

# RIP Twitter API: A eulogy to its vast research contributions

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Data and code available here

## Abstract

Since 2006, Twitter’s Application Programming Interface has been a treasure trove of high-quality data for researchers studying everything from the spread of misinformation, to social psychology and emergency management. However, in the spring of 2023, Twitter (now called X) began charging \$42,000/month for its Enterprise access level—an essential death knell for researcher use. Lacking sufficient funds to pay this monthly fee, academics are now scrambling to continue their research without this important data source. This study collects and tabulates the number of studies, number of citations, dates, major disciplines, and major topic areas of studies that used Twitter data between 2006 and 2023. While we cannot know for certain what will be lost now that Twitter data is cost prohibitive, we can illustrate its research value during the time it was available. A search of 8 databases and 3 related Application Programming Interfaces found that since 2006, a total of 27,453 studies have been published in 7,432 publication venues, with 1,303,142 citations, across 14 disciplines. Major disciplines include: computational social science, engineering, data science, social media studies, public health, and medicine. Major topics include: information dissemination, assessing the credibility of tweets, strategies for conducting data research, detecting and analyzing major events, and studying human behavior. Twitter data studies have increased every year since 2006, but following Twitter’s decision to begin charging for data in the spring of 2023, the number of studies published in 2023 decreased by 13% compared to 2022. We assume that much of the data used for studies published in 2023 were collected prior to Twitter’s shutdown, and thus the number of new studies are likely to decline in subsequent years.

## Introduction

For 18 years, Twitter’s Application Programming Interface (API) has been a gold mine of data for researchers studying everything from the spread of misinformation, to social

psychology and emergency management [1] [2] [3]. However, within a year of Elon Musk’s purchase of the platform in April, 2022, Twitter (now called X, however for clarity we will refer to the platform as “Twitter” for the remainder of this paper) has begun charging \$42,000/month for its Enterprise access level [4], and now requires researchers to get permission each time they need to share tweet IDs with other researchers [5], making peer review and research replicability much more difficult. Lacking sufficient funds to pay this monthly fee, academics are now scrambling to continue their research without this important data source [6]. This paper aims to highlight what may be lost if Twitter data continues to be cost prohibitive. To this end, we want to understand just how many Twitter data-based academic papers, across all disciplines, have been published during the years of available data (2006-2023).

We specify the disciplines to which the majority of studies belong, and highlight some of the most common topics explored in the literature. While we cannot know for certain what will be lost now that Twitter’s API is cost prohibitive, we can illustrate the enormous value of social media data by examining the research conducted while Twitter’s API was available to researchers. It is worth mentioning that while the API was available for researchers, following the Cambridge Analytica scandal in 2018, Twitter began implementing restrictions on its API, including an application process which vetted users before granting access, and implementing download limits such as 300 tweets/retweets per 3 hours [7]. The research we found spans the academic disciplines including: computational social science, engineering, data science, social media studies, public health, and medicine. In addition, governing bodies are currently passing legislation, such as the European Union’s Digital Services Act of 2022 [8], to require or incentivize technology companies (such as Twitter) to provide open access to their data. We hope this paper will help inform these decisions by showing the kinds of knowledge that are likely to be lost if policies do not change and open access to social media data does not return.

Other studies have undertaken similar inquiries, collecting and analyzing studies that use social media data, but often with a much narrower, discipline-specific approach, or by using the single search term “Twitter” resulting in a much broader corpus. In one example, researchers examined 83 articles, all of which addressed the use of social media to predict public election results [9]. In another example, researchers analyzed 156 studies, examining the role of social media in vaccine hesitancy [10]. Another study reviewed the literature of Arabic sentiment analysis using Twitter data [11]. Exploring Twitter studies with a more comprehensive approach, Karami et al. conducted a systematic literature review. Using the single search term “Twitter” in 3 databases, this study captured 18,849 studies and conducted frequency analysis, topic modeling (Latent Dirichlet Allocation), topic analysis, and trend exploration to quantify the ideas and concepts studied between 2006-2019 [12]. In a similar study, Yu and Munoz-Justicia conducted a bibliometric analysis of Twitter studies. This study also used the sole search term “Twitter” in a single database (Web of Science). In addition to analyzing the topic areas of 19,205 studies, this study undertook a performance analysis of 5 categories of data (Annual Scientific Production, Most Relevant Sources, Most Productive Authors, Most Cited Publications, Most Relevant Keywords), along with a country-collaboration analysis and a thematic analysis to quantify the major topics of study [13].

In contrast, our study showcases a comprehensive and up-to-date collection of studies from all disciplines during the 18 years the API was available to researchers. Rather than broadly collecting all studies containing the single term “Twitter”, we sought to capture only studies that specifically utilized Twitter user data. To identify these studies, we conducted a search across 8 databases, and updated previous searches to include studies up to December, 2023. Additionally, our study calculated incoming

citations (papers that cited the papers in our dataset) for each study along with the total incoming citations for the corpus, in order to quantify the influence of this body of work. Our study also identified prominent disciplines, topics, publication venues, date distributions, and illustrates the drop off in studies following the closure of Twitter’s free API in early 2022. We collected a total of 27,453 unique studies, in 7,432 distinct publication venues (journals and conferences), with 1,303,142 incoming citations, spanning 18 years, and across 14 disciplines.

## Materials and Methods

### Data Collection

Our aim was to collect and analyze as many studies as we could that used Twitter data as the focus of inquiry. We began our search in 2006 since that was the year Twitter opened its API to academic researchers. Given the fractured landscape of literature databases, it was necessary to collect studies from a wide variety of sources in order to capture the maximum number of studies from every possible discipline. As a starting point, we conducted a broad search using Web of Science, one of the most comprehensive, multidisciplinary databases available. Searching the topics field, which included title, abstract, and author keywords (Topics = twitter NEAR/3 data OR twitter NEAR/3 api OR twitter NEAR/3 dataset), we located 3628 articles. Utilizing Web of Science’s built-in “Analyze Results” feature, we found that the top disciplines included: Computer Science, Engineering, Information Science, Communications, Public and Environmental Health, and Multidisciplinary Sciences. We then referenced the University of Washington’s library guides for each of these disciplines to identify the most relevant research databases (see below), and then set about searching each database. All searches used some version of our initial search string, adjusting proximity operators as appropriate, and searching primarily in the topic, title, abstract, and keyword fields S1 Appendix. We also found that adding “NOT survey” to the string eliminated studies that simply used Twitter to disseminate surveys or find participants for data collection. Finally, we fine-tuned each search to include only journal articles, conference papers, dissertations, and preprints.

In Table 1 we list each database along with the number of results found, and the percentage of relevant studies within each results list. The statistical software, R, was used to randomize results for sampling. For each database S1 Appendix, a minimum of 50 sample studies were examined by hand to determine if they met one of three criteria: utilized Twitter data in the study, examined novel ways of extracting and studying Twitter data, or reviewed the literature of Twitter-based studies. To label sample studies relevant/not relevant, we found that most studies explicitly stated in their abstract if they utilized Twitter data. For example, “The researchers analyzed 100,000 tweets with hashtags #coronavirus. . .” [14]. In a minority of cases, when the abstracts were unclear, we examined methodology sections for confirmation. The most common reasons for labeling “not relevant” were studies that used Twitter to disseminate surveys, analyzed surveys about Twitter use, and studies that mentioned Twitter, but actually examined Sina Weibo, China’s Twitter alternative, or another social media platform.

In the case of Engineering Village, the web-based database limits downloads to 1000 studies within a given search. With such a large number of relevant studies published in this database (over 36,000), we deemed it essential to find another way to access these studies. Elsevier (publisher) offers two APIs for Engineering Village: the search API, and the retrieval API. We utilized R exclusively to access these data. Using the search string “(twitter AND data) OR (twitter AND api) OR (twitter AND dataset) NOT survey” we used the search API to obtain the “doc id” for each study, and then used

**Table 1.** Database Search Results

Database	Number of Results	Percent Relevant
LISS/LISTA (Library Science Databases - EBSCO)	1660	82
Web of Science (SCI-EXPANDED, SSCI, AHCI, ESCI)	11,617	82
Global Health	563	80
ACM Digital Library	1997	92
IEEE Xplore	4930	97
Engineering Village (Compendex)	21,574	86
Engineering Village (Inspec)	14,664	88

the retrieval API to obtain metadata for a total of 36,238 studies. Extensive computational programming with R and Excel was required to unnest, clean, wrangle, and analyze the data. We combined the Engineering Village dataset with the dataset created from the other six databases, removed duplicates by DOI, title, and abstract, using R’s “distinct” function, and randomized to create the final dataset.

To quantify influence, we tabulated the incoming citations for each study in the dataset via the Crossref REST API. The final dataset (27,453 articles) includes: title, abstract, date of publication, manuscript date, document type, publisher (venue), publishing company, DOI, and citation count. Data and code available here

## Data Analysis

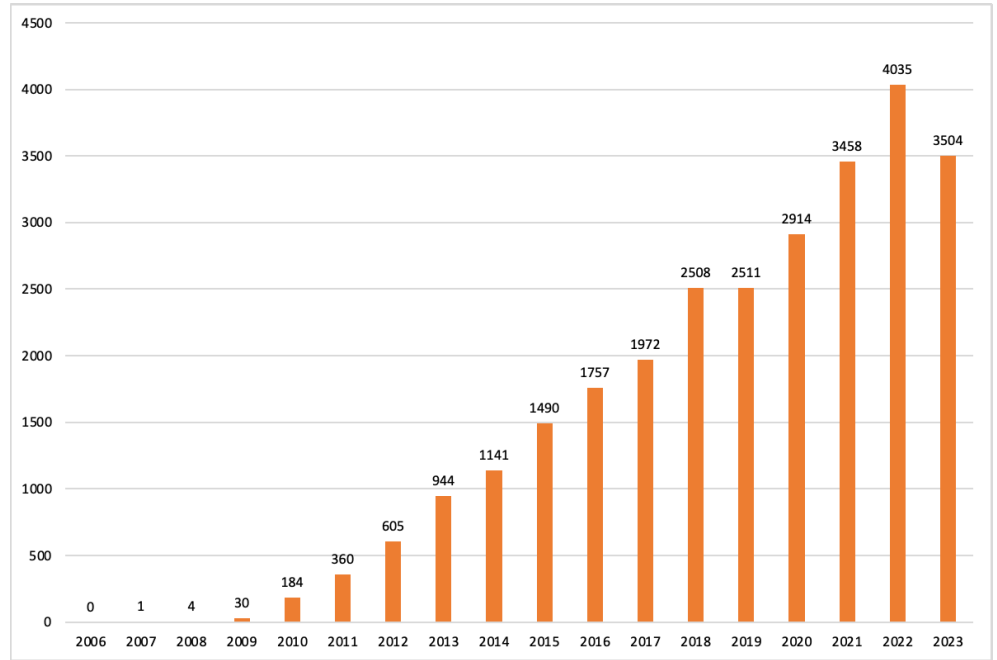
The distribution of study dates was assembled in Excel Fig 1. We ranked the top 100 publication venues, in R, by the number of published Twitter-based studies, then extracted the top 10 publication venues from this list and visualized the results in Fig 2. Next, we assigned disciplines by hand S2 Appendix to each of the top 100 publication venues, calculated the percentage for each discipline, and visualized the results in Fig 3. To identify the most influential studies, and to provide a secondary analysis of disciplines within the corpus Fig 4, we ranked the studies by their number of incoming citations, and then labeled the top 100 studies’ disciplines by hand S3 Appendix. Finally, to ascertain the main topics covered in the corpus, we examined the 5 most cited studies from each major discipline (Data Science, Social Science, Social Media, Public Health, Psychology, Information Science, Emergency Management, Education, Business, and Artificial Intelligence). We read each abstract, noting the main themes in each. We then grouped themes into common topics S4 Appendix.

## Results

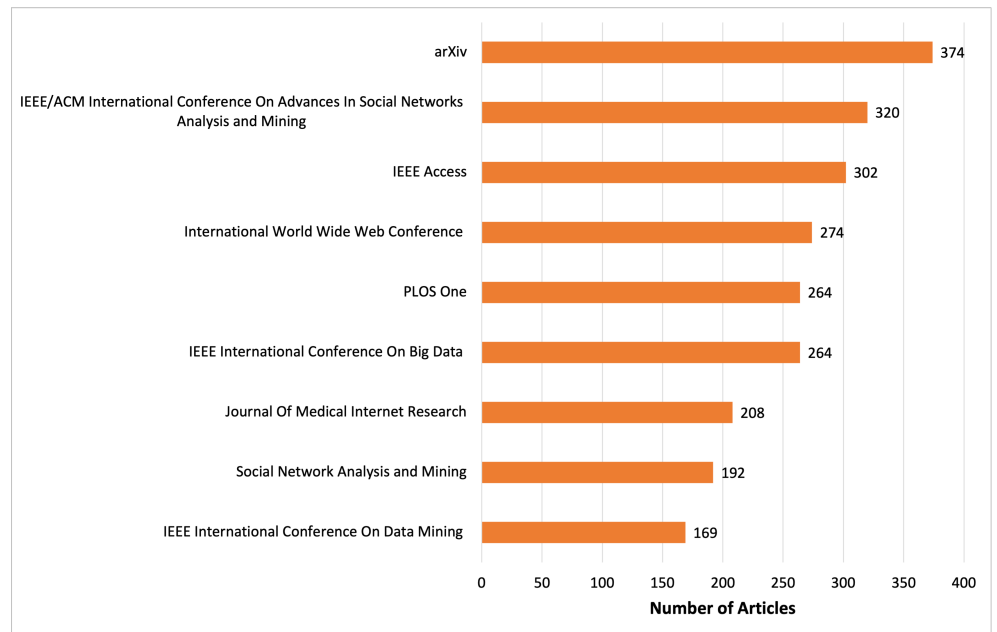
This inquiry identified a total of 27,453 unique studies ([link to Final Dataset](#)) using and/or studying Twitter user data. The first study to use Twitter data that we uncovered was “Why we Twitter: Understanding microblogging usage and communities,” published in August 2007 by Java et al. at the University of Maryland [15]. Examining the topological and geographical properties of Twitter’s social network, the article explored the virtually uncharted territory of how people find each other and interact on social media. While Twitter’s API became available in 2006, we did not find any articles published until this article in August, 2007.

The studies we collected were published in 7,432 distinct publication venues, with 1,303,142 incoming citations, over a span of 18 years, and across 14 broad disciplines.

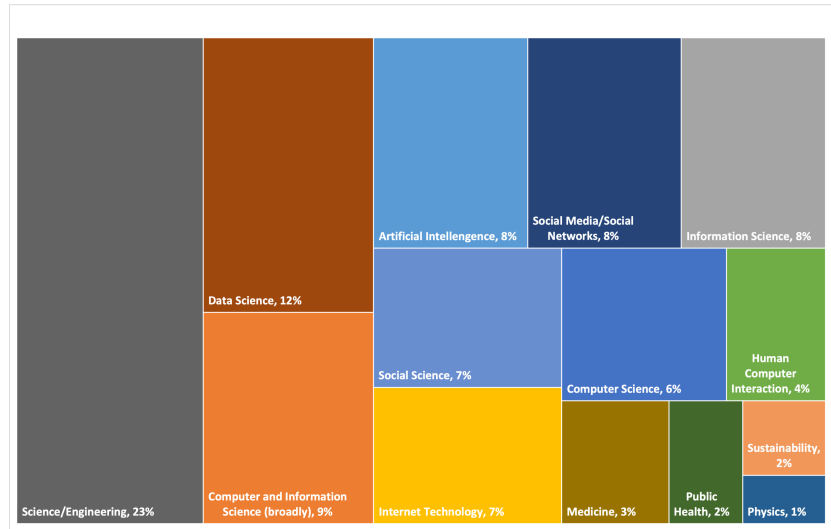
**Fig 1.** Number of Studies as of Dec 12, 2023



**Fig 2.** Top 10 Publication Venues



**Fig 3.** Top Disciplines by Publication Venue



**Fig 4.** Top Disciplines by Number of Citations

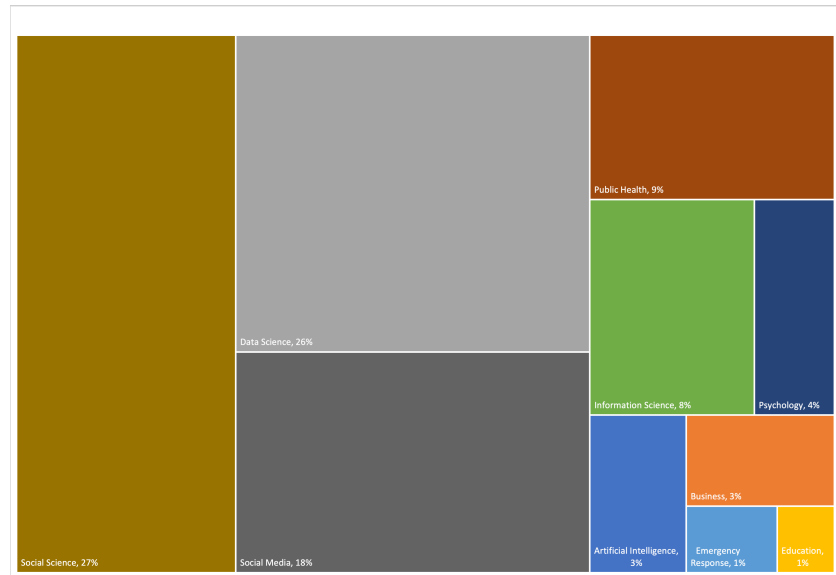


Fig 1 shows the spread of published studies between the years 2006 and 2023. Fig 2 shows the top 10 publication venues, ranked by the number of Twitter-based studies they each have published.

To understand the spread of disciplines within the corpus, we took a two-pronged approach. First, Fig 3 shows the percentage of each discipline as determined by the top 100 publication venues' titles and/or website content S2 Appendix. Science/Engineering comprised 23% of the studies. Data Science comprised 12%, followed by Computer and Information Science at 9%. Artificial Intelligence, Social Media, and Information Science each comprised 8%, and the remaining 32% were shared between Social Science, Internet Technology, Computer Science, Human-Computer Interaction, Medicine, Public Health, Sustainability, and Physics.

Second, Fig 4 shows the percentage of each discipline as determined by assigning disciplines to the top 100 most-cited studies S3 Appendix. In all, studies within the corpus were cited 1,303,142 times according to our Crossref analysis. It is important to note that this is only an approximation. There are many ways to count citations (ie. Crossref, Google Scholar, Web of Science), and each can differ considerably. Within these top-cited studies, Social Science comprised the highest number of studies at 27%, with a total of 16,010 citations. Data Science comprised 26% of the studies with a total of 15,255 citations, Social Media Studies comprised 18% with a total of 10,625 citations, and the remaining 29% included: Public Health, Business, Artificial Intelligence, Psychology, Information Science, Education, and Emergency Response.

Table 2 provides a brief analysis of the most common topics discussed within the corpus. Topics included: information dissemination, assessing the credibility of tweets, strategies for conducting data research, detecting and analyzing major events, and studying human behavior S4 Appendix.

**Table 2.** Topic Analysis

Main Topics Identified by Hand	Examples
Information Dissemination	Factors contributing to dissemination How does ideology impact dissemination Identifying influential users
Assessing the credibility of tweets	True vs fake news
Strategies for conducting data research	Sentiment analysis Topic modeling Geolocation
Detecting and analyzing major events	Pandemic Earthquakes
Studying human behavior	Political analysis and prediction Misuse and misunderstanding of antibiotics marketing/promotion of consumer products Stock market performance Mental health analysis

## Discussion

Between 2006 and 2022 Twitter data has been widely and increasingly used in academic research Fig 1, and spans a wide swath of academic disciplines. However, the number of studies decreased by 13% in 2023, compared to the number of published studies in 2022, once Twitter began charging for its API Fig 1. We assume that much of the data used for studies published in 2023 were collected prior to Twitter's February, 2023 API shutdown, and thus the number of new studies are likely to continue declining in the coming years. We suggest a future study to collect these same data and analyze in a

similar manner to obtain a more clear picture of the long term impact of Twitter's API shutdown. This vulnerability demonstrates that researchers may have relied too heavily on Twitter data while it was available. We also wonder if researchers are currently paying too little attention to Twitter data now that it is no longer available, especially in light of the fact that it remains a major voice around the world for news and public opinion.

We employed two distinct strategies to analyze the spread of disciplines within the corpus, resulting in two substantially different groupings. It is worth noting the difficulty we found in assigning disciplines. Several categories overlap (ie. Data Science, Computer Science, Computer and Information Science, and Internet Technology), and our assignments were subjective. Another researcher might assign different disciplines, thus ending up with different percentage spreads in Fig 3 Fig 4.

Our first strategy (publication venue-based) focused on the overall disciplines of the top 100 publication venues Fig 3. We analyzed the name of each top venue to determine the overall discipline S2 Appendix. For example, the International Journal Of Advanced Computer Science and Applications was assigned to the Computer Science discipline. In instances when the name alone was inconclusive, we explored the organization's website to confirm the discipline. For example, the journal name Multimedia Tools and Applications does not clearly state a discipline, thus further investigation into the journal's website was needed to reveal an overall discipline of Science/Engineering. We acknowledge that any one venue may contain a variety of disciplinary studies, therefore this strategy lacks specificity. At the same time, this strategy resulted in a wider array of disciplines than our study-based strategy, in particular the inclusion of Science/Engineering, and the differentiation between Data Science, Computer and Information Science, Computer Science, and Internet Technology. This may have been a result of the way publishers defined their venues.

Our second strategy (study-based) focused on the studies themselves to determine disciplines, rather than on the publication venue names Fig 4. Disciplines were assigned by reading the title and abstract from each of the top 100 most-cited studies, and then choosing the discipline that fit best based on a set of definitions S3 Appendix. We believe this strategy provided a more accurate analysis of which disciplines were most strongly represented in the corpus. In these results Fig 4, Social Science comprised 27% of the studies (up from 7% in the publication venue-based strategy). Perhaps this increase is a result of researchers publishing Social Science studies in non-Social Science publications, therefore leading us to label them under different disciplines in our first strategy. Similarly, Data Science comprised 26% of the studies (up from 12% in the publication-based strategy). We believe this difference may have occurred because Data Science studies were published in journals or conferences with overall disciplines of Computer Science, Computer and Information Science, or Internet Technology. Additionally, the study-based strategy illustrated the influence of this body of research in the academic world, with 1,303,142 incoming citations.

We wish to acknowledge three limitations to our study. While researchers use data from many different social media platforms (such as Facebook and Reddit), we chose to focus solely on studies utilizing Twitter data. Twitter has historically been the most common source of social media data [16] due to its ease of use, open access, and its public nature, and thus offered the most comprehensive view into the topics and disciplines studied by researchers. We also acknowledge that we did not search every available database. We aimed to search the largest and most comprehensive databases covering the widest variety of disciplines. Some databases were excluded (ie. Academic Search Complete and PubMed) because all results were duplicates from other databases, while another (Communication Source) was excluded because it yielded a relevancy rate well below 80%. We were able to collect 36,238 studies from Engineering Village via



their API, however the many hours required to access these data could hamper future researchers with limited time. Additionally, we did not search the full-text of papers. Instead, we searched metadata including: title, abstract, keywords, publication venue, publication date, and others. While most of the databases we searched did not offer a full-text search option, two did (ACM Digital Library and IEEE Xplore), and a new search using the full-text field may produce additional papers.

## Conclusion

Since 2006, Twitter's API has been a treasure trove of high-quality data. However, in the spring of 2023, Twitter began charging \$42,000/month for its Enterprise Access level. Lacking sufficient funds to pay this monthly fee, academics are now scrambling to continue their research. This paper illustrates the enormous value of social media data across the academic disciplines, and highlights what may be lost if social media data continues to be cost prohibitive. A search of 8 databases and 3 related APIs found that since 2006, a total of 27,453 studies have been published in 7,432 distinct publications venues, with 1,303,142 incoming citations, across 14 disciplines. Alarming, while Twitter data studies have increased every year since 2006, since Twitter's decision to begin charging researchers for data last year, the number of studies has decreased by 13% as compared to the year before. We suggest a future study to update these data in subsequent years to give a more clear picture of the long term impact of Twitter's API shutdown.

## Acknowledgments

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## References

1. Vosoughi S, Roy D, Aral S. The spread of true and false news online. *Science* [Internet]. 2018;359(6380):1146–51. Available from: <http://dx.doi.org/10.1126/science.aap9559>
2. Golder SA, Macy MW. Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. *Science* [Internet]. 2011;333(6051):1878–81. Available from: <http://dx.doi.org/10.1126/science.1202775>
3. Yin J, Lampert A, Cameron M, Robinson B, Power R. Using social media to enhance emergency situation awareness. *IEEE Intell Syst* [Internet]. 2012;27(6):52–9. Available from: <http://dx.doi.org/10.1109/mis.2012.6>
4. Getting started with the Twitter API [Internet]. Twitter. [cited 2024 Feb 24]. Available from: <https://developer.twitter.com/en/docs/twitter-api/getting-started/about-twitter-api>
5. Developer Agreement and Policy [Internet]. Twitter. [cited 2024 Feb 24]. Available from: <https://developer.twitter.com/en/developer-terms/agreement-and-policy>

6. Ledford H. Researchers scramble as Twitter plans to end free data access. *Nature* [Internet]. 2023;614(7949):602–3. Available from: <http://dx.doi.org/10.1038/d41586-023-00460-z>
7. Hutchinson A. Twitter continues its efforts to fight spam and misuse with new API restrictions [Internet]. *Social Media Today*. 2018 [cited 2024 Feb 24]. Available from: <https://www.socialmediatoday.com/news/twitter-continues-its-efforts-to-fight-spam-and-misuse-with-new-api-restric/528533/>
8. Sebastian KS. The EU’s Digital Services Act and its impact on online platforms [Internet]. *EU Law Working Papers* [Internet]. 2024;85. Available from: <https://law.stanford.edu/publications/no-85-the-eus-digital-services-act-and-its-impact-on-online-platforms/>
9. Brito KDS, Filho RLCS, Adeodato PJL. A systematic review of predicting elections based on social media data: Research challenges and future directions. *IEEE Trans Comput Soc Syst* [Internet]. 2021;8(4):819–43. Available from: <http://dx.doi.org/10.1109/tcss.2021.3063660>
10. Cascini F, Pantovic A, Al-Ajlouni YA, Failla G, Puleo V, Melnyk A, et al. Social media and attitudes towards a COVID-19 vaccination: A systematic review of the literature. *EClinicalMedicine* [Internet]. 2022;48(101454):101454. Available from: <http://dx.doi.org/10.1016/j.eclinm.2022.101454>
11. Alqurashi T. Arabic Sentiment Analysis for Twitter Data: A Systematic Literature Review. *Engineering. Technology & Applied Science Research* [Internet]. 2023;13(2):10292–300. Available from: <https://etasr.com/index.php/ETASR/article/view/5662>
12. Karami A, Lundy M, Webb F, Dwivedi YK. Twitter and research: A systematic literature review through text mining. *IEEE Access* [Internet]. 2020;8:67698–717. Available from: <http://dx.doi.org/10.1109/access.2020.2983656>
13. Yu J, Muñoz-Justicia J. A bibliometric overview of Twitter-related studies indexed in Web of science. *Future Internet* [Internet]. 2020;12(5):91. Available from: <http://dx.doi.org/10.3390/fi12050091>
14. Pandey D, Wairya S, Pradhan B, Wangmo. Understanding COVID-19 response by twitter users: A text analysis approach. *Heliyon* [Internet]. 2022;8(8):e09994. Available from: <http://dx.doi.org/10.1016/j.heliyon.2022.e09994>
15. Java A, Song X, Finin T, Tseng B. Why we twitter: Understanding microblogging usage and communities. *Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 workshop on Web mining and social network analysis*. [Internet]. 2007 Aug 12; New York, USA: p. 56-65.
16. Tromble R. Where have all the data gone? A critical reflection on academic digital research in the post-API age. *Soc Media Soc* [Internet]. 2021;7(1):205630512198892. Available from: <http://dx.doi.org/10.1177/2056305121988929>
17. Robinson B. X Corp lawsuits target data scraping. *The National Law Review*. 2023 Aug; XIV(1). Available from: <https://www.natlawreview.com/article/x-corp-lawsuits-target-data-scraping>

# Supporting information

## S1 Appendix. Database Search Strings and Sampling Results

\*These data were collected and sampled in June, 2023. We recollected and updated our data in December, 2023 for the final numbers seen in Table 1 and throughout the paper, however for the sake of time, we relied on the June, 2023 data for relevance percentages.

*Library and Information Science Source and Library Information Science and Technology Abstracts*

<https://www.ebsco.com/products/research-databases/library-information-science-and-technology-abstracts>.

"Twitter N3 data OR twitter N3 api OR twitter N3 dataset" NOT survey, \*filtered for conferences, journals, and magazines only \*All Text for all fields

- 1608 results
- 82% relevance (50 paper sample)

*Web of Science (SCI-EXPANDED, SSCI, AHCI, ESCI)*

<https://clarivate.com/products/scientific-and-academic-research/research-discovery-and-workflow-solutions/webofscience-platform/>

"(twitter AND data) OR (twitter AND api) OR (twitter AND dataset) NOT (survey)"

- 10811 results
- 82% relevance (75 paper sample)

*Global Health Database*

<https://www.ebsco.com/products/research-databases/global-health>

"(twitter AND data) OR (twitter AND api) OR (twitter AND dataset)"

- 536 results
- 80% relevance (50 paper sample)

*ACM Digital Library*

<https://dl.acm.org/>

"(twitter AND data) OR (twitter AND api) OR (twitter AND dataset) NOT (survey)" \*abstracts only

- 1950 results
- 92% relevance (50 paper sample)

*IEEE Xplore*

<https://ieeexplore.ieee.org/Xplore/home.jsp>

"Twitter NEAR/3 data OR twitter NEAR/3 api OR twitter NEAR/3 dataset NOT survey" \*filtered out books

- 3509 results
- 97% relevance (50 paper sample)

*Engineering Village API*

<https://dev.elsevier.com/>

Query = (((((twitter AND data) OR (twitter AND api) OR (twitter AND dataset) NOT survey) WN ALL)) NOT (({ch} OR {ip} OR {bk} OR {er} OR {tb} OR {ed}) WN DT))

*Compex Database*

- 20,813 results
- 86% relevance (50 paper sample)

*Inspec Database*

- 15,013 results
- 88% relevance (50 paper sample)

## S2 Appendix. Top 100 Publications and Their Assigned Disciplines

\*For detailed discipline assignments see Final\_Dataset\_Dec2023 at [github.com/ryanmurt/Twitter](https://github.com/ryanmurt/Twitter) (Top Disc by Pub June #s tab)

\*\*Disciplines were assigned by examining the name of the journal or conference and/or the "About" section of the organization's website and applying the following definitions:

\*\*\*Numbers based on data collected in June 2023

Disciplines	Definitions used to assign
Social Science	Focus of study of human behavior, including psychology
Data Science	Focus is on the tools for manipulating and analyzing the data
Computer Science	Focus is on programing/designing the software tool
Social Media	Focus is on understanding how the social media tool works, how the technology functions. Similar to Social Science, but related to how human behavior is impacted by the technology, more than purely human tendencies in society. How the tool functions and how it enables social interaction.
Internet Technology	A broad category of studying all things internet/world wide web
Computer and Information Science	This is the most broad category for things related to computers, data, and internet technology. We chose this discipline when the publication did not fit into a more specific category and seemed to encompass all aspects of the field.
Information Science	Focus of study is on locating, accessing or organizing information.
Science/Engineering	Focus of study is on a non-computer/information science field such as engineering (excluding physics).
Artificial Intelligence, Human-Computer Interaction, Physics, Public Health, Medicine, Sustainability	These remaining disciplines are easily distinguished by name of publication and/or organization's website.

### S3 Appendix. Assigning Disciplines to 100 Most-Cited Studies

\*For detailed discipline assignments see Final\_Dataset\_Dec2023 at [github.com/ryanmurt/Twitter](https://github.com/ryanmurt/Twitter) (Top Disc by Most Cited tab)

\*\*Disciplines were assigned by reading titles and abstracts and applying the following definitions:

Disciplines:	Definitions used to assign
Social Science	A focus on social human behavior. How do people behave? This is often in the context of social media in this corpus, but always with a focus on human behavior.
Data Science	A focus on the mechanics of data and information, ie. sentiment analysis, topic modeling, other tools for programming and data analysis.
Social Media	A focus is on the technology itself, ie. studying or designing a tool used to identify influential users on Twitter. How does information spread on Twitter? Looks at how the technology works, rather than how people think and act.
Public Health	A focus on using Twitter to study public health issues, often looking at how a public health concern is discussed in tweets and retweets.
Business	A focus on business, marketing, promotions
Artificial Intelligence	A focus on the creation of AI or the uses of AI in social media and other technologies.
Psychology	A focus on human psychology within the context of Twitter and tweets. Often examining tweets to better understand a specific psychological question.
Info Science	A focus on finding, organizing, and making data available
Education	A focus on the use of Twitter in educational settings.
Emergency Response	A focus on using Twitter to detect and respond to natural disasters, pandemics, and other emergencies.

## S4 Appendix. Main Topics Identified by Hand

\*Taken from Final\_Dataset\_Dec2023 at  
[github.com/ryanmurt/Twitter](https://github.com/ryanmurt/Twitter). (bottom of Top Disc by Most Cited tab)

### Topics taken from the 5 most cited studies from each discipline:

The spread of true vs false news  
Factors contributing to the spread of content on Twitter  
The practice of retweeting on Twitter  
How do ideological preferences impact the exchange of information?  
How do emotions impact retweets? Info diffusion  
Identifying influential users on Twitter  
automatic methods for assessing the credibility of tweets.  
Using Twitter to follow and analyze public attention (ie. During a pandemic)  
Analyzing privacy in social media.  
What causes certain content to be retweeted more than others?  
Strategies for tracking health concerns, outbreaks, understanding health information disparities in communities  
Studying misuse and misunderstanding of the use of antibiotics  
A study of how twitter data is used in health research.  
Studying the marketing and promotion of an e-cigarette from a public health perspective  
Using Twitter to identify influenza outbreaks faster  
Efficacy of conducting psychological tests online  
Using twitter to identify diurnal and seasonal mood rhythms across the world  
Efficacy of conducting psychological tests online  
Using tweets to understand consumer sentiment toward brands.  
Proposes a way of classifying tweet content to mitigate user overwhelm from too much content  
Using geospatial data from twitter to identify and track events such as earthquakes  
Understanding how social media can be used in higher education settings. A review of the literature.  
A general study of what twitter is, how and why people use it.  
Strategy for geolocating users based on tweet content  
A new strategy for topic-modeling. How to train the topic model to a specific dataset and achieve more accurate topics.  
What new technologies need to be developed to support the field of genomics?  
Strategy for sentiment analysis  
Comparing twitter, FB and Youtube for understanding and influencing consumer brand communication. Preferences?  
Text mining strategy for analyzing customer sentiments about 3 pizza chains  
Understanding how social media impacts effectuation  
Strategy for text mining consumer sentiments toward specific brands  
Research about how social media can be used to support the supply chain management field: practices, networking, stakeholder engagement, demand shaping, product development  
Strategies for using AI in sentiment/opinion analysis  
Using AI to identify fake news on social media..a specific framework  
Using AI for sentiment analysis

Using sentiment analysis to help business organizations gain business insight into consumer opinions  
Strategy for using AI in sentiment analysis of tweets.

**Most common topics:**

How information spreads on social media (ie. True vs fake news, factors contributing to retweeting/spread)  
How does ideology impact spread?  
Identifying influential users, methods for assessing credibility of tweets,  
Identifying and analyzing major events (pandemic, earthquake, influenza,  
Studying behavior such as misuse and misunderstanding of antibiotics, the marketing/promotion of consumer products  
Studying moods cross culturally (diurnal and seasonal)