Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 June 2022 doi:10.20944/preprints202206.0146.v1

Data Descriptor

A Large-Scale Dataset of Twitter Chatter about Online Learning during the Current COVID-19 Omicron Wave

Nirmalya Thakur

Department of Electrical Engineering and Computer Science, University of Cincinnati, Cincinnati, OH 45221-0030, U.S.A.; thakurna@mail.uc.edu

Abstract: The COVID-19 Omicron variant, reported to be the most immune evasive variant of COVID-19, is resulting in a surge of COVID-19 cases globally. This has caused schools, colleges, and universities in different parts of the world to transition to online learning. As a result, social media platforms such as Twitter are seeing an increase in conversations related to online learning. Mining such conversations, such as Tweets, to develop a dataset can serve as a data resource for interdisciplinary research related to the analysis of interest, views, opinions, perspectives, attitudes, and feedback towards online learning during the current surge of COVID-19 cases caused by the Omicron variant. Therefore this work presents a large-scale public Twitter dataset of conversations about online learning since the first detected case of the COVID-19 Omicron variant in November 2021. The dataset is compliant with the privacy policy, developer agreement, and guidelines for content redistribution of Twitter, as well as with the FAIR principles (Findability, Accessibility, Interoperability, and Reusability) principles for scientific data management. The paper also briefly outlines some potential applications in the fields of Big Data, Data Mining, Natural Language Processing, and their related disciplines, with a specific focus on online learning during this Omicron wave that may be studied, explored, and investigated by using this dataset.

Dataset: https://doi.org/10.5281/zenodo.6624081

Dataset License: CC-BY 4.0

Keywords: COVID-19; COVID; Omicron; online learning; remote learning; online education; Twitter; dataset; Tweets; social media; Big Data

1. Introduction

The first cases of the COVID-19 pandemic, caused by the SARS-CoV-2 virus, were recorded in a seafood market in Wuhan, China, in December 2019 [1]. Since then, the virus has spread to all the countries of the world. At the time of writing this paper, globally, there have been 535,342,382 cases with 6,320,324 deaths [2]. Since the initial cases in China, the SARS-CoV-2 virus has undergone multiple mutations, and as a result, several variants have been detected in different parts of the world. Some of these include – Alpha (B.1.1.7), Beta (B.1.351), Gamma (P.1), Delta (B.1.617.2), Epsilon (B.1.427 B.1.429), Eta (B.1.525), Iota (B.1.526), Kappa (B.1.617.1), Zeta (P.2), Mu (B.1.621, B.1.621.1), and Omicron (B.1.1.529, BA.1, BA.1.1, BA.2, BA.3, BA.4 and BA.5) [3]. Out of all these variants, the Omicron variant, first detected on 24th November 2021 from a sample collected on 9th November 2021, was classified as a Variant of Concern (VOC) by World Health Organization (WHO) on 26th November 2021 [4]. The Omicron variant has a spike protein that contains 30 mutations [5]. It has been reported to be the most immune evasive variant of COVID-19 and to present very strong resistance against antibody-based or plasma-based treatments [6]. According to WHO, the new cases due to this Omicron variant have been “off the charts” and are setting new records in terms of COVID-19 cases all over the world [7]. The Omicron variant currently accounts for 86% of the COVID-19 cases worldwide [8], and some of the countries that have recorded the most cases due to the SARS-CoV-2 Omicron variant include – the United Kingdom (1,138,814 cases), U.S.A. (945,470 cases), Germany (245,120 cases), Denmark (218,106 cases), France (110,959 cases), Canada (92,341 cases), Japan (71,056 cases), India (56,125 cases), Australia (46,576 cases), Sweden (43,400 cases), Israel (39,908 cases), Poland (33,436 cases), and Brazil (32,880 cases) [9].

Since the beginning of the pandemic, several countries in the world, such as – India [10], United States [11], United Kingdom [12], Spain [13], Greece [14], Italy [15], Austria [16], Nigeria [17], China [18], New Zealand [19], Ireland [20], Germany [21], South Africa [22], Australia [23], France, [24], Norway [25], and several more [26], went on a complete lockdown with work from home and remote work guidelines that affected several industries and sectors. Out of all these sectors that were impacted by the nationwide lockdowns and the associated guidelines in different parts of the world, the education sector was an important one. On a global scale, universities, colleges, and schools had to switch to online education, which required its faculty, administrators, staff, and students to get familiarized with online learning and the associated tools and platforms that were necessary for this new norm of education. Online learning may be broadly defined as *"learning experiences in synchronous or asynchronous environments using different devices (e.g., mobile phones, laptops, etc.) with internet access. In these environments, students can be anywhere (independent) to learn and interact with instructors and other students"* [27]. Online learning has a range of synonyms, and some of the most commonly used synonyms include remote education, online education, virtual education, remote learning, e-learning, distance education, virtual learning, asynchronous learning, and blended learning [27].

On a global scale, more than 43,518,726 students were affected due to in-person school closures [28]. Due to the worldwide adoption and familiarization with various forms of tools, platforms, software, and hardware necessary for online education, the online education market is rapidly booming and is expected to reach more than USD 350 billion by 2025 [29]. Due to COVID-19, the closing of universities, colleges, and schools was recorded in 188 countries [30], and 90% of the countries reported a switch to one or more forms of online learning [31]. Despite these promising numbers, 31% (463 million) of students in schools (in pre-primary to secondary education) could not adopt online learning either due to lack of technologies, training, or accessibility, and 75% of students who belonged to the poorest households could not switch to the technologies required for online learning [31].

With the advancements in vaccine research and other forms of treatment of COVID-19 towards the later part of 2020 [32-34] and in compliance with the recommendations from various local and national policy-making bodies, several universities, colleges, and schools started to transition to hybrid learning (both online and in-person) as well as completely in-person learning [35]. However, this was associated with several challenges [36], including a surge of COVID-19 cases in students, educators, and staff members, increase of stress and anxiety in both students and their parents, and need for allocation of funds by these educational institutions to conduct classes in a socially distant manner, for procurement of hand sanitizers, and disinfectants. Despite these challenges, education continued in both hybrid and in-person forms for a few months. However, due to the recent global surge in COVID-19 cases due to the Omicron variant [7-9], several educational institutions all over the world have transitioned back to online learning since the beginning of 2022, and several are in the process of transitioning to online learning over the next few months [37-42].

The modern-day Internet of Everything lifestyle [43] is characterized by people spending more time on the internet than ever before, with a specific focus on social media platforms. The use of social media platforms has skyrocketed in the recent past [44]. Social media usage characteristics include conversations on diverse topics such as recent issues, global challenges, emerging technologies, news, current events, politics, family, relationships, and career opportunities [45]. Twitter, one such social media platform, used by people of almost all age groups [46,47], has been rapidly gaining popularity in all parts of the world and is currently the second most visited social media platform [48]. At present, there are about 192 million daily active users on Twitter, and approximately 500 million tweets are posted on Twitter every day [49]. Mining of social media conversations, for instance, Tweets, to develop datasets has been of significant interest to the scientific community in the areas of Big Data, Data Mining, and Natural Language Processing, as can be seen from these recent works where relevant Tweets were mined to develop Twitter datasets on 2020 U.S. Presidential Elections [50], 2022 Russia Ukraine war [51], climate change [52], natural hazards [53], European Migration Crisis [54], movies [55], toxic behavior amongst adolescents [56], music [57], civil unrest [58], drug safety [59], and Inflammatory Bowel Disease [60].

In the context of the recent surge of COVID-19 cases due to the Omicron variant and its impact on the education sector, there has been a significant increase in conversations on Twitter related to online learning. Mining such conversations to develop a dataset can serve as a data resource for interdisciplinary research related to the analysis of interest, views, opinions, perspectives, attitudes, and feedback towards online learning during the current surge of COVID-19 cases caused due to this variant.

Previous works related to online learning since the outbreak of COVID-19 have focused on analyzing some of these factors only in certain geographic regions, mostly by using surveys, and not on a global scale by analyzing conversations from all over the world, such as Tweets. Prior works related to the development of Twitter datasets related to COVID-19 have also not focused on mining relevant tweets related to online learning. To address these limitations, this work proposes a dataset of about 50,000 Tweet IDs (that correspond to the same number of Tweets) about online learning that was posted on Twitter from 9th November 2021 to 28th May 2022, which is publicly available at https://doi.org/10.5281/zenodo.6624081. The earliest date was selected as 9th November 2021, as the Omicron variant was detected for the first time in a sample that was collected on this date. 28th May 2022 was the most recent date as per the time of data collection and writing of this paper.

The rest of the paper is organized as follows. Section 2 presents an overview of recent works in this field. The methodology that was followed for the development of this dataset is presented in Section 3. Section 4 provides the description of the dataset. Section 5 briefly discusses a few potential applications of this dataset. The conclusion and scope for future work are presented in Section 6, which is followed by references.

2. Literature Review

There has been a significant amount of research related to online learning since the global outbreak of COVID-19. These include - analysis and study of student perspectives [61], perceptions of educators [62], psychological impacts on students [63], barriers to online learning [64], student attitudes [65], student experiences [66], strategies implemented by teachers [67], student satisfaction [68], perspectives of students [69], mental health of students [70], student responses and actions [71], stress detection [72], online systems adopted and the associated challenges [73], difference in access and participation amongst students [74], effect on the learning status of students [75], student well-being [76], student readiness [77], new teaching strategies and models [78], use of virtual reality technology [79], ethno-cultural competence [80], degrees of student adaptation [81], student views [82], methodologies for online inclusion [83], academic integration [84], impact of using Google Classroom [85], degrees of user satisfaction with different platforms [86], educational outcomes [87], challenges faced by educators [88], impact of student diversity towards the effectiveness of online learning [89], and awareness and knowledge of students towards online learning [90].

In terms of mining relevant conversations related to a specific topic on Twitter since the outbreak of COVID-19, the prior works in this field have focused on the development of datasets for healthcare misinformation [91], misleading information [92], vaccine misinformation [93], patient identification [94], updates related to vaccine development [95], and rumors related to COVID-19 [96].

Despite these emerging works in the fields of online learning and the development of Twitter datasets, there exist multiple limitations. First, these works in the field of online learning have been confined to studying or analyzing the success or failure, degrees of acceptance, and associated factors related to online learning in specific geographic regions such as Pakistan [61], Indonesia [62,63,66,67], Philippines [64], UAE [65], Saudi Arabia [68], Jordan [69], Kazakhstan [70], Ghana [71], Saudi Arabia [72], Bangladesh [73], United States [74,77], India [75], United Kingdom [76], Germany [77], UAE [78], Ukraine [79], Russia [80], Spain [81], Greece [82], Italy [83], Austria [84], Nigeria [85], China [86], Australia [87], South Africa [88], Taiwan [89], and Sri Lanka [90], and not at a global level. Second, due to the lack of datasets such as Twitter conversations related to online learning from global users, the data that were analyzed in these studies were mostly in the form of surveys that were conducted in these respective geographic regions. Third, the Twitter datasets related to COVID-19 [91-96] do not focus on online learning and the ongoing chatter on Twitter about the same amidst the global rise of COVID-19 cases due to the Omicron variant. The dataset proposed in this paper aims to address all these limitations.

3. Methodology

This section describes the methodology that was followed for the development of this dataset publicly available at https://doi.org/10.5281/zenodo.6624081. The raw version of the dataset (presented in the form of 6 .txt files) contains 52,868 Tweet IDs corresponding to 52,868 tweets about online learning publicly posted on Twitter from 9th November 2021 (sample collected on this date was the first case of Omicron) to 28th May 2022 (the most recent date at the time of data collection). This section also outlines how this work and the associated dataset development is in compliance with the privacy policy, developer agreement, and guidelines for content redistribution of Twitter, as well as follows the FAIR principles (Findability, Accessibility, Interoperability, and Reusability) principles for scientific data management. These are discussed in Sections 3.1, 3.2, and 3.3, respectively.

3.1. Process for Dataset Development

As this work focuses on developing a Twitter dataset, the privacy policy, developer agreement, and guidelines for content redistribution of Twitter [97,98] were thoroughly studied, and after studying the same, it was concluded that mining relevant tweets from Twitter to develop a dataset (comprising only Tweet IDs) is in compliance with all these policies of Twitter. Therefore this dataset contains only Tweet IDs and does not contain any other information related to the respective Tweets that were mined. A detailed explanation of this compliance is mentioned in Section 3.2.

The tweets were collected by using the Search Twitter "operator" [99] available in RapidMiner studio [100]. RapidMiner is a data science platform that allows the development, implementation, and testing of various algorithms, processes, and applications in the fields of Big Data, Data Mining, Data Science, Artificial Intelligence, Machine Learning, and their related areas. There are various RapidMiner products available such as RapidMiner Studio, RapidMiner AI Hub, and RapidMiner Radoop. For this work, the RapidMiner studio, version 9.10, was downloaded and installed on a laptop with the Microsoft Windows 10 Home operating system with Intel(R) Pentium(R) Silver N5030 CPU @ 1.10GHz, 1101 Mhz, 4 Core(s), and 4 Logical Processor(s). In the RapidMiner platform, "process" and "operator" are two commonly used terminologies. An "operator" represents a specific function or operation that can be used to fetch data from a social media platform such as Twitter based on a specific set of guidelines or to perform a specific operation on a dataset. RapidMiner has a number of in-built "operators". It also allows users to develop "operators" from scratch. A collection of "operators" that are connected in a logical sequence to achieve the desired purpose is called a "process". A "process" may also contain just one "operator" if the complete functionality of the "process" can be found in one in-built or user-defined "operator". The Search Twitter "operator", an in-built "operator" of RapidMiner, works by connecting with the Twitter API and by complying with the Twitter API standard search policies [101] to fetch tweets between two given dates that contain one or more keywords or phrases which are provided as input to this "operator". As there are different keywords that Twitter users can use to refer to both COVID-19, the Omicron variant, and online learning, therefore a bag of words was developed based on studying commonly used synonyms, phrases, and terms used to refer to online learning [102], COVID-19 and the Omicron variant [103]. These synonyms, terms, and phrases, all of which were included in the data collection process, are shown in Table 1.

Table 1. List of commonly used synonyms, terms, and phrases for online learning and COVID-19.

Terminology	List of synonyms and Terms
COVID-19	Omicron, COVID, COVID19, coronavirus, coronaviruspandemic, COVID-19, corona, coronaoutbreak, omicron variant, SARS CoV-2, corona virus
online learning	online education, online learning, remote education, remote learning, e-learning, elearning, distance learning, distance education, virtual learning, virtual education, online teaching, remote teaching, virtual teaching, online class, online classes, remote class, remote classes, distance class, distance classes, virtual class, virtual classes, online course, online courses, remote course, remote courses, distance course, distance courses, virtual course, virtual courses, online school, virtual school, remote school, online college, online university, virtual college, virtual university, remote college, remote university, online lecture, virtual lecture, remote lecture, online lectures, virtual lectures, remote lectures

Tweets were searched using this "process" that comprised the Search Twitter "operator" in a way that it consisted of at least one synonym or term or phrase used to refer to COVID-19 and at least one synonym or term or phrase used to refer to online learning. The Search Twitter "operator" is not case-sensitive, so it returned the tweets based on keyword matching by ignoring the case (uppercase or lowercase).

The output of this RapidMiner "process" comprised of multiple attributes such as the Tweet ID, Tweet Source (the source used to post the Tweet such as Twitter for Android, Twitter for IOS, etc.), Text of the Tweet, Retweet count, and the username of the Twitter user who posted the Tweet, all of which is public information that can be mined in compliance with the guidelines set forth in the Twitter API standard search policies. However, as per the developer policy, privacy policy, and content redistribution guidelines of Twitter, all the attributes other than the Tweet IDs were deleted by using data filters. Therefore, the dataset consists of only Tweet IDs. These Tweet IDs were grouped into different .txt files based on the associated keywords representing tweets related to both online learning and the Omicron variant of COVID-19. The description and details of these dataset files are presented in Section 4.

The complete information associated with a tweet, such as the text of a tweet, user name, user ID, timestamp, retweet count, etc., can be obtained from a Tweet ID by following a process known as hydration of Tweet ID [104]. Researchers in the field of Big Data, Data Mining, and Natural Language Processing, with a specific focus on Twitter research, have developed multiple tools for hydration of Tweet IDs. Some of the most commonly used tools include – the Hydrator app [105], Social Media Mining Toolkit [106], and Twarc [107], all of which work by complying with the policies of accessing the Twitter API. Any of these tools can be used on this dataset to obtain the associated information, such as the text of a tweet, user name, user I.D., timestamp, and retweet count for all the Tweet I.D.s. A step-by-step process on how to use one of these tools – the Hydrator app for hydrating all the Tweet IDs in this dataset is mentioned in Appendix A.

A couple of things are worth mentioning here. First, Twitter allows users the option to delete a tweet which would mean that there would be no retrievable Tweet text and other related information (upon hydration) for a Tweet ID of a deleted tweet. All the Tweet IDs available in this dataset correspond to tweets that have not been deleted at the time of writing this paper. Second, the Twitter API's standard search feature does not return an exhaustive list of tweets that were posted in a specific date range. So, it is possible that multiple tweets that might have been posted in between this date range were not returned by the Twitter API's standard search feature when the data collection was performed and are thus not a part of this dataset.

3.2. Compliance with Twitter Policies

The privacy policy of Twitter [97] states – *"Twitter is public and Tweets are immediately viewable and searchable by anyone around the world"*. To add, the Twitter developer agreement [98] defines tweets as *"public data"*. The guidelines for Twitter content redistribution [98] state – "*If you provide Twitter Content to third parties, including downloadable datasets or via an API, you may only distribute Tweet I.D.s, Direct Message I.D.s, and/or User I.D.s (except as described below)*. It also states - *"We also grant special permissions to academic researchers sharing Tweet I.D.s and User I.D.s for non-commercial research purposes. Academic researchers are permitted to distribute an unlimited number of Tweet I.D.s and/or User I.D.s if they are doing so on behalf of an academic institution and for the sole purpose of non-commercial research."* Therefore, it may be concluded that mining relevant tweets from Twitter to develop a dataset (comprising only Tweet IDs) and sharing the same is in compliance with the privacy policy, developer agreement, and content redistribution guidelines of Twitter.

3.3. Compliance with FAIR

This section outlines how this dataset is compliant with the FAIR principles (Findability, Accessibility, Interoperability, and Reusability) principles for scientific data management [108]. The dataset is findable as it has a unique and permanent DOI, which was assigned by Zenodo. The dataset is accessible online. It is interoperable due to the use of .txt files for data representation that can be downloaded, read, and analyzed across different computer systems and applications. The dataset is re-usable as the associated tweets and related information such as user ID, user name, retweet count, etc., for all the Tweet IDs can be obtained by the process of hydration in compliance with Twitter policies (Appendix A), for data analysis and interpretation.

4. Data Description

This section provides a detailed description of this dataset. The raw version of the dataset comprises 52,868 Tweet IDs corresponding to 52,868 tweets about online learning posted on Twitter between 9th November 2021 (the sample collected on this date was the first case of Omicron) to 28th May 2022 (the most recent date at the time of data collection). The dataset is available at https://doi.org/10.5281/zenodo.6624081. It comprises 7 .txt files. The raw version of this dataset comprises 6 .txt files (TweetIDs_Corona Virus.txt, TweetIDs_Corona.txt, TweetIDs_Coronavirus.txt, TweetIDs_Covid.txt, TweetIDs _Omicron.txt, and TweetIDs_SARS CoV2.txt) that contain Tweet IDs grouped together based on certain synonyms or terms that were used to refer to online learning and the Omicron variant of COVID-19 in the respective tweets. Table 2 presents the description of each of these raw dataset files along with the number of Tweet IDs present in each of them. Several tweets were recorded that fit into the description corresponding to multiple such groups. An example of such as tweet is – *"new variant of covid is very dangerous #Omicron .Looking at the situation of covid and do classes online and also get mid semester exam online then why exam online, Take exam online. @RGPVBhopal #OmicronVariant #rgpvexam #rgpvexam2021"*. So, according to the definition for grouping of these Tweet IDs, the Tweet ID of this tweet is present in both the .txt files - TweetIDs_Covid.txt and TweetIDs_Omicron.txt. Therefore, data preprocessing was performed for the removal of such duplicate tweets, and after the removal of these duplicate tweets, a total of 46,208 unique tweets were recorded. The tweet IDs corresponding to all these unique tweets is presented in the dataset file with filename - TweetIDs_Duplicates_Removed.txt. Table 3 presents a random collection of 7 tweets from this dataset. In this Table, "Serial No." refers to the serial number and not the Tweet ID.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 June 2022 doi:10.20944/preprints202206.0146.v1

Table 2. Description of all the files present in this dataset.

Filename	No. of Tweet IDs	Description
TweetIDs_Corona Virus.txt	321	Tweet I.D.s correspond to tweets that comprised the keywords – "corona virus" and one or more keywords/terms that refer to online learning
TweetIDs_Corona.txt	1819	Tweet I.D.s correspond to tweets that comprised the keyword – "corona" or "coronaoutbreak" and one or more keywords/terms that refer to online learning
TweetIDs_Coronavirus.txt	1429	Tweet I.D.s correspond to tweets that comprised the keywords – "coronavirus" or "coronaviruspandemic" and one or more keywords/terms that refer to online learning
TweetIDs_Covid.txt	41088	Tweet I.D.s correspond to tweets that comprised the keywords – "COVID" or "COVID19" or "COVID-19" and one or more keywords/terms that refer to online learning
TweetIDs_Omicron.txt	8198	Tweet I.D.s correspond to tweets that comprised the keywords – "omicron" or "omicron variant" and one or more keywords/terms that refer to online learning
TweetIDs_SARS CoV2.txt	13	Tweet I.D.s correspond to tweets that comprised the keyword – "SARS-CoV-2" and one or more keywords/terms that refer to online learning
TweetIDs_Duplicates_Removed.txt	46208	A collection of unique Tweet I.D.s from all the 6 .txt files mentioned above, made available after data preprocessing, data clearing, and removal of duplicate tweets

Table 3. A random collection of 10 tweets from this dataset.

Serial No.	Tweet text
1	In view of the third wave of the Corona virus pandemic, the Government of West Bengal in School Education Department has decided to start online classes for Classes X and XII and Banglar Shiksha Durbhashe for classes VI to X respectively from 17th January 2022.
2	As a teacher myself, I would consider: A) If students are not engaging in virtual lectures/classes, maybe they weren't engaging as much as I thought in-person either. B) Wanting to be in-person is less important than preventing the COVID spread.
3	Many sudents of Arid Uni have been tested positive for Covid most probably Omicron ,in this grim situ Online exam is inevitable . Authorities must consider the option of Online in the best intrest of Students health as well as staff #AridianLivesMatter
4	Teaching College in BC During Omicron, Day 41: 100% attended online class. Since the start of term, 60% of students reported contracting COVID.
5	University of Hawaii campuses extend online classes until 31st January amid the Covid-19 omicron spike! #bbn #Hawaii #COVID19 #Omicron #college #uhawaii
6	Students at UT Arlington and UT Dallas will begin their spring semester with online classes because of the COVID-19 omicron variant.
7	University of Cincinnati moves to online classes to start the first two weeks of the Spring 2022 semester due to high Covid-19 omicron case numbers in Greater Cincinnati! #bbn #Covid #Omicron #Cincinnati #Ohio #uofcincy #collegecovid

5. Potential Applications: Brief Overview

This dataset of about 50,000 Tweet IDs is expected to help advance interdisciplinary research in different fields such as Big Data, Data Science, Data Mining, Natural Language Processing, Healthcare, and their related disciplines. A few potential applications and use-case scenarios that may be investigated using this dataset include performing sentiment analysis [109], performing aspect-based sentiment analysis [110], predicting popular tweets [111], detecting sarcasm [112], developing topic modeling [113], tracking retweeting patterns [114], ranking tweets [115], performing content value analysis [116], tracking credibility of information [117], detecting conspiracy theories [118], predicting emoji usage patterns [119], studying the relevance of information [120], detecting satire [121], detecting deception [122], extracting categorical topics and emerging issues [123], characterizing Twitter users [124], and detection of Twitter user demographics [125] in the context of Twitter chatter related to online learning during the current Omicron wave of COVID-19.

6. Conclusion

The outbreak of COVID-19 led to schools, colleges, and universities in almost all parts of the world closing and transitioning to online learning. The development of vaccines and other forms of treatment towards the end of 2020 led to some of these educational institutions re-opening and starting to function in a hybrid as well as in a completely in-person manner. The recent surge of the COVID-19 cases globally due to the Omicron variant, the most immune evasive variant of COVID-19 that presents very strong resistance against antibody-based or plasma-based treatments, has resulted in several such educational institutions switching to online learning once again. This has led to an increase in the number of online conversations, specifically on Twitter, related to online learning since the first detected case of the Omicron variant in November 2021. Mining such tweets to develop a dataset would serve as a data resource for interdisciplinary research related to the analysis of interest, views, opinions, perspectives, attitudes, and feedback towards online learning during the current surge of COVID-19 cases caused due to this variant. The prior works in this field did not focus on the development of a similar data resource. Therefore, this work proposes a public dataset of about 50,000 Tweet IDs (that correspond to the same number of tweets) about online learning posted on Twitter between 9th November 2021 (the sample collected on this date was the first case of Omicron) to 28th May 2022 (the most recent date at the time of data collection). The raw version of the dataset that contains 52,868 Tweet IDs, as well as the cleaned and preprocessed version that contains 46,208 unique Tweet IDs, are presented. The dataset is compliant with the privacy policy, developer agreement, and guidelines for content redistribution of Twitter, as well as with the FAIR principles (Findability, Accessibility, Interoperability, and Reusability) principles for scientific data management. Future work on this project would involve updating the dataset with more recent tweets to ensure that the scientific community has access to the recent data in this regard.

Funding: This research received no external funding

Data Availability Statement: The data presented in this study are publicly available at https://doi.org/10.5281/zenodo.6624081

Conflicts of Interest: The author declares no conflict of interest

Appendix A

The following is the step-by-step process for using the Hydrator app [105] to hydrate this dataset or, in other words, to obtain the text of the tweet, user I.D., user name, retweet count, language, tweet URL, source, and other public information related to all the Tweet IDs present in this dataset. The Hydrator app works in compliance with the policies for accessing and calling the Twitter API.

1. Download and install the desktop version of the Hydrator app from https://github.com/DocNow/hydrator/releases.
2. Click on the “Link Twitter Account” button on the Hydrator app to connect the app to an active Twitter account.
3. Click on the “Add” button to upload one of the dataset files (in .txt format, such as TweetIDs_Omicron.txt). This process adds the dataset file to the Hydrator app.

4. If the file upload is successful, the Hydrator app will show the total number of Tweet IDs present in the file. For instance, for the file - "TweetIDs_Omicron.txt ", the app would show the Number of Tweet I.D.s as 8198.
5. Provide details for the respective fields: Title, Creator, Publisher, and URL in the app, and click on "Add Dataset" to add this dataset to the app.
6. The app would automatically redirect to the "Datasets" tab. Click on the "Start" button to start hydrating the Tweet IDs. During the hydration process, the progress indicator would increase, indicating the number of Tweet IDs that have been successfully hydrated and the number of Tweet IDs that are pending hydration.
7. After the hydration process ends, a .jsonl file would be generated by the app that the user can choose to save on the local storage.
8. The app would also display a "CSV" button in place of the "Start" button. Clicking on this "CSV" button would generate a .csv file with detailed information about the tweets, which would include the text of the tweet, user I.D., user name, retweet count, language, tweet URL, source, and other public information related to the tweet.
9. Repeat steps 3-8 for hydrating all the files of this dataset.

References

1. Wu, Y.-C.; Chen, C.-S.; Chan, Y.-J. Overview of the 2019 Novel Coronavirus (2019-NCoV): The Pathogen of Severe Specific Contagious Pneumonia (SSCP): The Pathogen of Severe Specific Contagious Pneumonia (SSCP). J. Chin. Med. Assoc. 2020, 83, 1, doi:10.1097/JCMA.0000000000000270.
2. COVID Live - Coronavirus Statistics - Worldometer Available online: https://www.worldometers.info/coronavirus/ (accessed on 6 June 2022).
3. CDC SARS-CoV-2 Variant Classifications and Definitions Available online: https://www.cdc.gov/coronavirus/2019-ncov/variants/variant-classifications.html (accessed on 6 June 2022).
4. Classification of Omicron (B.1.1.529): SARS-CoV-2 Variant of Concern Available online: https://www.who.int/news/item/26-11-2021-classification-of-omicron-(b.1.1.529)-sars-cov-2-variant-of-concern (accessed on 6 June 2022).
5. Gobeil, S.M.-C.; Henderson, R.; Stalls, V.; Janowska, K.; Huang, X.; May, A.; Speakman, M.; Beaudoin, E.; Manne, K.; Li, D.; et al. Structural Diversity of the SARS-CoV-2 Omicron Spike. Mol. Cell 2022, 82, 2050-2068.e6, doi:10.1016/j.molcel.2022.03.028.
6. Schmidt, F.; Muecksch, F.; Weisblum, Y.; Da Silva, J.; Bednarski, E.; Cho, A.; Wang, Z.; Gaebler, C.; Caskey, M.; Nussenzweig, M.C.; et al. Plasma Neutralization of the SARS-CoV-2 Omicron Variant. N. Engl. J. Med. 2022, 386, 599–601, doi:10.1056/NEJMc2119641.
7. Feiner, L. WHO Says Omicron Cases Are "off the Charts" as Global Infections Set New Records Available online: https://www.cnbc.com/2022/01/12/who-says-omicron-cases-are-off-the-charts-as-global-infections-set-new-records.html (accessed on 6 June 2022).
8. Weekly Epidemiological Update on COVID-19 - 22 March 2022 Available online: https://www.who.int/publications/m/item/weekly-epidemiological-update-on-covid-19---22-march-2022 (accessed on 6 June 2022).
9. SARS-CoV-2 Omicron Variant Cases Worldwide 2022 Available online: https://www.statista.com/statistics/1279100/number-omicron-variant-worldwide-by-country/ (accessed on 6 June 2022).
10. The Lancet India under COVID-19 Lockdown. Lancet 2020, 395, 1315, doi:10.1016/S0140-6736(20)30938-7.
11. Surano, F.V.; Porfiri, M.; Rizzo, A. Analysis of Lockdown Perception in the United States during the COVID-19 Pandemic. Eur. Phys. J. Spec. Top. 2021, 1–9, doi:10.1140/epjs/s11734-021-00265-z.
12. Jallow, H.; Renukappa, S.; Suresh, S. The Impact of COVID-19 Outbreak on United Kingdom Infrastructure Sector. Smart Sustain. Built Environ. 2021, 10, 581–593, doi:10.1108/sasbe-05-2020-0068.
13. Tejedor, S.; Cervi, L.; Pérez-Escoda, A.; Jumbo, F.T. Digital Literacy and Higher Education during COVID-19 Lockdown: Spain, Italy, and Ecuador. Publications 2020, 8, 48, doi:10.3390/publications8040048.
14. Fountoulakis, K.N.; Apostolidou, M.K.; Atsiova, M.B.; Filippidou, A.K.; Florou, A.K.; Gousiou, D.S.; Katsara, A.R.; Mantzari, S.N.; Padouva-Markoulaki, M.; Papatriantafyllou, E.I.; et al. Self-Reported Changes in Anxiety, Depression and Suicidality during the COVID-19 Lockdown in Greece. J. Affect. Disord. 2021, 279, 624–629, doi:10.1016/j.jad.2020.10.061.
15. Guzzetta, G.; Riccardo, F.; Marziano, V.; Poletti, P.; Trentini, F.; Bella, A.; Andrianou, X.; Del Manso, M.; Fabiani, M.; Bellino, S.; et al. The Impact of a Nation-Wide Lockdown on COVID-19 Transmissibility in Italy. arXiv [q-bio.PE] 2020, doi:10.48550/ARXIV.2004.12338.
16. Probst, T.; Stippl, P.; Pieh, C. Changes in Provision of Psychotherapy in the Early Weeks of the COVID-19 Lockdown in Austria. Int. J. Environ. Res. Public Health 2020, 17, 3815, doi:10.3390/ijerph17113815.

17. Oyediran, W.O.; Omoare, A.M.; Owoyemi, M.A.; Adejobi, A.O.; Fasasi, R.B. Prospects and Limitations of E-Learning Application in Private Tertiary Institutions amidst COVID-19 Lockdown in Nigeria. Heliyon 2020, 6, e05457, doi:10.1016/j.heliyon.2020.e05457.
18. Lau, H.; Khosrawipour, V.; Kocbach, P.; Mikolajczyk, A.; Schubert, J.; Bania, J.; Khosrawipour, T. The Positive Impact of Lockdown in Wuhan on Containing the COVID-19 Outbreak in China. J. Travel Med. 2020, 27, doi:10.1093/jtm/taaa037.
19. Chan, D.Z.; Stewart, R.A.; Kerr, A.J.; Dicker, B.; Kyle, C.V.; Adamson, P.D.; Devlin, G.; Edmond, J.; El-Jack, S.; Elliott, J.M.; et al. The Impact of a National COVID-19 Lockdown on Acute Coronary Syndrome Hospitalisations in New Zealand (ANZACS-QI 55). Lancet Reg Health West Pac 2020, 5, 100056, doi:10.1016/j.lanwpc.2020.100056.
20. Fahy, S.; Moore, J.; Kelly, M.; Flannery, O.; Kenny, P. Analysing the Variation in Volume and Nature of Trauma Presentations during COVID-19 Lockdown in Ireland. Bone & Joint Open 2020, 1, 261–266, doi:10.1302/2633-1462.16.bjo-2020-0040.r1.
21. Lemenager, T.; Neissner, M.; Koopmann, A.; Reinhard, I.; Georgiadou, E.; Müller, A.; Kiefer, F.; Hillemacher, T. COVID-19 Lockdown Restrictions and Online Media Consumption in Germany. Int. J. Environ. Res. Public Health 2020, 18, 14, doi:10.3390/ijerph18010014.
22. Stiegler, N.; Bouchard, J.-P. South Africa: Challenges and Successes of the COVID-19 Lockdown. Ann. Med. Psychol. (Paris) 2020, 178, 695–698, doi:10.1016/j.amp.2020.05.006.
23. Matheson, A.; McGannon, C.J.; Malhotra, A.; Palmer, K.R.; Stewart, A.E.; Wallace, E.M.; Mol, B.W.; Hodges, R.J.; Rolnik, D.L. Prematurity Rates during the Coronavirus Disease 2019 (COVID-19) Pandemic Lockdown in Melbourne, Australia. Obstet. Gynecol. 2021, 137, 405–407, doi:10.1097/AOG.0000000000004236.
24. Di Domenico, L.; Pullano, G.; Sabbatini, C.E.; Boëlle, P.-Y.; Colizza, V. Impact of Lockdown on COVID-19 Epidemic in Île-de-France and Possible Exit Strategies. BMC Med. 2020, 18, 240, doi:10.1186/s12916-020-01698-4.
25. Lehmann, S.; Skogen, J.C.; Haug, E.; Mæland, S.; Fadnes, L.T.; Sandal, G.M.; Hysing, M.; Bjørknes, R. Perceived Consequences and Worries among Youth in Norway during the COVID-19 Pandemic Lockdown. Scand. J. Public Health 2021, 49, 755–765, doi:10.1177/1403494821993714.
26. Onyeaka, H.; Anumudu, C.K.; Al-Sharify, Z.T.; Egele-Godswill, E.; Mbaegbu, P. COVID-19 Pandemic: A Review of the Global Lockdown and Its Far-Reaching Effects. Sci. Prog. 2021, 104, 368504211019854, doi:10.1177/00368504211019854.
27. Singh, V.; Thurman, A. How Many Ways Can We Define Online Learning? A Systematic Literature Review of Definitions of Online Learning (1988-2018). Am. J. Distance Educ. 2019, 33, 289–306, doi:10.1080/08923647.2019.1663082.
28. Education: From Disruption to Recovery, UNSECO Report Available online: https://en.unesco.org/covid19/educationresponse (accessed on 6 June 2022).
29. Research Online Education Market Study 2019 Available online: https://www.globenewswire.com/news-release/2019/12/17/1961785/0/en/Online-Education-Market-Study-2019-World-Market-Projected-to-Reach-350-Billion-by-2025-Dominated-by-the-United-States-and-China.html (accessed on 6 June 2022).
30. Education and COVID-19 Available online: https://data.unicef.org/topic/education/covid-19/ (accessed on 6 June 2022).
31. COVID-19: Are Children Able to Continue Learning during School Closures? Available online: https://data.unicef.org/resources/remote-learning-reachability-factsheet/ (accessed on 6 June 2022).
32. Stasi, C.; Fallani, S.; Voller, F.; Silvestri, C. Treatment for COVID-19: An Overview. Eur. J. Pharmacol. 2020, 889, 173644, doi:10.1016/j.ejphar.2020.173644.
33. Peng, Y.; Tao, H.; Satyanarayanan, S.K.; Jin, K.; Su, H. A Comprehensive Summary of the Knowledge on COVID-19 Treatment. Aging Dis. 2021, 12, 155–191, doi:10.14336/AD.2020.1124.
34. Bartoli, A.; Gabrielli, F.; Alicandro, T.; Nascimbeni, F.; Andreone, P. COVID-19 Treatment Options: A Difficult Journey between Failed Attempts and Experimental Drugs. Intern. Emerg. Med. 2021, 16, 281–308, doi:10.1007/s11739-020-02569-9.
35. REOPENING SCHOOLS AFTER COVID-19 CLOSURES Considerations for States Available online: http://files.eric.ed.gov/fulltext/ED609236.pdf (accessed on 6 June 2022).
36. Gunawan, M.; Setiawan, A.A.; Leonita, I.; Neville School Reopening during COVID-19 Pandemic: Is It Safe? A Systematic Review. J. Asian Med. Stud. Assoc. 2022.
37. Lockdowns, School Closures Return to Mainland China Available online: https://www.usnews.com/news/education-news/articles/2022-03-14/lockdowns-school-closures-return-to-mainland-china (accessed on 6 June 2022).
38. Sachdev, C. India Postpones In-School Learning as Omicron Surges Available online: https://theworld.org/stories/2022-01-07/india-postpones-school-learning-omicron-surges (accessed on 6 June 2022).
39. School Systems around the World Debate New Closures as Omicron Spreads Available online: https://www.washingtonpost.com/world/2022/01/07/global-school-closures-omicron/ (accessed on 6 June 2022).
40. Nearly 6,000 Public Schools in Japan at Least Partially Closed amid Omicron Wave Available online: https://www.japantimes.co.jp/news/2022/02/04/national/school-closures-omicron/ (accessed on 8 June 2022).
41. Khan, N. Hong Kong to Shut Schools to Fight Omicron; Foreigners Rush to Leave. Wall St. J. (East Ed) 2022.
42. COLLIN BINKLEY (Associated Press) Dozens of US Colleges Starting Semester Online Available online: https://www.10tv.com/article/news/nation-world/colleges-online-omicron-covid-remote-learning/507-63ea4bd0-9ccf-40cd-a373-e54da40e2fdb (accessed on 6 June 2022).
43. Snyder, T.; Byrd, G. The Internet of Everything. Computer (Long Beach Calif.) 2017, 50, 8–9, doi:10.1109/mc.2017.179.
44. Boulianne, S. Social Media Use and Participation: A Meta-Analysis of Current Research. Inf. Commun. Soc. 2015, 18, 524–538, doi:10.1080/1369118x.2015.1008542.
45. Kavada, A. Social Media as Conversation: A Manifesto. Soc. Media Soc. 2015, 1, 205630511558079, doi:10.1177/2056305115580793.

46. Liu, Y.; Singh, L.; Mneimneh, Z. A Comparative Analysis of Classic and Deep Learning Models for Inferring Gender and Age of Twitter Users. In Proceedings of the Proceedings of the 2nd International Conference on Deep Learning Theory and Applications; SCITEPRESS - Science and Technology Publications, 2021.
47. Özbaş-Anbarlı, Z. Living in Digital Space: Everyday Life on Twitter. Commun. soc. 2021, 31–47, doi:10.15581/003.34.2.31-47.
48. Gruzd, A.; Wellman, B.; Takhteyev, Y. Imagining Twitter as an Imagined Community. Am. Behav. Sci. 2011, 55, 1294–1318, doi:10.1177/0002764211409378.
49. Aslam, S. Twitter by the Numbers (2022): Stats, Demographics & Fun Facts. Omnicoreagency.com 2022.
50. Chen, E.; Deb, A.; Ferrara, E. #Election2020: The First Public Twitter Dataset on the 2020 US Presidential Election. J. Comput. Soc. Sci. 2022, 5, 1–18, doi:10.1007/s42001-021-00117-9.
51. Haq, E.-U.; Tyson, G.; Lee, L.-H.; Braud, T.; Hui, P. Twitter Dataset for 2022 Russo-Ukrainian Crisis. arXiv [cs.SI] 2022, doi:10.48550/ARXIV.2203.02955.
52. Effrosynidis, D.; Karasakalidis, A.I.; Sylaios, G.; Arampatzis, A. The Climate Change Twitter Dataset. Expert Syst. Appl. 2022, 204, 117541, doi:10.1016/j.eswa.2022.117541.
53. Meng, L.; Dong, Z.S. Natural Hazards Twitter Dataset. arXiv [cs.SI] 2020, doi:10.48550/ARXIV.2004.14456.
54. Urchs, S.; Wendlinger, L.; Mitrovic, J.; Granitzer, M. MMoveT15: A Twitter Dataset for Extracting and Analysing Migration-Movement Data of the European Migration Crisis 2015. In Proceedings of the 2019 IEEE 28th International Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE); IEEE, 2019; pp. 146–149.
55. Dooms, S.; De Pessemier, T.; Martens, L. MovieTweetings: A Movie Rating Dataset Collected from Twitter. In Proceedings of the Workshop on Crowdsourcing and Human Computation for Recommender Systems (CrowdRec 2013), held in conjunction with the 7th ACM Conference on Recommender Systems (RecSys 2013); 2013.
56. Wijesiriwardene, T.; Inan, H.; Kursuncu, U.; Gaur, M.; Shalin, V.L.; Thirunarayan, K.; Sheth, A.; Arpinar, I.B. ALONE: A Dataset for Toxic Behavior among Adolescents on Twitter. In Lecture Notes in Computer Science; Springer International Publishing: Cham, 2020; pp. 427–439 ISBN 9783030609740.
57. 57.Zangerle, E.; Pichl, M.; Gassler, W.; Specht, G. #nowplaying Music Dataset: Extracting Listening Behavior from Twitter. In Proceedings of the Proceedings of the First International Workshop on Internet-Scale Multimedia Management - WISMM '14; ACM Press: New York, New York, USA, 2014.
58. Sech, J.; DeLucia, A.; Buczak, A.L.; Dredze, M. Civil Unrest on Twitter (CUT): A Dataset of Tweets to Support Research on Civil Unrest. In Proceedings of the Proceedings of the Sixth Workshop on Noisy User-generated Text (W-NUT 2020); Association for Computational Linguistics: Stroudsburg, PA, USA, 2020; pp. 215–221.
59. Tekumalla, R.; Banda, J.M. A Large-Scale Twitter Dataset for Drug Safety Applications Mined from Publicly Existing Resources. arXiv [cs.IR] 2020, doi:10.48550/ARXIV.2003.13900.
60. Stemmer, M.; Parmet, Y.; Ravid, G. What Are IBD Patients Talking about on Twitter? In ICT for Health, Accessibility and Wellbeing; Springer International Publishing: Cham, 2021; pp. 206–220 ISBN 9783030942083.
61. Adnan, M.; Anwar, K. Online Learning amid the COVID-19 Pandemic: Students' Perspectives.
62. Rasmitadila, R.; Aliyyah, R.R.; Rachmadtullah, R.; Samsudin, A.; Syaodih, E.; Nurtanto, M.; Tambunan, A.R.S. The Perceptions of Primary School Teachers of Online Learning during the COVID-19 Pandemic Period: A Case Study in Indonesia. J Ethn Cult Stud 2020, 7, 90, doi:10.29333/ejecs/388.
63. Irawan, A.W.; Dwisona, D.; Lestari, M. Psychological Impacts of Students on Online Learning during the Pandemic COVID-19. KONSELI J. Bimbing. dan Konseling (E-J.) 2020, 7, 53–60, doi:10.24042/kons.v7i1.6389.
64. Baticulon, R.E.; Sy, J.J.; Alberto, N.R.I.; Baron, M.B.C.; Mabulay, R.E.C.; Rizada, L.G.T.; Tiu, C.J.S.; Clarion, C.A.; Reyes, J.C.B. Barriers to Online Learning in the Time of COVID-19: A National Survey of Medical Students in the Philippines. Med. Sci. Educ. 2021, 31, 615–626, doi:10.1007/s40670-021-01231-z.
65. Hussein, E.; Daoud, S.; Alrabaiah, H.; Badawi, R. Exploring Undergraduate Students' Attitudes towards Emergency Online Learning during COVID-19: A Case from the UAE. Child. Youth Serv. Rev. 2020, 119, 105699, doi:10.1016/j.childyouth.2020.105699.
66. Famularsih, S. Students' Experiences in Using Online Learning Applications Due to COVID-19 in English Classroom. Stud. Learn. Teach. 2020, 1, 112–121, doi:10.46627/silet.v1i2.40.
67. Sutarto, S.; Sari, D.P.; Fathurrochman, I. Teacher Strategies in Online Learning to Increase Studentsâ€™ Interest in Learning during COVID-19 Pandemic. J. Konseling dan Pendidik. 2020, 8, 129, doi:10.29210/147800.
68. Almusharraf, N.; Khahro, S. Students Satisfaction with Online Learning Experiences during the COVID-19 Pandemic. Int. J. Emerg. Technol. Learn. 2020, 15, 246, doi:10.3991/ijet.v15i21.15647.
69. Al-Salman, S.; Haider, A.S. Jordanian University Students' Views on Emergency Online Learning during COVID-19. Online learn. 2021, 25, doi:10.24059/olj.v25i1.2470.
70. Bolatov, A.K.; Seisembekov, T.Z.; Askarova, A.Z.; Baikanova, R.K.; Smailova, D.S.; Fabbro, E. Online-Learning Due to COVID-19 Improved Mental Health among Medical Students. Med. Sci. Educ. 2020, 31, 1–10, doi:10.1007/s40670-020-01165-y.
71. Agormedah, E.K.; Adu Henaku, E.; Ayite, D.M.K.; Apori Ansah, E. Online Learning in Higher Education during COVID-19 Pandemic: A Case of Ghana. J. educ. technol. online learn. 2020, 3, 183–210, doi:10.31681/jetol.726441.
72. Moawad, R.A. Online Learning during the COVID- 19 Pandemic and Academic Stress in University Students. Rev. Rom. pentru Educ. Multidimens. 2020, 12, 100–107, doi:10.18662/rrem/12.1sup2/252.
73. Khan, M.M.; Rahman, S.M.T.; Islam, S.T.A. Online Education System in Bangladesh during COVID-19 Pandemic. Creat. Educ. 2021, 12, 441–452, doi:10.4236/ce.2021.122031.

74. Catalano, A.J.; Torff, B.; Anderson, K.S. Transitioning to Online Learning during the COVID-19 Pandemic: Differences in Access and Participation among Students in Disadvantaged School Districts. Int. J. Inf. Learn. Technol. 2021, 38, 258–270, doi:10.1108/ijilt-06-2020-0111.
75. Kapasia, N.; Paul, P.; Roy, A.; Saha, J.; Zaveri, A.; Mallick, R.; Barman, B.; Das, P.; Chouhan, P. Impact of Lockdown on Learning Status of Undergraduate and Postgraduate Students during COVID-19 Pandemic in West Bengal, India. Child. Youth Serv. Rev. 2020, 116, 105194, doi:10.1016/j.childyouth.2020.105194.
76. Burns, D.; Dagnall, N.; Holt, M. Assessing the Impact of the COVID-19 Pandemic on Student Wellbeing at Universities in the United Kingdom: A Conceptual Analysis. Front. Educ. 2020, 5, doi:10.3389/feduc.2020.582882.
77. Küsel, J.; Martin, F.; Markic, S. University Students' Readiness for Using Digital Media and Online Learning—Comparison between Germany and the USA. Educ. Sci. (Basel) 2020, 10, 313, doi:10.3390/educsci10110313.
78. al Darayseh, A.S. The Impact of COVID-19 Pandemic on Modes of Teaching Science in UAE Schools. Journal of Education and Practice 2020, 11, 110–115, doi:10.7176/jep/11-20-13.
79. Tsekhmister, Y.V.; Konovalova, T.; Tsekhmister, B.Y.; Agrawal, A.; Ghosh, D. Evaluation of Virtual Reality Technology and Online Teaching System for Medical Students in Ukraine during COVID-19 Pandemic. Int. J. Emerg. Technol. Learn. 2021, 16, 127–139, doi:10.3991/ijet.v16i23.26099.
80. Arsaliev, S.M.-K.; Andrienko, A.S. The Development of Ethnocultural Competence of University Students during COVID-19 Pandemic in Russia. In Proceedings of the Proceedings of the 2020 3rd International Seminar on Education Research and Social Science (ISERSS 2020); Atlantis Press: Paris, France, 2021.
81. Cárdenas-Cruz, A.; Gómez-Moreno, G.; Matas-Lara, A.; Romero-Palacios, P.J.; Parrilla-Ruiz, F.M. An Example of Adaptation: Experience of Virtual Clinical Skills Circuits of Internal Medicine Students at the Faculty of Medicine, University of Granada (Spain) during the COVID-19 Pandemic. Med. Educ. Online 2022, 27, 2040191, doi:10.1080/10872981.2022.2040191.
82. Papouli, E.; Chatzifotiou, S.; Tsairidis, C. The Use of Digital Technology at Home during the COVID-19 Outbreak:Views of Social Work Students in Greece. Soc. Work Educ. 2020, 39, 1107–1115, doi:10.1080/02615479.2020.1807496.
83. Parmigiani, D.; Benigno, V.; Giusto, M.; Silvaggio, C.; Sperandio, S. E-Inclusion: Online Special Education in Italy during the Covid-19 Pandemic. Technol. Pedagog. Educ. 2021, 30, 111–124, doi:10.1080/1475939x.2020.1856714.
84. Resch, K.; Alnahdi, G.; Schwab, S. Exploring the Effects of the COVID-19 Emergency Remote Education on Students' Social and Academic Integration in Higher Education in Austria. High. educ. res. dev. 2022, 1–15, doi:10.1080/07294360.2022.2040446.
85. Noah, O.O.; Gbemisola, K.O. Impact of Google Classroom as an Online Learning Delivery during COVID-19 Pandemic: The Case of a Secondary School in Nigeria. J. Educ. Soc. Behav. Sci. 2020, 53–61, doi:10.9734/jesbs/2020/v33i930259.
86. Chen, T.; Peng, L.; Yin, X.; Rong, J.; Yang, J.; Cong, G. Analysis of User Satisfaction with Online Education Platforms in China during the COVID-19 Pandemic. Healthcare (Basel) 2020, 8, 200, doi:10.3390/healthcare8030200.
87. Drane, C.; Vernon, L.; O'shea, S. The Impact of "learning at Home" on the Educational Outcomes of Vulnerable Children in Australia during the COVID-19 Pandemic Available online: https://www.ncsehe.edu.au/wp-content/uploads/2020/04/NCSEHE_V2_Final_literaturereview-learningathome-covid19-final_30042020.pdf (accessed on 6 June 2022).
88. Mukuna, K.R.; Aloka, P.J.O. Exploring Educators' Challenges of Online Learning in Covid-19 at a Rural School, South Africa. Int. J. Learn. Teach. Educ. Res. 2020, 19, 134–149, doi:10.26803/ijlter.19.10.8.
89. Hsiao, Y.-C. Impacts of Course Type and Student Gender on Distance Learning Performance: A Case Study in Taiwan. Educ. Inf. Technol. 2021, 26, 6807–6822, doi:10.1007/s10639-021-10538-8.
90. Nafrees, A.C.M.; Roshan, A.M.F.; Baanu, A.S.N.; Nihma, M.N.F.; Shibly, F.H.A. Awareness of Online Learning of Undergraduates during COVID 19 with Special Reference to South Eastern University of Sri Lanka. J. Phys. Conf. Ser. 2020, 1712, 012010, doi:10.1088/1742-6596/1712/1/012010.
91. Cui, L.; Lee, D. CoAID: COVID-19 Healthcare Misinformation Dataset. arXiv [cs.SI] 2020, doi:10.48550/ARXIV.2006.00885.
92. Elhadad, M.K.; Li, K.F.; Gebali, F. COVID-19-FAKES: A Twitter (Arabic/English) Dataset for Detecting Misleading Information on COVID-19. In Advances in Intelligent Networking and Collaborative Systems; Springer International Publishing: Cham, 2021; pp. 256–268 ISBN 9783030577957.
93. Hayawi, K.; Shahriar, S.; Serhani, M.A.; Taleb, I.; Mathew, S.S. ANTi-Vax: A Novel Twitter Dataset for COVID-19 Vaccine Misinformation Detection. Public Health 2022, 203, 23–30, doi:10.1016/j.puhe.2021.11.022.
94. Nasser, N.; Karim, L.; El Ouadrhiri, A.; Ali, A.; Khan, N. N-Gram Based Language Processing Using Twitter Dataset to Identify COVID-19 Patients. Sustain. Cities Soc. 2021, 72, 103048, doi:10.1016/j.scs.2021.103048.
95. DeVerna, M.R.; Pierri, F.; Truong, B.T.; Bollenbacher, J.; Axelrod, D.; Loynes, N.; Torres-Lugo, C.; Yang, K.-C.; Menczer, F.; Bryden, J. CoVaxxy: A Collection of English-Language Twitter Posts about COVID-19 Vaccines. arXiv [cs.SI] 2021.
96. Cheng, M.; Wang, S.; Yan, X.; Yang, T.; Wang, W.; Huang, Z.; Xiao, X.; Nazarian, S.; Bogdan, P. A COVID-19 Rumor Dataset. Front. Psychol. 2021, 12, 644801, doi:10.3389/fpsyg.2021.644801.
97. Privacy Policy Available online: https://twitter.com/en/privacy/previous/version_15 (accessed on 6 June 2022).
98. Developer Agreement and Policy Available online: https://developer.twitter.com/en/developer-terms/agreement-and-policy (accessed on 6 June 2022).
99. RapidMiner GmbH Search Twitter - RapidMiner Documentation Available online: https://docs.rapidminer.com/latest/studio/operators/data_access/applications/twitter/search_twitter.html (accessed on 6 June 2022).

100. Mierswa, I.; Wurst, M.; Klinkenberg, R.; Scholz, M.; Euler, T. YALE: Rapid Prototyping for Complex Data Mining Tasks. In Proceedings of the Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining - KDD '06; ACM Press: New York, New York, USA, 2006.
101. Using Standard Search Available online: https://developer.twitter.com/en/docs/twitter-api/v1/tweets/search/guides/standard-operators (accessed on 6 June 2022).
102. Alla Anohina Analysis of the Terminology Used in the Field of Virtual Learning. J. Educ. Techno. Soc. 2005, 8, 91–102.
103. Ma, H.; Shen, L.; Sun, H.; Xu, Z.; Hou, L.; Wu, S.; Fang, A.; Li, J.; Qian, Q. COVID Term: A Bilingual Terminology for COVID-19. BMC Med. Inform. Decis. Mak. 2021, 21, 231, doi:10.1186/s12911-021-01593-9.
104. Lamsal, R. Hydrating Tweet IDs Available online: https://theneuralblog.com/hydrating-tweet-ids/ (accessed on 6 June 2022).
105. Hydrator: Turn Tweet IDs into Twitter JSON & CSV from Your Desktop! Available online: https://github.com/DocNow/hydrator (accessed on 6 June 2022).
106. Tekumalla, R.; Banda, J.M. Social Media Mining Toolkit (SMMT). Genomics Inform. 2020, 18, e16, doi:10.5808/GI.2020.18.2.e16.
107. Twarc: A Command Line Tool (and Python Library) for Archiving Twitter JSON Available online: https://github.com/DocNow/twarc (accessed on 6 June 2022).
108. Wilkinson, M.D.; Dumontier, M.; Aalbersberg, I.J.; Appleton, G.; Axton, M.; Baak, A.; Blomberg, N.; Boiten, J.-W.; da Silva Santos, L.B.; Bourne, P.E.; et al. The FAIR Guiding Principles for Scientific Data Management and Stewardship. Sci. Data 2016, 3, 160018, doi:10.1038/sdata.2016.18.
109. Carvalho, J.; Plastino, A. On the Evaluation and Combination of State-of-the-Art Features in Twitter Sentiment Analysis. Artif. Intell. Rev. 2021, 54, 1887–1936, doi:10.1007/s10462-020-09895-6.
110. Wang, J.; Xu, B.; Zu, Y. Deep Learning for Aspect-Based Sentiment Analysis. In Proceedings of the 2021 International Conference on Machine Learning and Intelligent Systems Engineering (MLISE); IEEE, 2021; pp. 267–271.
111. Hong, L.; Dan, O.; Davison, B.D. Predicting Popular Messages in Twitter. In Proceedings of the Proceedings of the 20th international conference companion on World wide web - WWW '11; ACM Press: New York, New York, USA, 2011.
112. Bouazizi, M.; Otsuki Ohtsuki, T. A Pattern-Based Approach for Sarcasm Detection on Twitter. IEEE Access 2016, 4, 5477–5488, doi:10.1109/access.2016.2594194.
113. Alvarez-Melis, D.; Saveski, M. Topic Modeling in Twitter: Aggregating Tweets by Conversations. In Proceedings of the Tenth International AAAI Conference on Web and Social Media; 2016.
114. Boyd, D.; Golder, S.; Lotan, G. Tweet, Tweet, Retweet: Conversational Aspects of Retweeting on Twitter. In Proceedings of the 2010 43rd Hawaii International Conference on System Sciences; IEEE, 2010; pp. 1–10.
115. Uysal, I.; Croft, W.B. User Oriented Tweet Ranking: A Filtering Approach to Microblogs. In Proceedings of the Proceedings of the 20th ACM international conference on Information and knowledge management - CIKM '11; ACM Press: New York, New York, USA, 2011.
116. André, P.; Bernstein, M.; Luther, K. Who Gives a Tweet?: Evaluating Microblog Content Value. In Proceedings of the Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work - CSCW '12; ACM Press: New York, New York, USA, 2012.
117. Ito, J.; Song, J.; Toda, H.; Koike, Y.; Oyama, S. Assessment of Tweet Credibility with LDA Features. In Proceedings of the Proceedings of the 24th International Conference on World Wide Web - WWW '15 Companion; ACM Press: New York, New York, USA, 2015.
118. Stephens, M. A Geospatial Infodemic: Mapping Twitter Conspiracy Theories of COVID-19. Dialogues Hum. Geogr. 2020, 10, 276–281, doi:10.1177/2043820620935683.
119. Wu, C.; Wu, F.; Wu, S.; Huang, Y.; Xie, X. Tweet Emoji Prediction Using Hierarchical Model with Attention. In Proceedings of the Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers; ACM: New York, NY, USA, 2018.
120. Mccreadie, R.; Macdonald, C. Relevance in Microblogs: Enhancing Tweet Retrieval Using Hyperlinked Documents Available online: http://terrierteam.dcs.gla.ac.uk/publications/oair2013_McCreadie.pdf (accessed on 7 June 2022).
121. Salas-Zárate, M. del P.; Paredes-Valverde, M.A.; Rodriguez-García, M.Á.; Valencia-García, R.; Alor-Hernández, G. Automatic Detection of Satire in Twitter: A Psycholinguistic-Based Approach. Knowl. Based Syst. 2017, 128, 20–33, doi:10.1016/j.knosys.2017.04.009.
122. Alowibdi, J.S.; Buy, U.A.; Yu, P.S.; Ghani, S.; Mokbel, M. Deception Detection in Twitter. Soc. Netw. Anal. Min. 2015, 5, doi:10.1007/s13278-015-0273-1.
123. Zheng, L.; Han, K. Extracting Categorical Topics from Tweets Using Topic Model. In Information Retrieval Technology; Springer Berlin Heidelberg: Berlin, Heidelberg, 2013; pp. 86–96 ISBN 9783642450679.
124. Zahra, K.; Azam, F.; Butt, W.H.; Ilyas, F. A Framework for User Characterization Based on Tweets Using Machine Learning Algorithms. In Proceedings of the Proceedings of the 2018 VII International Conference on Network, Communication and Computing - ICNCC 2018; ACM Press: New York, New York, USA, 2018.
125. Sloan, L.; Morgan, J.; Housley, W.; Williams, M.; Edwards, A.; Burnap, P.; Rana, O. Knowing the Tweeters: Deriving Sociologically Relevant Demographics from Twitter. Sociol. Res. Online 2013, 18, 74–84, doi:10.5153/sro.3001.