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Mapping Platform-Mediated Proximities With the TikTok Global Observatory

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Abstract

Considering TikTok's increasing geopolitical influence, this article presents the TikTok Global Observatory (TKGO) as a case of data-reappropriation and introduces the concept of platform-mediated proximity as a counter-data mapping framework for data activist research. While TikTok enables global connection beyond local and cultural boundaries, its content is sensitive to locally specific conditions to which the platform provides no public insight. To counter this lack of transparency, the TKGO makes data for global and cross-national analysis of TikTok feeds available and navigable to the research community. The TKGO is an archive, updated daily, that collects the metadata of videos scraped from the non-logged-in web version of TikTok's for you page (FYP) across 197 countries and territories. The tool's main feature is a geographic map that allows users to view, filter, sort, and extrapolate the FYP data as prioritized in different geographical locations. This offers a unique access point for researchers, journalists, and activists investigating cross-national trends, content moderation, and content promotion. In this article, we firstly present the TKGO and contextually position its development in the contentious politics of data access, archiving, and mapping practices. Secondly, we elaborate on the notion of platform-mediated proximities, a conceptual lens that highlights how TikTok remediates geographical proximities through algorithmic content recommendation. Lastly, we apply this framework to the mapping of a three-month sample of the TKGO data, showing how TikTok's cross-national content prioritization patterns generate new geographical boundaries, observing regional and geopolitical clustering as well as notable exceptions.

Keywords

algorithmic audit; counter-data mapping; data activism; for you page; social media monitoring; TikTok

1. Introduction

In the wake of the Cambridge Analytica scandal, many platforms restricted access to their research application programming interfaces (APIs), a key means to procure insights into platforms' content (Bruns, 2021), making platform accountability efforts more complicated. In 2022, the European Union adopted the Digital Services Act (DSA), creating legally enforceable transparency obligations, including the crucial requirement to grant vetted researchers access to enable independent third-party scrutiny. Nonetheless, in 2023, major restrictions affected API-based research tools such as CrowdTangle (a monitoring tool for Facebook and Instagram), Pushshift (an archive of Reddit posts), and X's (formerly Twitter) academic research API. Recent inquiries show that, despite the Digital Services Act's ambitious provisions, platform compliance has so far remained limited (Trans et al., 2024).

For example, TikTok's virtual compute environment, a secure environment for conducting research on sensitive data, revealed some major limitations: Raw data cannot be downloaded and researchers must embed their analysis in scripts that TikTok pre-reviews, which return only aggregated outputs, often after long, opaque delays (Rincón et al., 2025). On the other hand, academic access via TikTok's research API is not a remedy: Persistent errors in the engagement metrics (Pearson et al., 2025), incomplete or inaccurate documentation, and undocumented exclusions mean that some publicly visible content is missing from the API, alongside other known limitations (Entrena-Serrano et al., 2025). More broadly, platform-provided access points (e.g., ad libraries and standard APIs) enable content retrieval and only limited metadata but they do not give researchers access to the concrete, user-level impressions needed to analyse personalisation and targeting (Beraldo et al., 2021). These gaps compromise standard audit methods like data donations (Araujo et al., 2022) and sock-puppets (Sandvig et al., 2014), as they rely on the accuracy and completeness of the data made available by the platform.

Another important point, central to this contribution, is that none of the data access methods provided by TikTok allow for the analysis of its recommender system, nor do they allow for the analysis of how videos are suggested to users according to their location. Considering the growing interdependence between platforms and nation-states (Flew, 2023), enabling researchers to investigate the geographical dimension of platforms' recommender systems is crucial.

Despite TikTok's rapid global diffusion, systematic evidence on cross-national variation on TikTok remains limited. In particular, the literature lacks an analysis that couples broad country coverage with a longitudinal perspective capable of tracking changes over time. The TikTok Global Observatory (TKGO) tackles this issue by archiving recommendations as they appear on the for you page (FYP) of non-authenticated users across several countries and territories. It provides a live updated dashboard where researchers can explore the recommender system's outputs across the world. The TKGO reclaims data from TikTok and makes it available to researchers interested in cross-country analysis and in monitoring the geopolitical dimension of the platform. Introducing and illustrating this case, the present study offers an exploratory cross-national, time-aware examination of TikTok's FYP, focused on the question: How does TikTok's recommendation algorithm re-mediate geographical patterns?

This question is particularly salient in light of the contrasting tensions between, on the one hand, the push toward cultural homogenization driven by the circulation of content on global platforms and, on the other hand, the push toward cultural fragmentation promoted by resurgent nationalism. The former would point toward a more integrated ecosystem, in which users across countries are largely exposed to the same content, whereas the latter would suggest the emergence of isolated, country-specific TikTok spheres.

This article is structured as follows. First, in the literature review, we discuss the political implications of TikTok's content diffusion, then we reflect on the implications for cross-national data mapping and the way in which social media can create a new type of proximity that is not only geographical, but also algorithmic. Second, we present the TKGO as a case of data re-appropriation and counter-mapping. Third, in Section 4, we describe the dataset and the analysis framework developed in this study. Fourth, in Section 5, we present our analysis of the global reach of TikTok's recommendation system and of the resulting re-mediation of geographical proximity. Finally, we discuss the implications of localized recommendations on TikTok and the way the platform segments its content based on users' location data, claiming that monitoring and mapping geolocated recommendations are essential to keep platforms accountable.

2. Reappropriating TikTok Data as a Case of Counter-Data Mapping

Despite affording global connectivity, the platform ecosystem is highly sensitive to local conditions and cultural boundaries (Rogers, 2019). In terms of content circulation, social media operate as a double-edged sword (Balogun & Aruoture, 2024): On the one hand, they contribute to cultural homogenization by enabling the global circulation of cultural trends; on the other hand, they can function as resources for promoting diversity, offering spaces for documenting and celebrating local cultures.

In geopolitical terms, concerns are emerging around the rise of a "splinternet," the fragmentation of a once single open online space into isolated spaces shaped by national borders and corporate infrastructures (Lemley, 2021). Not only have governments in various cases intervened at the legal, commercial, and infrastructural levels in order to reinstate control over information diffusion (Pallin, 2017), but private platforms operating globally have also adapted to regulations and political pressures on a national level (Biddle et al., 2020). For example, a 2022 investigation on TikTok showed how, shortly after Russia's invasion of Ukraine, the platform banned access to all non-Russian content for Russian users by removing an estimated 95% of previously accessible international content (Romano et al., 2023). Such a severe content restriction entailed the direct contribution of TikTok (Romano et al., 2022), highlighting local politics and platform power as a barrier to access for local users. This underscores the importance of understanding content prioritization policies across national borders.

Given the restrictions that platforms impose on data access, reappropriating data becomes essential to achieve this goal. For the sake of transparency and scrutiny of globally opaque social media algorithms, conceptualizing and visualizing cross-national recommendations can offer alternative perspectives on how and where content is disseminated. We understand this as a case of counter mapping, i.e., the alternative mapping of space that bears the potential of exposing power dynamics and creating new perspectives about power (Aleman & Martinez, 2024). Considering the centrality of data reappropriation and alternative mapping, such initiatives fall in line with the consolidation of counter-data mapping within the repertoire of media activism (Jeppesen & Sartoretto, 2023), a tendency rooted in the broader paradigm of data activist research (Kazansky et al., 2019; Milan & van der Velden, 2016). For example, the Mapping Police Violence project reappropriated and visualized data on police killings to expose their systemic nature and underlying racial patterns (Dalton & Stallmann, 2018). During the Covid-19 pandemic, marginalized communities appropriated data to create alternative maps that revealed social and racial inequalities obscured by official dashboards (Jeppesen & Sartoretto, 2023). Similarly, D'Ignazio et al. (2025) document counter-data initiatives that produced alternative databases and maps to make visible under-recorded cases of feminicide. In this vein, data circulating on social media, despite being tightly controlled by platforms, can be reappropriated and critically visualized through counter-mapping practices, as illustrated by our study of TikTok.

Reaching 1,59 billion users, TikTok has become one of the most popular and influential social media networks (Dixon, 2025) since its global launch in 2017. The platform allows its users to create and upload videos through various editing functions, enabling experimental audiovisual expressions of creativity (Cervi & Divon, 2023). Its distinct and highly personalized algorithmically-curated feed (the FYP) is TikTok's primary feature, which allows users to discover new content other users have uploaded (Ionescu & Licu, 2023).

TikTok is growing in political and geopolitical relevance. A steadily increasing number of young adults are using the platforms as a source of news (Tomasik & Matsa, 2024). Encouraging a playful approach to politics and activism, it reportedly lowers the barrier to political participation (Cervi & Divon, 2023). However, the algorithmically-driven feed risks intensifying echo chambers and fuelling polarization (Li et al., 2025). Insights into how the platform's data-driven algorithms work, meaning how content is prioritized or hidden from public consumption, remain undisclosed by the company. Illuminating this opacity serves as a form of contention and resistance in datafied societies (Beraldo & Milan, 2019). In this sense, TikTok data is not neutral; it is inherently political, reflecting and reinforcing societal power dynamics while shaping the information that users encounter, the communities they engage with, and the broader public discourse.

Mapping cross-national recommendations on TikTok enables the research community to monitor the type of content that circulates on and is promoted by the platform. This opens up a number of analytical directions, including dissecting the logic of virality, mapping cultural trends, and tracking the spread of misinformation. The focus of this article, however, lies on what we term "platform-mediated proximity"—i.e., forms of proximity among countries mediated by algorithmic recommendations. Proximity, conventionally understood as geographic spatial relations, can be reinterpreted through the logic of algorithmic distribution as cross-national similarities in recommended content implicitly establish forms of cultural or discursive links. These are not necessarily dictated by spatial proximity but are shaped by the interaction between platform governance and country-specific policies. This underscores how platforms act as mediators of cross-national connections as they play an active role in producing cross-country relations as opposed to simply reflecting existing relationships between countries. Therefore, platform-mediated cross-national proximities can themselves be understood through the lens of counter-data mapping. Similarly to how grassroots counter-maps reveal and withstand "hegemonic narratives through a process of social cartography" by uplifting "community experiences and epistemologies" (Jeppesen & Sartoretto, 2023, p. 153), examining cross-national recommendations can help materialize the otherwise hidden logic of platform power.

With this article, we emphasize the importance of enabling and empowering civil society actors, educators, researchers, and journalists to challenge this power through accessible methods (Kazansky et al., 2019) by enabling third-party audits and further scrutiny of the cross-national dynamics of content curation. Furthermore, we contribute to studies of algorithmic governance by reconceptualizing the notion of cross-national proximity from the perspective of a platform's recommender system. Such a framework can contribute to exposing harmful platform dynamics at a transnational level and to making space for new forms of accountability.

3. The TKGO

This section briefly describes the TKGO, a case of counter data mapping developed by the non-profit organization AI Forensics, on which the present study is based. The TKGO archives local versions of TikTok's FYP and maps them to enable cross-national research and to monitor the dynamics of platform-mediated proximities. Hence, we conceptualize it as a case of data reappropriation and counter-mapping that takes a "critical stance towards datafication" and contests its power relations (Beraldo & Milan, 2019).

3.1. Downloading FYP Data

Since December 2022, the TKGO has been collecting FYP from the HTML page of the TikTok website data four times per day across 197 countries and territories. Every instance of data collection retrieves an average of eight recommended videos (in a range between five and nine), corresponding to the (variable) number of videos that TikTok preloads on its webpage upon access, for a total of around 5,000 daily videos. It relies on a quite stable and simple data collection technique that does not require account creation.

The data is collected from the videos displayed when accessing tiktok.com/foryoupage using a browser configured exclusively for this purpose without being logged in and without any interaction with the website (meaning no scrolling, liking, or other actions). Specifically, we used cURL (a command-line tool that lets you transfer data to or from a server) to download the JSON file with the first batch of videos, including their metadata, that TikTok preloads on the homepage for users. TikTok preloads these videos for people accessing TikTok via a web browser to avoid waiting times between interactions with the first videos and the following ones. Once the user starts to scroll or engage with the first batch of preloaded videos, new batches of on average eight videos (in a range between five and nine) are loaded one after the other (TikTok, 2020). In the case of this data collection, only the first pre-loaded batch is considered, as the other batches are loaded only after the user engages with the first batch (TikTok, 2020). In this case, the platform likely predominantly selects the videos based on two variables: the country of the IP address used and the time of the request. While it would be interesting to complement our data with the subsequent batches, doing so would require a substantially more demanding infrastructural setup as it would necessitate simulating user interactions to manually load additional content.

3.1.1. Residential IPs Network

To investigate the different FYP recommendations across countries, TKGO replicates each data collection instance across all the IPs available on Bright Data, a service that offers residential IPs across the world. Residential IPs are generally considered better for research purposes than virtual private networks, which route web requests through a location different from the physical location of the device making the request. Virtual private networks' IPs are usually publicly known, hence even if they mask the real location of a user, it is quite easy for a system to detect that the user is dissimulating their location. Conversely, residential IP services make an additional effort to not publicly disclose the list of IPs they use, making it almost impossible for platforms to detect them. This allows the tool to evade TikTok's attempts to identify and block users who are manipulating their location. Therefore, we replicate the data collection across 197 countries and territories (see the list of countries in the Supplementary File for a full list).

3.2. TKGO: A Public Tool

The web application of the TKGO is composed of a main map of the world and a sidebar displaying the globally top recommended videos and their respective metadata (e.g., description, author, engagement metrics). By selecting a single country on the map, the sidebar displays the top recommended videos for that specific country. It is also possible to select a specific timeframe or to query for a specific keyword, highlighting where videos containing that keyword are recommended (see Figure 1).

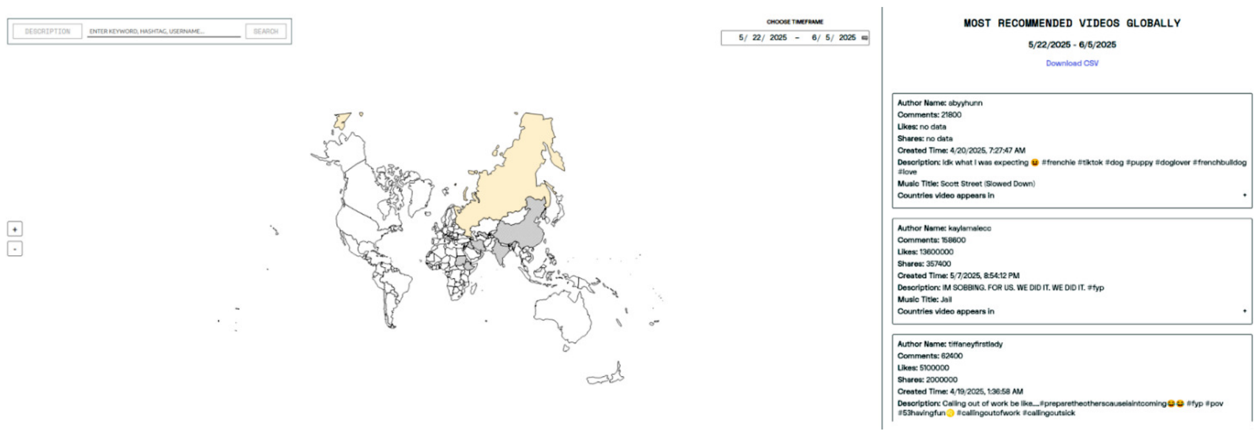

Figure 1. A screenshot of the TKGO: A world map with a word and time filter on the left, and a sidebar with the recommended videos list on the right side. Source: AI Forensics (2025).

All the collected data is made available to researchers in two different ways: to the public, through TKGO as a web application, showing an interactive map to explore a limited set of the most prominent recommendations; and to vetted researchers, through ad hoc requests, providing access to the entire collection in the form of CSV files.

3.3. Limitations

We acknowledge that unlogged-in access to the FYP through a web browser is not how most users access TikTok since TikTok's algorithm relies on personalization, presenting users with content related to previously inferred interests. While this implies that the TKGO data cannot be used to study algorithmic personalization and individual filter bubbles, the cross-country nature of its data provides a unique opportunity to study global content circulation and to understand how the platform remediates geographic boundaries.

Moreover, the preloaded recommendations served to non-logged-in users act as a showroom of the platform, targeted to potential users with the aim of luring them into the system. This means that, most likely, these recommendations do not include borderline and or niche content but rather a collection of content generic enough to cater to different categories of users. For the sake of exploring platform-mediated proximities, this type of content is better suited than personalized recommendations that would introduce much more variability.

TKGO's data collection, even if longitudinal and cross-national, cannot be considered exhaustive. With residential IPs, it is not always known in which specific areas of a certain country/territory the access point is given. In some countries, however, regional differences are quite relevant, calling for even finer-grained local collection. Further, the frequency of data collection, set to four times a day, is arbitrary. Increasing the frequency of recommendations would generate a more representative sample.

3.4. Ethical Issues

According to TikTok's Terms of Service, Developer Terms of Service, and Community Guidelines ("How we combat," 2024), the platform forbids the scraping and collection of data. However, within the context of the European Union, Article 40, paragraph 12 of the Digital Services Act states that publicly accessible data (e.g., public posts, visible metadata) should be accessible in real time to researchers inside and outside the EU (Regulation of the European Parliament and of the Council of 19 October 2022, 2022, Article 40). The European regulation allows public scrutiny of potential systemic risks that platforms could pose to society, such as negative effects on civic discourse and electoral processes that could arise from cross-national disparities. We view the regulation as a possible remedy for the long-term information asymmetry between platforms and users/researchers. We argue that our data collection supports the process of enforcing Article 40 (12) to hold the platform more accountable and allow for independent assessment of potential risks related to its recommender system.

The entirety of our collected data is stored on secure servers hosted in Europe, encrypted at rest, with a data retention period of a maximum of two years. Data older than that is accessible to researchers only after anonymization. In general, TKGO does not provide the full list of content collected but makes available in its public web version only the content published by users who have more than 500,000 followers, which we treat as high-visibility content of public interest. Access to the full dataset is provided only through a vetted research request process designed to balance transparency, reproducibility, and privacy, consistent with the context-sensitive, harm-minimizing approach to data storage and dissemination recommended by the Association of Internet Researchers' Internet Research Ethics 3.0 guidelines (Franzke et al., 2020).

4. Methodology

The findings presented in this article are an illustration of possible analytical directions afforded by the TKGO datasets. As detailed in this section, we focused on a subset of the sample and performed an exploratory analysis centered around the framework of platform-mediated proximity.

As explained earlier, the TKGO collects up to nine videos four times a day from the FYP of non-logged-in users based in each of the 197 countries and territories considered. To display the possible analytical directions of the tool, we focus on the nine weeks ranging from December 9, 2022, to February 9, 2023. Upon inspection of the dataset, it became clear that a few inconsistencies in the data collection required further data cleaning. To equalize the number of videos collected per instance (generally ranging between five and nine), we aggregated observations into weekly intervals and verified that weekly counts were relatively consistent for this time period (they ranged between 36,367 and 39,761 recommendations). Then we analyzed country-level distributions and excluded 17 countries with fewer than 130 observations per week to ensure reliable comparisons.

Our final dataset consisted of 15,963 video recommendations. Each dataset entry consisted of the following metadata: A unique video identifier (a numerical identifier of the recommended video); a country code (the ISO-2 code of the country to which the video has been recommended); the curl time (the datetime at which the data collection was performed); and DiversificationID. The DiversificationID is a topical label automatically generated by TikTok that is not available through official channels like TikTok's API but only through web-scraping, and can be used to assess the general content of the videos (Semenova et al., 2024). In this study, we did not analyze any personal information of accounts with fewer than 500,000 followers.

Our analyses focused on patterns emerging from the recommendations of TikTok content across countries and territories worldwide. First, we computed the distribution of videos per country. This allowed us to evaluate to what extent TikTok's videos are recommended globally, or conversely, to what extent TikTok's FYP is country-specific. We then focused on the 52 videos that were recommended in at least 100 countries. A cursory content analysis was conducted on this sample of videos in order to get a sense of what kind of content is pushed on a more global scale by the platform.

The core of our methodological contribution consists of the operationalization of a relational-geographical approach to the study of recommendation patterns. For this, we use network analysis as a framework to map relations and compute metrics about countries based on the patterns of co-recommendation expressed by our dataset. First, we created a bipartite graph, a network graph connecting nodes belonging to different classes, linking each video to the country to which it was recommended. Then we applied a so-called "projection" in order to convert it into a unipartite graph (i.e., a network graph connecting nodes belonging to the same class); in other words, we transformed the video-to-country graph into a network graph in which countries are connected among each other (country-to-country graph) based on patterns of co-recommendation. We used the network graph visualization software Gephi (https://gephi.org) to visually map the projected network graphs (mapping country-to-country relations) and to visually inspect their general properties. We used the force-directed layout algorithm ForceAtlas2 to spatialize the nodes of the graph, meaning that the closer two countries appear visually, the more video recommendations they share.

As a result, we were able to map the algorithmically-mediated spatial relations among countries for which we collected TikTok recommendations, and compare them to other geographical and cultural patterns. We inspected these relations visually through the network graph. However, computationally, we developed three indexes that characterized the structure of the country-to-country network, and plotted their evolution over time: the isolation index, the proximity index, and the regionality index.

The isolation index is a node-level index (i.e., an index related to each individual country) that measures the extent to which a country tends to receive country-specific recommendations; hence, it is more disconnected from the global recommendation network:

- For each video node, we first compute its locality as the inverse of its degree (i.e., number of connections); videos connected to fewer countries will get a higher locality weight.

- For each country node, isolation is measured as the ratio between the sum of the locality indexes of each neighbour (i.e., video connected to the country) and the number of the node's neighbours.
- If a country's recommended videos are widely recommended to other countries, then the country is less isolated. If it has no video at all, it is treated as fully isolated.

In other words, the isolation index measures how much a country relies on local videos (either country-specific or connected to a few other countries), rather than more global ones.

The proximity index is an edge-level index (i.e., an index related to the connection among countries) that measures the extent to which a pair of countries tends to receive common recommendations, hence resulting in them being particularly close to each other in the overall network:

- For each projected edge (i.e., link among countries), a weight is defined as the number of recommendations that the two countries share.
- The weight is subsequently normalized, dividing its value by the smaller number of recommendations among the two countries (which corresponds to the maximum value the weight can have), in order to account for the uneven number of recommendations per country we collected.
- If two countries share many of the same recommendations, their proximity index will be higher. If two countries do not share any recommendations, their proximity index will be zero.

In other words, the proximity index measures how close two countries are in terms of TikTok's content recommendations.

The regionality index is a graph-level index (i.e., an index related to the overall network among countries) that measures the extent to which countries within the same geographical region (e.g., continent) tend to receive the same recommendations, as compared to countries belonging to different geographical regions:

- For each projected edge (i.e., link among countries), a proximity index is calculated as above.
- Internal proximity is calculated as the sum of the proximity of countries belonging to the same geographical area. Total proximity is instead the sum of the proximity among all existing country pairs.
- The regionality index is calculated as the ratio between internal proximity and total proximity provided.
- If recommendations tend to be shared among countries within the same region, the regionality index will be higher.

In other words, the regionality index measures the extent to which recommendations tend to stay within certain geographical regions, rather than transcending them.

5. Findings

5.1. Video Distribution Across Countries

In Figure 2, we can see the distribution of videos across countries on a log-scaled axis, so the steep left-to-right drop reflects orders of magnitude: most videos are recommended in 1–5 countries, and counts fall rapidly as reach expands, yielding a highly skewed, long-tailed distribution. Our analysis shows that

69.28% of the content is recommended in only one country, comprising most of the recommendations; 90.50% are recommended in no more than four countries, and 98.39% of the videos are recommended in 20 countries or fewer. Only a small minority of videos (0.07%, 52 videos) reach more than 100 countries—the true global breakouts. Occasional small spikes at specific country counts may stem from market availability, geo-targeting rules, or coordinated distribution patterns. Here, "reach" means the number of distinct countries with at least one recommendation for the video across the three months, not the volume of recommendations within each country.

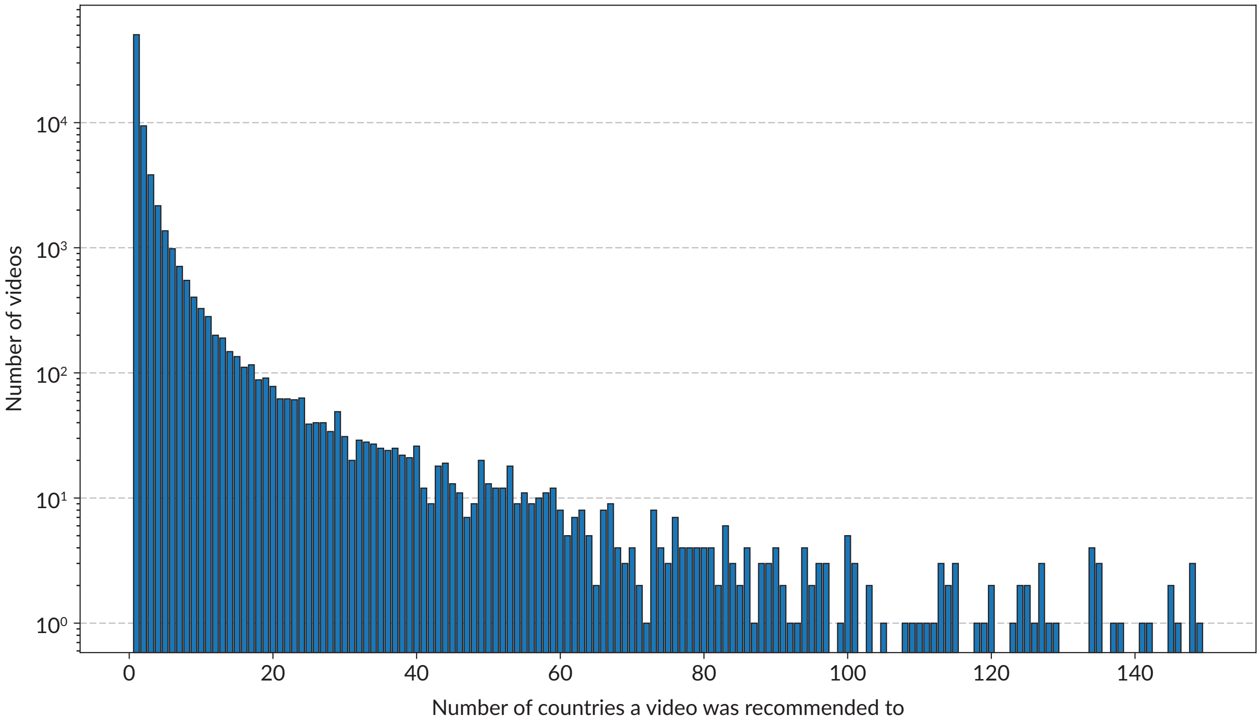

Figure 2. Distribution of videos by the number of countries they were recommended in.

To better understand the types of videos that are most recommended across countries, we conducted a qualitative analysis of the top 20 most recommended videos in our dataset, and we considered only two channels in the top 20 that had more than one video appear. This analysis is supposed to only give a glimpse of what type of qualitative analysis can be done with the dataset, but further researchers should expand the scale to make observations generalizable.

We found that the influencer Kristina Kika Kim (@kikakiim) has the highest presence in the top 20 videos, with eight total videos appearing. Kika Kim also published the most recommended video in our data collection, with 2,513 occurrences, almost one thousand times more than the second most frequently recommended video (1,469 occurrences), where she shows a makeup routine (represented in Figure 3). Kristina Kim is a 22-year-old Japanese TikTok star based in Kazakhstan, and primarily working for American and Asian audiences: She is known for creating lip-sync, point-of-view, and dance videos on the platform.

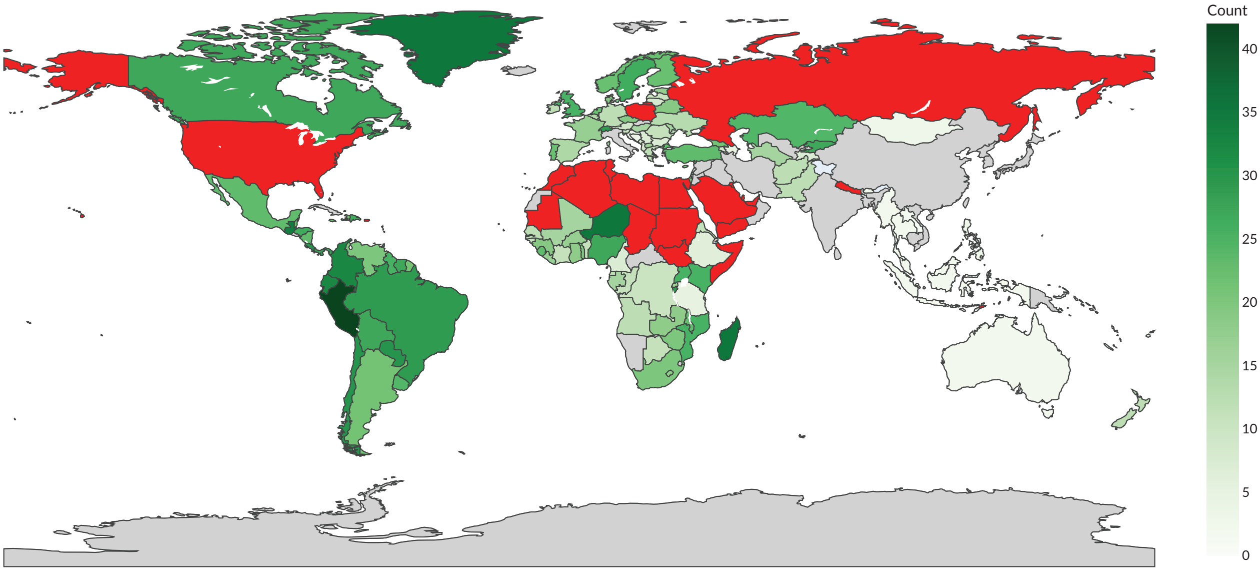

Figure 3. Geographical distribution of the most recommended Kristina Kika Kim video. Note: Recommended countries are shown in green, non-recommended countries in red, and those with unavailable data are in grey.

There is only one other influencer who appears more than once (three times) in the top 20 most frequently recommended videos in our dataset: the French TikToker Deborah Yowa, known for creating ASMR food content. Her TikToks feature her eating different foods following a list of emojis in the form of a challenge. Her most recommended video has 926 in our dataset (represented in Figure 4).

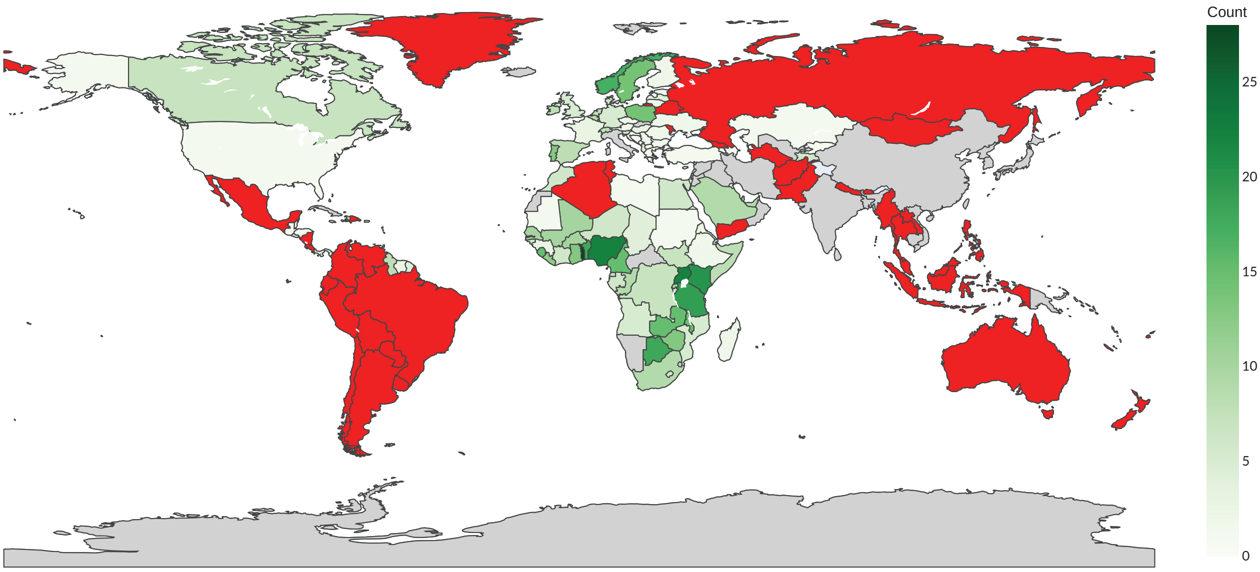

Figure 4. Geographical distribution of the most recommended Deborah Yowa video. Note: Recommended countries are shown in green, non-recommended countries in red, and those with unavailable data are in grey.

In general, looking at the topical labels (called Diversification IDs) attributed by the platform to the top 20 videos, the set seems to be skewed toward short-form, visual entertainment, and lifestyle, which is recognized to be typical TikTok content. The dominant themes are dance and performance ("Finger Dance & Basic Dance," "Singing & Dancing," "Lip-sync," "Talents"), alongside food content ("Cooking," "Food Display," "Mukbangs & Tasting," "Food & Drink"), and personal care and style ("Hair," "Beauty & Care," "Beauty & Style"). There are also two videos identified with family-oriented clips ("Babies," "Family & Relationship"), but they could also fall into the category of dance and performance, as they only mention "father" and "son" but in an ironic way, while showing some dance moves. Only one video contained a direct ad of a product, in this case, a phone cover, and it is the video with the fewest likes, comments, and shares among the top 20, suggesting that its presence could be related to a non-organic diffusion of the content such as through a paid advertising campaign. Looking at the most frequent labels attributed by the platform to the videos recommended to only one country, we can see a similar distribution: The most frequent are again performance, lip-sync, comedy, entertainment, and lifestyle. In practice, what we found was mostly highly shareable clips like dance challenges and lip-syncs, cooking and tasting reactions, and beauty routines aimed at the mainstream public; those videos are dominant in our dataset, likely reflecting their overall prominence on the platform, and they are also more likely to be recommended to users who are not logged in, rather than more niche content.

All the videos in the top 20 were recommended in at least 118 countries, and some in up to 154 (the most recommended videos from Kika Kim), meaning all of them were videos with an almost global reach. No video reached the whole list of countries in the timeframe we analyzed and the differences in geographical reach are quite prominent, even among the most recommended videos. As we can see, comparing the countries in which the most recommended videos from the two influencers are shown, the differences are striking. While Kika Kim is quite often recommended in South America, Deborah Yowa is completely absent from there, and instead, she is present in North Africa, where Kim is not being recommended.

5.2. Geographical Patterns in the Co-Recommendation Network

Figure 5 represents the network graph connecting countries based on patterns of co-recommendations. This means that the more two countries are recommended the same set of videos the more connected they are, and the closer they are displayed in the network visualization. The nodes representing the countries have been colored according to their respective continent, so that an assessment of the clustering of colors in the graph space provides an idea of the extent to which classical geographical proximity maps into platform-mediated proximity. The visualization refers to the overall timeframe of nine weeks.

A visual analysis of the graph provides a number of insights into how TikTok remediates classical patterns of geographical proximity. While the few quasi-global videos discussed before provide a backbone of universal connectivity, a number of distinctive patterns emerge. Most of the countries (around 150) are grouped in a macro cluster, while some (e.g., Bangladesh, Russia, US) are pushed to the periphery of the graph—i.e., they are isolated from the global recommendation network. Despite the overall background of connectivity, we can observe that certain connections among countries are being foregrounded, as noticeable by thicker edges. The distribution of the colors of the nodes indicates that countries tend to cluster around pre-existing regional groups—not only continents, but also finer-grained regional divisions such as North Africa and Sahara-bordering countries or the ex-USSR countries in Europe. There are, however, a few exceptions to this like Puerto Rico, Guam, and Niue. A more precise analysis also revealed some unexpected connections such as Mongolia and Micronesia, Monaco and Albania, and Gibraltar and the Faroe Islands.

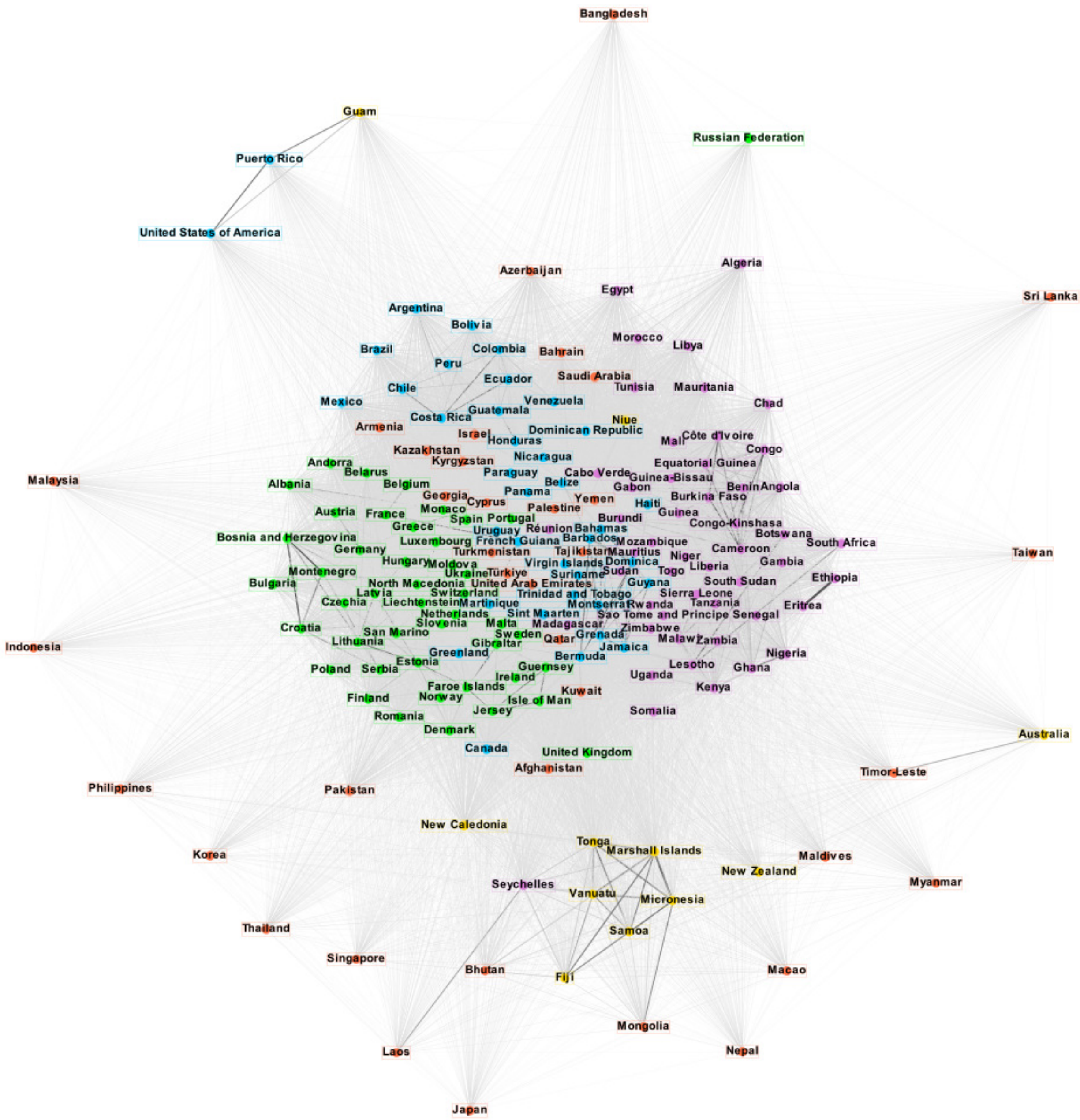

Figure 5. Country-to-country network graph (projection of country-to-video). Note: The colors are according to continents—Africa is violet, America is blue, Asia is orange, Europe is green, and Oceania is yellow.

In order to evaluate more precisely which countries tend to be served country-specific recommendations, rather than sharing recommendations extensively with others, we computed an Isolation Index. Table 1 reports the 20 countries that are most isolated from the global recommendation network. We can observe how most of these countries belong to South-East Asia and Oceania, and include several islands. Notably, countries like Russia and the US are both significantly isolated from the global network.

Moving to inspect the stronger connections, Table 2 lists the 20 pairs of countries that score the highest in terms of proximity. This index, corresponding to the weight of the country-to-country network, measures the extent to which two countries tend to have the same content recommended to them. We can note how the pairs of countries sharing the most all belong to the same geographical region. The most tightly connected regions appear to be the Horn of Africa, the Baltic countries, the Balkans, Micronesia, Polynesia, and the Caribbean.

Table 1. List of top 20 countries per isolation index.

#	Country	Isolation Index
1	Bangladesh	0.98
2	Sri Lanka	0.95
3	Taiwan	0.91
4	Indonesia	0.91
5	Nepal	0.90
6	Japan	0.88
7	Malaysia	0.88
8	Russia	0.86
9	Myanmar	0.84
10	Korea	0.83
11	Thailand	0.82
12	Philippines	0.82
13	Singapore	0.79
14	Australia	0.78
15	Laos	0.72
16	Guam	0.69
17	New Zealand	0.68
18	US	0.68
19	Maldives	0.66
20	Puerto Rico	0.64

Table 2. List of top 20 country pairs per proximity index.

#	Country1	Country2	Proximity Index
1	Ethiopia	Eritrea	0.58
2	Micronesia	Marshall Islands	0.50
3	Latvia	Lithuania	0.43
4	Tonga	Micronesia	0.42
5	Barbados	Bahamas	0.41
6	Grenada	Dominica	0.41
7	Vanuatu	Marshall Islands	0.40
8	Grenada	Barbados	0.40
9	Tonga	Marshall Islands	0.40
10	Dominica	Barbados	0.40
11	Tonga	Samoa	0.40
12	Serbia	Montenegro	0.38
13	Croatia	Bosnia and Herzegovina	0.38
14	North Macedonia	Montenegro	0.38
15	Vanuatu	Tonga	0.38
16	Vanuatu	Micronesia	0.37
17	Bosnia and Herzegovina	Montenegro	0.37
18	Latvia	Estonia	0.37
19	Montserrat	Dominica	0.37
20	Isle of Man	Jersey	0.36

The tendency of countries to cluster according to pre-existing regional borders has been measured as the regionality index—i.e., the proportion between (weighted) edges within regions (in this case, continents) and the total. In the timeframe considered, this score is 0.34, indicating that despite the overall regional clustering, there is room for non-regional connections.

6. Discussion

By analyzing the recommendations served over time on the browser version of TikTok's FYP to unlogged-in users, we can compare the content delivered to users by manipulating only their IP address location. Even in a timeframe of nine weeks, we can see threads consolidating across the world, giving us a glimpse into the logic that drives algorithmic recommendations on the platform. The data shown to all users accessing the homepage without logging in and without any interaction with the platform represents the most public type of data that can be found on TikTok, and is therefore a useful way to study the showroom of the platform around the world and how algorithmic recommendations shape the content served around the world.

6.1. Virality Is Never Really Global

As we saw, analysing the videos' distribution across countries and comparing the geographical reach of the most frequently recommended videos in our dataset, even the most viral videos are not recommended all over the world but only in a subset of countries, which seem to be chosen not randomly but rather according to where a certain user base might be more present. In the example we made, it seems that content can be spread across a continent in a quite homogeneous way (as in the case of South America for the most recommended video in our dataset), but can be excluded from other regions like North Africa.

Our analysis suggests that there is not a single type of virality if we look at virality from a cross-national perspective. Saying a video is viral because it generated a lot of engagement and interactions might be reductive, as we should always geographically locate virality. It is as important to know a video is viral as to know *where* the video is viral. Once a video becomes viral in a certain region, it will then be recommended in proximate countries, but this does not mean that it will necessarily achieve a global reach. It seems that similarities across countries, like regulation, language, and cultural and geographical proximity, are key to understanding how TikTok's algorithm works across the world. To study these factors contributing to defining the virality of content, we designed the proximity, isolation, and regionality indexes.

6.2. Proximity

Creating a network graph of the countries based on the number of recommendations they share, we can see that the geographical proximity of countries and territories plays a major role in determining which content is suggested where. Countries on the same continent tend to cluster together, such as Europe, Africa, and South-Central America, and are grouped together in different parts of the network graph. At the same time, not all the continents are so proximate to each other based solely on continental appurtenances. Particularly, Asia is clearly divided into two: West Asian countries like Armenia, Israel, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, Georgia, Türkiye, the Arab Emirates, Yemen, Palestine, Qatar, and Kuwait are quite distant from East Asian countries. These East Asian countries, like Malaysia, the Philippines, Korea, Taiwan, Singapore, Laos, Japan, Nepal, Macao, and Myanmar, seem to have fewer connections to the main cluster at the center of the graphic. Instead, they remain on the periphery of the network, possibly suggesting they might have more country-specific recommendations and some common recommendations shared among them as West Asian countries. Similarly, many of the island countries belonging to Oceania and like New Caledonia, Tonga, Marshall Islands, Vanuatu, Micronesia, Samoa, Fiji, and New Zealand are clustered together and some of them have among the highest values of proximity like Micronesia-Marshall Islands (0.50), Tonga-Micronesia (0.42), or Vanuatu-Marshall Islands (0.40), possibly reflecting the relatively limited volume of locally produced content in these countries. More generally, many of the top 20 country pairs by proximity index involve geographically close, small-population countries. This pattern may indicate that smaller countries generate less distinct content and therefore receive largely overlapping recommendations, as if they were treated similarly by the algorithm. Interestingly, while most of the West Asian countries receive among the highest values in the isolation index—indicating that they occupy peripheral positions in the network and are not strongly connected to one another—the island countries from Oceania, although located outside of the main cluster at the center of the network, are closely connected. As a result, they do not show up in the top 20 isolation index table, due to the strong connections between them. This example refines Lemley's (2021) account of the "splinternet," showing that before two countries fully sever ties, partial internet blocks plus shared social platforms can produce an algorithmic split that isolates them without cutting them off entirely.

Also, inside the European continent, some countries share more recommendations, creating a sub-region with stronger relations between states. For example, Latvia, Lithuania, and Estonia (ex-USSR), Bosnia and Herzegovina, Montenegro, Croatia, and Serbia (ex-Yugoslavia), are closely connected: Latvia–Lithuania (0.43), Serbia–Montenegro (0.38), and Croatia–Bosnia and Herzegovina (0.38). They are among the countries that are more strongly related to each other, as they share not only geographical proximity but also cultural proximity, which results in platform-mediated proximity. It is important to note how such strong connections do not necessarily involve countries with a shared (official) language, a factor that could help explain the algorithmic proximity even more.

6.3. Isolation and Content Moderation

At the same time, Oceanian island countries share many recommendations with other island countries like the Seychelles, which belong to the African continent, which cluster in a different part of the network. Another country that does not cluster together with the other countries of its continent is the Polynesian Pacific island of Niue: Even if it is a state "freely associated" with New Zealand and geographically positioned in Oceania, it shares most of its recommendations with South American countries and some African countries instead of grouping together with the other Oceanian island countries. Similarly, the US shares many of the recommendations with Puerto Rico (situated in North America) and Guam (part of Oceania), two of the US territories defined as "permanently inhabited territories" where citizens acquire US citizenship by birth, and they elect non-voting members to the US House of Representatives who can introduce new legislation. Those three countries have a high isolation index score (between 0.69 and 0.64), and they appear in the top 20 list of the most isolated countries, showing that their closeness is also distancing them from the rest of the countries, probably because the US has a high volume of new content published and a lot of country-specific recommendations. Interestingly, the US Virgin Islands, although a permanently inhabited US territory, does not receive recommendations similar to those of the US, Guam, or Puerto Rico. Instead, they cluster with the main group, suggesting either the absence of a distinct set of recommendations or alignment with geographically proximate countries. This indicates that the platform does not treat the US Virgin Islands as algorithmically close to the US, despite their comparable legislative status.

Looking at the most isolated countries with the highest values in the isolation index, besides the East Asian countries that show a similar pattern of being outside the main cluster, we also find countries like Russia and Bangladesh where specific censorship rules have been approved. After the large-scale invasion of Ukraine started on the 24th of February 2022, Russia blocked several non-Russian social media, accusing them of non-compliance with the "anti-fake news" law (Troianovski & Safronova, 2022). Researchers have shown that TikTok was not among the platforms blocked, even though a major update on the type of content recommended to users with a Russian IP was developed, making most of the international content not accessible for them and creating a sort of nationalized version of the platform able to comply with the strict censorship regulation (Romano et al., 2022). Similarly to Russia, Bangladesh, the most isolated country in our dataset, banned TikTok for a period in 2021 after a human trafficking network was found to have been using it to recruit young users. After being reintroduced, TikTok was definitively banned from Bangladesh in 2024, as an act of repression against the quota reform movement (Turzo, 2024). While it was not banned during the period considered in our dataset, it is possible to consider that the platform was recommending a more isolated subset of content in this country to avoid further problems with regulators. TikTok was also banned from government devices in December 2022 in Taiwan, during the timeframe considered in this article, and it was banned in 2018 in Indonesia for a few days. Similar cases also happened in most of the other highly isolated countries. This could suggest that political pressure from national governments against the platform with specific regulations could lead the platform to create a more moderated version of the app in certain countries, highlighting how algorithmic recommendations are driven by different socio-economic factors, not only technical developments, including regulations and political events, as described by Bucher (2016). As she argues, algorithmic power is conditional and eventful; real-time counter-mapping of censorship and platform systems shows it is exercised at specific moments, in conjunction with other forms of power, rather than continuously possessed (Bucher, 2018).

7. Conclusion

In this article, we presented the first global and live-updated dataset of geolocated recommendations on TikTok. The TKGO represents a new opportunity for researchers to explore the geographical dimension of algorithmic content's prioritization and moderation. Its data collection is independent from any platform interference and represents a working example of data re-appropriation and counter-mapping in the field of algorithmic studies.

The geographical distribution of some of the most recommended videos in our dataset suggests that virality is never truly global, but rather regional. The country-to-country network and the proximity, regionality, and isolation indexes that describe its structural properties provide a replicable framework to study and monitor the relations among countries emerging from algorithmic recommendations. Our analysis shows how TikTok's recommender system tends to follow pre-existing geographies such as continents and sub-regions. However, it also shows how some countries are more isolated than others, meaning they have a more country-specific set of recommendations. We also found cases of countries not following the general schema of the continents and subregions, but rather following regulations and legislative boundaries. The TKGO counter-data mapping effort can help reduce the opacity surrounding the platform-mediated proximity effect.

The present study comes with limitations, and we point out ways to improve the reliability of our analysis. First, due to its exploratory nature, this study focused on a timeframe of a few weeks, whereas the dataset now comprises about three years of data. Monitoring the evolution of these indexes over time could provide near-real-time insights into platform politics across different geographical contexts. Second, another limitation concerns the small number of videos collected in each observation. This is an inherent constraint of our data collection technique, which does not allow us to automate scrolling to retrieve additional content. As a result, it is possible that videos appearing beyond the first page are systematically different from those initially pre-loaded. Implementing such a setup would require substantially higher bandwidth, rendering it unsustainable in practice. Future work that explores content beyond the first set of pre-loaded videos would help strengthen the reliability of our results. Third, on a similar note of statistical reliability, a more in-depth assessment of the patterns explored here should include a focus on within-country variance, in order to assess whether the observed cross-country variance is explained by geographical factors rather than by a generally highly variable composition of recommendations.

There are also a number of analytical directions that this article did not consider, but that represent a useful expansion of our approach. First, in this study, we checked the distribution of the most recommended videos across countries but we did not check the diffusion of the most viral videos. This different angle could be used to find more discrepancies and similarities among countries, as well as to study the platform's logic of virality. Second, we did not systematically engage with the content of the videos upon which the scrutinized proximities depend. In particular, we did not systematically assess the effect of shared language, likely an important variable—albeit, according to our findings, not always a determinant. Understanding the role of (minority) language in driving platform-mediated proximities will help shed light on TikTok's cultural politics. Similarly, we only conducted a qualitative exploration of the 20 most-recommended videos in our dataset. This does not allow us to reliably identify the drivers behind their popularity, as doing so would require a substantially larger sample and systematic statistical analysis. Our goal in this section is simply to provide a glimpse of the content we encountered; a larger-scale quantitative analysis would be needed to draw more generalizable conclusions. Finally, further initiatives could replicate the data collection and analysis framework we presented in this article on other platforms, enabling comparative analysis and establishing a cross-platform observatory.

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Conflict of Interests

The authors declare no conflict of interest.

Data Availability

All the data collected for this study are available on request to researchers able to meet privacy standards. A version of the dataset without accounts with less than 500,000 followers can be accessed on the website of the TikTok Global Observatory. The measures on data protection for this article have been reviewed by the Ethics Committee of the Universitat Oberta de Catalunya and approved with the code CE25-TE31.

LLMs Disclosure

The authors employed generative AI tools to refine grammar and sentence fluency. The authors have reviewed and validated all submission content.

Supplementary Material

Supplementary material for this article is available online in the format provided by the author (unedited).

References

AI Forensics. (2025). *TikTok global observatory*. https://tkgo.aiforensics.org

Aleman, E., & Martinez, R. (2024). "It's like they are using our data against us." Counter-cartographies of AI literacy. *Reading Research Quarterly*, *59*(4), 665–677. https://doi.org/10.1002/rrq.574

Araujo, T., Ausloos, J., van Atteveldt, W., Loecherbach, F., Moeller, J., Ohme, J., Trilling, D., van de Velde, B., de Vreese, C., & Welbers, K. (2022). OSD2F: An open-source data donation framework. *Computational Communication Research*, *4*(2), 372–387.

Balogun, S. K., & Aruoture, E. (2024). Cultural homogenization vs. cultural diversity: Social media's double-edged sword in the age of globalization. *African Journal of Social and Behavioural Sciences*, *14*(4), 1491–1512. https://journals.aphriapub.com/index.php/AJSBS/article/view/2722

Beraldo, D., & Milan, S. (2019). From data politics to the contentious politics of data. *Big Data & Society*, *6*(2). https://doi.org/10.1177/2053951719885967

Beraldo, D., Milan, S., de Vos, J., Agosti, C., Sotic, B. N., Vliegenthart, R., Kruikemeier, S., Otto, L. P., Vermeer, S. A. M., Chu, X., & Votta, F. (2021). Political advertising exposed: tracking Facebook ads in the 2021 Dutch elections. *Internet Policy Review*. https://policyreview.info/articles/news/political-advertising-exposed-tracking-facebook-ads-2021-dutch-elections/1543

Biddle, S., Ribeiro, P. V., & Dias, T. (2020, March 16). Invisible censorship: TikTok told moderators to suppress posts by "ugly" people and the poor to attract new users. *The intercept*. https://theintercept.com/2020/03/16/tiktok-app-moderators-users-discrimination

Bruns, A. (2021). After the 'APIcalypse': Social media platforms and their fight against critical scholarly research. In S. Walker, D. Mercea, & M. Bastos (Eds.), *Disinformation and data lockdown on social platforms* (pp. 14–36). Routledge.

Bucher, T. (2016). Neither black nor box: Ways of knowing algorithms. In *Innovative methods in media and communication research* (pp. 81–98). Springer.

Bucher, T. (2018). *If...then: Algorithmic power and politics*. Oxford University Press.

Cervi, L., & Divon, T. (2023). Playful activism: Memetic performances of Palestinian resistance in TikTok #Challenges. *Social Media + Society*, *9*(1). https://doi.org/10.1177/20563051231157607

Dalton, C. M., & Stallmann, T. (2018). Counter-mapping data science. *The Canadian Geographer/Le Géographe Canadien*, *62*(1), 93–101. https://doi.org/10.1111/cag.12398

D'Ignazio, C., Cruxên, I., Martinez Cuba, A., Suarez Val, H., Dogan, A., & Ansari, N. (2025). Geographies of missing data: Spatializing counterdata production against feminicide. *Environment and Planning D: Society and Space*, *43*(1), 29–50.

Dixon, S. J. (2025). *Most popular social networks worldwide as of February 2025, by number of monthly active users*. Statista. https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users

Entrena-Serrano, C., Degeling, M., Romano, S., & Çetin, R. B. (2025). *TikTok's research API: Problems without explanations*. arXiv. https://doi.org/10.48550/arXiv.2506.09746

Flew, T. (2023). The return of the regulatory state: Nation-states as policy actors in digital platform governance. In C. Padovani, V. Wavre, A. Hintz, G. Goggin, & P. Iosifidis (Eds.), *Global communication governance at the crossroads* (pp. 161–178). Springer.

Franzke, A. S., Bechmann, A., Zimmer, M., Ess, C. M., & Association of Internet Researchers. (2020). *Internet research: Ethical guidelines 3.0*. Association of Internet Researchers. https://aoir.org/reports/ethics3.pdf

How we combat unauthorized data scraping of TikTok. (2024, October 25). *TikTok Privacy Center Blog*. www.tiktok.com/privacy/blog/how-we-combat-scraping/en

Ionescu, C. G., & Licu, M. (2023). Are TikTok algorithms influencing users' self-perceived identities and personal values? A mini review. *Social Sciences*, *12*(8), Article 465. https://doi.org/10.3390/socsci12080465

Jeppesen, S., & Sartoretto, P. (2023). Cartographies of resistance: Counter-data mapping as the new frontier of digital media activism. *Media and Communication*, *11*(1), 150–162. https://doi.org/10.17645/mac.v11i1.6043

Kazansky, B., Torres, G., van der Velden, L., Wissenbach, K., & Milan, S. (2019). 14: Data for the social good: Toward a data-activist research agenda. In A. Daly, S. K. Devitt, & M. Mann (Eds.), *Good data* (pp. 244-259). Hogeschool van Amsterdam. https://research.hva.nl/en/publications/good-data

Lemley, M. A. (2021). *The splinternet*. SSRN. https://doi.org/10.2139/ssrn.3664027

Tomasik, E., & Matsa, K. E. (2024, September 25). 1 in 5 Americans now regularly get news on TikTok, up sharply from 2020. *Pew Research Center*. https://www.pewresearch.org/short-reads/2024/09/17/more-americans-regularly-get-news-on-tiktok-especially-young-adults

Li, Y., Cheng, Z., & De Zúñiga, H. G. (2025). TikTok's political landscape: Examining echo chambers and political expression dynamics. *New Media & Society*. Advance online publication. https://doi.org/10.1177/14614448251339755

Milan, S., & van der Velden, L. (2016). The alternative epistemologies of data activism. *Digital Culture & Society*, *2(2)*, 57–74. https://doi.org/10.14361/dcs-2016-0205

Pallin, C. V. (2017). Internet control through ownership: The case of Russia. *Post-Soviet Affairs*, *33*(1), 16–33. https://doi.org/10.1080/1060586X.2015.1121712

Pearson, G. D., Silver, N. A., Robinson, J. Y., Azadi, M., Schillo, B. A., & Kreslake, J. M. (2025). Beyond the margin of error: a systematic and replicable audit of the TikTok research API. *Information, Communication & Society*, *28*(3), 452–470.

Regulation (EU) 2022/2065 of the European Parliament and of the Council of 19 October 2022 on a Single Market for Digital Services (Digital Services Act) and amending Directive 2000/31/EC, Article 40. (2022). *Official Journal of the European Union*, L 277. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32022R2065

Rincón, D. A., Denkovski, O., Romano, S., & Degeling, M. (2025). *Unpacking TikTok's data access illusion*. Tech Policy Press. https://www.techpolicy.press/unpacking-tiktoks-data-access-illusion

Rogers, R. (2019). *Doing digital methods*. Sage.

Romano, S., Faddoul, M., Agosti, C., Giorgi, G., & Doherty, L. (2022). *Tracking Exposed special report: TikTok content restriction in Russia*. Tracking Exposed. https://tracking.exposed/pdf/tiktok-russia-15march2022.pdf

Romano, S., Kerby, N., Schüler, M., Beraldo, D., & Rama, I. (2023). The impact of TikTok policies on information flows during times of war: Evidence of 'splinternet' and 'shadow-promotion' in Russia. *AoIR Selected Papers of Internet Research*, *2023*. https://doi.org/10.5210/spir.v2023i0.13487

Sandvig, C., Hamilton, K., Karahalios, K., & Langbort, C. (2014, May 22). Auditing algorithms: Research methods for detecting discrimination on internet platforms [Paper presentation]. Data and discrimination: Converting critical concerns into productive inquiry, Seattle, WA, USA.

Semenova, A., Degeling, M., & Hess, G. (2024, August 26). Understanding TikTok's For You Feed. *auditing TikTok*. https://tiktok-audit.com/blog/2024/For-You-Feed

TikTok. (2020). *How TikTok recommends videos #ForYou*. https://newsroom.tiktok.com/en-us/how-tiktok-recommends-videos-for-you

Trans, M., Beraldo, D., Draisci, L., Afsahi, L., Brennan, M., Goldschmidt, V., Grendarova, T., Hamilton, H., Keskin, M., Papasokratous, M., Rossetti, G., Webb, M., Williams, J., & Xu, H. (2024). *APIcalypse now: Redefining data access regimes in the face of the Digital Services Act*. Digital Methods Initiative. www.digitalmethods.net/Dmi/WinterSchool2024APIcalypse

Troianovski, A., & Safronova, V., (2022, March 4). Russia takes censorship to new extremes, stifling war coverage. *The New York Times*. www.nytimes.com/2022/03/04/world/europe/russia-censorship-media-crackdown.html

Turzo, M. A. P. (2024). *The impact of digital platforms on Bangladesh's 2024 student-led revolution: Analysing the role of social media as a catalyst*. ResearcGate Preprint. www.researchgate.net/publication/383669262_The_Impact_of_Digital_Platforms_on_Bangladesh%27s_2024_Student-Led_Revolution_Analysing_the_Role_of_Social_Media_as_a_Catalyst

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