

# **Forgetful by Design? A Critical Audit of YouTube's Search API for Academic Research**

Bernhard Rieder<sup>a</sup>, Adrián Padilla<sup>b\*</sup>, and Òscar Coromina<sup>c</sup>

*<sup>a</sup>Mediastudies Department, University, City, Country; <sup>b</sup>Department of Communication and Advertising, Euncet Business School, Terrassa, Spain; <sup>c</sup>Department of Audiovisual Communication and Advertising, Universitat Autònoma de Barcelona, Barcelona, Spain*

\* Adrián Padilla, Euncet Business School, Dpt. of Communication and Advertising, Camí del Mas Rubial 1, 08225 Terrassa, Spain; Email: apadilla@euncet.com

Bernhard Rieder is Associate Professor of New Media and Digital Culture at the University of Amsterdam and a collaborator with the Digital Methods Initiative. His research focuses on the history, theory, and politics of software and on the role algorithms play in the production of knowledge and culture. This work includes the development, application, and analysis of computational research methods and the investigation of political and economic challenges posed by large online platforms.

Adrián Padilla is Professor of Communication and Digital Audiences at EUNCET Business School. His research focuses on the social and cultural impact of user-generated content platforms and social networks, with a particular interest in the phenomenon of disinformation and YouTube. He specializes in data collection using API-based methods, data mining, and computational methods applied to social sciences research.

Òscar Coromina is a Serra Hunter Fellow at the Faculty of Communication Studies at the Universitat Autònoma de Barcelona and a member of the STS-B research group at the same institution. His work focuses on the mediation of digital platforms in politics, culture, and knowledge production, and he has a long track record of research using digital and computational methods.

# Forgetful by Design? A Critical Audit of YouTube's Search API for Academic Research

This paper critically audits the search endpoint of YouTube's Data API (v3), a common tool for academic research. Through systematic weekly searches over six months using eleven queries, we identify major limitations regarding completeness, representativeness, consistency, and bias. Our findings reveal substantial differences between ranking parameters like *relevance* and *date* in terms of video recall and precision, with *relevance* often retrieving numerous off-topic videos. We also find severe temporal decay, as the number of findable videos for a specific period dramatically decreases after just 20-60 days from the publication date, potentially hampering many different research designs. Furthermore, search results lack consistency, with identical queries yielding different video sets over time, compromising replicability. A case study on the European Parliament elections highlights how these issues impact research outcomes. While the paper offers several mitigation strategies, it concludes that the API's search function, potentially prioritizing 'freshness' over comprehensive retrieval, is not adequate for robust academic research, especially concerning Digital Services Act requirements.

Keywords: YouTube API; API audit; social media research; research methodology;

## Introduction

Since the early days of social media, researchers have continually struggled with the question of how to access relevant data to study these platforms. While the period until roughly 2015 has been characterized as a 'Wild West', where academics could 'compile huge troughs of data with few constraints' (Puschmann, 2019, p.1582), the aftermath of the Cambridge Analytica scandal contributed to what has been termed an 'APIcalypse' (Bruns, 2019), where platforms like Facebook and Instagram, in particular, heavily curtailed researchers' capacity to collect data. The following 'Post-API Age' (Freelon, 2018) saw attempts at creating Industry-Academic partnerships like Social Science One (King & Persily, 2018) to fill the void, but these initiatives were hardly successful. The

EU's Digital Services Act (DSA), which came into force in 2022 and continues to be implemented, is set to disrupt the research landscape once more, as it includes specific access provisions for researchers studying 'very large online platforms'. In its wake, the major players - including Facebook, Instagram, TikTok, YouTube, and Twitter (now X) - have introduced, repurposed, or reactivated APIs and launched bespoke data access programs specifically for (European) researchers. Although encouraging, these initiatives raise questions about the scope and limitations of access, including coverage, completeness, representativeness, and other 'data quality' issues that affect researchers' capacity to generate knowledge.

Scholars have long discussed the central, yet ambivalent role APIs play in academic research (e.g., Giletto et al., 2012; Driscoll, 2014). Despite the recognition that 'social media companies not only control researchers' access to data, but can also manipulate their systems in a way that affects the findings' (Graham, 2024, n.p.) attention to data quality is scarce outside of an overall limited number of studies that focus specifically on the issue. Twitter, long lauded as the platform most open to researchers (e.g., Tromble, 2021), is a notable exception as it has received considerable scrutiny when it comes to assessing data quality over the years (Morstatter et al., 2013 and 2014; Pfeffer et al., 2023). YouTube, the second most visited website in the world<sup>1</sup>, has remained largely unexamined, however. This is particularly surprising, as the YouTube Data API (v3) was already introduced in 2014 and has overall changed relatively little, although the initially very generous daily quotas provided to developers and researchers were steadily reduced over time. When the company introduced its researcher program<sup>2</sup> in July 2022, it primarily promised eligible academics 'as much

---

<sup>1</sup> <https://www.similarweb.com/top-websites/>

<sup>2</sup> <https://research.youtube.com>

quota as required for their research’, resulting in ‘expanded access to global video metadata across the entire public YouTube corpus via API’ (YouTube Research - How It Works, n.d.). But even before that, hundreds of studies relying on the API or API-based software like the YouTube Data Tools (Rieder, 2015) had been published in most cases without much scrutiny given to data quality. Certainly, researchers may mention, for example, that the search endpoint is limited to 500 results per query or that the (now deprecated) ‘related videos’ feature is only a partial approximation of the platform’s recommender system. Beyond a series of papers discussing specific sampling techniques (e.g., Zhou et al., 2011; Malik & Tian, 2017; Bärthel, 2018; Rieder et al., 2020), we are not aware of any systematic attempts to evaluate the characteristics, quality, and limitations of the data YouTube makes available through its API.

Given that the DSA transforms data access for researchers from a benevolent gesture into a legal obligation, this paper aims to investigate the search endpoint of YouTube’s Data API, which has been frequently used by researchers across various disciplines to analyze the videos published on one of the leading social media platforms. Despite the widespread reliance on the search feature, there is limited understanding of query matching, coverage, representativeness, and the impact of different ranking parameters on the collection of empirical evidence. To investigate these questions, we adopted a ‘maximalist’ strategy designed to assemble the largest number of videos for a given query and ran comprehensive weekly searches for eleven queries over a span of six months. Our goal was to better understand how videos are made visible (or invisible) through search and what implications this has for the knowledge researchers can generate. In this paper, we provide both a critical analysis and recommendations for addressing the significant problems we encountered.

The paper proceeds in four steps. First, we briefly survey how researchers have been using the search endpoint, introduce existing API audits for social media platforms, and discuss data collection on YouTube. Second, we outline our methodology, including data collection strategies, analytical techniques, and limitations. Third, we present our findings in aggregate statistical terms as well as through a short case study designed to make them more accessible to researchers from less quantitative disciplines. Finally, we discuss implications for research, provide recommendations for future studies using the search endpoint, and suggest how YouTube could amend its systems to better serve academic audiences and comply with legal obligations.

## **Literature review**

### ***Research using the search endpoint***

As one of the most widely used social media platforms, YouTube has attracted considerable attention from researchers across a wide range of disciplines, including sociology, media studies, health communication, and political science. While YouTube's Data API has several methods that can be used for data collection, including access to channels' video lists and user comments, the search endpoint, which takes a text query as input and retrieves metadata for up to 500 videos as output, has been the main entry point for researchers. Studies relying on search generally follow one of two methodological strategies.

First, researchers may access the endpoint without any temporal restrictions, either following a more qualitative or exploratory protocol without much concern for questions of completeness or representativeness, or focusing on information visibility, trying to simulate what a user would see if they were to use the same query. For example, Pires et al. (2023) queried the API with names of online delivery services to

find videos where delivery riders talk about their experiences. Instead of relying on the full 250 videos found, they reduced their sample manually to 40, a strategy often seen in studies that emphasize in-depth qualitative analysis over representative sampling. Research centering information visibility often follows the report by Pandey et al. (2010) on H1N1 influenza videos, carrying some variation of ‘YouTube as a source of information on’ in the title. While these studies sometimes scrape YouTube’s website instead of using the API, they can be considered prototypical for a larger set of work interested in ‘the type of content average users are likely to come across when searching for information’ (Marchal et al., 2020, p.2) on what is regularly referred to as the second largest search engine in the world (Khan & Malik, 2022). Although studies of this kind are affected by questions of completeness and bias, their primary concern from a data collection perspective is the comparability of API- and website-results, given potential factors such as localization or personalization.

Second, and more crucial for the purposes of this paper, numerous studies concentrate on specific events and timeframes, aiming to reconstruct how an issue was portrayed or reported through YouTube videos. Inwood and Zappavigna (2023), for example, used the search endpoint to investigate conspiracy videos published in the 24-hr period after the Notre Dame cathedral fire in 2019; Oliva et al. (2024) tried to reconstruct the debate after Spanish YouTuber El Rubius announced that he was moving to Andorra for tax reasons; Al-Zaman (2022) and Porreca et al. (2020) used the YouTube Data Tools’ ‘one search per day’ feature - the method we use in this paper and discuss further down - to exhaustively sample, measure, and track videos related to, respectively, Islam and vaccination. These cases underscore the critical need for the search endpoint to provide accurate and consistent results, which is vital for analyzing key social issues in both current studies and future historical research (Weller, 2016).

Our larger survey of papers following either one of these methods revealed that there is overall little attention paid to the characteristics and limitations of the search endpoint. Many papers do not report the specific day a search was made and settings for the crucial *order* parameter, which has striking effects on results, are hardly mentioned. To shed light on what this means for the reliability and validity of YouTube research, particularly when following the second methodological strategy, our paper proposes an exploratory audit of the search endpoint. The following section examines similar research conducted on other social media platforms.

### ***Sampling bias and representativeness in APIs***

Research on social media data has consistently revealed significant challenges related to sampling bias and representativeness, even when data is collected through sanctioned platform APIs. This has raised broader questions about the integrity of research relying on APIs that function as ‘black boxes’ primarily designed to serve business or operational needs (Driscoll, 2014). However, given that academics often lack viable alternatives, it is essential to understand the biases that exist and how they impact research.

A foundational contribution to this context comes from Morstatter et al. (2013), who compared Twitter’s Streaming API, which provides a 1% sample of public data, with the platform’s Firehose API, granting full access. Their findings highlight significant discrepancies between the two, including variances in geographic coverage, network structure, and topic distribution, particularly pronounced during high-activity events. Further investigations by Morstatter et al. (2014) and Tromble et al. (2017) delved into the conditions under which such biases emerge, pointing to real-time trends and data spikes during major events as key amplifiers. Together, these studies underscore the importance of caution when interpreting findings derived from

API-restricted data, as these samples may not adequately represent the broader platform activity.

Similarly, Rieder et al. (2015) provided a critique of Facebook's Graph API, emphasizing the limitations of data access in the wake of increasing restrictions. They examined a large dataset obtained from Facebook Pages and identified discrepancies in the representativeness of user interactions, pointing out how platform design influences what researchers can study. Villegas (2016) further explored challenges in data retention on Facebook, documenting how content such as posts and comments can 'disappear' over time due to platform-specific data curation practices. Ho (2020) extended this discussion by reverse-engineering Facebook's ranking algorithms, revealing how specific types of content are prioritized or excluded from API results. These studies highlight that, regardless of the platform, APIs may impose unseen biases that can affect research outcomes by limiting researchers' access to high-quality samples.

Even when platforms offer expanded access under academic research programs, significant challenges may persist. Pearson et al. (2024) conducted a systematic audit of TikTok's research API - launched in July 2022 - by comparing API-retrieved metrics (e.g., comments, likes, and views) with the data displayed on the site's user interface. Their findings revealed systematic discrepancies, again putting into question the utility and reliability of official data access provisions.

While the idiosyncrasies of these social media platforms are increasingly well-documented, few studies have specifically addressed data collection on YouTube. Given the platform's central role in the digital media ecosystem, the recent expansion of API access for eligible researchers, and the widespread reliance on the search endpoint, it is crucial to better understand the level of data quality one can expect.



### *The YouTube Data API*

Although YouTube has not been the primary focus in the ongoing discourse surrounding the ‘APIcalypse’ (Bruns, 2019), the platform’s data access provisions have undergone two significant changes since the introduction of the YouTube Data API (v3), both of which have directly impacted researchers. First, API quotas have been progressively reduced, making large-scale studies increasingly difficult without resorting to alternative methods such as web scraping. While YouTube’s researcher program offers some relief by providing vetted projects with enhanced access, its scope remains limited and subject to the platform’s vetting process. Second, the removal of the ‘related videos’ feature in 2023 - a feature that, although limited, allowed some examination of algorithmic pathways - has further constrained researchers’ ability to analyze YouTube’s recommendation system.

The quality of data access through YouTube’s Data API presents a mixed picture. On the one hand, it offers a variety of methods to collect detailed data, with generally fewer restrictions than other platforms. On the other hand, there are notable limitations, such as the unavailability of video transcripts, the absence of a flag to identify Shorts, the impossibility to know whether a video is monetized, or the absence of reasons for why a video or channel is missing. The official API documentation is often silent when it comes to reporting or explaining these and other limitations. Developers therefore frequently exchange technical insights, undocumented behavior, and workarounds in forums like Stack Overflow, for example, how to check whether a video is a Short<sup>3</sup>. But these solutions often involve scraping the necessary information

---

3

<https://stackoverflow.com/questions/71192605/how-do-i-get-youtube-shorts-from-youtube-api-data-v3>

from the platform's web interface, a practice that potentially forces researchers into a legal grey zone.

One of the areas where researchers have addressed data collection specifics on YouTube are methods for collecting representative samples from the company's vast content library. The most feasible method to create a random sample for all of YouTube, 'random prefix sampling', was initially introduced by Zhou et al. (2011) and more recently validated by McGrady et al. (2023). Bärthel (2018) experimented with random search queries to trace overall trends on YouTube over time. While these methods are effective for analyzing macro-level trends, they are hardly practical for topic-specific studies as a random sample would have to be exceedingly large to contain enough videos covering individual cases or issues. The same goes for the large-scale crawling method implemented by Rieder et al. (2020). Most researchers studying specific issues therefore rely on the Data API's search function to create a collection of videos to analyze.

As Malik and Tian (2017) noted, however, the search endpoint's restriction to 500 results makes it unsuitable for large-scale data retrieval. For many studies this limitation may not be a barrier, particularly for those focused on less popular topics, specific geographic and linguistic contexts, or narrowly defined timeframes, where the number of relevant videos may be smaller. But even then, the question remains how YouTube's search system actually selects and ranks videos. While we know little in terms of technical specifics, Rieder et al. (2018) demonstrated that search rankings can fluctuate significantly, especially for 'newsy' queries that experience high levels of uploads and user engagement. This volatility underscores the importance of timing in data collection and highlights the challenges of replicating studies that depend on search-based data.

Given the prevalence of query-based approaches in YouTube research, this paper explores several critical questions surrounding the search endpoint: How do different ranking parameters change which videos are matched to a given query? How does temporal distance affect search outcomes? What are the implications of these findings for researchers? And finally, how can researchers adapt their data collection strategies to mitigate limitations and enhance the robustness of their studies?

## **Method**

To analyze the Data API's search endpoint in detail, this paper takes a 'maximalist' approach and tries to collect exhaustive samples for a set of queries. We rely on a method used by researchers (e.g., Porreca et al., 2020; Al-Zaman, 2022; Violot et al., 2024) to circumvent the search endpoints' limit to 500 results per query. Instead of making only one call to the search endpoint, the 'one search per day' principle cuts a longer timeframe into several days (or other intervals) and makes a separate call for videos published on each one of these days. For example, when searching for videos published in a specific week, one could make seven individual calls to the API, each one limited to a single day, yielding up to 3500 videos instead of 500. If the search endpoint were to allow for full coverage of the underlying population of relevant videos, this would enable full retrieval for all but the largest topics, where video production exceeds 500 videos per day. For this paper, we used the YouTube Data Tools (Rieder, 2015), which implemented a 'one search per day' feature in 2018, and ran searches for eleven queries weekly over the span of six months starting in April 2024. For each query, we set the starting date to October 15, 2023 and requested up to 500 results per day.

The Data API's search endpoint, however, adds another layer of complexity by offering several ranking principles through the *order* parameter, with limited

information on how they differ beyond very general terms. While YouTube mentions<sup>4</sup> content match, engagement, and quality as the main factors for search overall, the API documentation on the differences between ranking principles is sparse:

- *date* – Resources are sorted in reverse chronological order based on the date they were created.
- *rating* – Resources are sorted from highest to lowest rating.
- *relevance* – Resources are sorted based on their relevance to the search query. This is the default value for this parameter.
- *title* – Resources are sorted alphabetically by title.
- *viewCount* – Resources are sorted from highest to lowest number of views. For live broadcasts, videos are sorted by number of concurrent viewers while the broadcasts are ongoing.

Since *relevance* is the default option for the *order* parameter and most papers<sup>5</sup> seem to rely on it, we focused on this ranking principle. To keep the already very high API quota cost for our project in check, we only used *date* ranking for comparison after we noticed that other parameters were producing largely similar results. We chose our queries based on our issue expertise and to roughly represent ‘typical’ keywords researchers may use, covering health, political, and popular culture topics, some connected to a specific event. While this limited selection reduces generalizability,

---

<sup>4</sup> [https://www.youtube.com/intl/en\\_us/howyoutubeworks/product-features/search/](https://www.youtube.com/intl/en_us/howyoutubeworks/product-features/search/)

<sup>5</sup> Although we did not systematically survey papers using the search endpoint, we reviewed a substantial number and observed that few studies report on the ranking setting used.

throwing a larger net was infeasible due to the high API quota cost<sup>6</sup> of the ‘one search per day’ approach. The queries we chose were: ‘Andrew Tate’, ‘Angela Merkel’, ‘Carles Puigdemont’, ‘European Parliament election’, ‘Eurovision’, ‘Gaza ceasefire’, ‘Geert Wilders’, ‘Mukbang’, ‘Obesity’, ‘Ukraine war’, and ‘Ursula von der Leyen’. We added quotation marks to each query; however, to enhance readability, we use square brackets to mark queries in the following sections.

To analyze the collected search results, we pursued two different yet complementary approaches. In the first step, we identified broader patterns across queries and documented our findings primarily in quantitative terms. Our initial examination of the different ranking principles yielded varied results, with the *relevance* setting providing substantially more videos, many of which seemed unrelated to the search queries. Therefore, we first investigated content matching by searching for the query text in the title, description, and tags of each video. Next, we assessed temporal coverage, as we had reasons to believe that the search endpoint exhibits a strong recency bias, making historical research problematic. Finally, we examined sample consistency to understand how results differed between weekly searches. Although our analysis was limited to eleven queries, which somewhat constrains generalization, these three approaches yielded a mostly coherent picture that likely applies to the search feature overall. In the second step, we focused on a specific query - [European Parliament election] - to incorporate qualitative elements and contextualize the consequences of our findings, making them more accessible to a less quantitatively inclined audience.

---

<sup>6</sup> YouTube’s Web-API manages use through a quota system where every call to the API has a certain cost. The ‘one search per day’ principle is specifically ‘expensive’ since it makes a separate search for each day in the timeframe.

## Findings

### *Query precision: important differences between ranking parameters*

Our first analysis focuses on the differences between the *relevance* and *date* ranking principles. Table 1 summarizes our findings and indicates, depending on the query, small to very large differences in terms of the number of videos retrieved. While some of the highest volume queries like [Andrew Tate], [Eurovision], [Mukbang], and [Ukraine war] produced ‘only’ up to twice the number of videos for *relevance*, this went up to over three ([Obesity]), four ([Gaza ceasefire]), five ([Angela Merkel]) or eight ([European Parliament election]) times for others. Since some of the lower volume queries ([Carles Puigdemont], [Geert Wilders], [Ursula von der Leyen]) did not yield such large differences, this is not simply an effect of *relevance* trying to fetch more results for less prominent topics.

Table 1: Dataset overview for our eleven queries.

query	precision (%)		videos retrieved (with keyword filtering)		% volume difference between date and relevance (with keyword filtering)
	date	relevance	date	relevance	
andrew tate	96.6	91.9	114469 (110522)	135459 (124448)	+18.3% (+12.6%)
angela merkel	82.5	33.6	4629 (3821)	27433 (9229)	+492.6% (+141.5%)
carles puigdemont	98.8	93.9	7311 (7223)	11926 (11194)	+63.1% (+54.9%)
european parliament election	57.6	17.2	8933 (5145)	72767 (12499)	+714.5% (+142.9%)
eurovision	95.3	53.8	72580 (69201)	141927 (76383)	+95.5% (+10.3%)
gaza ceasefire	84.5	50.6	23501 (19859)	107329 (54290)	+356.7% (+173.3%)
geert wilders	95.8	68.3	5089 (4874)	9663 (6603)	+89.8% (+35.4%)
mukbang	95.3	82.3	226394 (215813)	254098 (209005)	+12.2% (-3.1%)
obesity	77.3	33.1	44737 (34593)	157398 (52124)	+251.8% (+50.6%)
ukraine war	84	73.4	123028 (103290)	159649 (117196)	+29.7% (+13.4%)
ursula von der leyen	90.8	78	14805 (13440)	25709 (20049)	+73.6% (+49.1%)

Since qualitative inspection, especially for [European Parliament election] (see section 5), showed that many of the retrieved videos had nothing to do with the query,

we operationalized a measure of precision by searching for our queries<sup>7</sup> in the title, description, and tags of each video. While this method can be problematic from a research perspective due to keyword spam or keywords only appearing in the videos themselves, it allows for good comparison between the two ranking principles under scrutiny. The results (Table 1) show higher precision for *date* in all instances, but the difference again varies between queries. We observed lower differences for exceptionally high-volume queries like [Andrew Tate], [Mukbang], and [Ukraine war] and could speculate that such high-volume queries provide enough videos to saturate *relevance* ranking; but given that YouTube’s search system almost certainly<sup>8</sup> uses a large language model like BERT (Devlin et al., 2018) to represent text, we may see the effects of semantic shifts that are specific to each query.

Although the higher level of what information retrieval researchers (e.g., Manning et al., 2008, p.5) call *precision* (which percentage of videos match the query) may render *date* search more attractive at first glance, *relevance* has in almost all cases higher *recall* (how many matching videos are retrieved), yielding more videos that match the search terms in the title, description, or tag field. The exception is [Mukbang], the highest volume query in our sample, where the 500 results per day limit probably keeps *relevance* ranking from finding even more videos, conferring an advantage to the higher-precision *date* matching.

---

<sup>7</sup> We modified some of the queries for better results, for example, for the query [european parliament election], we searched for ‘europe\* AND elect\*’ and we only used last names for politicians.

<sup>8</sup> Google announced in 2019 that they were using BERT for search

<https://blog.google/products/search/search-language-understanding-bert/>

While one could argue that the ‘expansive’ behavior of *relevance* option simulates what users see when they search, as *relevance* is also the default option on the website and app, it renders quantitative overviews for topics problematic. As we will argue further down, researchers may want to use *relevance* ordering in combination with keyword filtering for all but the largest volume queries.

### ***Temporal distance: videos can no longer be found***

Although researchers must consider the important differences between ranking parameters, this paper’s main findings concern temporal distance. The following charts, summarize the central problem with YouTube’s search function emblematically:

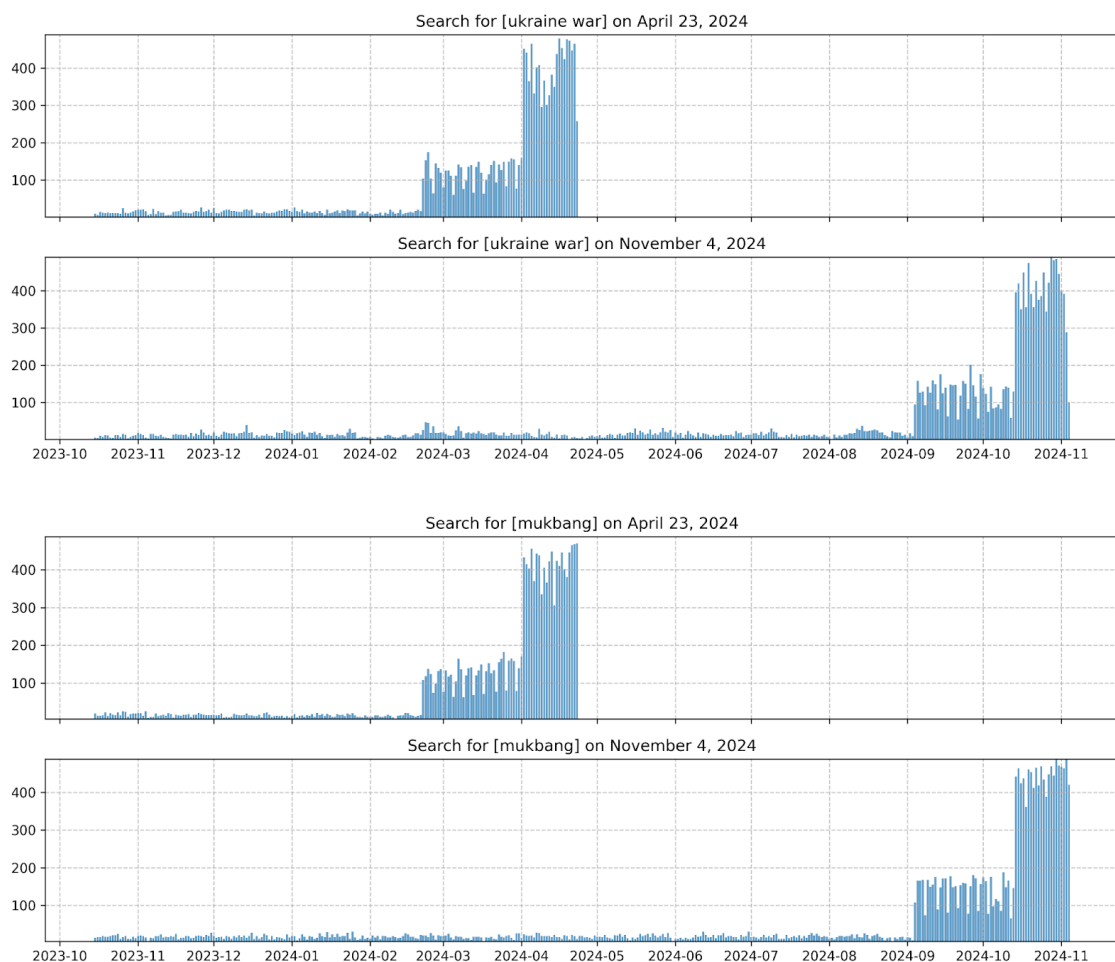




Figure 1. Videos per day, published from October 15, 2023 onwards, for the queries [Ukraine war] (top) and [Mukbang] (bottom), searched on April 23, 2024 and November 4, 2024.

Figure 1 shows very similar - and very problematic - behavior for two queries, [Ukraine war] and [Mukbang], that should have little to nothing in common. We searched for both queries on separate dates (April 23, 2024 and November 4, 2024), using the same starting point (October 15, 2023). In both cases, we notice a period of 20 days before the search date where results average around 450 videos per day, followed by 40 days with around 130 videos per day, ending in a flat tail with about 20 videos or less found per day. A large majority of videos found in the first search (April) no longer appeared in the second search (November), although most, if not all, were still available on the platform. The three ‘phases’ - head, middle, and tail - could be distinguished in most of our queries (Figure 2), regardless of when the search was conducted. This means that the volume of videos retrieved does not reflect the actual content published on the platform but is instead shaped by design decisions that result in a very significant recency bias. For researchers studying a particular event or timeframe, this means that the number of videos they can retrieve will drop heavily only 20 days after the chosen date and again 40 days later. Scholars that miss these cutoffs, which includes anybody doing any kind of historical research, should expect to retrieve markedly impoverished samples.

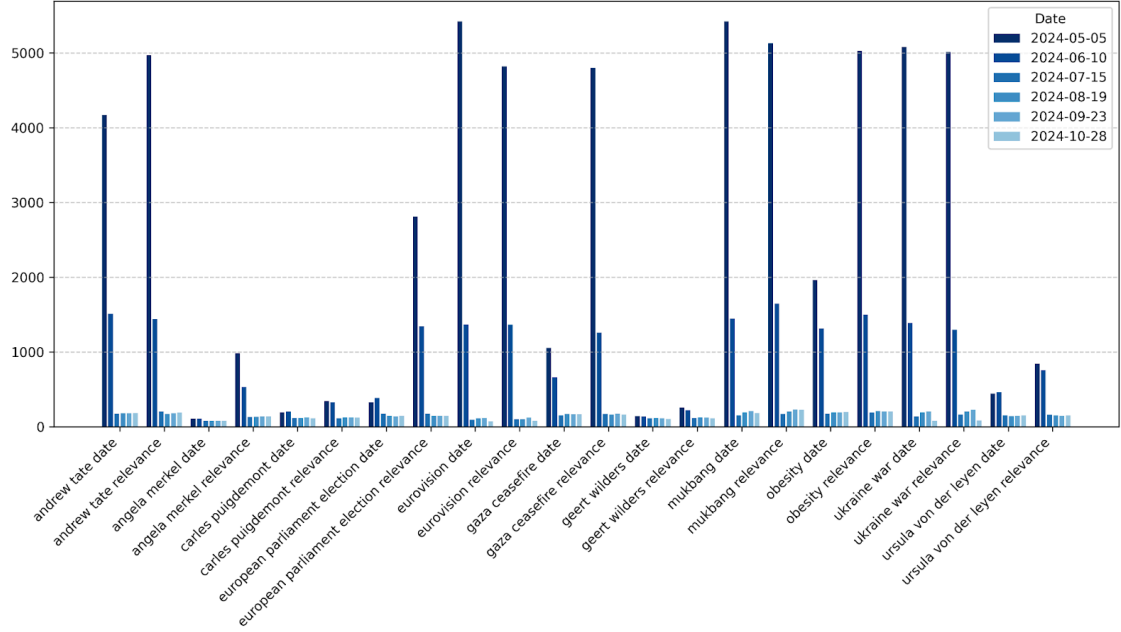


Figure 2. Number of videos published between April 20, 2024 and May 4, 2024 for all our queries, searched for on six separate dates with both *relevance* and *date* ranking.

As Figure 2 shows, the effect is more pronounced for higher volume queries and for *relevance* ranking. Searches ranked by *date* for [Angela Merkel], [Carles Puigdemont], and [Geert Wilders], show little or no drop-off at later dates, although we can observe such an effect when using the default *relevance* settings.

A plain explanation for this behavior is that the search endpoint is not designed with researchers and their specific needs in mind. While we have not been able to find any kind of public commentary on the matter, earlier publications coming out of YouTube itself (e.g., Covington et al., 2016) emphasize concepts such as ‘freshness’ and put a strong emphasis on serving recent videos. The impression that YouTube’s search feature is indeed more of a recommendation engine than a traditional information retrieval system was further strengthened when we applied keyword filtering to measure precision for the search phases we discovered. Except for [Mukbang], where the head contained the highest percentage of matching videos, all our queries showed a

systematic gain in precision when moving from the head to the tail. The overall emphasis of *relevance* ranking, in particular, is serving recent videos that may only be peripherally related to the actual search query.

***Consistency: datasets cannot be replicated***

A third issue arising from the behavior of YouTube’s Data API is the uncertainty regarding the consistency of samples collected through the search endpoint. Our analysis indicates that the videos retrieved in each extraction may vary, even when using the same parameters.



Figure 3. New and old videos published between May 7 and May 13, 2024 for searches over three consecutive weeks.

To test for consistency, we compared the results for three separate searches (Figure 3), each one a week apart, over the same timeframe. We searched for videos published the week before the first search to make sure that the timeframe would still be in the 20-day head phase for each search. We then separated ‘new’ and ‘old’ videos depending on whether a video was present in the week or weeks before. For example, using *relevance*, [Mukbang] yielded 2407 videos for the first week, all considered new, since this was our first search. The week after, we received only 775 videos from the first search and 1510 that were new. In the last week, we still added 1437 new videos published in the same timeframe. These results indicate that the number of videos retrieved by the API not only fluctuates across extractions but also that each search introduces new videos not seen before and omits videos that were present in previous iterations.

Unsurprisingly, this effect is more pronounced for high-volume queries like [Mukbang], [Obesity], [Eurovision], and [Ukraine war]. But even lower volume queries like [Carles Puigdemont] and [Angela Merkel] are affected, indicating that this is not just due to result volume hitting some limitation. We also observe that *relevance* ranking is less consistent than *date* ranking, although the latter is still far from stable. This lack of consistency hinders the ability to replicate studies, potentially leading to divergent conclusions even when data collection and analysis are conducted under identical conditions.

### **Case study: the European Parliament elections**

To make these issues more tangible, especially for audiences outside of technical

disciplines such as the computational social sciences, this section delves into the effects of the observed limitations through a case study focused on the European Parliament elections held between June 6 and 9, 2024. We posit that scholars interested in studying the election campaign would likely select the month leading up to June 9 as their observation period and default to *relevance* ranking. For data collection, we chose five search dates, each spaced five weeks apart, beginning on June 10.

When looking at the data, we first notice, in line with Table 1, that the precision for this query is particularly low (57.6% using *date* and 17.2% with *relevance* as ranking method). A significant number of videos, for example, deal with UK immigration issues and the general elections in India that happened during a similar timeframe. In these situations, where many of the retrieved videos are unrelated to our case study, it is necessary to consider applying keyword filtering. In our example, filtering with the terms ‘europe\* AND elect\*’ (which includes variations such as ‘european’, ‘election’, ‘electoral’, etc.) in title, description, or tags, the combined dataset of 8941 videos is reduced to only 2244 (Table 2). Despite our initial query [European Parliament election] explicitly including quotes, *relevance* throws a much wider net and even *date* - although much more precise - includes many videos that can hardly be considered on topic. Researchers will have to decide within the context of their research projects whether keyword filtering is required or appropriate, but at least for this case study, the combination of *relevance* ranking and keyword filtering yields the best results.

Table 2. Number of retrieved videos published between May 9 and June 9, 2024 for the query [European Parliament election] on five search dates.

search date	relevance		date	
	no of videos (% loss)	no of videos with keyword filtering (% loss)	no of videos (% loss)	no of videos with keyword filtering (% loss)
2024-06-10	8354	2105	2259	1458
2024-07-15	3035 (-63.6%)	1246 (-40.8%)	1498 (-33.6%)	1004 (-31.1%)
2024-08-19	635 (-92.3%)	500 (-76.2%)	586 (-74.0%)	480 (-67.0%)
2024-09-23	621 (-92.5%)	491 (-76.6%)	593 (-76.7%)	481 (-67.0%)
2024-10-28	610 (-92.6%)	485 (-76.9%)	580 (-76.3%)	472 (-67.6%)
overall	8941	2244	2383	1501

Table 2 shows the number of videos we found on our five consecutive search dates, spaced five weeks apart, starting on June 10, the day after the elections. The extraction timeframe for the five searches is identical: the month leading up to June 9. This experiment helps us explain how the same extraction, conducted at different times, can yield different results and observe how the number of videos the API offers for this period decreases over time. We again notice that *relevance* retrieves not only many more videos, but also more videos that match our keywords. Most importantly, however, we notice the very significant drop-off in volume as we move away from the observation period. Compared to the first search on June 10, waiting five weeks means that results are reduced by about 41% with keyword filtering (from 2105 to 1246) and 64% without (from 8354 to 3035). If we search ten weeks later, we lose 76% and 92% respectively, compared to the search directly following the end of the observation period. After that, search volume remains relatively stable. This lines up with the head, middle, and tail sections identified further up; and while *date* ranking shows less precipitous drop-offs, the same pattern applies. Finally, since the overall number of videos found across all five searches is higher than the number of videos in the first search, we conclude that this is not merely a drop-off problem but also a consistency issue.

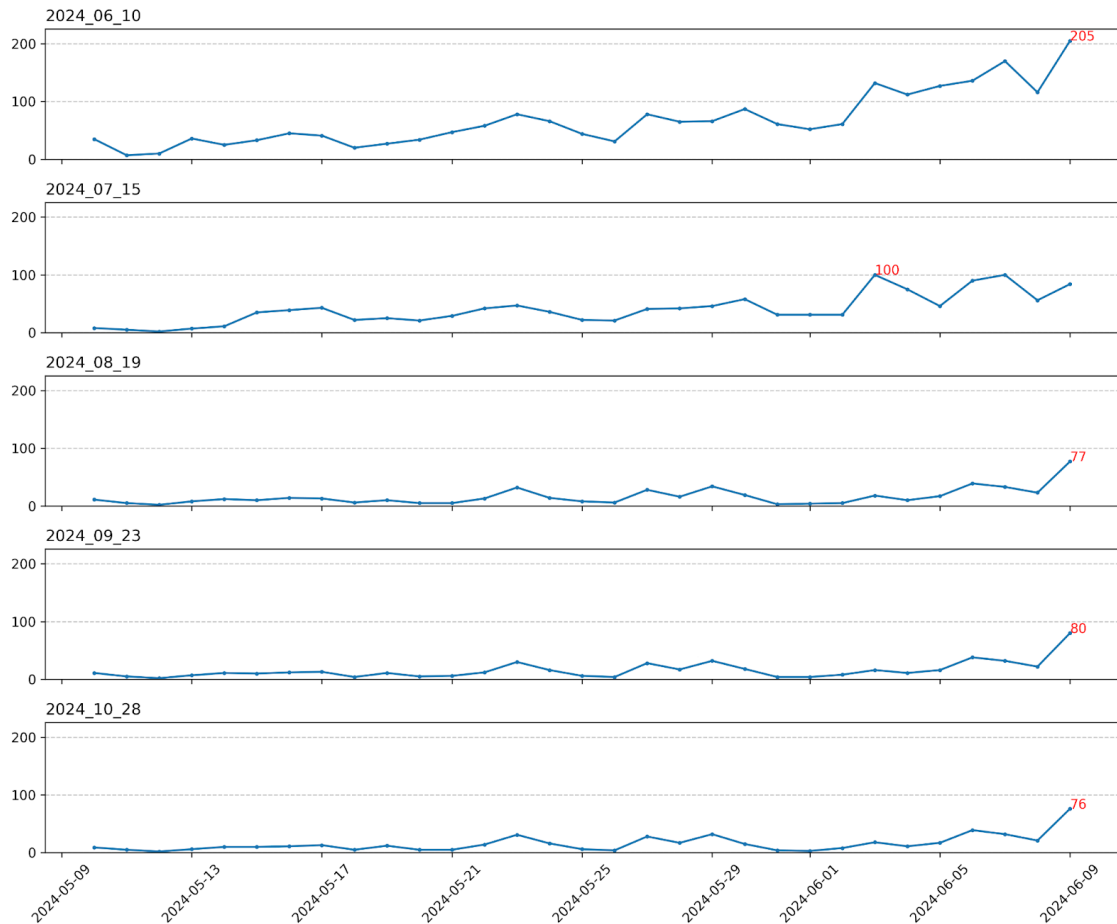


Figure 4. Videos per day for five searches over the same observation period, with keyword filtering.

How does the loss of videos occur throughout the extractions, and how would this affect our understanding of a phenomenon's evolution? As Figure 4 illustrates, the reduction in findable videos does not completely flatten temporal variation, as the general form of the curve remains at least somewhat similar (e.g., an uptick towards the end of the period). However, the differences are still significant. In our case, we believe that evaluating the evolution of the European election campaign based on any search other than the first can lead to a biased assessment of peak moments or the overall volume of the conversation on YouTube. While we can never be certain that we have retrieved *all* relevant videos, quantitative claims about the volume of videos published



around an issue become increasingly problematic as we move further in time from the period of interest.

Since researchers often focus on the most viewed videos when selecting units to analyze, we also investigated how many of the top 10 videos on a certain search date are still present in the weeks that follow (whether in the top 10 or in any position within the dataset). We again found that increased temporal distance implies a significant loss, at least for this case study. For example, of the top 10 most viewed videos in the first of our five searches, nine were still present five weeks later, dropping down to five afterwards. This means that over half of the videos that had important view numbers just after the end of the European Parliament elections were no longer found four months later, although all of them were still available on YouTube when we checked manually.

## **Discussion and recommendations**

Our findings document three main problems with the search endpoint of YouTube's Data API. First, ranking parameters exhibit very different behaviors, with *relevance* returning the largest number of videos but also - depending on the query - many videos that are clearly unrelated to the issue specified by the search query. Second, we observed a consistent and very significant drop-off in search coverage as search dates moved further away from video publication dates. Researchers hoping to study an event through the lens of YouTube videos will find strikingly fewer videos if they wait with their search, particularly if they exceed 60 days. As our European Parliament election case study has shown, the videos no longer covered are not low-visibility clips, but potentially some of the most viewed, making the loss even more problematic. Third, the API does not provide a stable set of videos for a given query, meaning that identical queries for the same topic can yield different outputs over time.

Although these problems manifest to varying degrees for different issues, with high-volume queries likely being the most problematic, they introduce significant uncertainty regarding completeness, representativeness, consistency, and bias in any research project relying on the search endpoint. Research that investigates what YouTube serves about a particular subject to its users at a specific point in time may be less affected. However, any project aiming to study the videos published around a given topic can hardly be confident about their sample. While metadata for any public video can still be collected, if videos no longer appear in searches after a few weeks, it becomes impossible to reconstruct how an issue was portrayed or reported through YouTube videos. Efforts to quantify the spread of misinformation during a public health crisis, identify the first outlet to report a major event, or trace the evolution of political discourse over time are significantly constrained. Given YouTube's importance in the larger digital media environment, these findings contribute to existing critiques of the use of APIs in academic research (e.g., Giletto et al., 2012; Driscoll, 2014; Graham, 2024; Tromble, 2021).

Despite these challenges, several methodological strategies can help mitigate the risks associated with the potentially incomplete and unstable datasets collected through the search endpoint. First, researchers may opt for an entirely different data collection method. Approaches based on crawling (Rieder et al., 2020) and random sampling (Zhou et al., 2011; McGrady et al., 2023), may be attractive for larger studies. Researchers also have the option to use channels, which represent less of a data collection problem, as an entry point.

Second, especially researchers analyzing contemporary events should initiate data collection as early as possible to avoid losing access to relevant content. While questions about what we have called the 'head' - the moving 20-day period yielding the

highest number of results - remain, particularly for large volume queries, searches falling within this window will produce the best results.

Third, repeating searches can help maximize dataset coverage and account for variations in query results. This can mean making a search per day over a longer timeframe but even running one search after another can yield previously undiscovered videos. In a small experiment using the high-volume query [chatgpt] and focusing on a single day, we were able to collect 773 videos when searching ten times in a row instead of the initial 456 results.

Fourth, using several different keywords or keyword combinations may yield a larger set of videos and compensate for the opaque matching behavior we observed. This may, however, increase the complexity of subsequent filtering stages.

Most of these strategies come with additional costs, both in terms of time and API quota units, and researchers will need to decide whether these investments are justified and feasible within the context of their specific research designs. While we generally recommend a combination of exhaustive data collection and purposeful filtering, whether automated or manual, some level of uncertainty remains in the current situation. Regardless of the actual methodological choices made, we hope that researchers relying on YouTube's API to collect evidence become more aware of the inherent problems and report their decisions more diligently. Although the repeatability of data collection is heavily compromised in any case, knowledge of the exact timeframes and parameters used would provide readers with a clearer understanding of the reliability and generalizability of a given study.

## **Conclusion**

This paper has documented significant problems regarding query matching, completeness, temporal distance, and consistency in the search endpoint of YouTube's

Data API. Most importantly, researchers hoping to study issues or events lying more than 60 days in the past risk collecting highly incomplete samples, with many or most relevant videos missing. The quota increase through YouTube’s academic research program is appreciated, but the assertion that it grants ‘access to global video metadata across the entire public YouTube corpus’ (YouTube Research - How It Works, n.d.) is only valid in theory given the observed behavior and may foster an undue sense of confidence. Currently, we do not find the search feature of the Data API to be robust enough to meet the broader requirements of the DSA for enabling researchers to study the systemic risks associated with very large online platforms.

While this paper can hopefully raise awareness among researchers about the issues at hand and offer several mitigation strategies, only YouTube can implement structural solutions. We propose two key improvements. First, YouTube should enhance the Search Endpoint. For a company of YouTube’s scale, including all publicly listed videos in the search endpoint should be feasible. Although certain decisions may be driven by competitive advantage, we do not see this as applicable in this context. As an alternative, YouTube could create a search endpoint exclusively for vetted researchers. Second, YouTube should improve documentation. While we have speculated about reasons for the observed behavior of the search endpoint in this paper, our evidence often only highlights problems or irregularities without providing strong claims about universally applicable principles. Although search and ranking systems may be probabilistic and not fully explainable in causal terms, YouTube’s engineers should be able to describe, for instance, the differences between order options more effectively than we can and offer actionable advice to researchers. Given that YouTube has been more accommodating to third-party research than most other social media platforms, we are optimistic that the company will consider these suggestions.

The issues documented in this study highlight broader concerns about the opacity of large online platforms and the challenges researchers encounter when studying them. While we hold that these companies must provide better tools and guidance to the academic community, we also believe that researchers need to invest more effort into critically evaluating data access provisions. We therefore hope this paper will inspire other groups to explore the numerous remaining questions about the possibilities and limitations of studying YouTube through data collection.

## References

- Al-Zaman, Md. S. (2022). Social mediatization of religion: Islamic videos on YouTube. *Heliyon*, 8(3). <https://doi.org/10.1016/j.heliyon.2022.e09083>
- Bärthel, M. (2018). YouTube channels, uploads and views: A statistical analysis of the past 10 years. *Convergence: The International Journal of Research into New Media Technologies*, 24(1), 16–32. <https://doi.org/10.1177/1354856517736979>
- Bruns, A. (2019). After the ‘APIcalypse’: Social media platforms and their fight against critical scholarly research. *Information, Communication & Society*, 22(11), 1544–1566. <https://doi.org/10.1080/1369118X.2019.1637447>
- Covington, P., Adams, J., & Sargin, E. (2016). Deep Neural Networks for YouTube Recommendations. *Proceedings of the 10th ACM Conference on Recommender Systems - RecSys '16*, 191–198. <https://doi.org/10.1145/2959100.2959190>
- Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). *BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding*. arXiv. <https://doi.org/10.48550/arXiv.1810.04805>

- Driscoll, K. (2014). *Working Within a Black Box: Transparency in the Collection and Production of Big Twitter Data*. 20.
- Freelon, D. (2018). Computational Research in the Post-API Age. *Political Communication*, 35(4), 665–668. <https://doi.org/10.1080/10584609.2018.1477506>
- Giglietto, F., Rossi, L., & Bennato, D. (2012). The Open Laboratory: Limits and Possibilities of Using Facebook, Twitter, and YouTube as a Research Data Source. *Journal of Technology in Human Services*, 30(3–4), 145–159. <https://doi.org/10.1080/15228835.2012.743797>
- Graham, T. (2024, October 3). *Is big tech harming society? To find out, we need research – but it's being manipulated by big tech itself*. The Conversation. <http://theconversation.com/is-big-tech-harming-society-to-find-out-we-need-research-but-its-being-manipulated-by-big-tech-itself-240110>
- Ho, J. C.-T. (2020). How biased is the sample? Reverse engineering the ranking algorithm of Facebook's Graph application programming interface. *Big Data & Society*, 7(1). <https://doi.org/10.1177/2053951720905874>
- Inwood, O., & Zappavigna, M. (2023). Conspiracy Theories and White Supremacy on YouTube: Exploring Affiliation and Legitimation Strategies in YouTube Comments. *Social Media + Society*, 9(1). <https://doi.org/10.1177/20563051221150410>
- Khan, M. L., & Malik, A. (2022). Researching YouTube: Methods, Tools, and Analytics. In A. Quan-Haase & L. Sloan, *The SAGE Handbook of Social Media Research Methods* (pp. 651–663). SAGE. <https://doi.org/10.4135/9781529782943.n45>
- King, G., & Persily, N. (2019). A New Model for Industry–Academic Partnerships. *PS:*

*Political Science & Politics*, 1–7. <https://doi.org/10.1017/S1049096519001021>

Malik, H., & Tian, Z. (2017). A Framework for Collecting YouTube Meta-Data. *Procedia Computer Science*, 113, 194–201. <https://doi.org/10.1016/j.procs.2017.08.347>

Manning, C. D., Raghavan, P., & Schütze, H. (2008). *Introduction to Information Retrieval*. Cambridge University Press.

Marchal, N., Au, H., & Howard, P. N. (2020). *Coronavirus News and Information on YouTube*:

McGrady, R., Zheng, K., Curran, R., Baumgartner, J., & Zuckerman, E. (2023). Dialing for Videos: A Random Sample of YouTube. *Journal of Quantitative Description: Digital Media*, 3. <https://doi.org/10.51685/jqd.2023.022>

Morstatter, F., Pfeffer, J., & Liu, H. (2014, January 30). When is it Biased? Assessing the Representativeness of Twitter’s Streaming API. *ArXiv*.  
<http://arxiv.org/abs/1401.7909>

Morstatter, F., Pfeffer, J., Liu, H., & Carley, K. (2013). Is the Sample Good Enough? Comparing Data from Twitter’s Streaming API with Twitter’s Firehose. *Proceedings of the International AAAI Conference on Web and Social Media*, 7(1), 400–408.  
<https://doi.org/10.1609/icwsm.v7i1.14401>

Oliva, M., Tomasena, J. M., & Anglada-Pujol, O. (2023). ‘Kids, these YouTubers are stealing from you’: Influencers and online discussions about taxes. *Information, Communication & Society*, 1–18. <https://doi.org/10.1080/1369118X.2023.2179374>

Pandey, A., Patni, N., Singh, M., Sood, A., & Singh, G. (2010). YouTube As a Source of Information on the H1N1 Influenza Pandemic. *American Journal of Preventive*

*Medicine*, 38(3), e1–e3. <https://doi.org/10.1016/j.amepre.2009.11.007>

Pearson, G. D. H., Silver, N. A., Robinson, J. Y., Azadi, M., Schillo, B. A., & Kreslake, J. M. (2024). Beyond the margin of error: A systematic and replicable audit of the TikTok research API. *Information, Communication & Society*, 1–19.  
<https://doi.org/10.1080/1369118X.2024.2420032>

Pfeffer, J., Mooseder, A., Lasser, J., Hammer, L., Stritzel, O., & Garcia, D. (2023). This Sample Seems to Be Good Enough! Assessing Coverage and Temporal Reliability of Twitter’s Academic API. *Proceedings of the International AAAI Conference on Web and Social Media*, 17, 720–729. <https://doi.org/10.1609/icwsm.v17i1.22182>

Pires, F., Tomasena, J. M., & Piña, M. (2023). Delivery riders’ cultural production in Spain: A thematic analysis of their self-representation on YouTube. *Convergence*, 1–17.  
<https://doi.org/10.1177/13548565231161252>

Porreca, A., Scozzari, F., & Di Nicola, M. (2020). Using text mining and sentiment analysis to analyse YouTube Italian videos concerning vaccination. *BMC Public Health*, 20(1). <https://doi.org/10.1186/s12889-020-8342-4>

Puschmann, C. (2019). An end to the wild west of social media research: A response to Axel Bruns. *Information, Communication & Society*, 22(11), 1582–1589.  
<https://doi.org/10.1080/1369118X.2019.1646300>

Rieder, B. (2015). *YouTube Data Tools* [Computer software].  
<https://ytdt.digitalmethods.net>

Rieder, B., Abdulla, R., Poell, T., Woltering, R., & Zack, L. (2015). Data critique and analytical opportunities for very large Facebook Pages: Lessons learned from exploring



“We are all Khaled Said.” *Big Data & Society*, 2(2).

<https://doi.org/10.1177/2053951715614980>

Rieder, B., Coromina, Ò., & Matamoros-Fernández, A. (2020). Mapping YouTube. *First Monday*. <https://doi.org/10.5210/fm.v25i8.10667>

Rieder, B., Matamoros-Fernández, A., & Coromina, Ò. (2018). From ranking algorithms to ‘ranking cultures’: Investigating the modulation of visibility in YouTube search results. *Convergence: The International Journal of Research into New Media Technologies*, 24(1), 50–68. <https://doi.org/10.1177/1354856517736982>

Tromble, R. (2021). Where Have All the Data Gone? A Critical Reflection on Academic Digital Research in the Post-API Age. *Social Media + Society*, 7(1). <https://doi.org/10.1177/2056305121988929>

Tromble, R., Storz, A., & Stockmann, D. (2017). We Don’t Know What We Don’t Know: When and How the Use of Twitter’s Public APIs Biases Scientific Inference. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3079927>

Villegas, E. B. (2016). Facebook and its Disappearing Posts: Data Collection Approaches on Fan-Pages for Social Scientists. *The Journal of Social Media in Society*, 5(1), 160–188.

Violot, C., Elmas, T., Bilogrevic, I., & Humbert, M. (2024). Shorts vs. Regular Videos on YouTube: A Comparative Analysis of User Engagement and Content Creation Trends. *ACM Web Science Conference*, 213–223. <https://doi.org/10.1145/3614419.3644023>

Weller, K. (2016). The digital traces of user-generated content: How social media data

may become the historical sources of the future. In A. Foster & P. Rafferty (Eds.), *Managing Digital Cultural Objects* (pp. 61–86).

<https://doi.org/10.29085/9781783301539.004>

*YouTube Research—How It Works*. (n.d.). YouTube. Retrieved January 8, 2025, from <https://research.youtube/how-it-works/>

Zhou, J., Li, Y., Adhikari, V. K., & Zhang, Z.-L. (2011). Counting YouTube videos via random prefix sampling. *Proceedings of the 2011 ACM SIGCOMM Conference on Internet Measurement Conference*, 371–380. <https://doi.org/10.1145/2068816.2068851>