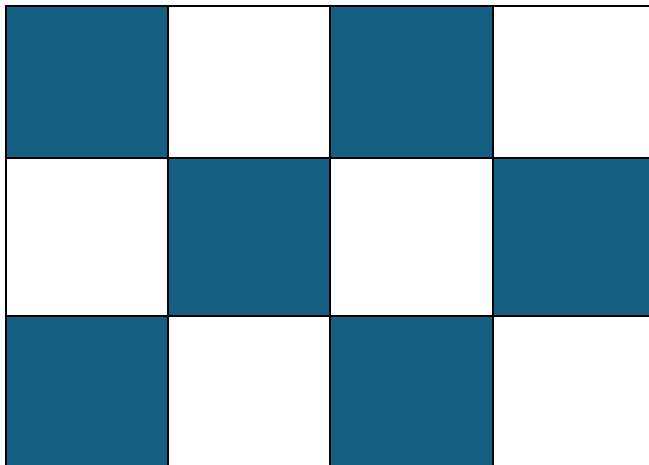# TikTok Regional Election Monitoring 2024: Methods Report

Version 1.0, 10/10/2024

Authors

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Summary

Title	TikTok Regional Election Monitoring 2024: Methods Report
Study population	Content appearing in TikTok feeds of politically neutral users in three German states (Brandenburg, Saxony, Thuringia).
Unit of analysis	Videos appearing in the user feed (i.e. "For You" page or after searching for content.
Clustering	Information on videos is clustered by state, user, and user session.
Data collection mode	Data collected through Social Research Bots (SRBs), a framework introduced by the authors which builds on "sock puppet audits". This approach involves monitoring content exposure of accounts created by the researchers through web scraping in conjunction with APIs. Data is collected in real-time.
Data collection period	August 13, 2024 – October 6, 2024 (55 days), Saxony: N= 7 SRBs/Accounts Thuringia: N= 8 SRBs/Accounts Brandenburg: N= 19 SRBs/Accounts
Languages	German
Observations	Saxony: N= 44,349 Thuringia: N= 58,469 Brandenburg: N= 126,989
Accessibility	Data access is granted on request. PSMM is working on a public-use file pending further data processing and publication.

1. Background

This report outlines the methods employed in conducting the study titled *"TikTok Regional Election Monitoring in Germany 2024."* The study was produced by the Potsdam Social Media Monitor (PSMM), which was established in 2024 within the Faculty of Economics and Social Sciences at the University of Potsdam.

2. Research question

The primary research question of this project was to assess the effectiveness of different political parties in reaching potential voters on TikTok. Specifically, the study aimed to examine the extent to which politically neutral young voters are exposed to political content from far-right populist, moderate, and left leaning parties without actively seeking it out.

This research was initially motivated by the significant rise in support for the right-wing populist party, Alternative for Germany (AfD), among young voters in various elections in 2024. Notably, in the 2024 European elections in Germany, the AfD's vote share among 16- to 24-year-olds tripled compared to the 2019 election, a result that surprised many political observers. These trends further solidified in state elections with high vote shares from voters under 24 in Thuringia (AfD: 38%), Saxony (AfD: 31%), and Brandenburg (AfD: 31%), where this party received by far the most votes among young voters.

Social media has become one of the primary sources through which young people stay informed about current events. TikTok, in particular, is highly popular among younger audiences, with 64% of Germans under the age of 24 reporting usage of the platform within the last four weeks, spending an average of 43 minutes per day on it (Bobzien/Kalleitner/Kohler/Verwiebe, 2023). Additionally, 40% of young adults in the U.S. and 30% in Germany cite accessing news as one of their reasons for using TikTok (mpfs, 2023, PEW Research 2024). Given these trends, TikTok plays a significant role in shaping the political views and opinions of young people.

3. Research design

Studies based on social media data have used a variety of approaches including APIs (Breuer, Kmetty, Haim, & Stier, 2023; Trezza, 2023), data donation and tracking (Boeschoten, Ausloos, Möller, Araujo, & Oberski, 2022; Clemm von Hohenberg et al., 2024; Ohme et al., 2024), quantitative content analysis of posts by parties and politicians (Schöll, Gallego, & Le Mens, 2024), online surveys among social media users (Marquart, Ohme, & Möller, 2020), and qualitative approaches (Bishop, 2019; Bluteau, 2021; Ritter, 2022; Snelson, 2019). These approaches have in common that they primarily collect observational data.

In this study, data was collected using Social Research Bots (SRBs) – a novel framework introduced for collecting social media data (Wolfgram et al., 2024). The approach combines web scraping, sock puppet audits (Asplund, Eslami, Sundaram, Sandvig, & Karahalios, 2020; Bandy, 2021; Srba et al., 2023) and APIs with social science approaches to causal inference (namely, experimental variation of treatments).

The present report describes the data underlying the initial report (see psmm.info). A more detailed journal contribution on the technicalities of the approach as well as a discussion on its application, advantages, and disadvantages for social scientific research is currently under review.

4. Study population

The data is not created from a sample of a finite population and does thus not allow descriptive inferences on a general population. The population to which the data is referring to is the daily content that appears in the feeds of political neutral TikTok users from ideal-typical subpopulations. The subpopulations are defined by the state of residence (Brandenburg, Saxony, Thuringia) gender (female, male, divers and unspecified), age (17-23, 44) and political interest (high, low) – see Table 1 for the complete list of subpopulations. We stress that not all targeted subpopulations were actually implemented (see below).

The data allows inferences on the feeds of real persons to the extent that they belong to a subpopulation of the SRBs. Descriptive inferences to the feeds of broader real-world populations are possible to the extent that persons like the SRBs do exist, or to the extent that the SRB's feeds represent the feeds for broader classes of real-world persons.

Causal inference regarding the effects of the SRBs characteristics on the content the SRBs are exposed to requires an homogeneity assumption, as it is common practice in experimental research (Kohler, Kreuter, & Stuart, 2019).

Table 1: Targeted subpopulations

Population	State	Gender	Age	Political Interest
BB-F1	Brandenburg	Female	17-23	Low
BB-F2	Brandenburg	Female	17-23	High
BB-F3	Brandenburg	Female	44	Low
BB-F4	Brandenburg	Female	44	High
BB-M1	Brandenburg	Male	17-23	Low
BB-M2	Brandenburg	Male	17-23	High
BB-M3	Brandenburg	Male	44	Low
BB-M4	Brandenburg	Male	44	High
BB-F1	Brandenburg	Diverse	17-23	Low
BB-F2	Brandenburg	Diverse	17-23	High
BB-F3	Brandenburg	Diverse	44	Low
BB-F4	Brandenburg	Diverse	44	High
BB-M1	Brandenburg	Not specified	17-23	Low
BB-M2	Brandenburg	Not specified	17-23	High
BB-M3	Brandenburg	Not specified	44	Low
BB-M4	Brandenburg	Not specified	44	High
SA-F1	Saxony	Female	17-23	Low
SA-F2	Saxony	Female	17-23	High
SA-F3	Saxony	Male	17-23	Low
SA-F4	Saxony	Male	17-23	High
SA-M1	Saxony	Diverse	17-23	Low
SA-M2	Saxony	Diverse	17-23	High
SA-M3	Saxony	Not specified	17-23	Low
SA-M4	Saxony	Not specified	17-23	High
TH-F1	Thuringia	Female	17-23	Low
TH-F2	Thuringia	Female	17-23	High
TH-F3	Thuringia	Male	17-23	Low
TH-F4	Thuringia	Male	17-23	High
TH-M1	Thuringia	Diverse	17-23	Low
TH-M2	Thuringia	Diverse	17-23	High
TH-M3	Thuringia	Not specified	17-23	Low
TH-M4	Thuringia	Not specified	17-23	High

5. Data collection

Note: We aim to provide comprehensive details on the data collection process to facilitate reproducibility. However, certain technical aspects of data extraction are intentionally limited to preserve the potential for future application of the method across social media platforms. For any additional inquiries, we encourage readers to contact the authors directly.

5.1. Bot design

Between August 13, 2024 – October 6, 2024, we deployed one SRB on TikTok for each of the 32 subpopulations in Table 1. However, due to server capacity limitations in Saxony, subpopulation SA-F1 could not be implemented. In Brandenburg, to fully utilize the available resources, the subpopulations BB-M1 and BB-F2 were each implemented twice, while BB-F1 and BB-M2 were implemented three times.

The inclusion of different age groups and genders was determined using profile information such as pronouns and dates of birth. Geographic diversity was achieved by utilizing servers in various locations across Saxony, Thuringia, and Brandenburg, through which the SRBs accessed their accounts.

All SRBs were designed to avoid any clear display of partisanship. To ensure this, they actively searched for content using non-political hashtags, including those related to humor, travel, and cooking. Political interest was introduced by searching for election-related content without seeking partisan material or revealing any political stance. For a full list of hashtags used, see Table 2.

Table 2: Hashtags to control search behavior of SRBs

Non-political hashtags		Political hashtags	
German	English	German	English
#freunde	#friends	#landagswahlen2024	#stateelections2024
#fürdich	#foryou	#wahlen2024	#elections2024
#hunde	#dogs		
#ideen	#ideas		
#kochen	#cooking		
#lustig	#comic		
#reisen	#travelling		
#witzig	#funny		

The SRBs were programmed to scroll through their "For You" page until a video with hashtags relevant to their interests appeared. Once identified, the SRB would watch the video in full, but no longer than 2 minutes and then like the video. To ensure balance in the interest of the SRBs over time, we "nudged" the SRBs once per session, after 35–45 videos, toward one of

their assigned interests at random. We refer to nudging when bots searched for a specific hashtag in the top search bar rather than simply scrolling through their feed. The combination of general feed browsing with occasional nudges avoids pushing SRBs into a specific category of content too early while ensuring variation in exposure across diverse types of behavior. In the case of SRBs with an interest in elections, videos with political content are watched but not liked. By this, we stipulate that politically interested users may watch videos with opposing ideological viewpoints merely out of interest, but not because they support the contents.[1]

The SRBs scrolled through the suggested videos for approximately one hour each day without engaging with other accounts. The SRBs did not leave comments, did not follow other accounts or publish their own content. Hence, the SRBs were not supposed to exert any influence on the TikTok ecosystem and only act as passive observers.

5.2. Data extraction, structure & measurements

During the study period, a total of 229,807 videos were collected – 44,349 in Saxony, 58,469 in Thuringia, and 126,989 in Brandenburg. The data collection included all videos that were shown to the SRBs by the platform, including engagement metrics (number of likes, shares and comments), video description, video creator, used hashtags and music. Data was extracted from the platform in real-time using dynamic web scraping techniques via Python (Selenium) (for details see Wolfgram et al., 2024).

Table 3: Structure of the dataset

SRB-ID	Date	Time	Video-ID	Variables
1	20240901	10:21	A1b2c3	…
1	20240901	10:22	Q6r7s8	…
:	:	:	:	:
1	20240902	12:53	G2h314	:
:	:	:	:	:
2	20240901	16:23		:
:	:	:	:	:

---

[1] The SRBs did, however, like content including political parties when they found it indirectly and through other interests, for example when a political hashtag was included with other hashtags of interest. This emulated, to a degree, the natural user behavior and gave us a rough measurement of the increase in party content an SRB gets when it starts to engage with a particular party.

Additionally, metadata of political videos was collected using Pyktok ([Freelon et al. 2024](#)). Specifically, we collected engagement metrics (views, shares, comments), time and location of the upload, or information on whether the video contains advertising.

Table 3 illustrates the structure of the data created from the SRBs. The data is best described as a hierarchical data set with video events nested in sessions and SRBs. Or, stated differently, for each SRB we have observations on each video presented to them in their daily sessions.

The variables obtained to describe each video are shown in Table 4, including an anonymized real-world example for one specific unit. The entry in the variable "description" was translated into English.

Table 4: Variables

Variable	Example
Author	deep_thought_42
Description	Today, deep_thought_42 shows you 5 ideas for your kitchen that do not make sense at all! Which is your favorite? #küchenideen
Hashtags	küchenideen
Likes	37,700
Comments	227
Shares	1,850
Views	425,000
Watched	True
Liked	False
Saved	False
Duration (s)	180
Create Time	25.05.2024 13:42
Location	AT
Verified	False
Advertisement	False

The key variables of interest are exposure to
- Official party accounts (OPAs), and

- Party-affiliated content (PAC).

For the operationalization exposure to OPAs we counted any video in the feed uploaded by an OPA. The OPA include each party's first 10 election list candidates of Brandenburg, Saxony and Thuringia, the one or two leaders of the Federal party, the federal party account, and the regional party accounts including their youth organizations; see Table A2 in the Appendix.

For the operationalization of exposure to PACs we counted all videos with hashtags in its description associated with a political party; see Table A2 in the Appendix for a full list of those hashtags.

Table 5: Summary of social research bot activity

State	A., Political interest	B. Total number of exposed videos	C. Total number of watched videos	D. Total number of liked videos	E. Total number of exposed videos from OPAs	F. Total number of videos with party hashtags
Saxony	high	22,154	6,347	4,842	35	722
Saxony	low	22,195	6,121	4,719	10	312
Thuringia	high	29,383	7,916	6,001	61	1,000
Thuringia	low	29,086	8,562	6,521	14	498
Brandenburg	high	70,011	20,530	15,600	121	2,363
Brandenburg	low	56,978	17,014	13,039	10	729

Note: Table reports aggregate statics of all created bots by state and type of behavior (showing political interest or not, see column A). Column E: OPAs stands for Official party accounts and includes accounts linked to parties at the federal level and the regional level, the respective youth organizations of the parties and the top 10 election candidates of each party in each state, given they were TikTok members. Column F: This includes videos involving party-specific hashtags regardless of who uploaded the video (official and unofficial accounts).

In addition to the collection of data from the feeds of the SRBs, we collected information directly from the user accounts of the OPAs. This was done using clockwork's TikTok Data Extractor. Specifically, we scraped the OPAs profiles and their posted content daily. This allowed us to monitor which actors were providing how much input to TikTok and via which relevant political creators. This is an important control variable for identifying the causal effects of TikTok's algorithm on the content that ended up in the SRB's user feeds.

Table 5 provides a summary of the SRBs' activity. The table shows that while the SRBs watched roughly the same number of videos, the total number of videos they were exposed to varied significantly. It also highlights that the politically interested SRBs were exposed to a much higher volume of videos from party representatives and videos containing party-related hashtags. This suggests that the interventions designed for the SRBs successfully triggered the intended response from the TikTok algorithm.

6. Data accessibility

The research team is committed to making a public-use dataset available to researchers, pending further publication of results in academic journals. The data will be anonymized and partially aggregated to ensure compliance with data protection laws. This process is being closely coordinated with the Data Protection Officer at the University of Potsdam.

In the meantime, any additional requests for information about the data or collaboration opportunities for further research should be directed to the authors. The report will be updated once the data becomes accessible online.

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APPENDIX

Table A 1: Sample of official political party content authors on TikTok

party	state	tiktok-id	youth organization
afd	federal	@afdfraktionimbundestag	no
afd	federal	@junge_alternative_	yes
afd	brandenburg	@afd_brandenburg	no
afd	sachsen	@afdsachsen	no
afd	sachsen	@ja_sachsen	yes
afd	thueringen	@afd.thueringen	no
afd	brandenburg	@dennis_hohloch	no
afd	brandenburg	@felixhwteichner	no
afd	brandenburg	@dominik.kaufner	no
afd	brandenburg	@lhuenich	no
afd	brandenburg	@benfilter	no
afd	brandenburg	@jeanpascal.hohm	no
afd	brandenburg	@anna.leisten	yes
afd	sachsen	@andre_wendt_afd	no
afd	sachsen	@sebastian_wippel	no
afd	sachsen	@thomasthumm	no
afd	sachsen	@jonas.duenzel	no
afd	sachsen	@alexander_wiesner	no
afd	thueringen	@bjoernhoecke	no
afd	thueringen	@stefan.moeller.afd	no
afd	thueringen	@wiebke.muhsal	no
afd	thueringen	@cottaafd	no
afd	thueringen	@rimuehl	no
afd	thueringen	@engelheric	yes
bsw	federal	@buendnis_sahraw	no
bsw	federal	@bsw_bt	no
bsw	sachsen	@bsw.sachsen.partei	no

bsw	thueringen	@bsw_thueringen	no
bsw	thueringen	@steffen.quasebarth	no
cdu	federal	@cducsu	no
cdu	federal	@insidecdu	no
cdu	federal	@junge_union	yes
cdu	brandenburg	@cdubrandenburg	no
cdu	sachsen	@cdu.sachsen	no
cdu	thueringen	@cdu_thueringen	no
cdu	sachsen	@michael.kretschmer.privat	no
cdu	sachsen	@barbara_klepsch	no
cdu	sachsen	@andreasbuehl	no
fdp	federal	@fdpbt	no
fdp	sachsen	@fdp.sachsen	no
fdp	thueringen	@fdpthueringen	no
fdp	federal	@carina.konrad	no
fdp	thueringen	@thomaslkemmerich	no
fdp	thueringen	@robertmartinmontag	no
gruene	federal	@diegruenen	no
gruene	federal	@gruene_jugend	yes
gruene	brandenburg	@gruenebbg	no
gruene	sachsen	@gruenesachsen	no
gruene	sachsen	@gruenejugend.sachsen	yes
gruene	thueringen	@gruene_th	no
gruene	thueringen	@gruenejugend_thueringen	yes
gruene	sachsen	@wolfram.gnther	no
gruene	thueringen	@madeleine_henfling	no
gruene	thueringen	@bernhard.stengele	no
gruene	thueringen	@lau.ra_wahl	no
gruene	thueringen	@rsnndh	no
gruene	thueringen	@doreen.denstdt	no
linke	federal	@die.linke	no
linke	federal	@linksjugend.solid	yes

linke	brandenburg	@die_linke_brandenburg	no
linke	sachsen	@dielinke.sachsen	no
linke	sachsen	@linksfraktion.sachsen	no
linke	sachsen	@linksjugendsolidsachsen	yes
linke	thueringen	@die_linke_th	no
linke	thueringen	@linksjugend_th	yes
linke	sachsen	@senf_paul	no
linke	sachsen	@bohmeniaa	no
linke	sachsen	@soy.jojoo	no
linke	thueringen	@bodo.ramelow	no
linke	thueringen	@anja.mueller.thl	no
spd	federal	@spdbt	no
spd	federal	@deinespd	no
spd	federal	@jusos.de	yes
spd	brandenburg	@spdfraktionbrandenburg	no
spd	thueringen	@jusos_th	yes
spd	brandenburg	@wolfgang.roick.mdl	no
spd	sachsen	@petrakoepping	no
spd	sachsen	@henning.homann	no
spd	sachsen	@sophiekochj	no
spd	sachsen	@simone_lang_	no
spd	sachsen	@albrechtpallas	no
spd	sachsen	@laurastellbrink	no
spd	sachsen	@mareike_2000	yes
spd	thueringen	@lutz.liebscher	no

Table A 2: List of hashtags to identify party-affiliated content on TikTok

Party	Hashtags
SPD	"spd", "sozialdemokratischeparteideutschlands", "spdde", "spdbt", "spdfrauen", "spdfraktion", "olafscholz", "larsklingbeil", "saskiaesken", "jusos", "sozialdemokraten", "sozialdemokratischepartei", "dietmarwoidke", "woidke", "norbertwalterborjans", "hubertusheil", "franziskagiffey", "spdbpt", "spdpartei", "spdthueringen", "spdthüringen", "spdsachsen", "spdbrandenburg", "teamscholz", "teamklingbeil", "teamesken", "scholz", "lauterbach", "katjaposchmann", "wolfgangroick", "petrakoepping", "henninghomann", "simonelang", "albrechtpallas", "laurastellbrink", "lutzliebscher", "larsklingbeil", "kevinkuehnert", "mareikeschneider"
CDU	"cdu", "christlichdemokratischeunion", "cdufraktion", "cduthueringen", "cduthüringen", "friedrichmerz", "kretschmer", "mariovoigt", "merz", "michaelkretschmer", "voigt", "cdude", "cducsu", "teamcdu", "cdufraktionbt", "jungeunion", "mittelstandsunion", "frauenunion", "cdusachsen", "cdubrandenburg", "cdubb", "cduthueringen", "cduthüringen", "cdusachsenanhalt", "janredmann", "rainergenilke", "frankbommert", "barbaraklepsch", "andreasbuehl", "julianbruening"
FDP	"fdp", "freiedemokratischepartei", "fdpbt", "fdpfraktion", "christianlindner", "christiandürr", "christianduerr", "marieagnesstrackzimmermann", "lindner", "duerr", "dürr", "kubicki", "wolfgangkubicki", "bettinastarkwatzinger", "marco", "buschmann", "marcobuschmann", "volker", "wissing", "volkerwissing", "fdpthueringen", "fdpthüringen", "fdpsachsen", "fdpbrandenburg", "jungeliberale", "teamfdp", "fdpwaehlen", "strackzimmermann", "thomaskemmerich", "robertmartinmontag", "johannesvogel", "carinakonrad"
Grüne	"grüne", "gruene", "bündnis90diegrünen", "buendnis90diegruenen", "diegrünen", "diegruenen", "gruenebundestag", "grünebundestag", "landesstimmegrün", "landesstimmegruen", "grünejugend", "gruenejugend", "annalenabaerbock", "ricardalang", "omidnouripour", "habeck", "roberthabeck", "baerbock", "gruenejugend", "gruenethueringen", "grünethüringen", "gruenesachsen", "grünesachsen", "gruenebrandenburg", "grünebrandenburg", "katringoering", "cemözdemir", "cemoezdemir", "claudiaroth", "katringoertingeckardt", "tonihofreiter", "renatekuenast", "winfriedkretschmann", "isabellhiekel", "katjameier", "wolframguenther", "madeleinehenfling", "bernhardstengele", "laurawahl", "doreendenstaedt", "emilybuening", "svenjaappuhn", "katharinastolla"

Die Linke	"dielinke", "linke", "linksfraktion", "dielinkeimdeutschenbundestag", "bodo", "ramelow", "bodoramelow", "teambodo", "linkspartei", "linksjugend", "solid", "jankorte", "dietmarbartsch", "amiramohamed", "gregor", "gysi", "gregorgysi", "katjakipping", "klauslederer", "linkethueringen", "linkethüringen", "linkesachsen", "linkebrandenburg", "teamlinke", "sebastianwalter", "kathrindannenberg", "isabellevandre", "yasminkirsten", "sandranehlsen", "paulsenf", "anjamueller", "janinewissler", "martinschirdewan"
BSW	"bsw", "buendnissachwahl", "bündnissachwahl", "bswpartei", "sarah", "bswvgsachsen", "sahra", "sahrawagenknecht", "bündnissarahwagenknecht", "buendnissarahwagenknecht", "bündnissahrawagenknecht", "buendnissahrawagenknecht", "sarahwagenknecht", "wagenknecht", "amiramohamedali", "fabiodemasi", "christianleye", "bswbundestagsfraktion", "bswsachsen", "bswthueringen", "bswthüringen", "bswbrandenburg", "bswteam", "teambsw", "bswwaehlen", "steffenquasebarth"
AFD	"afd", "alternativefuerdeutschland", "afdfraktion", "afdimbundestag", "aliceweidel", "tinochtrupalla", "hoecke", "höcke", "afdde", "afdfraktionbundestag", "alternativefürdeutschland", "alternative", "joergurban", "chrupalla", "weidel", "bjoernhoecke", "bjoernhöcke", "gauland", "vonstroch", "beatrixvonstorch", "afdkompakt", "afdparteimitglied", "jungealternative", "afdwaehlen", "teamafd", "afdwählenwirkt", "afdwaehlenwirkt", "blauewelle", "afdimbundestag", "afdimlandtag", "afdthueringen", "afdthüringen", "afdsachsen", "afdbb", "afdbrandenburg", "christophberndt", "dennishohloch", "felixteichner", "dominikkaufner", "larshuenich", "benfilter", "jeanpascalhohm", "andrewendt", "sebastianwippel", "thomasthumm", "alexanderwiesner", "stefanmoeller", "wiebkemuhsal", "berndbaumann", "hannesgnauck", "annaleisten"