

# Analyzing radical visuals at scale

## How far-right groups mobilize on TikTok

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### Abstract

Research examining radical visual communication and its manifestation on the trending platform TikTok is limited. This paper presents a novel methodological framework for studying mobilization strategies of far-right groups on TikTok, employing a mixed-method approach that combines manual annotation, unsupervised image classification, and named-entity recognition to analyze the dynamics of radical visuals at scale. Differentiating between internal and external mobilization, we use popularity and engagement cues to investigate far-right mobilization efforts on TikTok within and outside their community. Our findings shed light on the effectiveness of unsupervised image classification when utilized within a broader mixed-method framework, as each observed far-right group employs unique platform characteristics. While Conspiracists flourish in terms of overall popularity and internal mobilization, nationalist and protest content succeeds by using a variety of persuasive visual content to attract and engage external audiences. The study contributes to existing literature by bridging the gap between visual political communication at scale and radicalization research. By offering insights into mobilization strategies of far-right groups, our study provides a foundation for policymakers, researchers, and online platforms to develop proactive measures to address the risks associated with the dissemination of extremist ideologies on social media.

Keywords: TikTok; Mobilization; Image Classification; Mixed Methods; Far Right; Radicalization; Protest

### 1. Introduction

Following the start of the pandemic in 2020, the German far right underwent a diversification in terms of narratives, social movements that use these new narratives, and spaces where they communicate online (Rogers, 2020; Rothut et al., 2023; Zehring & Domahidi, 2023). While large social media platforms 'deplatform' extreme accounts, the far right increasingly moves to alternative platforms that are less regulated (Rogers, 2020). In this context, first research hints toward an increase of far-right activity on TikTok and its function as a breeding ground for radicalization (Pre:Bunk, 2023).

Especially in the German context, initial evidence indicates a mass integration of various far-right actors such as politicians, protest groups (e.g., 'Querdenken'), social movements (e.g., 'QAnon' or the

'Identitarian movement'), and highly influential far-right figures on the platform (O'Connor, 2021). Thus, we aim to study the success of German far-right groups on TikTok, their popularity, content, and ability to mobilize by proposing a mixed-method approach consisting of manual annotation, unsupervised image classification, and automatic text extraction.

While 'far-right' is an umbrella term to subsume all kinds of right-wing groups (Pirro, 2023), we intend to examine the existence and characteristics of individual groups on TikTok in detail (RQ1) by conducting a Latent Class Analysis (LCA) of manually annotated accounts. With the categorization into far-right groups, we are able to evaluate the popularity and performance of far-right content in a more fine-grained approach. We assume the ultimate goal of far-right accounts is to create attention, increase followership, and gain influence (Goodwin et al., 2023). The potential to mobilize within the group's followership (=internally) and outside their community (=externally) is therefore linked to a video's popularity and engagement cues (RQ2). Finally, we use deep learning neural networks to classify, label and extract text from frames of TikTok videos by using Google's Vision API. The resulting texts and labels are combined with the LCA to characterize each group's content and its relationship with the group's success on TikTok (RQ3).

## 2. Literature Review & Theory

### 2.1 TikTok and the Far Right

TikTok was founded in 2017 and quickly became popular worldwide, especially among young users (Medina Serrano et al., 2020). The platform's architecture was first designed around music and dance; hence, most content contained imitation and choreography. Since then, and by introducing interaction and edit functions, creators are able to give context and interpretations to their videos (Cervi et al., 2021). In consequence, the platform has taken 'a serious turn' and got increasingly diversified, including political communication (Cervi & Divon, 2023; Medina Serrano et al., 2020). Central to the recent success of platforms such as TikTok is the recommendation algorithm, which fosters an increasing diversity in content, style, or format by curating what appears on individual users' home feeds. The 'For You' page (FYP) on TikTok algorithmically curates a selection of videos, prioritizing new and trending content over users' existing connections (Weimann & Masri, 2021; Zeng & Kaye, 2022), thereby enhancing the potential for any video to go viral and making the platform a hub for (political) mobilization (Zulli & Zulli, 2022). However, TikTok's algorithm is known for having a strong locking mechanism through which content that has been previously viewed or engaged with is prospectively prioritized (Gao et al., 2023). This tendency is also observed by Grandinetti and Bruinsma (2022), who find that TikTok's algorithm quickly adapts to polarized political content. As a result, users often encounter one-sided video content in many of their suggested videos. In this context, Medina Serrano et al. (2020) discovered a similar pattern in the US, revealing a partially polarized and isolated network between Republicans and Democrats on the platform.

Polarization, one-sided content, but also the favoring of less popular but trending new content displays a fruitful ground for radicalization and extremism: Weimann and Masri (2020, 2021) find an increase in the popularity of antisemitic content on TikTok. Hate, transphobic, or extreme speech flourish on the platform and can easily replace ordinary content once a user engaged with it (Little & Richards, 2021; Weimann & Masri, 2020). Consequently, single-issue-oriented social media influencers such as nationalists or conspiracists, but also populist radical-right politicians were found to be active on the platform (Albertazzi & Bonansinga, 2023; Boucher, 2022; O'Connor, 2021). This is especially worrisome because TikTok tends to have a younger user base, which is more vulnerable to radicalization since they are typically not yet settled in their political orientation (Schmid, 2013, p. 38). Thus, they are more easily caught in radical content, especially when presented as 'funny' or entertaining (Weimann & Masri, 2021;

Zeng & Kaye, 2022). Using sarcasm and memes, protest-related content, or activism, in general, was also found to be thriving on the platform, e.g., by making fun of supposedly hypocritical statements of mainstream politicians or media (Cervi & Divon, 2023). First research indicates that their activity on the platform is also linked to more offline protest participation (Boulianne & Lee, 2022), translating successful online mobilization efforts into offline actions.

Altogether, TikTok evolved into one of the leading platforms for political communication that may spark the activity of various ideological backgrounds and motives (Newman, 2022). Until now, there is no comprehensive review, however, of how prevalent different far-right groups are on the platform. Hence, this study asks:

*RQ1: What far-right groups can be found on TikTok?*

## **2.2 Far-right Mobilization and the Role of Online Engagement**

Political mobilization refers to the process by which candidates, parties, activists, and groups induce other people to participate (Rosenstone & Hansen, 1996). Especially for (radical) grassroots actors such as protest movements, articulating their views to the public is crucial. They spread ideological elements with the aim of activating ideology-conform behavior to ultimately aggregate individual efforts into a larger cause (Bennett & Segerberg, 2012). Factors like high visibility or embeddedness in large networks have been found to drive mobilization (Castelli Gattinara et al., 2022). Both visibility (i.e., the public awareness and attention a movement attracts) and embeddedness (i.e., the size of the network of supporters) can be fostered by successful TikTok communication.

Albeit traditionally associated with street protest activity, mobilization can also become apparent online and translate into the 'success' of TikTok content (Pirro & Gattinara, 2018). Social media communication opens a broad palette for possible mobilization cues, and the far right makes wide use of it (Caiani, 2022). TikTok and its algorithm can be employed for both, outwards-oriented and inwards-oriented mobilization. Outwards-oriented mobilization results in engagement (e.g., liking, commenting, sharing) from people who are not regularly viewing the communicator's content, but are rather incidentally exposed to it (e.g., by algorithmic means). It is aimed at gaining reach and public visibility, which, in turn, can further drive mobilization. Ultimately, outwards-oriented mobilization can aid the mainstreaming of far-right attitudes (Brown et al., 2023) and the recruitment of new followers (Boucher, 2022).

In contrast, inwards-oriented mobilization leads to internal engagement undertaken by an account's established followership. High levels of engagement can be associated with commitment to the communicator's goals. Thus, inwards-oriented mobilization is intended to increase ideological consolidation and support by sympathizers as well as to bond with them (e.g., replying/chatting in the comment section or publishing reply videos), aiming to stabilize and expand the support network. This form of engagement can strengthen in-group identification and isolation from diverging worldviews, fueling polarization and radicalization (Ayanian et al., 2019). High internal engagement is, thus, the most dominant sign of successful mobilization.

Content-related factors like online engagement can be a potential outcome and expression of more or less successful mobilization (i.e., high or low engagement). TikTok differentiates several engagement opportunities: publicly liking or commenting on a video functions as a means to overtly signal attention and cognitive processing of presented information, ultimately manifesting in public expression of approval (Macafee, 2013). Sharing content through one-to-one chats allows for the private exchange of thoughts and opinions among peers. Heiss et al. (2019) found that political posts containing mobilization cues were more frequently shared, pointing toward a relationship between mobilization efforts as a trigger on the content level and engagement activity on the audience level as a reflection of these efforts' success. Creating engagement among the followers speaks for internal mobilization. Creating engagement among

people not yet following can be interpreted as a sign of external mobilization. While these metrics can function as an expression of successful mobilization to a certain degree, we assume that creators have the intention to mobilize externally, creating outreach and recruiting new followers. Simultaneously, the content can aid the ideological consolidation of individuals already affiliated (i.e., followers). Relying on these engagement cues, we ask:

*RQ2: How successful are the far-right group's internal and external mobilization attempts?*

### 2.3 Analyzing (Radical) Visuals in Political Communication

The complexity and often computationally heavy task of extracting meaning from images is one main reason for the gap between the necessity of researching radical visuals and lacking quantitative and large-scale studies (Tanoli et al., 2022). Supervised approaches with pre-trained and classified images and videos need thousands if not millions of training data for a neural network to be self-learning and reliably performing (Lin et al., 2011). A possible and widely spread alternative are unsupervised approaches using algorithms (pre-)trained on detecting already classified objects (e.g., Google Vision, Microsoft Azure) (Omena et al., 2021).

The usefulness of these approaches typically depends on the researcher's aim of how to utilize images. Until now, processing large quantities of images was mainly subject in the field of protest observation and used in rather descriptive ways (Schwemmer et al., 2023). Image classification was, for example, used to examine the age and gender of political accounts (Medina Serrano et al., 2020), extract emotions from radical images (Marengo et al., 2022), colors in propaganda (Wang et al., 2022) or political ideology (Xi et al., 2020). In this study, we argue that unsupervised approaches can be further utilized in a mixed-method approach, combining image labels with context information and other processing methods. Several contributions were already made similarly: Peng (2021) used image classification to infer the overall aesthetic of politician images on Instagram, coded the biographical background of the politician, and explored which setting is most engaging. He found that a 'personal setting' in which the politician creates a kind of Vlog-style format created the most engagement. Clever et al. (2023) use the portrayed emotional valence and the corresponding text under Islamist propaganda images on Instagram to conduct not only image classification, but also to explore a semantic network of Islamist actors. Hashtags and complete topics on Instagram were 'hijacked' by the accounts to reach the public and to create local digital communities. Mitts et al. (2022) used image classification to extract, among other, violent objects (e.g., guns, blood) in ISIS propaganda and found that violent or extreme objects reduced recruitment effectiveness.

In a similar vein, this study aims to advance quantitative and computational video analysis employing unsupervised methods like image classification and text extraction, asking:

*RQ3: How does far-right groups' (visual) content on TikTok differentiate between each other?*

## 3. Methods

### 3.1 Data Collection

For collecting data, all annotators created a bot account following an initial list of German far-right accounts.<sup>1</sup> Far-right accounts are based on a list of far-right influencers from Rothut et al. (2023). 37 were on TikTok and served as seed list. Further, we added 79 German far-right politicians collected by Fuchs

<sup>1</sup> Ethical approval was granted by the Institutional Review Board of the Communication Department of the University of Vienna (Approval No. 20230314\_011)

(2023). Once following the seed list, we started watching videos and added accounts that were algorithmically proposed to us. Additionally, we checked already identified accounts for relevant hashtags that we used for further account exploration. We collected account and video metadata using the Python library 'pyktok' and the R package 'traktok,' and obtained the latest 30 videos through the 'tikapi' package, which is the current limit for data collection via these sources. This strategy resulted in 7,895 videos from 350 accounts.

### **3.2 Account Selection and Classification**

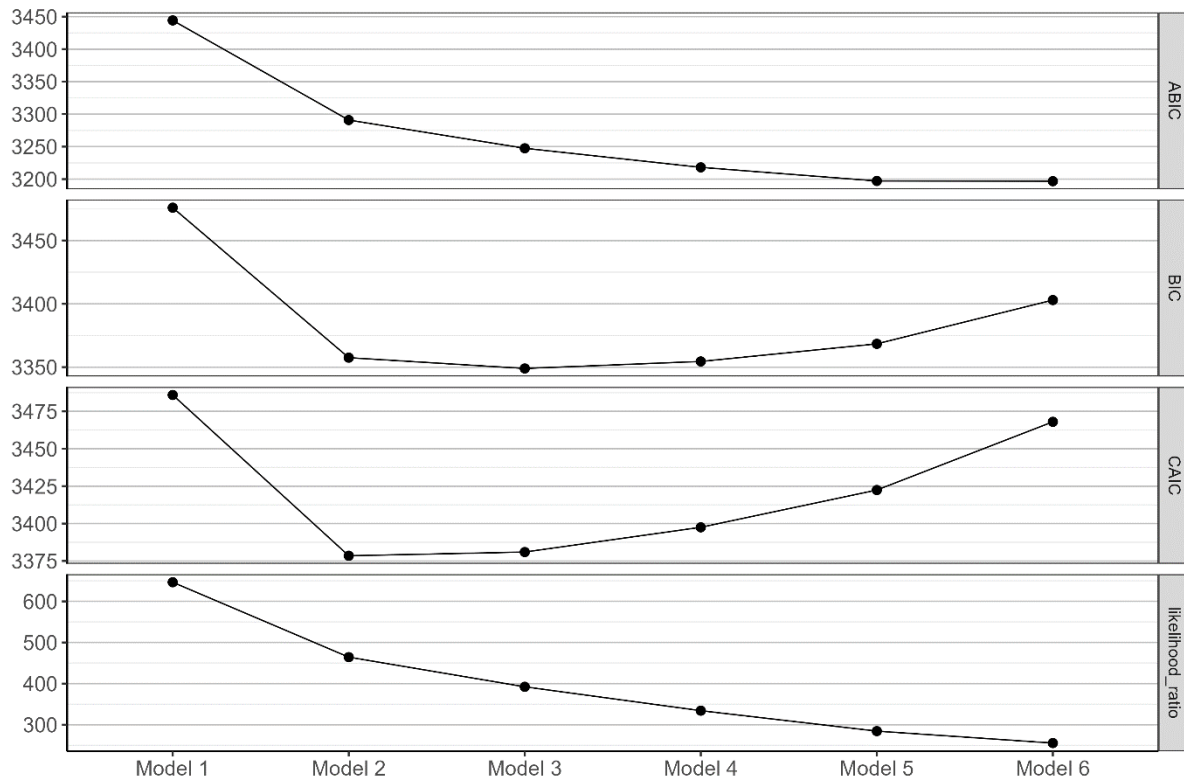
The classification of accounts in this study commenced with the codebook from Schulze et al. (2022) as a foundational reference, which was then extensively refined to be better suited for TikTok data and validated through two rounds of pretesting. Pretest results reached sufficient intercoder-reliability for the central variables (see supplemental material). The codebook for identifying and annotating far-right accounts entailed several context variables to specify account-based characteristics of the videos. An account (not every single video) represents one coding unit: The coder's impression of the latest videos, thumbnails, profile description, TikTok handle, and profile image were decisive for the annotations.

To evaluate the relevance of an account for our study, we coded whether far-right elements were visible in a dominant style. In total, we annotated the (non-)existence of nine elements subjected to far-right online discourse that are considered far-right indications in the scientific literature (for an overview, see Carter (2018)). Based on traditional far-right elements (Mudde, 2000, p. 187), we annotated the existence of nationalism, xenophobia, anti-elitism, authoritarianism, and anti-democratic features. Complementing these, we further added hate speech, fear speech, the existence of conspiracies and calls for or prevalence of protest offline and online. Each element's broader definition, how they are connected to the far-right, and how these elements contribute to radicalization or radicalized discourse are discussed within the codebook in the supplemental material: <https://osf.io/3vfkx>

Notably, the annotation of one specific far-right narrative does not necessarily mean that the account is part of the far right, nor that the narrative itself necessarily means it is of far-right nature. For example, conspiracies—even though often having an extreme and far-right core (Schulze et al., 2022)—could also be non-radical in nature, such as the belief in UFO sightings. Hence, we argue that an account can be coined of showing far-right elements only if a combination of elements is prevalent and, thus, only included accounts that showed at least two elements described above and showed a general far-right sentiment.

### **3.3 Latent Class Analysis**

Given the high number of far-right accounts in our database, the heterogeneity of the far right (Pirro, 2023), and to avoid multicollinearity between co-occurring elements, we chose to cluster them into groups. We conducted Latent Class Analysis (LCA) based on their ideological orientation. LCA assumes heterogeneous variables to be more adequately presented by a categorical latent cluster (Collins & Lanza, 2009). LCA is suited for binary annotations, whereas the best cluster option is the one with the lowest values for the Bayesian or Akaike Information Criterion (BIC & AIC) (Karnowski, 2017). If several models perform similarly, the semantically most plausible option should be chosen (Weller et al., 2020). After evaluating different model parameters in Figure 1, we chose the 4 class model as it performed similarly to model 3 but made much more sense semantically.



**Figure 1**

Model statistics ABIC, BIC, CAIC and likelihood ratio for different latent classes. Model 4 was chosen.

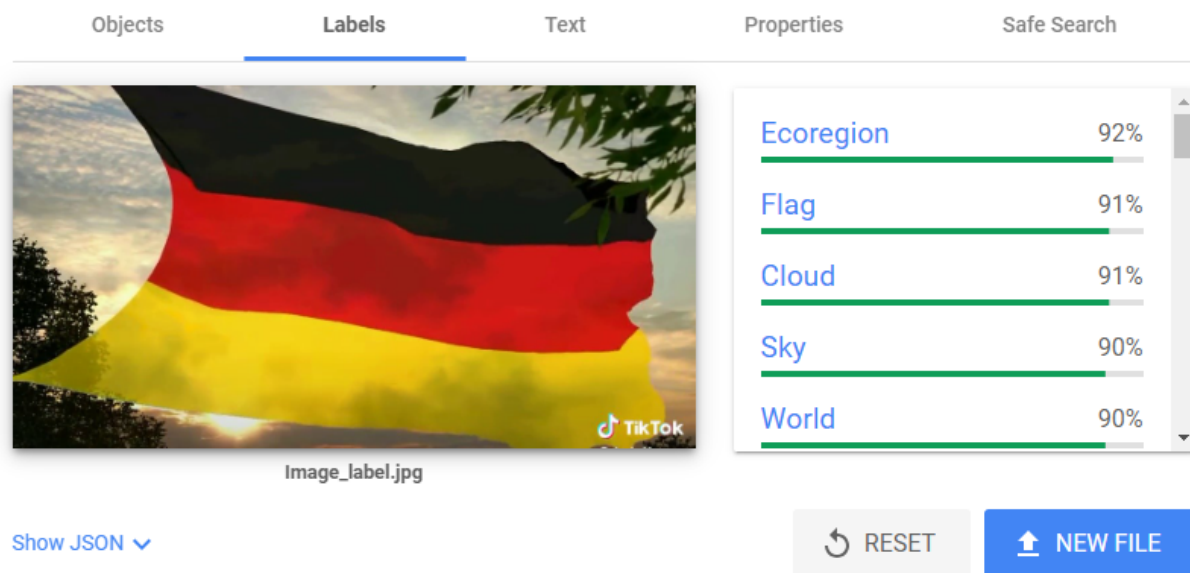
### 3.4 Image Classification

In order to analyze the individual video’s content, we extracted a number of frames from a video depending on its length and the assessed frame variation from the manual annotation, which served as a proxy for the degree of frame changes in the accounts’ videos. Hence, shorter videos from accounts with little frame changes have fewer frames extracted, while videos with longer videos and frequent frame changes have more frames extracted (see code segment).

```
def calculate_frames(video_length, content_variation):
    if video_length < 20:
        return 1 * content_variation
    elif 20 <= video_length <= 100:
        return 2 * content_variation
    else:
        return 3 * content_variation
```

In total, 32,500 frames were extracted from the videos. The frames were then processed and transferred to the Google Vision API for optical character recognition (OCR) and image classification using the 'googlecloudvisionR' package. The Google Vision API uses deep learning and computer vision techniques to label and classify images. The API takes an input image and applies a pre-trained Convolutional Neural Network (CNN) model to analyze the image’s content. Google only partially published the sources of the training data it uses to develop the CNN. From what is known, it is based on classified images provided by its in-house Google Image Search and Google Photos functionalities

(Schwemmer et al., 2020). The CNN uses classified images to recognize unique features associated with elements of an image (pixel combinations), allowing it to classify new images with similar elements accurately or to correct itself if its prediction for an element is not identical with the pre-trained classification (Chen & Chen, 2017). As the output of image classification, Google provides a range of labels associated with its probability score (e.g., Figure 2).

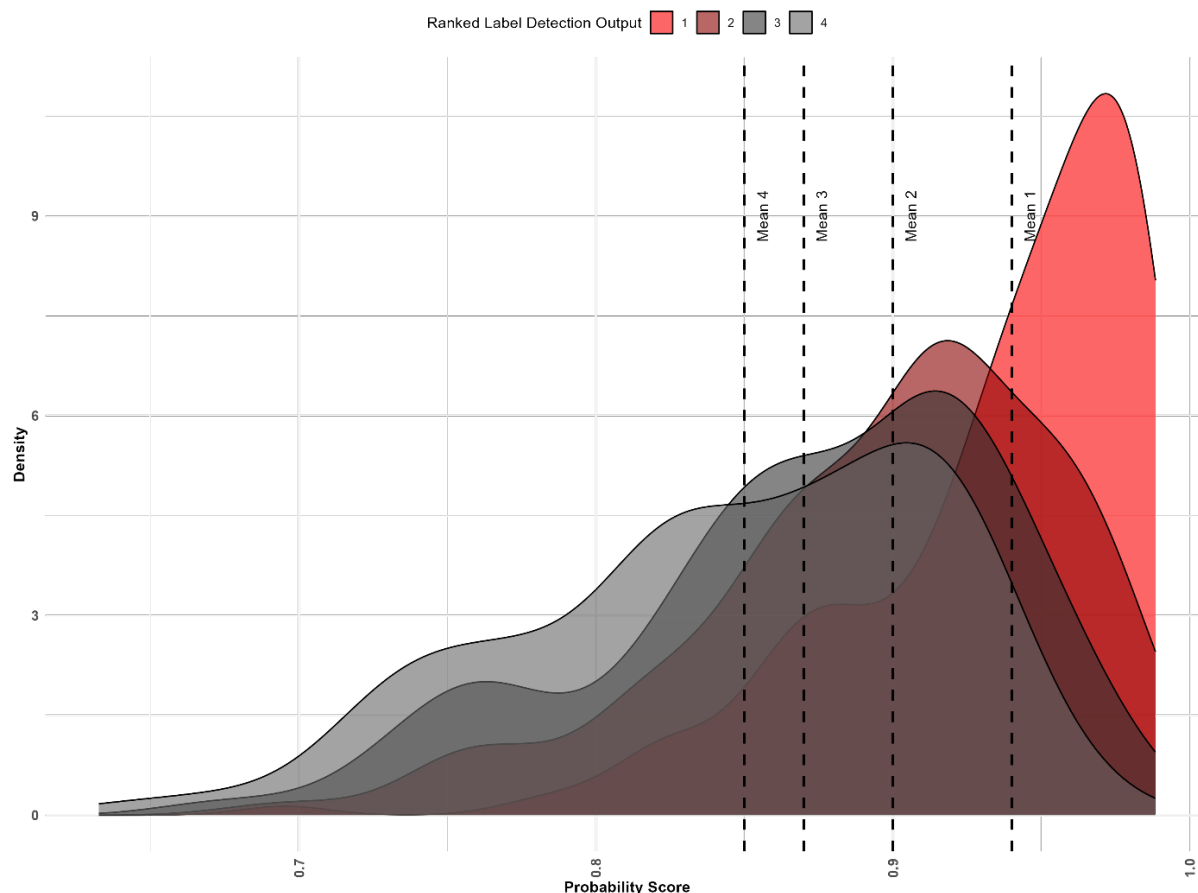


**Figure 2**

*Example output of Google Vision label classifications.*

As Hosseini et al. (2017) pointed out, Google Vision's classifier is not robust to noise, and performance decreases with unclear images. Because our images are frames extracted from videos that have natural camera movements, we sampled a test query of 200 frames and plotted the probability score for up to four labels for each frame (see Figure 3). Schwemmer et al. (2020) validated Google Vision's probability score by comparing manually annotated labels for an image with Google Vision's label for the same. They found that agreement increased with higher probability scores, and the performance in the higher probability range of Google Vision is quite adequate. However, inspecting the density of each output rank in Figure 3, we decided to only capture two labels for each frame as first, the probability flattened after the second label—decreasing the mean probability and hence, quality of the label—and second, to reduce the costs generated using the Google service. Ultimately, 65,000 labels were created.

The classifiers annotate images according to what they identify as a visual object and do not produce a specific meaning of an image. To tag each label and image with a broader meaning, the three authors independently categorized every top label occurring at least 100 times inductively into broader categories, considering the frame's context and example frames (see Table 6 in the supplement). The comparison revealed only little differences between the authors' categories. The differences were mainly a result of vague labels created by Google Vision, which were either re-categorized or excluded from the analysis after inspecting frames containing the specific label.



**Figure 3**  
 Density of label probability (= certainty) by output rank provided by Google Vision.

Further, we used Optical Character Recognition (OCR) to extract and classify words and sentences inserted in the video. We did this as textual elements in video frames provide essential context information. Google’s OCR algorithm is widely used in industry and academia as it is highly accurate for the most used languages, including German and English (Arief et al., 2018; Williams et al., 2020). In combination with the video’s description, we created a string vector for each video, classified the language, and pre-processed the text using Python and the ‘langdetect’ package. After cleaning the data, we used ‘SpaCy’ for Named Entity Recognition (NER). NER is based on a neural network classifier trained on large quantities of text on social media and web pages, classifying named entities into predefined categories such as person names, organizations, and locations. Derived entities can be used to assess the frame’s issue. Finally, image labels and textual data were combined with our manual annotation of TikTok accounts and their latent classes, creating a multimodal approach to characterize the German far-right on TikTok and their (internal and external) mobilization potential.

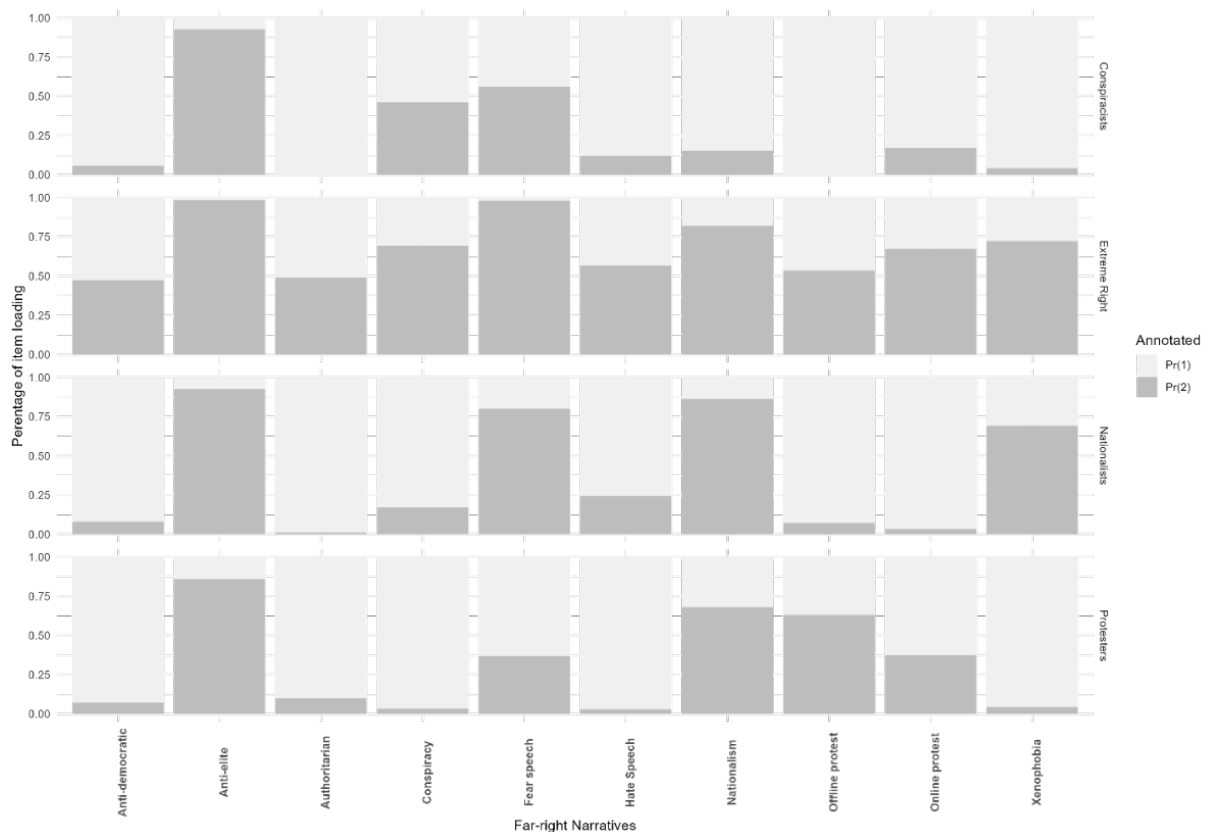
## 4. Results

### 4.1 Latent Class Analysis

To answer RQ1, inspecting the most prevalent far-right groups on TikTok, a four-class model performed best based on the manual annotations. Item shares for each group and far-right narrative are displayed in



Figure 4. We labeled the first group *Conspiracists* (n=98), as accounts show higher shares of conspiracies. Aligning with existing research (Ekman, 2022), the *Conspiracists* more intensely focus on fear speech and anti-elitism, as most far-right conspiracies entail the fear of being betrayed by elites. We coined the second group *Extreme Right* (n=58). While the group displayed proportions across all annotated items, they were unique in having exclusively high percentages in the most extreme categories: authoritarianism and anti-democratic narratives. Therefore, they represent the most extreme accounts in our sample. The third and largest group was labeled *Nationalists* (n=104). As unique traits, they have higher shares of xenophobia and nationalism. Combined with large quantities of fear speech and anti-elitism, they represent a more traditional, anti-migration, and patriotism-related branch of the far right. The last group consisted of *Protesters* (n=63) having higher shares of online and offline protest combined with anti-elitism and fear speech.



**Figure 4**

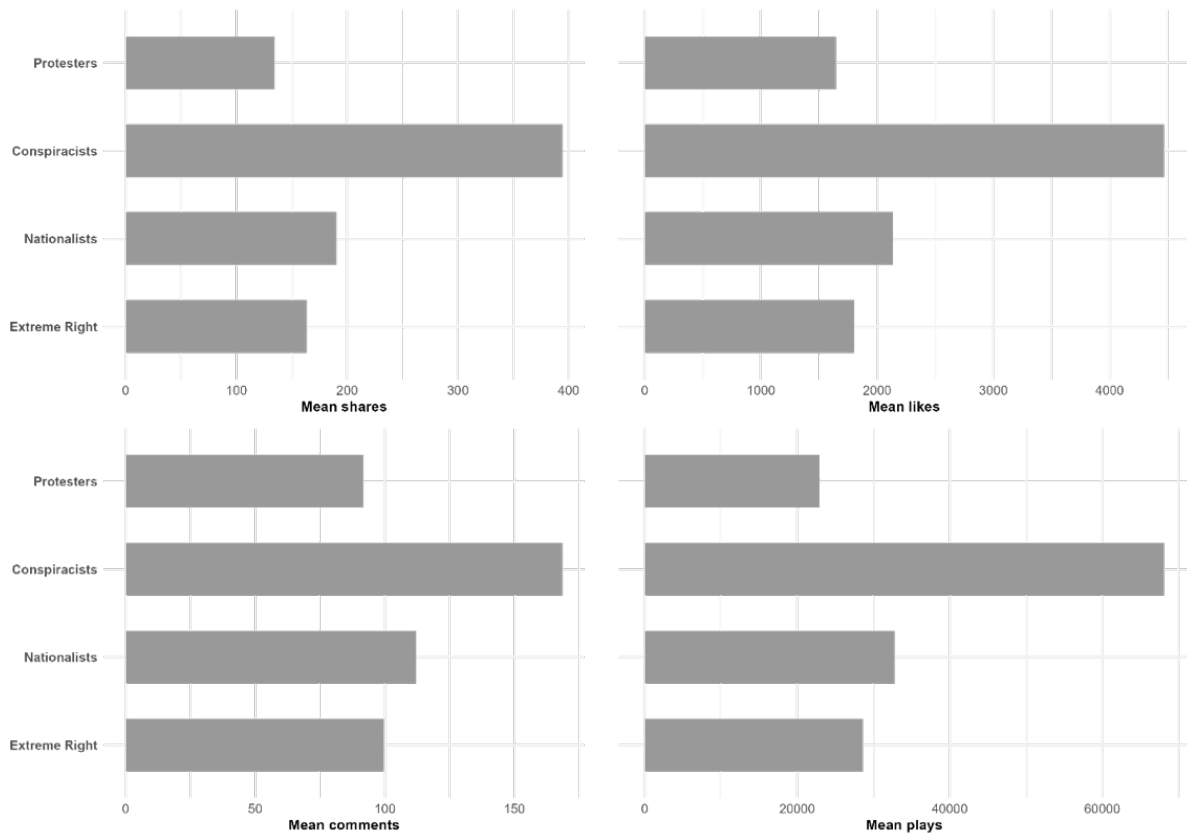
Latent classes and probability shares on far-right elements.

### 4.2 Popularity and Engagement

After LCA clustering, we inspected engagement cues and the videos’ labels and content through the lens of group membership. Starting with the groups’ overall popularity and engagement in Figure 5 and Table 1, we conducted a series of Kruskal-Wallis and pairwise Wilcoxon post-hoc tests for non-parametric independent samples to extrapolate significant differences between the groups in terms of their mean popularity (Dinno, 2015; Ostertagová et al., 2014).<sup>2</sup> We found that the *Conspiracists* are most popular on TikTok. With an average of 168 comments, 4,466 likes, 394 shares, and 68,078 views, all four popularity

<sup>2</sup> Kruskal-Wallis and Wilcoxon post-hoc test results and effect sizes are stored in the supplement in Table 2-5: <https://osf.io/3vfkn>

measures are significantly higher than the means of the other groups. The *Nationalists* and *Extreme Right* follow in popularity and do not differentiate in means except for the like count. Overall, the *Protesters* appeared to have the lowest popularity scores. This observation is not always significant, especially in comparison to the *Nationalists* and the *Extreme Right* where the mean share, like, and comment count is not significantly different to the *Protesters*. Albeit small effect sizes, *Conspiracists* tend to be by far most successful in mobilizing for their interests, followed by *Nationalists* and the *Extreme Right*.



**Figure 5**

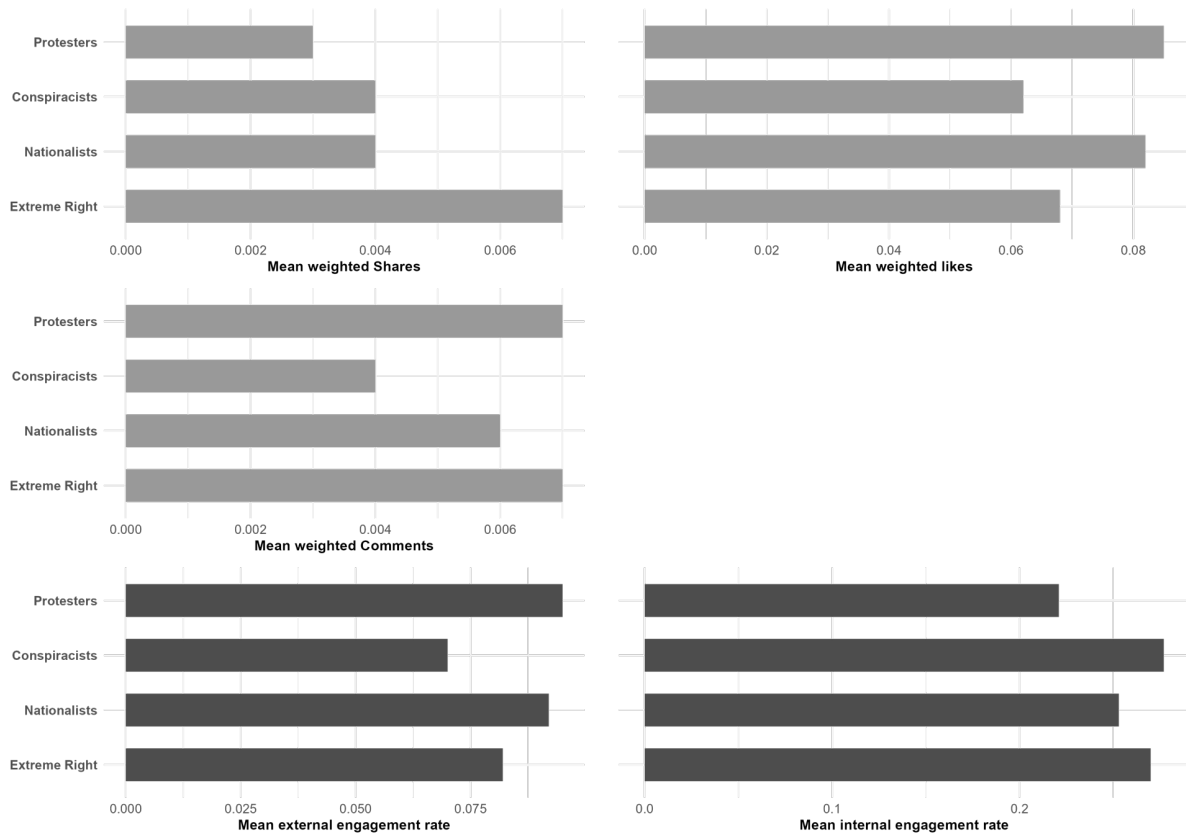
Mean popularity measures by latent class.

Exploring the ability to mobilize internally and externally through unweighted and sheer popularity in terms of likes, shares, comments, and views does not necessarily tell a complete picture. For instance, the observed popularity measures may be influenced by the mean follower count per group, as the *Conspiracists* also show the highest average follower count. Contrary, 'following someone' on TikTok is a rather diffuse and weak concept, as the viewer does not decide what they want to watch like on YouTube, nor do they necessarily need to actively click on a button to follow someone.<sup>3</sup>

Thus, and to explore the overall popularity of each group in terms of how engaging they are, we additionally weighted each measurement with the video’s play count in Table 1 or Figure 6. A different picture is revealed for likes and comments: Starting with the *Conspiracists*, they now have the smallest average comment count while being approximately on the same level of shares with *Nationalists*. In both groups, on average, only 0.4% of all viewers who watched a video also shared it. However, effect sizes

<sup>3</sup> There is no official statement by TikTok on this subject. See: [https://www.reddit.com/r/Tiktokhelp/comments/oa9igr/tiktok\\_making\\_me\\_follow\\_random\\_people](https://www.reddit.com/r/Tiktokhelp/comments/oa9igr/tiktok_making_me_follow_random_people)

were not significantly different between the Conspiracists and other groups. For mean comments and likes, effect sizes significantly differ between all groups, confirming that viewers engage less with conspiratorial content than viewers in the other groups. On average, only slightly above 6% of viewers like and 0.4% of viewers comment on conspiratorial videos. In comparison, viewers of videos from Protesters and Nationalists like above 8% of the content on average. For comments, the Extreme Right joins the ranks of the other two groups. All three generate significantly more comments than the Conspiracists with above 0.6 comments per view on average.



**Figure 6**

*Mean weighted engagement rates.*

To answer RQ2 on how the groups mobilized internally and externally, we also introduced the concept of internal and external engagement rates by dividing the popularity measures likes, shares, and comments by the play count (external) and the follower count (internal). Inspecting the indices' scores for the *Conspiracists* as a baseline, the group has the lowest external engagement rate. Only 7% of viewers engaged with their content, while *Protesters* (9.5%), *Nationalists* (9.2%) and the *Extreme Right* (8.2%) have higher mean external engagement. The Kruskal-Wallis and pairwise Wilcoxon post-hoc tests confirmed significant differences between all groups. Weighting the engagement by followers (i.e., internal engagement), the effect is no longer visible. In fact, protest content now has the lowest mean engagement with 22.1 %. This value is significantly different from all other groups. And yet again, *Conspiracists* have the highest internal engagement value with 27.77%. However, the margin is too small to be significantly higher than the mean values for the *Extreme Right* (27.0%) and *Nationalists* (25.3%). Regarding internal engagement rates, all three groups are comparable, with only protest content scoring lower.

**Table 1**

Mean (weighted) engagement and popularity rates.

	Extreme Right	Nationalists	Conspiracists	Protesters
Mean Views	28626 (220,792) B,D,F	32798 (175,679) B,D,F	68078 (293,503) B,D,F	22930 (106,118) B,D,F
Mean Shares	163 (1293) c	190 (1193) c	394 (1952) c	134 (769) c
Mean Diggs	1803 (22,497) A,b,C,D,e,F	2136 (12,113) A,b,C,D,e,F	4466 (25,291) A,b,C,D,e,F	1646 (7,555) A,b,C,D,e,F
Mean Comments	99.6 (455.7) B,c,D,e,F	112.2 (441.0) B,c,D,e,F	168.6 (623.4) B,c,D,e,F	91.6 (358.5) B,c,D,e,F
Weighted Mean Shares	0.007 (.025) B,D,e,F	0.004 (.007) B,D,e,F	0.004 (.006) B,D,e,F	0.003 (.005) B,D,e,F
Diggs	0.068 (.047) A,B,C,d,f	0.082 (.057) A,B,C,d,f	0.062 (.046) A,B,C,d,f	0.085 (.046) A,B,C,d,f
Comments	0.007 (.011) B,c,D,f	0.006 (.007) B,c,D,f	0.004 (.006) B,c,D,f	0.007 (.007) B,c,D,f
Engagement <sub>Internal</sub>	0.270 (2.411) c,d,e,F	0.253 (1.276) c,d,e,F	0.277 (1.590) c,d,e,F	0.221 (.760) c,d,e,F
Engagement <sub>External</sub>	0.082 (.063) A,B,C,D,e,F	0.092 (.060) A,B,C,D,e,F	0.070 (.049) A,B,C,D,e,F	0.095 (.049) A,B,C,D,e,F

**Note.** Base varies from n = 1,321 to 2,560 valid cases (see supplement). Weighted mean values are divided by view or play count. Arithmetic mean values are reported with standard deviation in brackets. The superscript "A" represents a significant relationship between the mean of *Extreme Right* and *Nationalists*; the superscript "B" indicates a significant relationship between the mean of *Extreme Right* and *Conspiracists*; the superscript "C" denotes a significant relationship between the mean of *Extreme Right* and *Protesters*; the superscript "D" represents a significant relationship between the mean of *Nationalists* and *Conspiracists*; the superscript "E" implies a significant relationship between the mean of *Nationalists* and *Protesters*; the superscript "F" points to a significant relationship between the mean of *Conspiracists* and *Protesters*. Superscript uppercase letters represent a significance level of  $p < 0.01$ , while superscript lowercase letters signify a significance level of  $p < 0.1$  or  $p < 0.05$ . No superscript letters indicate a non-significant relationship.

Overall, protest content was the least popular but had the highest mean external and lowest internal engagement rates. Conspiratorial content proves differently. *Conspiracists* posted the most popular content that produced among the lowest external but highest (though not significant) internal engagement rate. While the *Protesters* are able to mobilize and step beyond their 'bubble' (i.e., followers), the *Conspiracists* are not engaging for users not following them; within their followership, however, their inwards-oriented mobilization efforts seem to work out. Further, except for a noteworthy and significantly higher mean share for the *Extreme Right*, the *Nationalists* and *Extreme Right* are placed between both remaining groups in popularity and engagement indices. Their means could not be differentiated consistently, at least regarding engagement rates. However, *Nationalist* are far more successful in total popularity and mobilization potential than the more diverse but also more extreme accounts in the *Extreme Right*.

### 4.3 Labels and Content

To shed light on what content each group posted in our sample and to answer RQ3, the following section deals with content, its variability, and classified labels of the collected videos by group. Starting with label variation in Table 2, we counted the unique labels provided by Google Vision, weighted by the number of videos per group, and calculated the standard deviation of the counted label variation. Overall, the *Conspiracists* are yet again on top, with the highest number of unique labels (478), followed by *Nationalists* (428). In contrast, the *Protesters* (372) and *Extreme Right* (367) show less content variation. The same picture is visible when inspecting the weighted labels and the standard deviation of all groups.

**Table 2**

*Unique labels per latent class.*

Latent Class	Unique Labels	Unique Labels (weighted by video count)	Standard Deviance $\sigma$
Far Right	367	32.57	99.37
Nationalist	428	51.27	167.41
Conspiracists	478	47.61	173.35
Protesters	372	28.82	74.57

Afterward, we categorize video labels into broader categories. For details, see the Methods section and the supplemental material. Table 3 presents the broader categories and their relative share per group. Overall, the categories 'Environment', 'Commentary', 'Person or Body', and 'Face or Head' are among the most prevalent in all four groups. They are followed by less prevalent categories 'Emotionality', 'Car', 'Parliament', 'Media or News', and 'Colors or Design'. While the category distribution follows a clear pattern in groups that entail the same four categories to be the most prevalent, each group differs in the relative shares they have in most categories.

**Table 3**

*Label categories and top mentions entities in videos per class.*

Group	Label	N	Share	Top Entity	Share
Extreme Right	Person or Body	2177	0.23	german*	0.41
Extreme Right	Commentary	2142	0.23	ukraine	0.11
Extreme Right	Face or Head	1840	0.19	afd	0.10
Extreme Right	Environment	1546	0.16	russia	0.08
Extreme Right	Emotionality	496	0.05	berlin	0.08
Extreme Right	Parliament	406	0.04	helferich	0.07
Extreme Right	Media or News	377	0.04	youtube	0.04
Extreme Right	Car	324	0.03	usa	0.04
Extreme Right	Color or Design	167	0.02	bundestag	0.04
Nationalists	Person or Body	5629	0.30	german*	0.38

Nationalists	Face or Head	4149	0.22	afd	0.15
Nationalists	Commentary	2800	0.15	bundestag	0.11
Nationalists	Environment	2520	0.14	berlin	0.08
Nationalists	Emotionality	933	0.05	parliament	0.07
Nationalists	Parliament	834	0.05	ukraine	0.06
Nationalists	Media or News	662	0.04	cdu	0.04
Nationalists	Car	592	0.03	spd	0.04
Nationalists	Color or Design	378	0.02	chrupalla	0.03
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Conspiracists	Face or Head	5964	0.32	german*	0.30
Conspiracists	Person or Body	3829	0.21	ukraine	0.13
Conspiracists	Commentary	3168	0.17	russia	0.12
Conspiracists	Environment	2261	0.12	berlin	0.10
Conspiracists	Emotionality	966	0.05	afd	0.08
Conspiracists	Parliament	865	0.05	usa	0.06
Conspiracists	Media or News	530	0.03	youtube	0.06
Conspiracists	Car	494	0.03	parliament	0.05
Conspiracists	Color or Design	306	0.02	dubai	0.05
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Protesters	Face or Head	2233	0.26	german*	0.30
Protesters	Person or Body	1727	0.20	afd	0.12
Protesters	Environment	1468	0.17	bundestag	0.10
Protesters	Commentary	1350	0.16	guido reil	0.10
Protesters	Car	670	0.08	ukraine	0.08
Protesters	Emotionality	375	0.04	russia	0.07
Protesters	Parliament	306	0.04	berlin	0.07
Protesters	Media or News	284	0.03	saxony	0.07
Protesters	Color or Design	142	0.02	vaccine mandate	0.04

Starting with the *Extreme Right* group, frame labels are over-represented in the four largest categories. Only minor shares are visible in the smaller categories, and confirmed that the *Extreme Right* has only minor variations in content or visual elements in their videos. The combination of high shares on image elements that depict a person, body, or clothing was combined with an equal amount of shares on labels representing some commentary of that person (f.e. written text beneath or above the video). Together with protest content, they had the highest shares in the environment category, indicating that most of the videos in this group were produced in an outside environment within nature or cities. Inspecting the most mentioned entities, words referring to Germany have by far the most prevalent relative share (41%). The Russia-Ukraine war and politics in Berlin and the US are discussed in this group. Noteworthy is the mention of Matthias Helferich, a far-right AfD politician, who described himself as 'the friendly face of National Socialism' (Stickings, 2021).

In contrast, the *Nationalists*' content was less focused on commentary (only 11%) and more centered around spreading visuals of a complete person (30%) instead of only face or head (22%). The remaining label categories were marginal. Concerning textual content, Germany-related references were among the

most prevalent (38%) again. Interestingly, the remaining entities all refer to German politicians or politics except for 'Ukraine'. Qualitative inspection reveals that this may be due to plenty of parliamentary speeches being posted in this group.

The *Conspiracists* had the most prevalent share for labels depicting elements of a face or head (30%) and only marginal (13%) shares depicting a whole person, pointing toward a more 'Vlog'-like content style. Additionally, commentaries were also among the most prevalent category. Content-wise, the Russia-Ukraine war, German politics, and the USA played a significant role in videos of this group. Finally, the *Protesters* show large shares of both, showing the face or head (26%) and the complete body (20%). The categories environment (17%) and cars (8%) played an outstanding role in comparison. This is reasonable for this group since such settings are likely markers for street protests. Protest content was also not surprisingly focused on German politics but also on the Russia-Ukraine war and anti-vaccination.

## 5. Discussion

### 5.1 Far-Right Mobilization on TikTok

Following initial research about the emergence of extreme speech and individual actor types such as politicians on the platform TikTok, we found that a variety of far-right sub-groups are already active on the platform and once again show their talent as early adopters of new and emerging technologies (Pre:Bunk, 2023). All four groups have different visual and textual emphases in their videos, indicating diverse stylistics of the far right on TikTok. Starting with the *Extreme Right* and its total popularity, the group is the smallest in our sample and generates the lowest mean popularity aside from the *Protesters*. A possible explanation might be that stereotypical extreme content is often violent, inhumane, or, in general terms, more drastic and, thus, more repulsive and off-putting to the general public rather than generating attention or interaction (Schmid et al., 2022), including violence in images (Mitts et al., 2022). The *Extreme Right*'s unpopularity is also highlighted by their internal and external engagement rates: While they have among the lowest external engagement, internal engagement is high: Viewers already following them may have normalized views on violent or extreme content and hence view or engage with it more. This behaviour was also observed in similar contexts: A study investigating YouTube's recommendation system found a high degree of homogeneity in right-wing populist content, suggesting that users with right-wing orientations are likely to be exposed to and interact with similar content, potentially including extreme viewpoints (Röchert et al., 2020). Visual content analysis for this group revealed that the *Extreme Right* has less variability in its content and mainly focuses on German politics and the Russia-Ukraine war. Nevertheless, given their extreme communication, their average popularity is by no means marginal and confirms observations in existing research that depict plenty of extreme content on TikTok (O'Connor, 2021; Weimann & Masri, 2021).

*Nationalists* are more successful and prevalent on the platform, as they are the largest group, have the second most popular accounts, and second most engaged audience. Together with protest content, they generate the most external engagement and, thus, are exceptionally inviting to mainstream viewers. They also have the highest content variety, publishing anti-elite-centered, patriotic content about German politics. Insofar they share commonalities with the *Extreme Right*, but are more successful as they publish more variable but less extreme content. This result contradicts recent research, mainly on Telegram, that observes a relatively low or declining salience of typical nationalism-oriented topics and more focus of the German far right on conspiratorial content, protest, and anti-elitist topics during the pandemic (Schulze et al., 2022; Zehring & Domahidi, 2023). One possible explanation for this might be the great potential of TikTok's architecture to mobilize their followership and to reach into public discourse in contrast to Telegram, the platform these observations were made. This is also reflected when inspecting the engagement rate, as the *Nationalists* can generate among the highest mean engagement internally and

externally. Similar tendencies are also observed for nationalism-centered elite politicians within France, Italy, and Spain on TikTok (Albertazzi & Bonansinga, 2023).

*Conspiracists* constitute the most popular group in our sample. Interestingly, however, viewers of conspiratorial content are less engaged on (unweighted) average. Only when divided through followership, the internal engagement is on par with the second strongest mean from the *Extreme Right*. This suggesting that, for extreme and conspiratorial content, viewers are less likely to be mobilized by such content when first encountering it. However, when such content is approved, supported, or believed, viewers are more likely to engage and identify with it. This relationship was observed in similar contexts and is often referred to as going 'down the rabbit hole' or 'taking the red pill' and describes the process of identification with the presented attitudes while being increasingly isolated from other worldviews (Chapelan, 2021; O'Callaghan et al., 2015). In an ethnographic approach, Boucher (2022) found that TikTok's algorithm strongly supports building conspiratorial echo chambers, aligning with our finding that conspiratorial content has relatively weak external, but increased internal mobilization potential once viewers identify with such content. The Vlog and commentary style of this group's videos complements this finding. Vlogs create a sense of familiarity, intimacy, and closeness that is intended to persuade viewers (Baker, 2022). This style of content is essential for explaining the diverse reasons behind their beliefs on various issues, such as German politics, the Russia-Ukraine war, and US-related topics, thereby making them the most successful group in terms of internal mobilization.

The *Protesters* are the least popular group in sheer popularity. This is surprising as during the pandemic, the German protest movements not only grew in numbers but were also increasingly linked to far-right elements and even radicalization (Hunger et al., 2023). Their 'underperformance' might be partially explained by our study design as TikTok only allows to collect the latest 30 videos of an account. Thus, many videos were published after August 2022. During this time, Corona-related protests decreased in Germany significantly and hence might also influence the *Protesters'* ability to mobilize online (Zehring & Domahidi, 2023, Hutter et al., 2023). This is also reflected in the lowest internal engagement rate, as the observation period lies directly in the time span of the lowest momentum of the protest movement. Visual content that focuses on street protests, protest speeches about German politics, the Russia-Ukraine war, and compulsory vaccinations is less popular and generates less internal mobilization compared to content from any other group.

Overall, far-right movements are not monolithic, and their success depends on their ability to adapt to changing circumstances and appeal to different audiences (Caiani et al., 2012). In our sample on TikTok, especially the *Nationalists* and *Conspiracists* are successful in terms of popularity. The study also stresses the importance of considering in internal and external engagement differences as mobilization means. In this context, the platform may be used for inwards- and outwards-oriented mobilization as the platform's architecture allows to engage with public discourse and potentially creates echo chambers that may contribute to radicalization spirals' into the rabbit hole'. Contrary, protest and extreme content are seemingly not as dominating as on other video-centered platforms such as BitChute (Rauchfleisch & Kaiser, 2021). TikTok remains a platform for internal and external mobilization.

## 5.2 Processing Images at Scale

Unsupervised image classification algorithms are still a scarcely used method in radicalization and extremism research for many reasons, which are also visible in this study. For example, inspecting the total label variation of each group does not directly translate into actual differences in topic variety between groups and serves only as a proxy. Combining the higher label variation for the *Nationalists* and *Conspiracists* with the more diverse top entities from the NER analysis, however, helps underline a more robust and valid exploratory analysis. We, thus, want to highlight the advantages of using more visual-focused approaches to study radicalization, extremism, or protest. First and foremost, it enables a scaled-up mode of analysis for video and image central platforms such as TikTok and, thus, more generalized



research not only limited to text. Combined with in-video text extraction, most, if not all, optical implemented visuals can be extracted and analyzed. Nevertheless, to fully utilize image processing algorithms, combining a mixed-method approach with manual annotation or other natural-language-based approaches is advisable (Clever et al., 2023). Finally, the study's design is a starting point for similar research on radicalization, extremism, and protest to analyze further the emerging far right on TikTok.

### 5.3 Limitations

Of course, the study should not be read without considering its limitations. First and on a more methodological level, extracting frames and retrieving image labels does not fully cover the content of each video. Further, the classification algorithm does not extract meaning from the videos and should not be over-interpreted. In this context, recent research indicates biases in how Google Vision returns labels. For example, men were often labeled as spokespersons or businessmen. At the same time, women had more labels that focused on their appearance (Schwemmer et al., 2020). It is possible that we missed relevant information in the videos and that our results are structurally biased based on what Google Vision returns as labels. Possible future pathways in conducting a more meaningful or interpretation-centered approach are self-trained image classifiers. However, they must be highly tailored toward a specific research interest (e.g., videos containing violence). Another possible future opportunity is large-language models, such as GPT-4, that can increasingly extract meaning from visuals, even without pre-trained context data (OpenAI, 2023). However, the functionality was not available when conducting this study.

Second, because we did not compare far-right popularity on the platform with other ideological groups (e.g., far-left or Islamist groups) the success of the far right in this study is hard to compare in ideological terms. First research, however, indicates an extraordinary success of the far right as early adopters on the platform (Boulianne & Lee, 2022). Also, the study only collected and analyzed a small margin of far-right German TikTok and one can assume that far-right groups are growing in size as the popularity of TikTok increases. Our latent class approach only made observations for the most prevalent groups in our sample possible, and results likely deviate with increasing detail on the group level (i.e., differentiating between sub-groups of *Conspiracists*), or outside our sample. Furthermore, while we defined increasing engagement metrics as successful mobilization cues, it's important to note that engagement might not solely indicate agreement, but can also be used to express disagreement. Voicing dissent might be a reason why external engagement from the *Extreme Right* or the *Protesters* is higher than for the *Conspiracists* as the former may attract more dissent because of their more direct act or behavior against the current political system. The usage of (external) engagement as a marker of successful mobilization should, thus, be controlled for dissenting content in future research. It's equally significant to recognize that dissent should influence the algorithmic amplification of content in a similar way as supportive engagement acts, echoing the notion that 'bad advertisement is also advertisement,' and suggesting that all forms of attention, whether positive or negative, can boost visibility.

In this context, we also want to stress that internal and external engagement should only be seen as an approximation of inwards and outwards-oriented mobilization — especially as both metrics can entail overlaps and may influence each other. If many followers, for instance, like a video, it becomes more likely that the content is prioritized by the algorithm, leading it to be distributed to an increased amount of others via the FYP and aiding the recruitment of new followers. Conclusions about the exact relationship of internal and external engagement as well as the functioning and role of the recommendation algorithm is beyond the scope of this exploratory study. We hope to inspire future research to further explore these relationship.

Nevertheless, a lesson that can be learned from this study for policymakers and researchers is that far-right monitoring on TikTok needs to be institutionalized, as the platform evolves into one of the most used platforms of the far right, at least in terms of how much attention they are able to generate for

internal, but also external mobilization. The study's methodological approach was conducted with such a monitoring approach in mind and, hence, can be used to establish longitudinal monitoring of far-right TikTok by using the code provided in the supplement. Further research embedded in a more controlled setting is required to gain more insights into how and when adaption of such content occurs on an individual level (e.g., eye-tracking experiments to analyze which far-right visual elements generate attention; Schmid et al., 2022).

## 6. Conclusion

The rise of the far right on TikTok is a worrisome trend. Our analysis has shown that nationalist and conspiratorial content is thriving on the platform, having the highest popularity and most variety in content. The success of far-right TikTok reflects not only the political climate but also TikTok's algorithmic architecture. The platform's algorithm potentially promotes content that generates broad engagement and popularity by also favoring new and emerging content, regardless of its far-right nature. The study also contributes to the theoretical discussion about far-right online communication by displaying the variability, content, and engagement in and toward far-right visuals. While conspiratorial content generated less external engagement, its popularity and internal engagement are standing out. It, thus, confirms recent research that highlights *Conspiracists* as emerging within the far right. In contrast, far-right protest in our sample was the most publicly connectable group generating the highest external engagement.

Methodologically, this study is the first to combine visual content on TikTok in the field of radicalization and extremism research with manual annotation data to generate and retrieve meaning from image labels. The study is able to show a possible pathway for future research on how to use TikTok data and unsupervised image classification as the platform evolves into one of the most essential digital environments for the far right.

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