as a standard topic classification problem. Let $t$ denote a time period within a given day and assume that an individual encounters content $\mathbf{w}_t = (w_{t,1}, \ldots, w_{t,N_t})$ on 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.[53] 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 the content $\mathbf{w}_t$ relates to by $topics(\mathbf{w}_t) \subset \mathcal{T}$.[54] 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-

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

[54]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.

truth" indicator of whether the content encountered by an individual on $t$ is election-related:

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

We also define our empirical building block: an exposure – 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 the goal is to measure $E_t^*$ using $E_t(\mathcal{K})$, 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 that we observe an exposure to one of our 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 emphasize that this represents the exposure measure from Section 2.1.

A challenge in our setting is that our keywords had to be pre-specified, preventing us from selecting ex-post those with highest F1 scores that balance precision and recall. Nevertheless, we pre-specified a set of keywords which we ex-ante believed were predictive about 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 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 clearly 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. 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. In other words, 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.

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 still highly informative ex-post and among the most informative set we could have selected.[55]

**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.[56] 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.

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

[56] We do not calculate precision as ground truth labels are unavailable in this context.

# D Panel External Validity

In this appendix, we use two methods to assess the external validity of our analysis. First, we provide aggregate demographics of our sample and reweight our results. Second, we compare the set of applications installed and time spent to external benchmarks.

First, we consider the demographic composition of our sample using aggregate age and gender breakdowns of the panel and individual-level weights provided by Screenlake. The data collected by Screenlake is anonymous and disconnected from identifiers. Gender and age groups are inferred post-collection based on the inter-demographic relative likelihood of combinations of various brands, apps, and/or terms appearing on-screen. The demographic breakdowns are relatively stable over time, with our sample skewing male and younger (over 60% men and over half under the age of 35). We use individual-level weights to reweight our aggregation across individuals to be representative of the U.S. population on these dimensions.[57] In Appendix D.1, we present the re-weighted versions of our main results on election-related content consumption (Figures 1 and 2a).

Second, we compare our sample to the average U.S. adult in terms of app use. On the extensive margin, in Appendix D.2, we compare the set of installed applications on the individual's phone to a proxy for the market-level number of downloads via the Google Play store. We find that individuals in the sample have similar sets of applications installed, with a 0.88 correlation in the ranking of categories as well as a weighted correlation of 0.89 in the ranking of applications within our categories of interest between our sample and the Google Play Store. Screenlake users are more likely to have installed news applications than the broader population, suggesting that they may be potentially more engaged with news.

On the intensive margin, we compare app usage among Screenlake users to industry benchmarks and a representative sample collected via Prolific. As detailed in Appendix D.2, Screenlake users exhibit similar patterns of total phone and social media usage compared to other data sources. We find that, similar to our Prolific sample, once we remove Chrome usage, the median individual spends 5.5 hours on their phone each day.[58] When we look at social media usage, we find that the Screenlake users spend, on average, 3.22 hours per day on core social media applications, compared to the 2.5 hours spent by the average American reported in Kemp (2024).

We now discuss the details for each of these exercises.

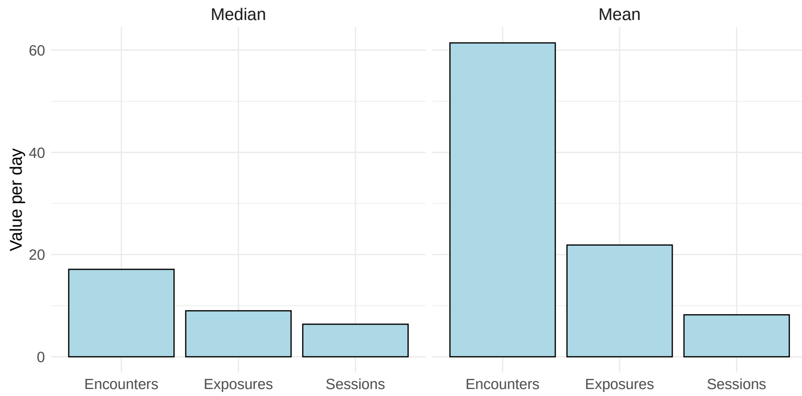
[57] The weights are calculated based on data release from the U.S. Census Bureau in 2023.

[58] We remove Chrome usage in both samples because our Prolific users spend a substantial amount of time in Chrome – likely filling out surveys that they have received on Prolific. As such, we drop this application since the same behavior is not expected from the Screenlake users.

## D.1 Reweighted Results

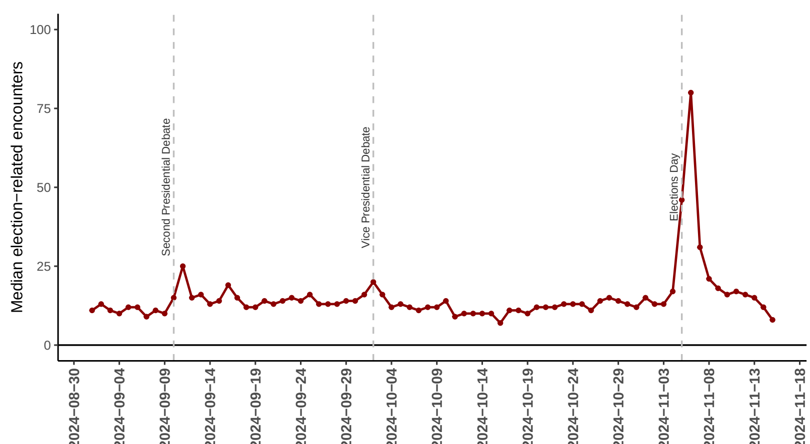
We reweight our results using individual-level weights and in Figure D.1 we present the reweighted version of Figure 1 and, in Figure D.2, we present the reweighted version of Figure 2a. While the reweighted data shows slightly elevated levels, the overall trend and magnitude remains consistent with our main results.

Figure D.1: Reweighted Election-Related Content Consumption




NOTES: The figure reports the median number of primary election-related encounters, exposures, and sessions among active devices for the median (left) and mean (right) user on an average day from September 1 to November 4th, 2024. We consider only the sample of devices where we observe data for at least 14 days during September-November 2024. This figure uses demographic weights provided by our data provider that reweights these individuals to be demographically representative on gender and age based on the 2023 U.S. census.

Figure D.2: Reweighted Political Encounters Over Time

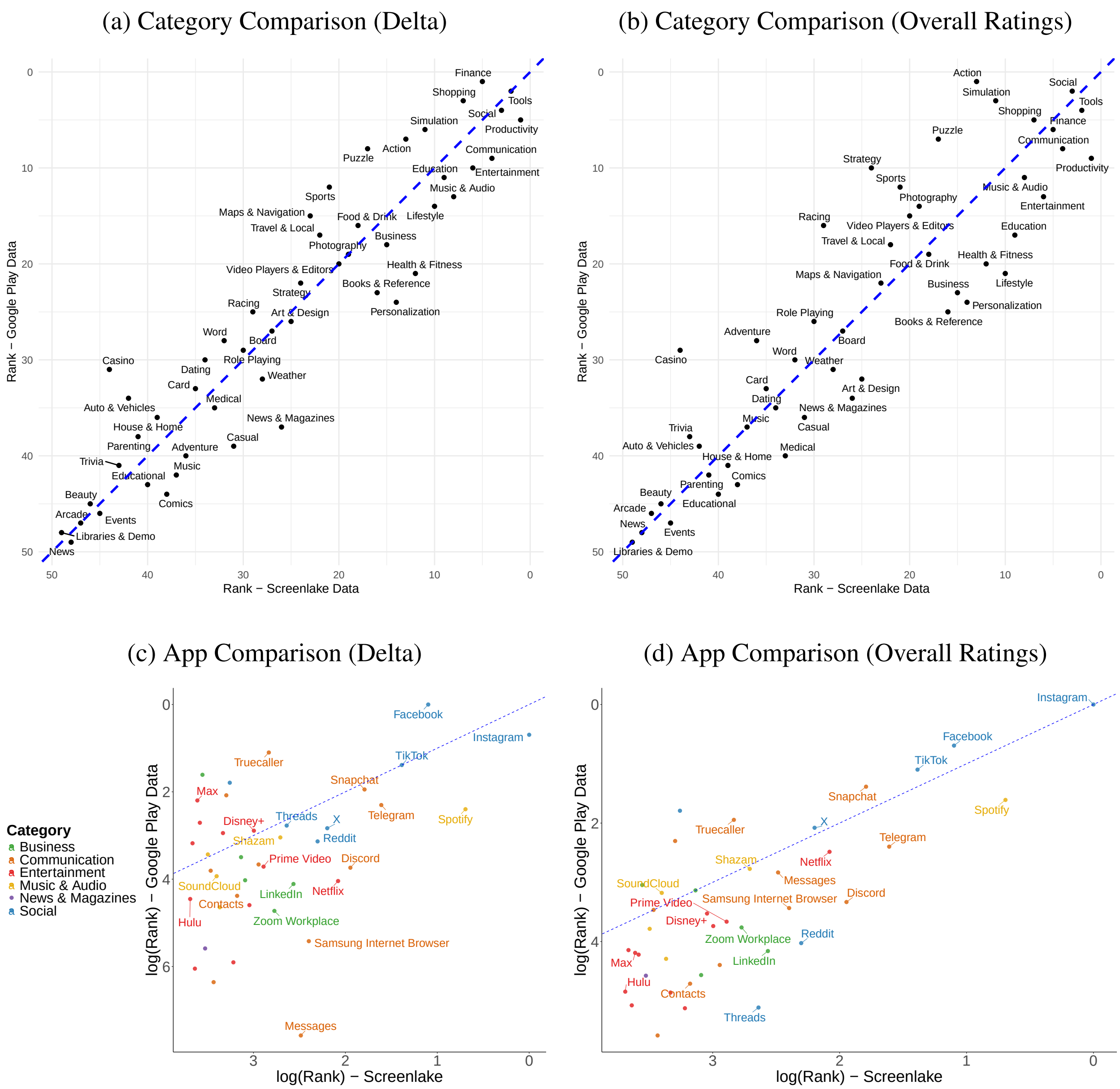



NOTES: The figure displays election-related encounters over time. It shows the median daily number of encounters per active user between September 1 and November 15, 2024. Vertical dashed lines indicate key political events: the Presidential Debate between Kamala Harris and Donald Trump (September 11),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

## D.2 Representativeness of App Distribution

We first analyze representativeness on the extensive margin – the installation of apps – and then the intensive margin – time usage across different applications.

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




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 (d), and using the difference between the cumulative number of ratings from January 2025 and October 2024 in (a) and (c). 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, while panels (c) and (d) provide a rank-rank plot of comparison across downloads at the application level.

### D.2.1 Comparison of Installations to Google Play Store Data

To analyze whether the apps individuals installed are representative, 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 ratings scraped during October 2024 and January 2025 for all applications with over 1 million downloads, or in the news and social categories.[59] 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).[60] 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 January 2025 and October 2024 data collection (denoted delta) measuring recent popularity.[61] 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 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 ensure that we consider only the set of applications that we observe both in our dataset as well as in the Google Play data.[62]

Figure D.3a shows a remarkably strong correlation between apps used among our sample and the Google Play data. Since there is wide heterogeneity in usage within categories across individuals, in this figure we compare the relative importance of categories across the two datasets. For both datasets, we sum across all of the individual applications within the dataset to obtain a total number of installations for the category and compare the relative rank across the datasets. We plot this in Figures D.3a and D.3b, using the delta measure and overall ratings respectively. 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

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

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

[61] 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.

[62] Across all individuals in our data, we observe 25113 unique applications.

primary analyses – news, communication, social, business, music & audio, and entertainment. We conduct the same ranking comparison exercise for applications and plot the results in Figures D.3c and D.3d for the delta measure and overall ratings, respectively. We use log rank as the difference between ranks corresponds to smaller difference in absolute downloads due to the skewed nature of app downloads as the rank increases. These figures show relative agreement in the installation between top applications. 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 0.891 for the delta measure and 0.921 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.

### D.2.2 Comparison of Time Usage to Benchmarks and Representative Sample

While the set 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 that covers the application version with 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).[63]

Industry benchmarks may not correspond precisely to the time period of analysis for our sample. To establish a representative baseline of smartphone usage for the same period, 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."[64]

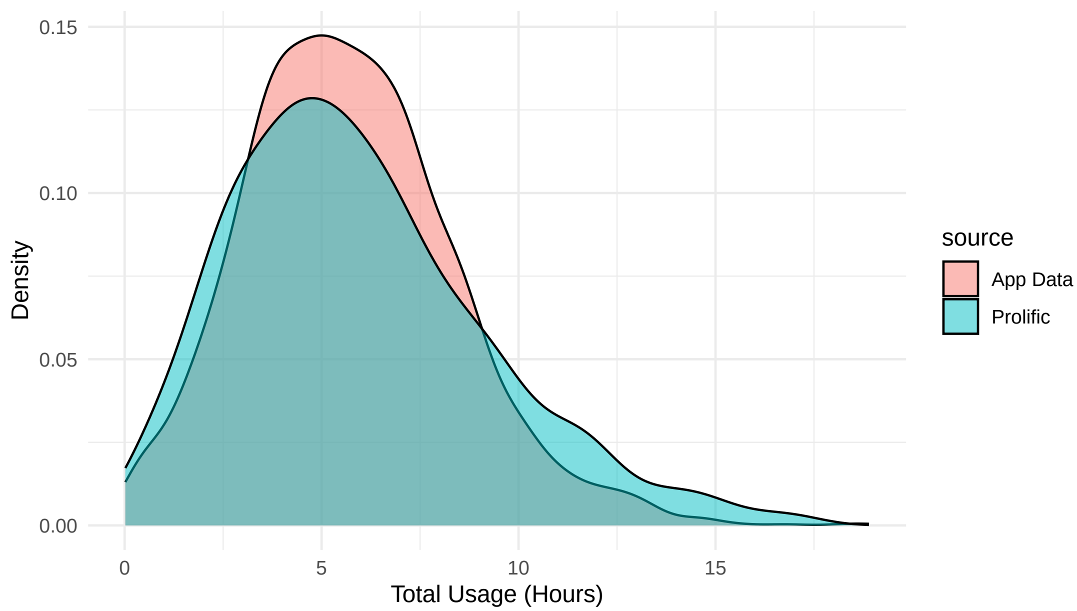
Figure D.4 shows that the distribution of overall phone usage is similar between our sample

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

[64] In order to extract the time usage from the screenshots we developed an OCR script using the OpenAI API. We thank Bharad Raghavan for assistance with this.

and the representative Prolific sample.[65] The median individuals in both samples spend a strikingly similar amount of time on their phone, 5.46 and 5.54 hours, respectively, in the Prolific and ScreenLake samples (a 1% difference). The average individual in the Prolific sample spends 5.95 hours on their phone, while the average individual in the ScreenLake sample spends 5.71 hours (a 4% difference). Consistent with this, the Prolific sample has a higher standard deviation relative to the ScreenLake sample. This is visually apparent in the kernel density of the estimate of the two distributions, presented in Figure D.4. Nonetheless, the results suggest that the ScreenLake population is reasonably similar in overall phone usage to the representative sample from Prolific.

Figure D.4: Distribution Comparison between 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 Prolific sample and for the Screenlake sample when an individual was active. We use Screenlake application usage data from December 19th, 2024 until January 25th, 2025 since it is reliable for this time period.

Next, we compare the time spent and usage of top applications – Facebook, Instagram, Netflix, Reddit, Snapchat, Spotify, TikTok, WhatsApp, X, and YouTube – across the Screenlake sample,

[65] 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 D.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 when an individual was active. We use Screenlake application usage data from December 19th, 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 second 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.

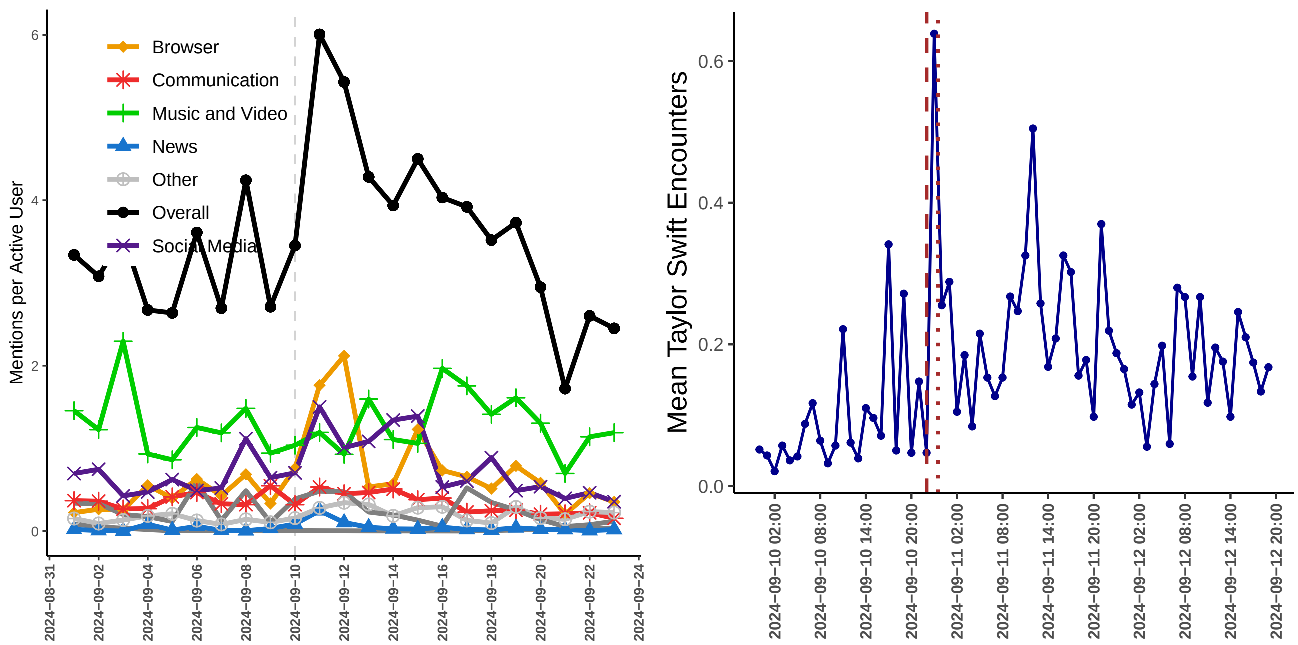
the Prolific sample, and a sample from a Pew Research Center survey.[66] The results are presented in Table D.1. One notable difference between the samples is that the fraction of WhatsApp and Instagram usage for the ScreenLake sample is higher than both the Prolific and Pew samples, while Facebook usage 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 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 and comparable to additional benchmark data from Kemp (2024). 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.

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

# 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 provide additional discussion and analysis of the effect of Taylor Swift's Instagram endorsement of Kamala Harris. It 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.[67,68]

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

[67]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.

[68]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.

Taylor Swift's endorsement provides an interesting case study as celebrity endorsements and, more broadly, exposure to election-related content comes from non-political figures on social media. 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 more relatively more likely to interact with Taylor Swift related content. We define 'Swifties' as individuals in our dataset that had above the median share 'non-political' exposures to the term 'Taylor Swift' (i.e., filtering out instances with a political surrounding word).[69,70] We measure the short-term effect of the endorsement on "Swifties" (treated individuals) and "non-Swifties" (control). We consider the following regression specification to assess the overall causal effect of the endorsement for a given individual $i$ and time period $t$:

$$Y_{i,t} = \sum_{t} \beta_t \Big(\text{Day}_t \times S_i\Big) + \gamma_t + \kappa_i + \epsilon_{it} \tag{3}$$

where $S_i$ indicates that individual $i$ is a Swiftie, $\gamma_t$ is daily fixed effects, and $\kappa_i$ denotes individual fixed effects. We cluster standard errors at the individual level.

Figure E.2 plots the estimated treatment effects, $\beta_t$, derived from estimating specification (3) 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

[69] We compute the share for each individual using their total exposures to Taylor Swift divided by the total number of exposures across all terms.

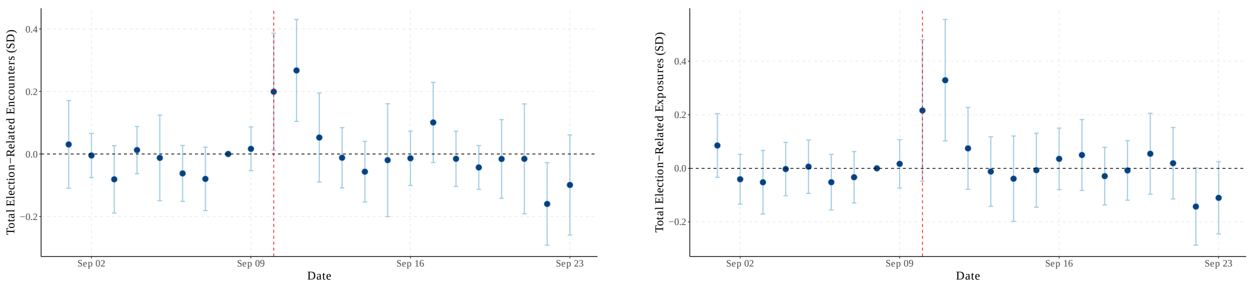
[70] Our results are robust to considering an alternative definition of 'Swifties' as individuals with at least one non-political encounter with the term 'Taylor Swift' in a music & video applications such as Spotify and YouTube. Given the popularity of Taylor Swift, this leads to 30.5% of the individuals that we observe being classified as 'Swifties'.

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.

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

(a) Election-Related Encounters

(b) Election-Related Exposures




NOTES: The 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 (3) with 95% confidence intervals of the estimated treatment effect shown, derived from standard errors clustered at the individual level. Each point represents the estimated difference in standardized daily election-related exposures (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).

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:

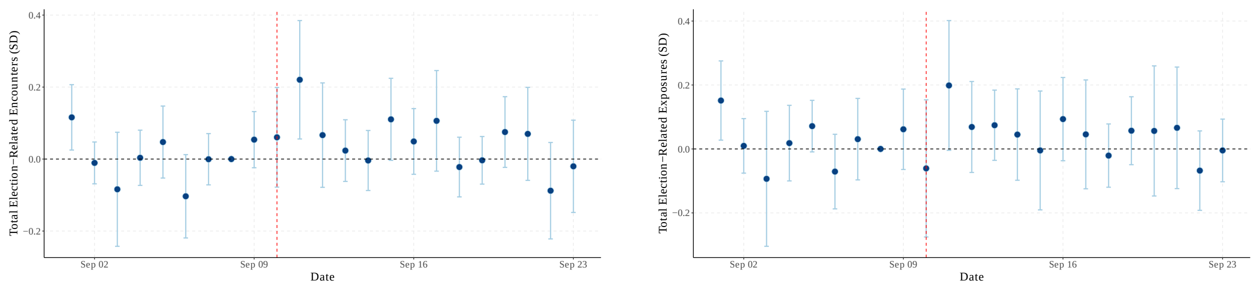
$$Y_{i,t} = \sum_t \beta_t \Big(\text{Day}_t \times S_i\Big) + \alpha_t \Big(\text{Day}_t \times Y_{i,-1}\Big) + \kappa_i + \epsilon_{it} \tag{4}$$

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, $\beta_t$, derived from estimating specification (4) and find similar patterns as our primary specification.

While the results in Section 3.2 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.

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

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




NOTES: The 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 (4) with 95% confidence intervals of the estimated treatment effect shown, derived from standard errors clustered at the individual level. 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).

# F Data Imputation Procedures

In this section we provide details for three imputation procedures that we use throughout the text: imputation of the state of an individual, the total time spent on the phone and individual applications, and the exposure to news sites via browsers.

## 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 using 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 device-level time zone metadata and cross-referenced it with the local time zones associated with each U.S. state. 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 actual 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 could assign each user 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, New York, Illinois, New Jersey, Massachusetts, Washington, Oregon, Virginia, Colorado, New Mexico, Minnesota, Rhode Island, Connecticut, Vermont, New Hampshire, Maine, Hawaii, Maryland, and Delaware.

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

Several states were excluded from this final political classification due to ambiguity in keyword identification. Specifically, references to "Dakota" and "Carolina" could not be reliably disaggregated into North/South Dakota or North/South Carolina, respectively. As a result, both "Dakota" and "Carolina" terms were excluded from the swing/blue/red categorization to avoid misclassification.

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 application categories, and the final set of rows for individual applications.

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 and, during the election day period, unfortunately we do not have reliable time usage data. We use data from December 18th, 2024 until January 25th, 2025 where we have reliable time usage data and can accurately match the encounters data to corresponding time usage 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

3, since the app records the on-screen encounters every three seconds. Then, we compute for each user their total phone time according to the unique number of exposures in a given day. We drop the 44 users for whom this time estimate yields higher than the application usage data, since it is likely that these users consistently have enabled the encounter permissions and not the time usage permissions, which results in 1980 users. For each of these users, we aggregate the application usage from the time usage data and the encounter data, respectively, over the entire time period. We use this to compute the fraction of time captured by the full set of encounters overall on the phone, by top applications, and by categories. We use the median of these estimates throughout the text when we want to approximate time spent using only encounter data for periods where we lack reliable time usage data. The results are presented in Table F.1.

## F.3 Browser News Website Imputation

We consider the following model-based imputation procedure for ascertaining 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 aggregated 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 $\phi_{iv}$ is the share of encounters from keyword group $v$ in category $i$. Similar to Figure 3, we compute $\phi_{iv}$ for the average user. 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 4a) that this is more heavily skewed towards election-related encounters on news applications and captures other important differences in content across other categories. The key assumption that we make in this section is that encounters on the browser are a convex combination of encounter distributions across application categories. The econometric problem is that we observe $x_v$ – the number of encounters across different topics within the browser for the average user – and consider that these counts are drawn from a multinomial distribution as well as that we know the distribution of encounters coming from each of the $i \in I$ categories, $\phi_{iv}$. Thus, the distribution of counts in the browser is given as follows:

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

The challenge is to estimate $\beta$, which is the share of 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: $\ell(\beta) = \sum_{v=1}^{V} x_v \log\left(\sum_{i=1}^{K} \beta_i \, \phi_{iv}\right)$ and estimate $\beta$ 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 others and so 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. Therefore, $\theta_i$ provides us with a measure of 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 is spent on news sites.

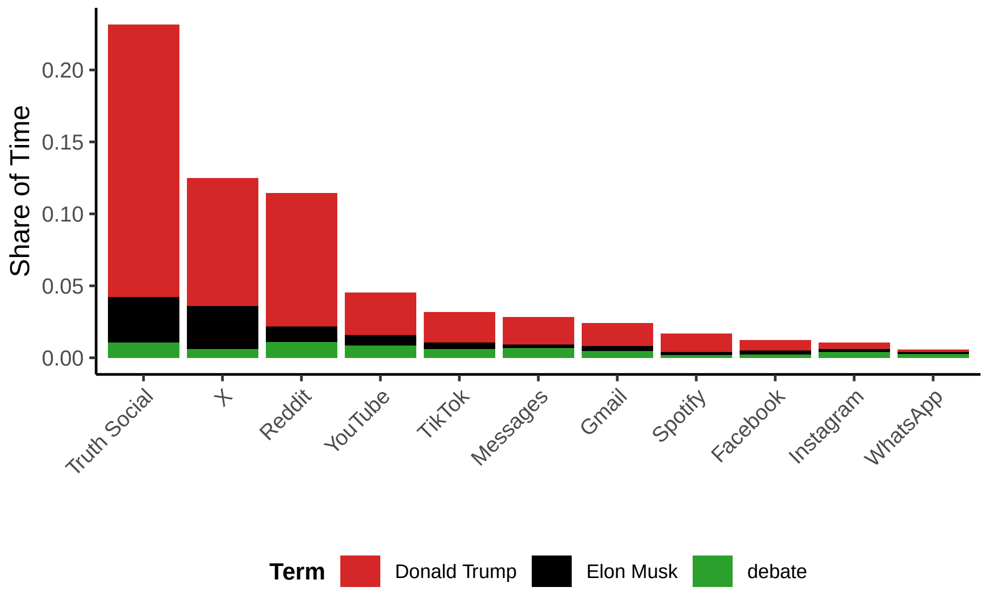
Our main interest, however, is understanding what fraction of election-related encounters on browsers come from news applications. We can compute this using our estimates via the following formulation:

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

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 $P\left(i = \text{News} \mid v = \text{election}\right) = 0.21$, 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 2.36% exposures in news applications and conclude that 8.62% of election-related exposures originate from either news applications or news websites visited in the browser.

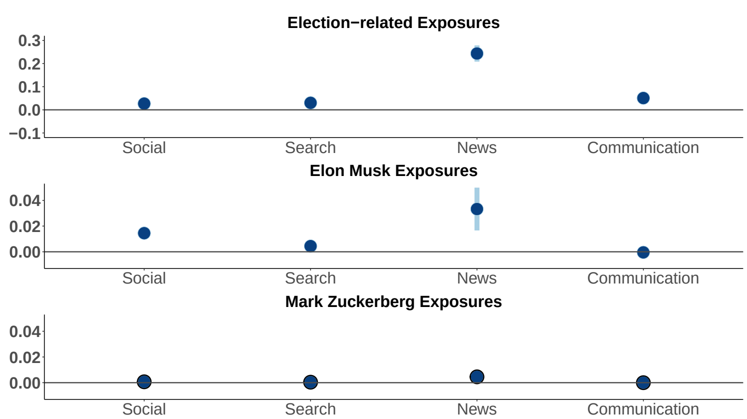
# G Additional Variance Decomposition Results

Figure G.1: Elon Musk and Donald Trump Share



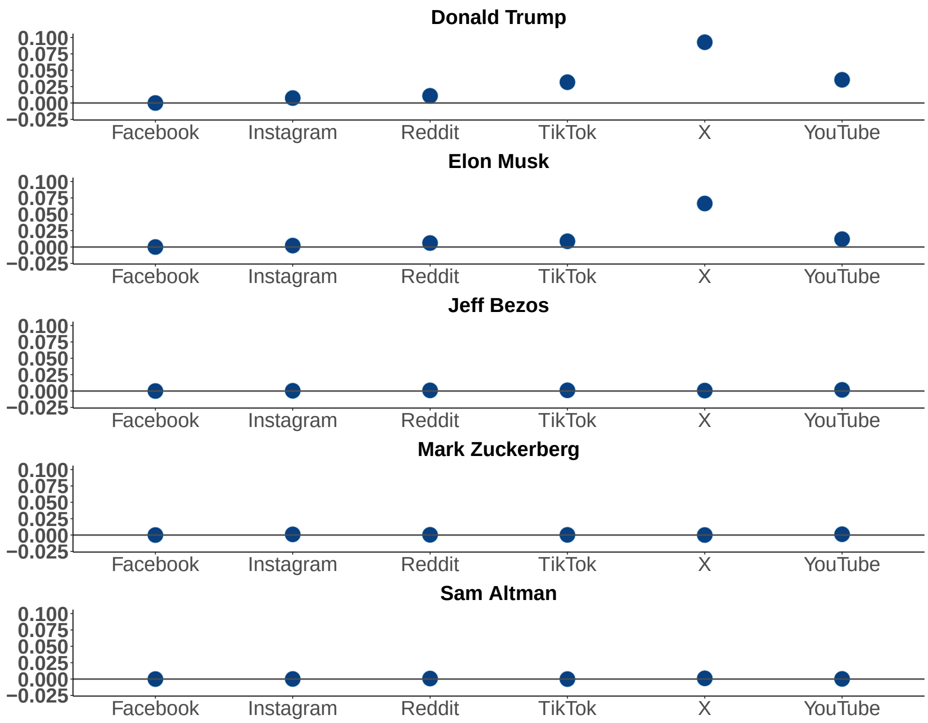

NOTES: This figure presents the share of total encounters, aggregated across users, of the terms ‘Donald Trump’, ‘Elon Musk’, and ‘debate’ across each of the presented applications. The figure uses data from September 1st until November 4th.

Figure G.2: App Fixed-Effects Across Application Categories




NOTES: This figure presents the estimated coefficients of the app fixed effects from Equation (1). We estimate this equation separately for each keyword, for all apps in the categories that appear 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 95% confidence intervals are constructed using standard errors clustered at the individual level. We exclude apps with fewer than 30 unique users and users with fewer than 30 unique apps.

Figure G.3: App Fixed-Effects Across Social Media Apps, Extended




NOTES: This figure presents the estimated coefficients of the app fixed effects from Equation (1). We estimate this equation separately for each keyword, for all social media apps that appear 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 95% confidence intervals are constructed using standard errors clustered at the individual level. We exclude apps with fewer than 30 unique users and users with fewer than 30 unique apps.

Table G.1: Variance decomposition (Weekly, Election-related keyword encounters)

| | All apps | Social | Communication |
|---|---|---|---|
| Individual FE | 0.99 | 0.76 | 0.81 |
| App FE | 0.07 | 0.24 | 0.13 |
| Time FE | 0.04 | 0.03 | 0.03 |
| Covariance of ind. & app FE | -0.11 | -0.00 | 0.05 |
| Covariance of ind. & time FE | -0.01 | -0.02 | -0.01 |
| Covariance of app & time FE | 0.02 | 0.00 | -0.00 |
| Adj. $R^2$ | 0.21 | 0.25 | 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, Social Media, and Other. 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 users with fewer than 30 unique apps.

Table G.2: Variance decomposition (Daily, Election-related keyword exposures)

| | All apps | Social | Communication |
|---|---|---|---|
| Individual FE | 0.92 | 0.71 | 0.83 |
| App FE | 0.10 | 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 | -0.03 | -0.01 | -0.01 |
| Covariance of app & time FE | 0.04 | 0.00 | -0.00 |
| Adj. $R^2$ | 0.22 | 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). 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, Social Media, and Other. 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 users with fewer than 30 unique apps.

Table G.3: Variance decomposition (Aggregated across time, Election-related keyword exposures)

| | All apps | Social | Communication |
|---|---|---|---|
| Individual FE | 0.97 | 0.74 | 0.81 |
| App FE | 0.09 | 0.27 | 0.14 |
| Time FE | 0.00 | 0.00 | 0.00 |
| Covariance of ind. & app FE | -0.07 | -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. $R^2$ | 0.13 | 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, Social Media, and Other. 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 users with fewer than 30 unique apps.

Table G.4: Variance decomposition (Weekly, Election-related keyword exposures, all apps)

| | All apps | Social | Communication |
|---|---|---|---|
| Individual FE | 0.83 | 0.65 | 0.79 |
| App FE | 0.12 | 0.30 | 0.13 |
| Time FE | 0.04 | 0.03 | 0.03 |
| Covariance of ind. & app FE | -0.02 | 0.03 | 0.06 |
| Covariance of ind. & time FE | -0.02 | -0.01 | -0.01 |
| Covariance of app & time FE | 0.05 | 0.00 | -0.00 |
| Adj. $R^2$ | 0.21 | 0.25 | 0.21 |
| $N$ 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, Social Media, and Other. 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 users with fewer than 30 unique apps.

# H Content Consumption Survey

In this section, we present results from a survey designed to provide additional evidence on two important claims and concerns of our main results.

First, recall that in Section 4 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. In this appendix we study 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 users encounter.

Second, one concern with our analysis is that it is based on a sample of individuals who choose to use screen management software. To test whether this impacts our results on election-related content consumption, we compare people with and without screen management software and find that individuals who use screen management software are not less politically engaged than those who do not. We now describe the survey design and results in more detail.

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.

## H.1 Over-Exposure to Content

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 4 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:

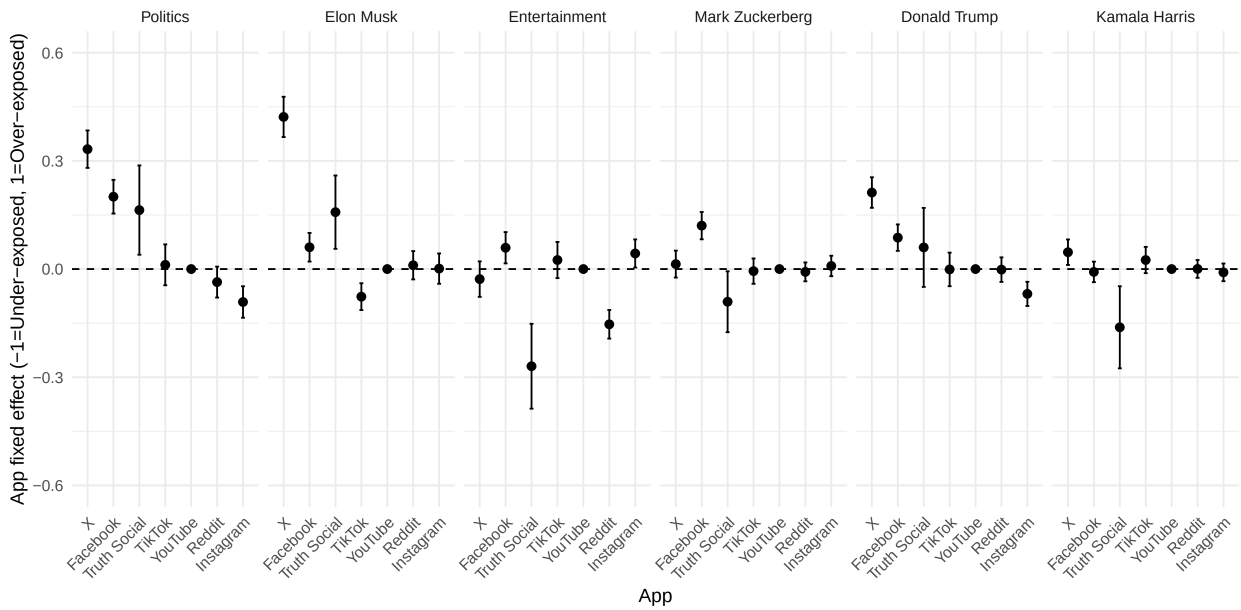
$$y_{ijt} = \beta_t \cdot \text{app}_j + \kappa_i + \epsilon_{ijt} \tag{5}$$

where $y_{ijt}$ is whether respondent $i$ felt they consumed too little (-1), the right amount (0), or too much (1) of topic $t$ on application $j$, $\kappa_i$ indicates respondent fixed effects, and $\text{app}_j$ is an indicator for application $j$. We 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 4 that isolate differences in content diets across applications. However, while in Section 4 the differences across applications could be driven by differences in how individuals use the applications, here the differences are in the *desired* level of content exposure. Thus, $\beta_t$ 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. Thus, a positive $\beta_t$ 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 $\beta_t$ systematically across all topics, it is possible that the application is difficult to personalize. However, if an application has a zero $\beta_t$, relative to other applications, for most topics and only a positive $\beta_t$ for some then it is possible that it over-prioritizes these types of content.

Figure H.1 plots the estimated $\beta$ for Equation (5) estimated for each topic separately with YouTube as the reference application. The results display a striking resemblance to our results from Section 4. 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 4 is that Facebook users report over, rather than under, consumption of politics, compared to YouTube, while in Section 4 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, nearly a year past the election. 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.[71]

Figure H.1: App Level Over-Exposure to Content




NOTES: This figure presents app fixed effects from equation (5), 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.

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:

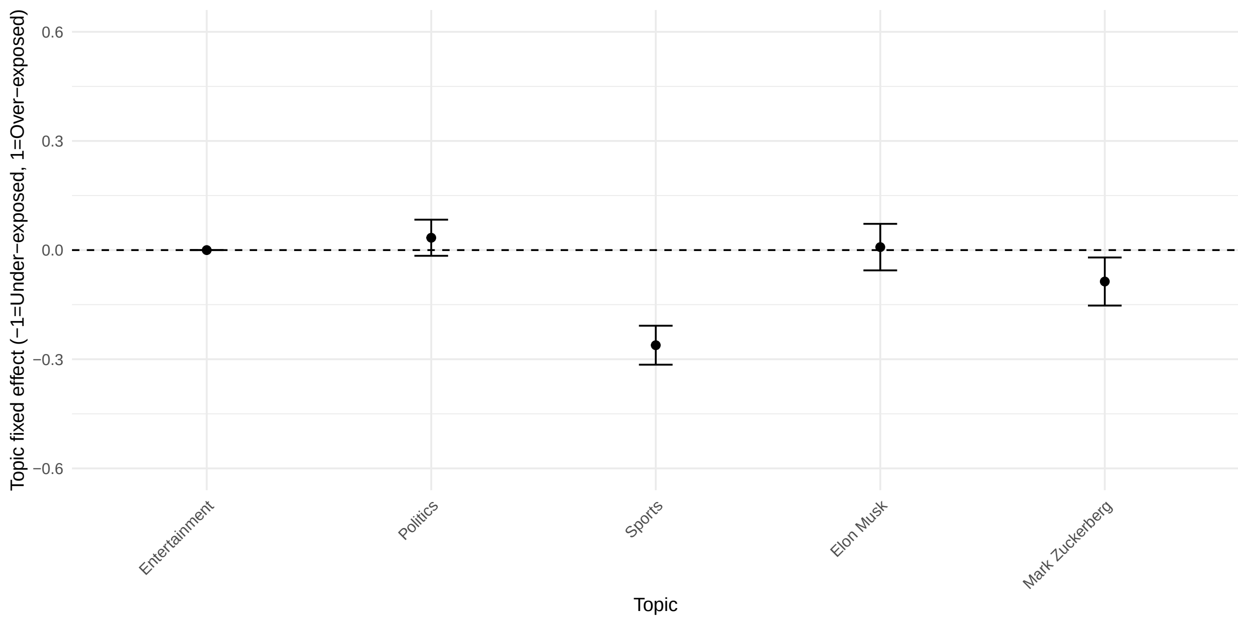
$$y_{it} = \beta \cdot \text{topic}_t + \kappa_i + \epsilon_{ij} \tag{6}$$

where we similarly cluster standard errors at the respondent level. The resulting estimates of $\beta$ are plotted in Figure H.2. Respondents report similar amounts of over-consumption of politics as 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 4 that individual fixed effects are the main

[71]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.

driver of heterogeneity in consumption, as the content individuals receive in aggregate tends to match their preferences.

Figure H.2: Overall Exposure to Content




NOTES: This figure presents app fixed effects from equation (6). 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.

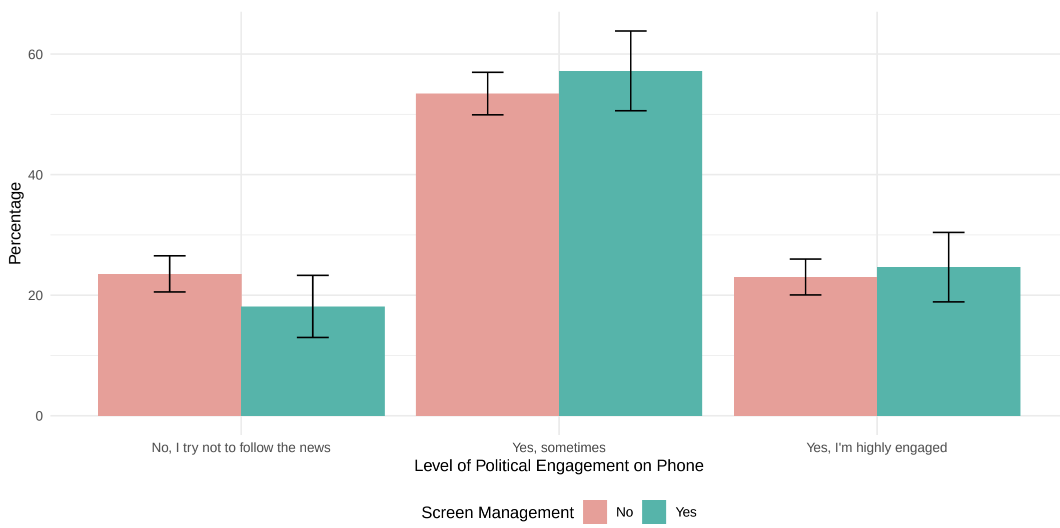
Putting these two results together, they paint a similar picture as Section 4, and suggest possible mechanisms. Given that 1) individuals' satisfaction with the amount of political content varies widely across apps, and 2) many are dissatisfied with their exposure (65% report over-consuming Elon Musk–related 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.

## H.2 Comparison of Individuals With and Without Screen Management Apps

In the final portion of the survey we wanted to characterize whether respondents who use screen management software self-report being more or less politically engaged on their phones. This is important to check as our data primarily comes from a screen management application. We asked respondents whether they use screen management software and 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 large fraction – 21.8% – of the sample 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 H.3 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.

Figure H.3: Screen Management and Political Engagement




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 bars represent 95% confidence intervals.

# I The Full Set of 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).

## I.1 Full set of election-related keywords

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

# J 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, 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