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What's Political on TikTok? Perceptions, Prevalence, and Patterns of Exposure to TikToks Users Perceive as Political

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Abstract

As its popularity soars across the U.S., TikTok has begun to draw criticism pertaining to political content on its platform. We conducted a study of 366 participants who used our browser-based tool to annotate videos from their personal TikTok feeds, marking those they perceived as political and briefly explaining why. We analyze the resulting data both qualitatively and quantitatively to answer three research questions investigating perceptions, prevalence, and patterns of user exposure to political content on TikTok. We answer these questions through qualitative coding of participants' responses, measuring rates of exposure to content users perceive as political, and running statistical tests to analyze patterns of overall and topic-specific exposure in relation to participant attributes. We developed a codebook with 32 political topics present in participant descriptions of political content, find that perceived-political content comprises 16.85% of participants' feeds on average, and that participants' age and interest in politics are associated with higher overall exposure to perceived-political content while gender and political ideology are associated with exposure to topic-specific content about gender and sexuality rights. We conclude with implications for user-centered studies of TikTok and other social media platforms, and directions for future work.

Code — https://github.com/Penn-HCI/tiktokpolperception

1 Introduction

With over a billion and a half users worldwide, TikTok is surging in global popularity, capturing both vast sectors of younger internet users and other demographic groups (Dixon 2024). While a third of U.S. adults have reported using TikTok, we know relatively little about what political content exists on the platform, how much of it users meaningfully engage with, or how users perceive this content (Gottfried 2024). Meanwhile, U.S. lawmakers have expressed concerns that TikTok poses a national security threat due to ownership by a Chinese parent company, ByteDance (U.S. House of Representatives, 118th Congress, 2nd Session 2024). These allegations suggest that TikTok could be intentionally exposing U.S. audiences to malicious content through its platform, whether Chinese propaganda or politically extreme and polarizing content (Dilanian 2024). Although TikTok has established trust and safety initiatives, like its Transparency and Accountability Center (TikTok 2026), there is still limited independent research on how politics appears on TikTok, one of the world's largest social media platforms.

We present a novel study with a user-centered view of how people perceive political content on TikTok. Using a mixed methods approach, we qualitatively evaluate participants' perception of politics and quantitatively explore patterns of association between user attributes and exposure to this content. We conduct a study with adult TikTok users based in the U.S. ($n = 366$), where each participant annotated videos in their logged-in "For You page" (FYP) that they perceived as political along with explanations in their own words, using our custom browser extension. We combine these participant annotations with responses to initial survey questions asking about participants' interest in and engagement with political content on TikTok.

We use this data to ask the following research questions:

RQ1: What kinds of content do TikTok users perceive to be political?

RQ2: How much content on TikTok do users perceive to be political?

RQ3: How does exposure to perceived-political content vary across user attributes?

To answer these questions, we hand-coded participant descriptions of the content they perceived as political on TikTok, investigated differences in user perceptions of political content, and conducted statistical tests examining associations between user attributes and reported exposure to perceived-political content.

We identified a total of 32 codes for political topics that appear in participants' short-form, free-text responses describing each TikTok video in their feed they perceived as political. These codes spanned formal political concepts relating to structures, actors, and processes within the official U.S. political system (e.g., LEGISLATION, POLITICIANS, ELECTIONS) and issue-specific topics that encompasses debates over rights, identity, public policy, and social justice concerns (e.g., RACE, SOCIAL ACTIVISM, IMMIGRATION).

Overall, we find that participants perceive 16.85% of TikTok videos in their FYP as political. Considering patterns in individual rates of exposure, we find that age and interest in politics are significantly associated with variation in this proportion across participants. We also test 16 theoretically-motivated pairs of user demographics and specific perceived-political topics, finding that women and more liberal-leaning people saw a larger number of videos they describe as relating to GENDER/SEXUALITY RIGHTS.

Finally, leveraging a subset of videos that appeared in multiple participants' feeds, we find that 37% of the individual observations in our data come from videos seen by multiple participants and that participants agree on whether the same video is political in 78% of cases but disagree in the reasons they provide in 68% of cases. Together, these findings suggest ways in which exposure to perceived-political content reflects a combination of overlapping content in users' feeds and differences in user perceptions.

This paper makes the following contributions:

1. We present a characterization of what content users perceive as political on TikTok, and to the best of our knowledge, the first studying users' TikTok feeds *in situ*.
2. We contribute a user-centered measurement and analysis of TikTok users' perceptions of political content, including the amount of content they see as well as initial patterns of association between user attributes and exposure to perceived-political content.
3. We provide a tool and materials, including a survey instrument and open-sourced browser extension, for running similar studies in the future measuring content directly from users' real TikTok feeds.

2 Related Work

We situate this paper at the intersection of research pertaining to news and politics on social media (e.g., Wang et al. 2024; Bandy and Diakopoulos 2021; Kulshrestha et al. 2017; Wang and Mark 2017), and human-centered empirical studies (e.g., Simpson and Semaan 2021; Le Compte and Klug 2021). From the perspective of academic research, TikTok is a relatively young social media site, gaining popularity in 2018 (Paul 2022). It has become known for its powerful recommendation algorithm, which adapts based on user attributes such as location, language, and engagement with content on the platform (Boeker and Urman 2022). Past work on other social platforms often relies on collecting data from a seed set of highly-followed political accounts, such as politicians or news media outlets (Guess et al. 2023a; Marquart, Ohme, and Möller 2020). But such accounts are less likely to be the central nodes of political content on TikTok, since the recommendation system appears to group users based on shared interests, feeding them highly personalized content instead of primarily relying on networks of followed accounts (Gerbaudo 2024).

Politics on TikTok The rise of TikTok as a platform for political engagement and information-sharing is a growing and important area of study, particularly given its popularity among younger demographic groups and its use as a source of news media. Recent studies by Pew Research Center have identified that 4 in 10 young adults in the U.S. regularly get news from TikTok, and that TikTok (55%) has surpassed Facebook (53%) in the amount of users reporting they regularly get news on the platform and is approaching Twitter/X (57%) (Tomasik and Matsa 2025). One recent study comparing TikTok to YouTube (an alternate and more dominant platform for video-based political content) found that TikTok encourages higher rates of content creation and that view counts on the platform are more dependent on virality than creator popularity (Guinaudeau, Munger, and Votta 2022). TikTok's emphasis on virality could amplify political content among younger users, particularly when the content is packaged as memes or entertainment (Brown, Pini, and Pavlidis 2024; Zeng and Abidin 2021). This effect is especially salient because TikTok has become a central platform for youth political engagement and activism (Karimi and Fox 2023; Literat and Kligler-Vilenchik 2023).

Empirical research about news and politics on the platform remains rare. In one landmark study, Medina Serrano, Papakyriakopoulos, and Hegelich (2020) scraped a large dataset of U.S. partisan videos marked with political hashtags, finding that political communication on TikTok is interactive and popular with younger age groups. Internationally, Berdón-Prieto, Herrero-Izquierdo, and Reguero-Sanz (2023) collected videos from Spanish political parties, finding them posting increasingly polarizing messages, but another content analysis study of several populist right-wing parties' posts found that extreme content might not drive engagement as much as humor and entertainment on the platform (González-Aguilar, Segado-Boj, and Makhortykh 2023). Other studies have examined how news agencies are adopting TikTok (Vázquez-Herrero, Negreira-Rey, and López-García 2022) and the use of TikTok by politicians in Spain (Cervi and Marín-Lladó 2021), Canada (Moir 2023), Peru (Cervi, Tejedor, and Blesa 2023), and Poland (Zamora-Medina, Suminas, and Fahmy 2023).

Although TikTok's feeds are highly personalized, none of these studies use feed-level data or assess user perceptions. While they provide some insights into TikTok's rapid growth as a source for news and politics, the reliance of prior work on collecting data from specific TikTok accounts or hashtags (which may overlook significant sources of political content) raises questions about the user experience. In this work, we focus on some of these questions, including how users perceive content as political on TikTok, how much content they perceive as political, and why (Zulli and Zulli 2020).

Politics on Other Platforms Perhaps the most heavily-studied platform for political content is X (formerly Twitter), where the largest share of users report seeing political content (Tomasik and Matsa 2025) and whose previous open data access policies made it a friendly choice for academics. Twitter has been studied with respect to political biases, both in users' own choices (Kulshrestha et al. 2017), and in its algorithms (Wang et al. 2024; Bandy and Diakopoulos 2021), as well as other related topics, like politicians' use of the platform (Hemphill, Otterbacher, and Shapiro

2013). Two other major platforms of study for political content are Instagram (Molem, Makri, and Mckay 2024) and Facebook (Bakshy, Messing, and Adamic 2015; Wang and Mark 2017); such studies have often been done in collaboration with Meta due to the company's restrictions on data access for outside researchers (Guess et al. 2023b; Nyhan et al. 2023; González-Bailón et al. 2023). These papers offer rare estimates of baseline rates of political content on the platform, reporting an average of 3.9% political news (González-Bailón et al. 2023) and 6.9% civic content (Nyhan et al. 2023) appearing in Facebook users' feeds. They offer an important point of comparison for the user-reported rates we observe in our study, but must be contextualized by the strict definitions of "politics" past work has used in contrast to the broader user-centric approach we adopt. The study most similar to a user-centered definition of political content is Guess et al. (2019), which examined the alignment between users' reported frequency of posting about politics and the observed quantity of political posts identified on their Facebook and Twitter accounts.

People's Perceptions of Politics The prior work we have described about political social media content, whether on TikTok or other platforms, has largely been conducted using top-down determinations by researchers about what constitutes political content, and has not directly investigated what users think is political and why in these settings. Instead, much of this work explicitly focuses on news content as a proxy for political content or content of political import (e.g., Wang et al. 2024; Nyhan et al. 2023; Robertson et al. 2023; Mayer et al. 2025), in large part because automated methods for detecting political content are challenging. Although political scientists have examined how people conceive of politics (Warren 1999) and democracy (Canache 2012), few studies extend this inquiry to social media.

An area in which differing opinions about political content online have become salient is political advertising. This occurs in cases such as Twitter/X's 2019 ban on political advertising (Dorsey 2019) — a decision since reversed (Dang 2023) — or when national governments have passed regulation about political advertisements (Dommett and Zhu 2023). In reaction, think tanks (Maria Puertas 2024; Jaursch 2020), the popular press (Conger 2019), and academics (Dommett and Zhu 2023; Papakyriakopoulos et al. 2022) all released reports on the complications of these policies. Such cases demonstrate the subjectivity of this matter and the difficulty in effectively categorizing political content. In this work, we aim to collect empirical data to grow the field's understanding of political content on TikTok from a user-centered perspective.

3 Data

We use a combination of survey response data, scraped web data from our participants' TikTok accounts collected via our custom browser extension, and participants' own annotations on that scraped content. Our study ran from July 2023 to September 2023 with a set of 366 participants recruited through Prolific (Prolific 2024), a common research participation site. Our participants first answered a series of survey questions related to their interest in politics and use of the TikTok platform, before downloading our custom extension and providing us with data directly from their TikTok feeds.

Participants. We set out to collect between 300 and 400 responses based on sample sizes in similar work on other social media platforms (e.g., Robertson et al. 2023; Wang et al. 2024). As the first study of its kind on TikTok, our analyses are exploratory and we did not have effect size estimates that we could use to run a power analysis informing the number of participants we would attempt to recruit. Due to the Prolific platform's requirements for tasks involving the downloading of external tools, and accounting for participant attrition, we recruited a larger pool of 1,126 participants, paying them $1 each to take our survey. At the end of the survey, we invited them to optionally download the tool and contribute data for an additional $6.80. The entire task (survey and data collection) was estimated to take 30 minutes, and participants completing both steps were compensated the equivalent of $15 per hour for a total of $7.80.

Survey. Our survey first asked participants for consent through a form approved (as was our entire study) by our university's Institutional Review Board. It next asked users to provide demographics identified as relevant by prior work: age, political ideology, employment status, educational level, and current state of residence. We collected additional demographic information about participants directly from Prolific, including sex and race. To confirm eligibility for the next phase of the study, we also asked whether participants had a TikTok account and how long they had been actively using their account—our inclusion criteria specified that any person over 18 years of age, currently residing in the U.S., with an existing TikTok account that they had actively used for at least a month could participate. Finally, we asked users a series of questions including asking them to estimate how much content they considered political they saw on TikTok, their level of interest in politics, and how they engaged with political content on the platform (including ignoring, watching, liking, commenting on, or sharing such videos). The screening survey ended with instructions for downloading, installing, and using the extension. The complete survey instrument is available in Appendix A.

Browser Extension. After completing our survey, eligible users were asked to download our custom Chrome browser extension. Upon doing so, they were given instructions to log in to their TikTok accounts in the same browser, and scroll through their TikTok feed. Our extension embedded a radio button and open-response box, asking participants whether or not each video in their feed was *political (in their own opinion)*, and to briefly describe *why or why not* (Figure 1). Participants were required to annotate at least 40 videos (regardless of the proportion they marked as political). We provided users the option to mark content as implicitly or explicitly political to prompt them to think more broadly about what they consider political content, rather than defaulting to a more formal or narrow definition, but for the analysis in this paper, we group both political categories together. As one of the contributions of this research,

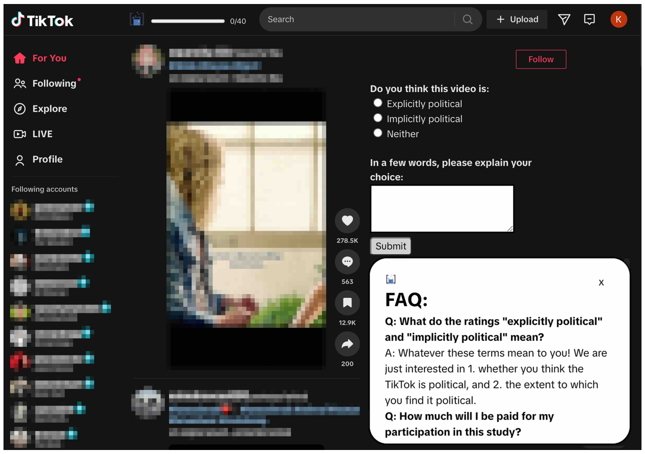

Figure 1: Screenshot of the web tool running on Tiktok. Participants can annotate videos with one of three radio buttons, explain their choice, and submit their response. Progress bar is shown in the upper left of the screen beside the TikTok logo, and Frequently Asked Questions are included in a scrollable interface on the bottom right.

we also open-source this tool for use by other researchers interested in collecting similar data from users' TikTok feeds at the following GitHub link: https://github.com/Penn-HCI/tiktokpolperception.

Participant Response Verification. To validate participants' annotations on TikTok videos and ensure good-faith effort in their responses, for each participant we manually reviewed one randomly selected video they annotated as political and one they annotated as not political. For each, we watched the video itself and checked whether the participant's free-response explanation aligned with what was actually presented in the video. As an additional robustness check against participants marking all videos as political (which would not have affected their pay, but which we suspected some participants misunderstood), we reviewed an additional four videos annotated as political for any participant whose overall data indicated that at least 50% of their feed was perceived-political. In total, we reviewed 766 video-explanation pairs (376 marked political and 390 marked nonpolitical), finding that all but one (which we excluded) had explanations relevant to the video's content.[1] Echoing our focus on users' own subjective perceptions of content, in this step we did not evaluate whether participants' political/not political radio button selections were objectively correct by our own metric. Rather, we only checked whether they had completed the task in good faith. As a result of this validation step, two users were identified who had marked all their videos as political, but explicitly stated in their free-text descriptions reasons they thoughts the videos were *not* political. We concluded that these two users misunderstood the task and excluded their data from analysis.

Final Dataset. We collected survey responses from 1,126 participants, 458 of whom met the eligibility criteria, and 375 ultimately downloaded our browser extension and completed our video annotation study. We test for differential attrition by comparing demographic distributions in the initial and final samples of respondents using χ^2 tests of independence. We find no statistically significant differences in the distributions of age ($\chi^2(5) = 6.75$, $p = 0.24$), sex ($\chi^2(2) = 1.34$, $p = 0.51$), or ethnicity ($\chi^2(4) = 2.33$, $p = 0.67$), indicating that attrition is not systematically related to these observed demographics.[2] Subsequently, we removed 7 participants' data whose video URLs were missing due to an error with the browser extension, (which was addressed before open-sourcing the tool), in addition to the two users who failed the response verification task.

Our final dataset for analysis comprised **15,154 video annotations** from **366 participants** across **11,312 unique TikToks**. Of these user-level annotations, 875 of which were labeled Explicitly Political (5.8%), 1,493 Implicitly Political (9.9%), and 12,786 Neither (84.4%). Table 1 shows the participants included in our final dataset are similar to U.S. demographics by sex (51.70% male) and race (68.73% White). We also actively recruited for a balanced sample by political leaning (53.42% Liberal, 34.78% Conservative, 11.80% Neutral). We note that this sample is certainly not representative of the base of all TikTok users, even within the U.S.; for example, 61% of U.S. teenagers report using TikTok on a daily basis (Faverio and Sidoti 2025), whereas our participants are restricted to legal adults. Moreover, we (and perhaps even TikTok itself) lack the demographic data about the full user base needed to gather a representative sample. Instead of representativeness, we aimed to recruit an ideologically, racially, and gender diverse pool.

4 Analysis Method

We used a mixed-methods approach both qualitatively analyzing and quantitatively comparing participant data. We first develop a codebook of political topics grounded in participants' own descriptions of content they perceive as political on TikTok. We then quantify exposure to perceived-political content and examine how both overall exposure and specific perceived political topics vary across user attributes.

Qualitatively Describing Politics (RQ1)

To identify *what kinds of content TikTok users perceive as political,* we developed a codebook via iterative, inductive coding, deriving categories directly from the free-form responses by participants describing the type of content they perceive as political on TikTok.

[1]The single exception, which we excluded from analysis, was a video marked "Neither" along with the annotation, "This is a movie scene," on a video by a content creator about growing vegetables in their home garden. After spot-checking the remaining annotations from this user and finding no further discrepancies, we retained their remaining data in the dataset.

[2]We can only test differential attrition for these three demographic values, as others including political ideology and level of education were only collected after the initial survey.

Sex	**Age**
51.7% Male	27.2% 18–24
48.3% Female	23.2% 25–30
	28.5% 31–40
	20.4% 41+
Ideology	**Education**
8.4% Very conservative	1.2% < High school
13.3% Moderately conservative	14.9% High school
13.3% Slightly conservative	25.4% Some college
11.8% Neutral	9.0% 2-year degree
11.8% Slightly liberal	40.6% 4-year degree
18.9% Moderately liberal	8.1% Professional degree
22.6% Very liberal	0.9% Doctorate
Ethnicity	
68.7% White	10.2% Asian
8.7% Black	6.8% Mixed
5.6% Other	

Table 1: Participant demographics (n = 366). Percentages may not sum to 100 due to rounding.

Codebook of Political Topics. The codebook was initially informed by a review of responses to the pre-experiment survey question asking participants "In two sentences or more, how would you describe the kinds of TikTok content you consider to be political, and what makes it political to you?" We used these survey responses to identify candidate categories because they capture a wide variety of ways people perceive politics and subsequently refined the codebook through multiple rounds of independent, deductive coding. Because the survey dataset was relatively small ($n = 366$), two authors were able to each code all individual responses during every round of coding. The initial codebook was refined over four rounds of coding the survey responses. In each, coders applied the current version of the codebook to all responses, after which inter-rater reliability was assessed using Cohen's κ, computed separately for each code. Coders then met to adjudicate disagreements, clarify code definitions, and determine whether additional codes were required. Disagreements were adjudicated through discussion and typically resulted in refinements to code definitions, which were incorporated into subsequent coding rounds. New codes were added only when both coders agreed that a concept was not captured by the existing schema. Iteration terminated when no new codes were introduced and inter-rater reliability was high for all codes (Cohen's $\kappa \geq 0.75$).

We subsequently updated the codebook using participants' short-form textual descriptions associated with videos they marked as "political" in their FYP. Two authors independently coded a random sample of 200 such annotations using the survey-derived codebook. Disagreements were adjudicated through discussion, and inter-rater reliability was again assessed at the code level (Cohen's $\kappa \geq 0.75$ for all codes). This process identified three additional codes that were not present in the survey responses but recurred in the video annotations, which we added to the codebook: HOUSING, CHARITY, and PRISON. After finalizing the codebook (32 codes total), one author applied it to the remaining 2,168 short-form descriptions. Appendix B includes the full set of codes, definitions, and code-level reliability statistics.

Quantifying the Prevalence of Politics (RQ2)

To identify *how much content TikTok users perceive as political,* we identified both the overall quantity of videos our participants perceived as political as well as the frequency that each code in our codebook appeared in their free-text descriptions of this content. Using data from participants' logged-in TikTok sessions collected by our browser extension, we first calculated the proportion of videos in each participant's feed they marked as either implicitly or explicitly political to report the overall average of perceived-political content. We then applied our codebook developed to answer RQ1 to the free-text descriptions tied to each video marked by participants as political, and reported the frequency that each code appeared in these explanations.

Correlating User Attributes with Political Exposure (RQ3)

To investigate *how exposure to perceived-politial content varies across user attributes,* we used a series of Ordinary Least Squares (OLS) regression models to identify user attributes correlated with user-reported rates of exposure to perceived-political content. We conducted two analyses using regressions to test whether user attributes are associated with (1) the amount of political content participants reported seeing in their feeds and (2) the frequency with which specific codes appeared in users' annotations of individual perceived-political videos. Before fitting these two types of models, we first preprocessed user responses to numeric values (See Appendix C).

Overall Prevalence of Politics. In the first analysis, we treat the proportion of participants' feeds annotated as political as the dependent variable and test whether participant attributes are associated with this value. The first model we use includes participant demographics (age, sex, ethnicity, level of education) and political ideology as the independent variables. We then include survey-reported values for interest in politics ("In general, how interested are you in politics?") and engagement with political content on TikTok ("In the past, how have you engaged with political content on TikTok, if at all?") in the second model, while controlling for all attributes included in the first model.

Specific Political Topics. In the second analysis, we investigate the relationship between participant attributes and specific types of political content, as described by the participants themselves. Rather than testing the relationship of all demographic variables with all codes, we restrict this exploratory analysis to theoretically-motivated tests to avoid the potential for p-hacking. We compare 16 pairs of specific topics with user attributes that have been shown to relate in prior literature, particularly population surveys from Pew:

- Gender and two codes: ABORTION (Osborne et al. 2022); GENDER/SEXUALITY RIGHTS (Parker, Horowitz, and Brown 2022).
- Ideology and nine codes: ABORTION (Osborne et al. 2022); GENDER/SEXUALITY RIGHTS (Parker, Horowitz, and Brown 2022); ENVIRONMENT (Tyson and Kennedy 2023); IMMIGRATION (Center 2024; Oliphant and Cera 2022; Oliphant and Copeland 2025); RACE (Hurst 2023); CRIME (Gramlich 2022); GUNS (Schaeffer 2024); PRISON (Gramlich 2021); POLICE (Parker et al. 2022; Gilberstadt 2020).
- Race and five codes: RACE (Hurst 2023); CRIME (Gramlich 2022); GUNS (Schaeffer 2024); PRISON (Gramlich 2021); POLICE (Parker et al. 2022; Gilberstadt 2020).

For each potential relationship tested, we run an OLS regression model controlling for all user demographics with the frequency of the target code in each user's FYP as the dependent variable. This resulted in nine different models (one for each unique code across all 16 tests), for which we perform a Bonferroni multiple-tests correction adjusting p-values for each model.

Videos Appearing in Multiple FYP's. A challenge in answering RQ3 is disentangling heterogeneity in *exposure* from heterogeneity in *perception*: did different users see meaningfully different content (because of identity attributes, interests, or some other factor), or did they see similar content but disagree in their characterization of it? For its benefits, resolving this question is a significant challenge for user-centered work like ours. A notable feature of our dataset useful in answering this question is the presence of a subset of videos seen and annotated by multiple participants; we refer to these as *repeated videos*. We find that 16% (1,825) of the 11,312 unique videos in our dataset appeared in the feeds of two or more participants, and these videos account for 37% (5,636) of the 15,154 annotated video observations. Each repeated video was seen by an average of 3.08 participants ($SD = 2.10$), and 97% of participants viewed at least one of these repeated videos.

We use the repeated video dataset to begin disentangling heterogeneity in participants' perceptions of political content. First, we examine agreement rates — whether cohorts of participants who viewed the same video perceived it in the same way with regard to political nature overall. We further examine the codes identified in user annotations of these videos to move beyond the binary classification and see if participants who saw the same video agreed in their reported reasons for *why* they perceived the video as political. The repeated videos dataset contains 228 videos marked as political by at least two participants (not necessarily unanimously labeled by all participants who saw the video) with accompanying annotations, and our codes of those annotations. We measure agreement in participant annotations by computing an inter-rater reliability score (Fleiss' κ) on these videos' codes. This score quantifies the degree to which participant descriptions of the videos matched.

Regression Robustness Checks. We further use the repeated videos to assess the sensitivity of the results from our regression analyses. We split the full dataset of 15,154 user annotations of videos into two subsets – the 5,636 annotations from repeated videos and the 9,518 annotations from non-repeated videos – and replicate our results from the full dataset using each of these two subsets for comparison.

For the regression analyses examining the overall prevalence of political content, which operate at the user level, we re-estimate each model using annotations only from the repeated videos and non-repeated videos, respectively. We compare coefficient estimates across models to assess the stability of their sign, magnitude, and statistical significance when using different subsets of the data. Analyses of specific political topics are conducted at the individual video level, where a boolean indicator for repeated videos is well defined (True if the video was repeated; otherwise, False). For these models, we assess robustness by interacting this boolean indicator with covariates that exhibit statistically significant associations in the full-sample models, allowing coefficients to vary between repeated and non-repeated videos and formally testing whether associations differ by video type.

5 Results

Political Topics in Participant Perceptions (RQ1)

Our first research question asks *"What kinds of content do TikTok users perceive to be political?"* To answer this question, we created a codebook via iterative, inductive coding to identify political topics included in user descriptions of TikTok videos they perceived as political.

Identified Political Topics. We identified **32 unique codes** for political topics participants mentioned in their descriptions of political content, shown in Figure 3 and listed in Appendix B. Across the entire codebook, codes covered a diverse range of topics, including POLITICIAN, ABORTION, ENVIRONMENT, RELIGION, and others. Illustrating our participants' descriptions of political content in more detail, we include several examples in Table 2. We include both the text of the participant's explanation of why they think a particular video is political, as well as the codes with which we annotated it. Table 2 also shows some of the ways references to news media appear in our data, an important subset of political content for researchers to consider as many people are turning to social media platforms, and especially TikTok, as a primary source of information about world events (Tomasik and Matsa 2025).

Proportion of Politics in Participant Feeds (RQ2)

Our second research question asks *"How much content on TikTok do users perceive to be political?"* To answer this question, we measured the proportion of each participant's feed they perceived as political as well as computed the average rate across participants. We additionally examined how frequently specific political topics appeared by analyzing the

User Response	Codes
"This relates back to gun laws."	Guns, Legislation
"Police body cam footage."	Police
"News story of a murder."	News, Crime
"Political news about the uk royalty."	News, International
"This is a woman talking about state laws in TN, the new anti-abortion and LGBTQ laws in that state."	Legislation, Abortion, Gender/Sexuality Rights
"Jobs, pandemic."	Econ, Covid
"Comedy video."	None

Table 2: Example user annotations and their assigned codes. Each user annotation is tied to a specific video the participant perceived as political.

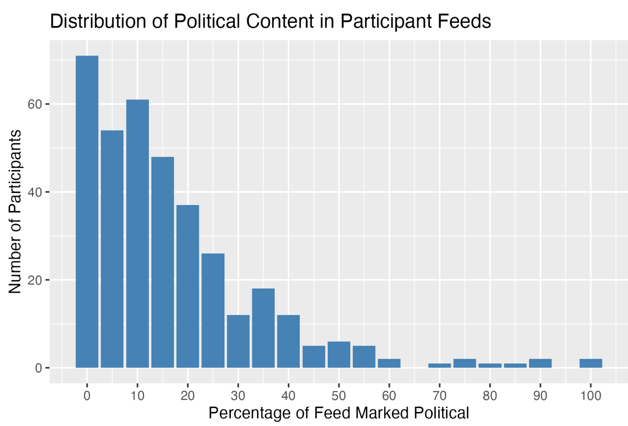

Figure 2: The percentage of perceived-political videos in participants' feeds was skewed, with an average of 16.85%.

relative frequency of each code in participants' descriptions of why they thought these videos were political.

Frequency of Perceived-Political Content. Across our entire study population, we collected an average of 41.4 videos per participant ($M = 41.4, SD = 16.1$) with our custom browser extension. On average, **16.85% of a participant's feed was marked perceived-political** ($M = 0.168, SD = 0.173$). Figure 2 shows the distribution of perceived-political videos in participant's feeds.

Frequency of Political Topics. We then analyzed the frequency with which each code in our codebook appeared in short-form descriptions of why participants perceived individual videos in their TikTok feed as political. Figure 3 visualizes the distribution of the full set of 32 codes across all perceived-political videos. (We exclude the None code for clarity.) The most frequent topic present was Gender/Sexuality Rights, appearing in 13% of user annotations. Race was also highly prevalent, referenced in 11% of annotations, followed by Police (9%), Economy (8%), Crime (6%), and Party/Ideology (5%).

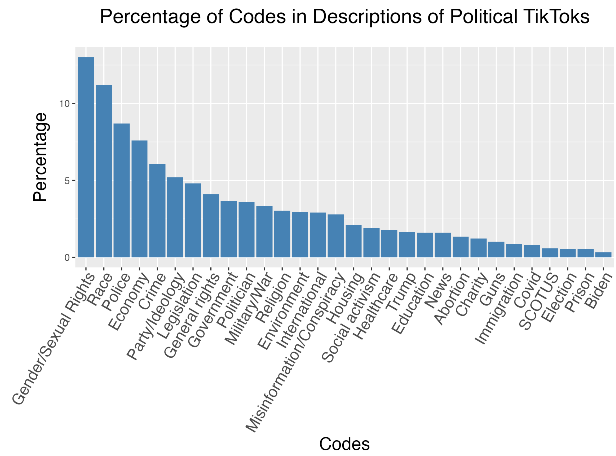

Figure 3: Percentage of all codes in participant descriptions of perceived-political TikTok videos. The highest percentage codes (Gender/Sexuality Rights, Race, Police, Economy, Crime) suggest that specific social issues are most commonly perceived in political content on TikTok.

Patterns of Political Exposure (RQ3)

Our third research question asks *"How does exposure to perceived-political content vary across user attributes?"* To answer this question, we use OLS regression models to investigate patterns of association between user attributes and rates of overall exposure to perceived-political content as well as specific types of political content.

Age Covaries with Overall Exposure. We first examined the association between participant demographics including political ideology and the quantity of political content participants reported observing in their feeds, finding that younger participants saw significantly more perceived-political content compared to older ones ($\beta = -0.003$, $p = 0.001$). We also observed a racial difference, with Asian participants perceiving more political content compared to White participants ($\beta = -0.067$, $p = 0.041$), though this result did not persist in our later analyses. Table 3 shows the result for age with the same coefficient estimate derived from the second model, while the full regression table for the first model is included in Appendix D.

Political Interest Covaries with Overall Exposure. To investigate the association between exposure to perceived-political content and two other relevant individual characteristics — political interest and engagement with political content on TikTok — we regress the proportion of perceived-political content on these two variables, while controlling for demographics and political ideology. Table 3 shows that participants who report higher interest in politics annotated a higher proportion of their feed as political ($\beta = 0.015$,

Variable	β	p-value	Sig.
Political Interest	0.015	**0.011**	**
Engagement	-0.028	0.200	
Ideology	-0.007	0.142	
Age	-0.003	<**0.001**	***
Education	0.002	0.815	
Sex (Male)	-0.030	0.129	
Race (Asian)	-0.054	0.100	
Race (Black)	-0.030	0.370	
Race (Mixed)	-0.008	0.840	
Race (Other)	0.012	0.784	
Intercept	0.279	<**0.001**	***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 3: Outputs from OLS regression model associating the proportion of videos participants perceived in their FYP as political and survey-reported values for interest in politics, engagement with political content on TikTok, political ideology, and user demographics. Younger and more politically interested participants exhibit higher rates of exposure to perceived-political content.

$p = 0.011$), but we observe no significant relationship between user-reported engagement with political content and relative exposure rates ($p = 0.200$). Previous results about age remain in this model, though the effect of race does not.

Sex and Ideology Covary with GENDER/SEXUALITY RIGHTS. Having primarily identified two participant attributes (age and self-reported interest in politics) that are linked to the overall amount of perceived-political content observed in participants' feeds, we next investigate the relationship between user attributes and specific types of political content. Across all 16 tests (after adjusting for multiple tests), the only significant results are that women ($\beta = -0.066$, $p < 0.001$) and more liberal-leaning participants ($\beta = -0.015$, $p = 0.002$) had higher rates of occurrence for the GENDER/SEXUALITY RIGHTS code in their descriptions of videos they marked as political.[3] The full set of results across all nine model are available in Appendix D.

Agreement in Perceptions of Repeated Videos. Participants' perceptions of whether a video was political concurred for 78% of repeated videos (1,426 of 1,825). Of these, 9.3% were unanimously perceived as political (135 videos), while the rest were unanimously perceived as not political (1,291 videos). We then examined participants' free-text annotations on repeated videos to investigate whether participants' descriptions of that content also agreed. We find that the majority of free-text descriptions (68%, or 156 videos) have low agreement (Fleiss' $\kappa \leq 0.75$).

Results are Robust Considering Repeated Videos. The coefficient for age derived from the full dataset remains consistent when considering the repeated ($\beta = -0.002$, $p = 0.021$) and non-repeated subsets ($\beta = -0.003$, $p = 0.003$). The same is true for political interest and both the repeated ($\beta = 0.013$, $p = 0.045$) and non-repeated ($\beta = 0.016$, $p = 0.015$) subsets. Finally, the association between sex and ideology and the frequency of the GENDER/SEXUALITY RIGHTS code remains stable in the interaction model. The coefficients derived from the full dataset are comparable to those derived from the interaction model when the indicator for repeated videos is false for both sex ($\beta = -0.075$, $p < 0.001$) and ideology ($\beta = -0.015$, $p < 0.001$). Moreover, the interaction terms comparing coefficient estimates between repeated and non-repeated videos are not statistically significant for either sex ($p = 0.136$) or ideology ($p = 0.807$), indicating no evidence that these associations differ across video types. Within the limits of our data, we find no evidence that associations between user attributes and perceived-political content differ systematically between repeated and non-repeated videos, indicating that our regression results are robust to this distinction.

6 Discussion

Summary of Key Findings. Our study examines the content TikTok users perceive to be political, along with the dynamics of their exposure to this content on the platform. We first focused on the kinds of content participants perceived as political on TikTok (**RQ1**). We developed a codebook with 32 entries spanning both formal political topics (e.g., POLITICIANS, LEGISLATION, ELECTIONS, and NEWS) as well as specific social and identity-based issues (e.g., HEALTHCARE, ABORTION, COVID, GENDER/SEXUALITY RIGHTS, and RACE). We then examined how much political content (overall and within sub-categories) TikTok users report seeing (**RQ2**). We find that 16.85% of videos in participants feeds, on average, are perceived as political by our participants as well as which codes are most common in participant descriptions of this content. Finally, we conducted an initial exploration into patterns of association between user attributes and the content participants perceived as political on TikTok (**RQ3**). We used OLS regression models to examine the relationship between user attributes and the proportion of each participant's FYP they perceived as political, finding that younger and more politically interested participants had higher rates of exposure to perceived-political content. We investigated potential relationships between participant demographics and the frequency of specific codes appearing in their descriptions of perceived-political content, finding that women and more liberal-leaning participants had significantly higher occurrences of the GENDER/SEXUALITY RIGHTS code. Finally, to begin disentangling the difference between users being shown objectively different content and potentially variable subjective perceptions of that content, we analyzed repeated

[3]Our models use women and liberals as the reference; a negative β means these groups had a positive association with the dependent variable.

videos. We found that 37% of the observations in our data were tied to repeated videos, participants agreed 78% of the time about whether a given video was political, participants disagreed 68% of the time in their provided reasons for why they thought a video was political, and that our results are robust considering the different subsets of our data.

User-Centric Definitions of Politics. One of the novel contributions of our study is the bottom-up, user-centric definition of political content as anything a specific participant personally deemed to be political, in contrast to much prior work that uses news as a proxy for politics (Robertson et al. 2018; Nyhan et al. 2023; Wang et al. 2024; Mayer et al. 2025) or limits itself to accounts for specific politicians and political parties (Guess et al. 2023a; Marquart, Ohme, and Möller 2020). We considered this approach and compared our data to the set of political accounts in Brown et al. (2024), a recently published dataset of cross-platform accounts for politicians, candidates, and campaigns. Out of the 2,368 videos perceived as political by our participants, only one (which appeared in four participants' FYP's) was posted by an account included in the Brown et al. (2024) dataset. We suspect something similar had we instead focused on news; very few of the videos we manually annotated came from official news organizations.[4] While there is still great value in focusing on political figures and "hard" news, existing research is biased towards these more definitionally precise and computationally scalable notions of political content that may risk missing a bigger picture.

Benchmarking Perceived-Political Content. Prior work provides rare but informative benchmarks for the prevalence of political content in social media feeds. Using platform-side classifiers and narrow definitions of politics, these studies report that approximately 3.9% of Facebook feed content is political news (González-Bailón et al. 2023) and 6.9% is civic content (Nyhan et al. 2023). While these estimates are not directly comparable to our user-centered measures, they offer useful context for interpreting the rates we observe. We find that on average 16.85% of our participants' TikTok FYP is perceived as political. This higher rate suggests that more traditional measures of political content in prior work may miss additional content that users themselves perceive as political. Alternately, the TikTok platform may contain a much larger share of political content than other platforms. These competing hypotheses open opportunities for future user-centered data collection of perceived-political content on other platforms.

Heterogeneity in Perceived-Political Exposure. While exploratory, our third set of analyses begins to unpack how exposure to perceived-political content varies across user attributes and, critically, what mechanisms may underlie these differences. Our regression tests show that younger and more politically interested participants perceive a higher proportion of content in their FYP as political, echoing the pattern found in prior work on news exposure on the platform (Tomasik and Matsa 2025). However, our data did not show a similar relationship with other user attributes we expected, like political ideology and education.

Interpreting these patterns requires distinguishing between at least two mechanisms: whether users of different identity subgroups are *exposed* to different content, or whether they encounter similar content but differ in how they *perceive* and interpret it. We begin to unpack this using the repeated videos in our dataset. While we observe that the repeated videos constitute 37% of our data, this only partly addresses the question of heterogeneity in *exposure*, which we plan to better address in future work involving engagement metrics for videos and a network analysis of how users and content are connected on the platform. But our present data is much more useful for interpreting the question of heterogeneity in *perceptions*. We found that participants agreed in their binary perception of whether repeated videos were political or not 78% of the time but disagreed in the reasons provided 68% of the time. The high level of agreement at the binary level appears to be masking widespread disagreement in the individual perceptions of videos, indicating that heterogeneity in perception operates at a more granular level than binary classification captures. This layered pattern of agreement and disagreement points to the need for future work that integrates measures for overlap in exposure, differences in interpretation, and user attributes, rather than relying solely on coarse classifications of political content.

Demographic Structure of Political Topics. Our study provides evidence that women and more liberal-leaning people are more likely to mention GENDER/SEXUALITY RIGHTS when describing content they perceive as political, but did not find evidence of similar associations with other topics and identity categories. Although our data do not allow us to distinguish between algorithmic personalization, correlated user behavior, or other mechanisms as the source of this association, these patterns suggest that exposure to specific political topics may occur within demographically and ideologically aligned subpopulations. Together, these findings point to a nuanced form of heterogeneity on TikTok, in which users differ both in how they interpret political content and in the demographic structure of shared exposure, highlighting important directions for future research.

Limitations & Future Work We see several opportunities to build off this work, addressing its limitations with future studies. While our study surfaced a wide range of specific political issues referenced in user annotations, we do not have sufficient data to deeply analyze each issue in isolation. As this was an exploratory study and the first of its kind, it was designed instead to provide enough data to examine overall patterns in perceived-political content. As the study evolved, however, we began coding individual annotations at a level of granularity that few prior studies have explored and it became clear that we lacked the volume of annotations needed for analyses across all codes. For example, some of our regression analyses may have lacked significance due to being underpowered. Future work could collect larger samples of user annotations for more robust comparisons across

[4]When validating our data, we kept track of any videos posted by accounts from official news sources, finding only one in the 200 we manually annotated.

specific political issues, or consider adopting a panel design in which multiple participants annotate the same set of TikTok videos to assess cross-user agreement. The latter would help identify sources of subjectivity and give more insight into what types of content are broadly recognized as political versus those that are more ambiguous.

Second, although we believe a user-centered approach is essential for capturing users' perceptions of political content, it introduces certain challenges. An unavoidable aspect of the design is its inability to distinguish between the competing mechanisms behind heterogeneity in exposure to perceived-political content discussed previously. Now that the present study has identified initial patterns of this heterogeneity, a logical follow-up would be to run a lab experiment where panels of participants are exposed to the same video, measuring differences in user perceptions and how that varies across user attributes. We plan to pursue this line of future work, informed by our initial findings suggesting that age, sex, political ideology, and interest in politics are important attributes on which to focus.

A final major area for improvement is the scope of our participant pool, which ideally would be larger and not limited to the United States, given TikTok's global reach. Even within the U.S., our pool is not representative of the country's or user base's population. Most notably, we exclude users under 18, despite the fact that a majority of U.S. teens use the platform and may be especially susceptible to political messaging encountered there (Faverio and Sidoti 2025). Relatedly, past research has shown that key political topics vary substantially by country and culture (Bevan, Jennings, and Wlezien 2016). This has implications not only for the type of users our study includes but also the types of political content our results reflect. Future studies of political content on TikTok covering more diverse populations, age groups, and geographic or cultural contexts are very much needed. Additionally, while we focused on structural patterns of perceived-political content exposure rather than transient events or short-term platform changes, our data reflect a snapshot in time. As TikTok approaches new ownership in the U.S., the findings from this study offer a valuable point of comparison for future work examining how the platform and the political content on it evolve over time.

7 Conclusion

This study provides the first feed-based investigation into the personalized content users perceive as political on TikTok, combining survey data with *in situ* user annotations on videos in participants' personalized TikTok feeds. We provide insights into three key questions regarding the perceptions, prevalence, and patterns of user exposure to perceived-political content on TikTok, in addition to releasing our browser-based data collection tool to facilitate future work in this domain. Our findings have implications for future studies of political content on TikTok, as well as other social media platforms. We hope these insights can inform discussions around platform regulation, content moderation, and algorithmic transparency, especially given the growing influence of TikTok among younger users.

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Paper Checklist

1. For most authors...
   (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? Yes. We believe our work furthers the understanding of politics on social media, while adhering to ethical guidelines and only reporting data about individual users in aggregate.
   (b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? Yes. We specifically state the contributions of the paper in the Introduction and both summarize the findings and also discuss these contributions in the Discussion.
   (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? Yes. We explain the necessity of developing a custom browser-based tool for data collection, a codebook for data annotation, as well as the statistical methods used to analyze the data.
   (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? Yes. We identify the rationale of the study sample and discuss its limitations as well as the unique qualities of user-centric definitions and data collection.

(e) Did you describe the limitations of your work? Yes. See Limitations & Future Work in the Discussion.

(f) Did you discuss any potential negative societal impacts of your work? We believe our work advances the conception of politics on social media and has no foreseeable negative societal impacts. Additionally, our browser-based tool has no foreseeable negative usecases.

(g) Did you discuss any potential misuse of your work? Yes. We discuss the limitations of our sample and the implications of drawing conclusions from some of the exploratory rsults presented in our paper.

(h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? Yes. We discuss that no attempt was made to deidentify participants and we provide full documentation and code for our browser extension for replication purposes. We do not release any of the data from our study because individual browsing data is personal and our IRB prohibits the release of this data.

(i) Have you read the ethics review guidelines and ensured that your paper conforms to them? Yes.

2. Additionally, if your study involves hypotheses testing...

(a) Did you clearly state the assumptions underlying all theoretical results? Yes. We discuss the assumptions for each of the 16 theoretically motivated regression tests we run for pairs of user demographics and the prevalence of specific perceived-political topics.

(b) Have you provided justifications for all theoretical results? Yes. We provide citations to social science literature motivating each of these 16 tests we run.

(c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? Yes. See Discussion section Demographic Structure of Political Topics.

(d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? Yes. We control for additional demographic features in each of the models testing these hypotheses and perform a Bonferroni multiple-tests correction.

(e) Did you address potential biases or limitations in your theoretical framework? Yes. We discuss the limitations of our sample and a major possible confound in answering RQ3. See section Heterogeneity in Perceived-Political Exposure.

(f) Have you related your theoretical results to the existing literature in social science? Yes. See the Discussion.

(g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? Yes. We discuss implications for policy professionals, social scientists, and civil society experts when better understanding political content on social media. See the Discussion.

3. Additionally, if you are including theoretical proofs...

(a) Did you state the full set of assumptions of all theoretical results? NA.

(b) Did you include complete proofs of all theoretical results? NA.

4. Additionally, if you ran machine learning experiments...

(a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? NA.

(b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? NA.

(c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? NA.

(d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? NA.

(e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? NA.

(f) Do you discuss what is “the cost“ of misclassification and fault (in)tolerance? NA.

5. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets, **without compromising anonymity**...

(a) If your work uses existing assets, did you cite the creators? Yes. We cite the Prolific research survey tool in the Data section.

(b) Did you mention the license of the assets? NA.

(c) Did you include any new assets in the supplemental material or as a URL? Yes. We provide the GitHub repository including our browser-based tool for other researchers to use. We do not release our data because individual browsing data is personal and our IRB prohibits the release of this data.

(d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? Yes. We discuss how our survey study asked participants to consent and how the study was approved by our IRB.

(e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? Yes. We discuss that our dataset does not contain any personally identifiable information or potentially offensive content beyond what participants already would encounter on the TikTok platform in their logged-in account.

(f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR (see **?**)? NA.

(g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset (see **?**)? NA.

6. Additionally, if you used crowdsourcing or conducted research with human subjects, **without compromising anonymity**...

(a) Did you include the full text of instructions given to participants and screenshots? Yes. We include a screenshot of our browser extension (Figure 1) as well as the full text of questions and answers in our survey (Appendix A).

(b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? Yes. We discuss IRB approval for our study. Furthermore, participants were not subject to any risk as they were already regular users of the TikTok platform.

(c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? Yes. We mention that we paid participants the equivalent of $15 per hour for a total of $7.80.

(d) Did you discuss how data is stored, shared, and deidentified? Yes. We discuss how data is stored and collected via our browser extension and that no attempt was made to deidentify data in our study.

A Survey Instrument

The full survey instrument used in our study is available in Table 6.

B Codebook

The following is the full codebook used to label participant descriptions of political content on TikTok. Table 7 includes the abbreviated name of the code, the full name of the code, inter-rater reliability measure (Cohen's κ) on the survey and the user short-form descriptions, and the full description for how the authors define content included in this code. For a full explanation of how Cohen's κ was calculated, see the Methods section. If a code was not present in the hand-coded data, "–" is shown to indicate that reliability could not be computed.

C Preprocessing Data for Regression Models

For demographic variables, we treat age as a continuous numeric category, race as a categorical variable with White as the reference value, and sex as a categorical variable with Female as the reference value. We convert level of education to a numeric value ranging from 1 (Less than high school) to 7 (Doctorate) and political ideology to a numeric value ranging from -3 (Very liberal) to 3 (Very conservative). We also preprocess survey responses to questions asking about participants' interest in politics and engagement with political content on TikTok. Participants' survey-reported interest in political content is reported on a 7-point Likert scale (Very uninterested to Very interested), which we convert to a numeric range from -3 to 3. We convert participants' reported engagement with political content to a numeric value using the following mapping: Commenting on a political video (3), Sharing a political video (2), Watching a political video (1), None of the above (0).

D Full Regression Results

Presented here are additional regression tables for the models described in the Results section. This includes Table 4 with the results for the model including only demographic variables as well as political ideology. We also include the full set of regression results for all 9 models run to compare the frequency of codes appearing in user annotations with respondent demographics in Table 5. The p-values reported in Table 5 are the values after applying the Bonferroni multiple-tests correction.

Variable	β	p-value	Sig.
Ideology	-0.008	0.092	
Age	-0.003	**0.001**	**
Education	0.005	0.532	
Sex (Male)	-0.025	0.208	
Race (Asian)	-0.067	**0.041**	**
Race (Black)	-0.029	0.396	
Race (Mixed)	-0.015	0.695	
Race (Other)	0.002	0.956	
Intercept	0.267	<**0.001**	***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 4: Outputs from OLS regression model associating the proportion of videos participants perceived in their FYP as political and demographics including political ideology.

Code	Gender & Sexuality			Abortion			Environment		
	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p
(Intercept)	0.109	0.033	**0.010**	0.013	0.012	2.577	0.024	0.018	1.638
Ideology	-0.015	0.004	**0.002**	-0.001	0.001	4.644	-0.001	0.002	7.263
Age	-0.001	0.001	1.987	0.000	0.000	2.525	0.000	0.000	2.772
Education	0.019	0.006	**0.008**	0.000	0.002	8.746	0.001	0.003	7.524
Sex (Male)	-0.066	0.016	$<$**0.001**	-0.013	0.006	0.158	-0.011	0.009	1.719
Ethnicity (Asian)	-0.040	0.027	1.287	0.002	0.010	7.490	-0.010	0.015	4.509
Ethnicity (Black)	-0.039	0.030	1.654	-0.016	0.011	1.278	-0.012	0.016	4.077
Ethnicity (Mixed)	0.006	0.029	7.482	-0.012	0.011	2.416	0.003	0.016	7.794
Ethnicity (Other)	-0.027	0.031	3.338	-0.010	0.011	3.201	-0.005	0.017	7.065
R^2 / adj. R^2	0.031 / 0.027			0.007 / 0.003			0.002 / -0.002		

Code	Immigration			Race			Crime		
	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p
(Intercept)	-0.006	0.010	4.878	0.004	0.031	8.041	0.038	0.023	0.918
Ideology	0.000	0.001	7.821	-0.007	0.004	0.539	0.001	0.003	5.598
Age	0.000	0.000	2.601	0.002	0.001	0.200	0.000	0.001	7.479
Education	0.001	0.002	3.564	0.014	0.005	0.076	0.004	0.004	3.303
Sex (Male)	0.002	0.005	5.643	-0.019	0.015	1.705	0.001	0.011	8.397
Ethnicity (Asian)	0.010	0.008	1.791	0.003	0.026	8.202	0.020	0.019	2.655
Ethnicity (Black)	0.000	0.009	8.991	0.008	0.028	6.909	-0.026	0.021	1.827
Ethnicity (Mixed)	-0.001	0.008	8.334	0.029	0.028	2.658	0.032	0.020	1.053
Ethnicity (Other)	0.009	0.009	2.853	-0.028	0.029	3.052	-0.022	0.021	2.745
R^2 / adj. R^2	0.002 / -0.002			0.011 / 0.007			0.004 / 0.000		

Code	Guns			Prison			Police		
	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p
(Intercept)	0.002	0.010	7.434	0.008	0.007	2.029	0.051	0.028	0.617
Ideology	-0.000	0.001	8.873	-0.000	0.001	7.024	-0.000	0.003	8.416
Age	-0.000	0.000	4.178	-0.000	0.000	5.704	-0.000	0.001	5.639
Education	0.004	0.002	0.316	-0.001	0.001	4.534	0.001	0.005	7.888
Sex (Male)	-0.002	0.005	6.050	0.003	0.003	3.582	-0.095	0.013	$<$**0.001**
Ethnicity (Asian)	-0.001	0.008	8.254	0.013	0.006	0.236	0.022	0.023	2.989
Ethnicity (Black)	0.003	0.009	6.849	-0.005	0.006	4.087	0.002	0.025	8.535
Ethnicity (Mixed)	-0.003	0.009	6.843	0.001	0.006	8.290	-0.043	0.025	0.721
Ethnicity (Other)	-0.009	0.009	2.723	-0.005	0.006	4.149	0.004	0.026	7.869
R^2 / adj. R^2	0.003 / -0.001			0.004 / 0.000			0.028 / 0.024		

Table 5: Outputs from OLS regression models associating the frequency of specific codes in participant annotations of videos they perceived as political and participant demographics. There are 9 models included in the figure, each with the same set of independent variables and 2059 observations. Reported p-values show the value after applying the Bonferroni multiple-tests correction.

Survey Section	Question	Possible Response(s)
Demographics	(D1) What is your age?	Integer response field.
	(D2) Which of the following best describes your employment status?	Multiple Choice: Student, Employed (Part time), Employed (Full time), Retired, Unemployed, Other.
	(D3) What is the highest level of education you have completed?	Multiple Choice: Less than high school, High school graduate, Some college, 2 year degree, 4 year degree, Professional degree, Doctorate.
	(D4) In which state do you currently reside?	All 50 U.S. states, including D.C. and Puerto Rico.
	(D5) In general, how interested are you in politics?	7-point Likert scale from very uninterested to very interested.
	(D6) Which of the following best describes your political views?	7-point Likert scale from very conservative to very liberal.
	(D7) Do you have a TikTok Account?	Multiple Choice: Yes/No. If not, *end survey*.
	(D8) For how long have you been actively using your TikTok account?	Multiple Choice: Multiple times a day, about once a day, a few times a week, once every week or two, or I hardly ever use TikTok.
	(D9) Which of the following do you do on TikTok?	Select all that apply: Viewing TikToks, Commenting on TikToks, Making TikToks, Sharing other people's TikToks with friends, None of the above, Other (with blank field).
Politics	(P1) How often do you see content you would personally consider to be political (whatever that means to you)?	Rate on a 100-point scale. If P1 ≥ 0, direct user to P2. Otherwise, skip to P4.
	(P2) In two sentences or more, how would you describe the kinds of TikTok content you consider to be political, and what makes it political to you?	Short answer field.
	(P3) In the past, how have you engaged with political content on TikTok, if at all?	Select all that apply: Ignore it and scroll past, Watching political TikToks, Commenting on political TikToks, Sharing political TikToks, Other (with blank field).
	(P4) Have you ever come across any videos on your TikTok feed that you believe contained false, misleading, or biased information?	Multiple Choice: Yes, No, Not sure. If yes, direct user to P5, otherwise skip to Q18.
	(P5) Please describe content you've seen on TikTok that you believe to be false, misleading, or biased.	Short answer field.
Extension Download	(Q18) Would you like to participate in a survey after downloading a Chrome browser extension?	The participant is provided with a preview of survey instructions, and given a choice (yes/no) on whether to download our extension and continue the study.

Table 6: Survey instrument presented to study participants, including initial questions about demographics, a series of questions asking about politics, and a final question regarding the browser survey.

#	Full Code Name (Abbrev.)	Cohen's κ		Definition
		Survey	**User Desc.**	
1	General Rights (GR)	1.000	1.000	Includes any mention of labor rights or rights for demographics which are not included in another code (i.e. trans-rights would be GSR). Anything about working conditions is also GR (not ECON).
2	Race/Ethnicity/Minority (RACE)	1.000	1.000	Includes any mention of rights or issues related to race. Also includes ethnicity or general mentions of minority groups.
3	Guns (GUNS)	1.000	0.886	Includes any mention of gun control and gun rights. Any response with a mention of guns is coded as GUNS.
4	Economy (ECON)	0.921	0.949	Includes any mention of something having to do with the economy. Mentions of taxes, minimum wage, inflation, labor, product boycotts are all sufficient. Note, mentions of taxes (L), student loans (EDU), and labor strikes (SA) are also coded as ECON.
5	Abortion (A)	0.983	1.000	Includes any mention of abortion.
6	Gender/Sexual Identity Rights (GSR)	0.986	0.979	Includes any mention of gender, sexuality, and LGBT issues.
7	Police (POLC)	1.000	1.000	Includes any mention of police or law enforcement.
8	Crime (CRIME)	1.000	0.823	Includes any mention of crime, including generic references to criminal justice. Mentions of police should be coded as police, and not crime in addition.
9	Military/War (MW)	1.000	1.000	Includes any mention of the military or war.
10	Religion (R)	1.000	1.000	Includes any mention of religion.
11	Education (EDU)	1.000	0.921	Includes any mention of schools, education policy, or student loans.
12	Environment (ENV)	1.000	1.000	Includes any mention of the environment or sustainability.
13	Healthcare (HC)	1.000	0.855	Includes any mention of hospitals, or healthcare.
14	Immigration (IMG)	1.000	1.000	Includes any mention of immigration.
15	COVID-19 (COVID)	1.000	1.000	Includes any mention of COVID-19.
16	Misinformation or Conspiracy (MC)	1.000	–	Includes any mention of misinformation / conspiracies.
17	Election (E)	0.957	–	Includes any mention of election-related content. Mentioning "politicians post more of these videos around elections" does not count as this category since the response does not use elections to define political content. Mentioning a "political candidate" should be coded as both election (E) and politician (PO). References to political debates are also included in E.
18	Social Activism (SA)	1.000	1.000	Includes any mention of activism, and references to collective action by individuals (strikes, boycotts, marches, protests, etc.).
19	News (NEWS)	0.980	1.000	Includes any references to "news" itself or mentions of "current events".

Continued on next page

Table 7: Codebook of political topics (continued).

#	Full Code Name (Abbrev.)	Cohen's κ Survey	Cohen's κ User Desc.	Definition
20	General Social or Political (GSP)	None	0.767	Includes any mentions or generic reference to something such as a "political issue" or "hot topic" or "social issues" or "politics in general." Or, if the participant implies that political content is a general category or wide range of things (i.e., no binary bucket for what is political content). This is a catch all for any generically phrased reference in the response about political or social issues without explicitly mentioning one (though it can occur in the same response as explicit mentions to social or political issues). Also mentions of "current political issues" and NOT "current political events" or similarly general references to political topics are treated as GSP and not NEWS. When there's references to a few specific things as examples or a general or more broader category it's GSP.
21	International (INTL)	0.974	0.828	Includes any mentions of other countries outside of the US. Also includes generic language specifying countries in general (e.g., "Any content that is focused on large cultural issue (e.g. racism, rights, etc.) that is related to a specific country I consider political.").
22	Politician (PO)	0.928	0.906	Includes any mention referencing a politician. Mentioning a "political candidate" should be coded as both election and politician. Does not include Trump/Biden since they are separate codes.
23	Trump (TRUMP)	1.000	1.000	Includes any keyword mention of TRUMP. Should not be coded as PO, only code as TRUMP.
24	Biden (BIDEN)	1.000	1.000	Includes any keyword mention of BIDEN. Should not be coded as PO, only code as BIDEN.
25	Party or Ideology (PARI)	0.977	0.928	Includes any keyword mention of specific party entities (i.e., democrats, republicans), or specific party entities (i.e., DNC, RNC), or mentions of specific political ideologies (i.e., liberal, conservative). (Note: 'videos persuading you of liberal values' would be coded as both PARI and O; PARI for mention of 'liberal values', and O for the persuasion of an opinion). Generic mentions of something like a 'political stance', simply "political party" is not sufficient. Mentions of "left", "right", "liberal", "conservative" are all sufficient.
26	Government (GOV)	0.943	0.886	Includes any mention of the government in general or institutions. Does not include POLC or SCOTUS.
27	Supreme Court (SCOTUS)	0.966	–	Includes any mention of the Supreme Court. Note that SCOTUS entries should not be coded as G unless there is a specific mention of government or government institutions besides the Supreme Court.
28	Legislation (L)	0.965	0.784	Includes any mention of legislation, laws, bills, and generic mentions of 'policy' that the government enacts/enforces. If taxes are mentioned as a law/policy, it is coded as both ECON and L.
29	Housing (HOUSING)	–	1.000	Includes any mention of house prices, rent, gentrification, housing precarity or homelessness.
30	Prison (PRISON)	–	1.000	Includes any mention of prisons, incarceration, jails.
31	Charity (CHARITY)	–	1.000	Includes voluntary acts of giving, donations.
32	None (NONE)	0.989	0.943	No mention of any definition about politics at all (i.e., 'funny animal tiktoks and wholesome couple tiktoks') should be coded as NONE.

Table 7: Codebook of political topics.