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Communication

Twitter Big Data as a Resource for Exoskeleton Research: A Large-Scale Dataset of about 140,000 Tweets and 100 Research Questions

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 exoskeleton technology has been rapidly advancing in the recent past due to its multitude of applications and diverse use-cases in assisted living, military, healthcare, firefighting, and industry 4.0. The exoskeleton market is projected to increase by multiple times of its current value within the next two years. Therefore, it is crucial to study the degree and trends of user interest, views, opinions, perspectives, attitudes, acceptance, feedback, engagement, buying behavior, and satisfaction, towards exoskeletons, for which the availability of Big Data of conversations about exoskeletons is necessary. The Internet of Everything style of today's living, characterized by people spending more time on the internet than ever before, with a specific focus on social media platforms, holds the potential for the development of such a dataset, by the mining of relevant social media conversations. Twitter, one such social media platform, is highly popular amongst all age groups, where the topics found in the conversation paradigms include emerging technologies such as exoskeletons. To address this research challenge, this work makes two scientific contributions to this field. First, it presents an open-access dataset of about 140,000 tweets about exoskeletons that were posted in a 5-year period from May 21, 2017, to May 21, 2022. Second, based on a comprehensive review of the recent works in the fields of Big Data, Natural Language Processing, Information Retrieval, Data Mining, Pattern Recognition, and Artificial Intelligence that may be applied to relevant Twitter data for advancing research, innovation, and discovery in the field of exoskeleton research, a total of 100 Research Questions are presented for researchers to study, analyze, evaluate, ideate, and investigate based on this dataset.

Keywords: exoskeleton; Twitter; Tweets; Big Data; social media; Data Mining; dataset; Data Science; Natural Language Processing; Information Retrieval

1. Introduction

A robotic exoskeleton may be broadly defined as a wearable electromechanical device developed with the primary objective of augmenting the physical performance, stamina, and abilities of the person who wears it [1]. Depending on the specific application for which the exoskeleton would be used, they differ in design, functionality, operation, and necessary maintenance [2]. Exoskeletons can be broadly classified as upper limb exoskeletons [3] and lower limb exoskeletons [4]. In the last few years, exoskeletons have been developed for specific body parts or joints. These include exoskeletons for the knee [5], shoulder [6], elbow [7], ankle [8], waist [9], hip [10], neck [11], spine [12], wrist [13], and index finger [14]. The exoskeleton technology has been rapidly advancing [15] in the recent past on account of its multitude of applications and use cases. Some of the applications of exoskeletons [16-18] include – (1) assisted living: helping older adults as well as people with various forms of disabilities to perform their daily routine tasks independently; (2) military: for augmenting productivity and lowering fatigue; (3) healthcare: to improve the quality of life of people who have lost one or more of their arms or legs or suffer paralysis in the same; (4) firefighting: to assist firefighters in climbing faster as well as for helping them to lift and carry heavy equipment's; (5) industry 4.0: to increase labor productivity, to assist in the transportation of heavy machinery, and to help workers in labor-intensive tasks. Given these diverse applications of exoskeletons and the projected increase in the same, the exoskeleton market is growing rapidly. It was USD 200 million in 2017 [19], and it is estimated to become USD 1.3 billion by the end of 2024 [20].

With the advent and rapid adoption of the Internet of Everything lifestyle [21], in recent times, people's everyday lives involve interacting with computers and a myriad of technology-based gadgets and devices in multiple ways while using various forms of Internet-based services and applications, a lot more than ever before [22, 23]. In this Internet of Everything era, the use of social media platforms has skyrocketed in the recent past [24]. Social media platforms have evolved and transformed into 'virtual' spaces via which people from all demographics communicate with each other to form their social support systems [25] and develop 'online' interpersonal relationships [26]. Such 'virtual' spaces consist of conversations on diverse topics such as emerging technologies, news, current events, politics, family, relationships, and career opportunities [27]. When such conversations are related to a specific technology, the study of the same can indicate the degree and trends of user interest, views, opinions, perspectives, attitudes, and feedback towards that specific technology [28]. Such inferences from conversations about a technology can serve a wide range of use cases such as the indication of the market potential [29], sales prediction [30], consumer engagement [31], technology acceptance [32], buying behavior [33], and customer satisfaction [34], just to name a few.

Twitter, one such social media platform, used by people of almost all age groups [35], has been rapidly gaining popularity in all parts of the world and is currently the second most visited social media platform [36]. At present, there are about 192 million daily active users on Twitter [20], and approximately 500 million tweets are posted on Twitter every day [37]. Therefore, mining and studying this Big Data of conversations from Twitter has been of significant interest to the research community. In the last few years, there have been several works in the fields of Big Data, Data Mining, and Natural Language Processing related to the development of datasets of Twitter conversations related to different topics, technologies, events, diseases, viruses, etc., such as – movies [38], COVID-19 [39], elections [40], toxic behavior amongst adolescents [41], music [42], natural hazards [43], personality traits [44], civil unrest [45], drug safety [46], climate change [47], hate speech [48], migration patterns [49], conspiracy theories [50], and Inflammatory Bowel Disease [51], just to name a few. Recent studies [52-54] have shown that sharing such data helps in the advancement of research, improves the quality of innovation, supports better investigation, and helps to avoid redundant efforts.

In view of the rapid advances in exoskeleton research in the recent past [15], its applicability for a wide range of use cases for diverse users with diverse needs [3-14], projected increase of the booming exoskeleton market to become USD 1.3 billion by the end of 2024 [20], and limitations in prior works in this field [3-14] that did not focus on mining social media conversations about exoskeletons which could have served as an information resource for studying user interest, views, opinions, perspectives, attitudes, acceptance, and feedback towards exoskeletons, it is crucial to develop a dataset of conversations related to exoskeletons. The work presented in this paper aims to address this research challenge by exploring the intersections of Big Data, Data Mining, Natural Language Processing, Information Retrieval, Internet of Everything, and their interrelated disciplines. It makes the following scientific contributions:

1. It presents a large-scale open-access Twitter dataset of 138,585 tweets (including original tweets, retweets, and replies) about exoskeletons posted on Twitter for a period of 5-years from May 21, 2017, to May 21, 2022. The dataset is available at https://dx.doi.org/10.21227/r5mv-ax79
2. Based on a comprehensive review of 108 emerging works in these fields, this paper discusses multiple interdisciplinary applications of this dataset and presents a list of 100 research questions for researchers to study, analyze, evaluate, ideate, and investigate based on this dataset.

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The rest of this paper is organized as follows. The methodology that was used to develop this dataset is presented in Section 2. Section 3 presents the results. Section 4 discusses multiple interdisciplinary applications of this dataset and presents 100 research questions for researchers to investigate. Section 5 concludes the paper by summarizing the scientific contributions of this research and discussing the scope for future work.

2. Methodology

This section describes the methodology that was followed for the development of this dataset, which is publicly available at https://dx.doi.org/10.21227/r5mv-ax79. The dataset contains the Tweet I.D.s of 138,585 tweets about exoskeletons that were posted over a 5-year period from May 21, 2017, to May 21, 2022. Here, May 21, 2022, is the most recent date of data collection at the time of writing this paper, and May 21, 2017, is the earliest date for which tweets could be mined when the process of data collection was started. As a central focus of this work involves developing a Twitter dataset, therefore the privacy policy, developer agreement, and guidelines for content redistribution of Twitter [55,56] were thoroughly studied. The privacy policy of Twitter [55] states – *"Twitter is public and Tweets are immediately viewable and searchable by anyone around the world"*. To add, the Twitter developer agreement [56] defines tweets as *"public data"*. The guidelines for Twitter content redistribution [56] state – "*If you provide Twitter Content to third parties, including downloadable datasets or via an API, you may only distribute Tweet IDs, Direct Message IDs, and/or User IDs (except as described below)*. It also states - *"We also grant special permissions to academic researchers sharing Tweet IDs and User IDs for non-commercial research purposes. Academic researchers are permitted to distribute an unlimited number of Tweet IDs and/or User IDs 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 I.D.s) is in compliance with the privacy policy, developer agreement, and content redistribution guidelines of Twitter (at the time of writing of this paper).

The tweets were collected by using the Search Twitter *operator* [57] in RapidMiner [58]. 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. Every application developed in RapidMiner is known as a *process*, and every RapidMiner *process* comprises one or more *operators*, which represent different operational features of the application. The Search Twitter *operator* works by building a connection with the Twitter API while following the rate limits for accessing Twitter data as per Twitter's policy [59]. This ensures that the Search Twitter operator functions by complying with the Twitter API standard search policies [60]. To use the Search Twitter *operator*, a *process* was developed in the RapidMiner studio that comprised this operator. The Search Twitter *operator* requires a mandatory input from the user for the query *field*. Here query represents a keyword or the set of keywords or phrases based on which relevant Tweets (Tweets containing that keyword or keywords or phrases) would be filtered and returned in the form of results.

So, to determine the input for this query field, the previous works [1-19] in the field of exoskeleton technology were studied to determine the most common phrases or set of keywords that are used to refer to the underlining exoskeleton systems. A list of phrases and keywords can be found from these works which include – *"Exoskeleton-Type Systems", "Upper-Limb Exoskeleton", "Indego Explorer Lower-Limb Exoskeleton", "Rehabilitation Exoskeleton," "Powered Knee Exoskeleton", "Exo4Work Shoulder Exoskeleton,", "Wearable Elbow Exoskeleton", "Powered Ankle Exoskeleton", "Wearable Waist Exoskeleton", "Powered Hip Exoskeleton", "Neck Supporting Exoskeleton", "Elastic Spine Exoskeleton", "Wrist Exoskeleton", "Robotic Exoskeleton", "Finger Exoskeleton", and "Lower Limb Exoskeleton"*. As can be seen from this collection of phrases, the keyword "exoskeleton" always exists in a phrase that is being used to refer to a specific kind of exoskeleton system. Therefore, in the *query* field of Search

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Twitter *operator*, only the keyword "exoskeleton" was entered. RapidMiner is not case-sensitive, so it ensured that the results would contain tweets where any form of upper case or lower case combinations have been used to spell the word "exoskeleton" in a tweet. The output of this *process* in RapidMiner that comprised the Search Twitter *operator* consisted of multiple attributes, which are mentioned in Table 1. This RapidMiner *process* was run multiple times and the results were merged together and develop the dataset and its associated files.

Table 1. Description of the attributes from the results of the RapidMiner *process* that used the Search Twitter *operator*.

Attribute Name	Description
Row no.	Row number of the results
Id	Twitter ID of the tweet
Created-At	Date and time when the tweet was posted
From-User	Twitter username of the user who posted the tweet
From-User-Id	Twitter User ID of the user who posted the tweet
To-User	Twitter username of the user whose tweet was replied to (if the tweet was a reply) in the current tweet
To-User-Id	Twitter user I.D. of the user whose tweet was replied to (if the tweet was a reply) in the current tweet
Language	Language of the tweet
Source	Source of the tweet to determine if the tweet was posted from an Android source, Twitter website, etc.
Text	Complete text of the tweet, including embedded URLs
Geo-Location-Latitude	Geo-Location (Latitude) of the user posting the tweet
Geo-Location-Longitude	Geo-Location (Longitude) of the user posting the tweet
Retweet Count	Retweet count of the tweet

To ensure compliance with the Privacy Policy, Developer Agreement, Content Redistribution guidelines of Twitter [55,56], for complete data anonymization, and to comply with the FAIR (Findability, Accessibility, Interoperability, and Reusability) principles for scientific data management [61], multiple data filters were introduced in the RapidMiner *process* to filter out all the attributes from the results, other than the "Id" attribute, that represents the unique Twitter ID for each tweet. After running the process, each time, these Tweet I.D.s were exported as a .csv file and then converted to a .txt file to facilitate easy hydration of the tweets (explained in Section 3) later on. As the dataset contains close to 140,000 Tweet I.D.s, to ensure that the process of hydration of the Tweet I.D.s is easy and less time-consuming, the dataset is divided into seven sets or files (7 .txt files) based on date ranges of the associated tweets. An overview of these sets is shown in Table 2. It is worth mentioning here that the Twitter API's standard search feature (that was used for the dataset development via the Search Twitter *operator* in RapidMiner) does not return a complete index of all Tweets in a date range. So, it is possible that multiple tweets about exoskeletons posted in the date range of May 21, 2017, to May 21, 2022, were not collected by the Twitter API's standard search and are thus not a part of this dataset. To add, 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. As per the best knowledge of the author, the set of 138,585 Tweet I.D.s present in this dataset correspond to tweets that have not been deleted at the time of writing this paper.

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Table 2. Characteristics of the Dataset Files with the associated Tweet ID count and Date Range.

Filename	Number of Twitter IDs	Date Range of the Tweets
Exoskeleton_TweetIDs_Set1.txt	22945	July 20, 2021 – May 21, 2022
Exoskeleton_TweetIDs_Set2.txt	19416	Dec 1, 2020 – July 19, 2021
Exoskeleton_TweetIDs_Set3.txt	16673	April 29, 2020 - Nov 30, 2020
Exoskeleton_TweetIDs_Set4.txt	16208	Oct 5, 2019 - Apr 28, 2020
Exoskeleton_TweetIDs_Set5.txt	17983	Feb 13, 2019 - Oct 4, 2019
Exoskeleton_TweetIDs_Set6.txt	34009	Nov 9, 2017 - Feb 12, 2019
Exoskeleton_TweetIDs_Set7.txt	11351	May 21, 2017 - Nov 8, 2017

3. Results and Discussions

As mentioned in Section 2, this dataset contains Tweet I.D.s corresponding to 138,585 tweets about exoskeletons posted on Twitter from May 21, 2017, to May 21, 2022. The complete information associated with a tweet, such as the text of a tweet, user name, user I.D., timestamp, retweet count, etc., can be obtained from a Tweet ID by following a process known as hydration of Tweet ID [62]. A simple example of this process can be observed by visiting this website [63] and entering any Tweet ID from this dataset. The website would immediately generate the URL of the associated Tweet that can be studied. However, in a realistic scenario repeating this step for 138,585 times would be a very difficult process. In view of the same and for processing of Twitter datasets, researchers in this field have developed various tools that can hydrate Tweet I.D.s. Some of the most popular tools include – Hydrator [64], Social Media Mining Toolkit [65], and Twarc [66]. In this section, the process of hydration in the context of using one of these tools – the Hydrator app, is explained, and a brief discussion about the results that would be obtained thereafter is also presented. In this context, results mean the complete information (text of the tweet, user I.D., user name, retweet count, language, tweet URL, source, and other public information related to the tweet) associated with each of the Tweet I.D.s in this dataset.

The following is the step-by-step process for using the Hydrator app to hydrate this dataset. For the purpose of this discussion, only one file from this dataset – "Exoskeleton_TweetIDs_Set2.txt" is being used.

1. Download and install the desktop version of the Hydrator app from this website [67]. The version that was used for this work is v0.30.0.
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 add a new dataset comprising only Tweet I.D.s (Figure 1). Browse and select the file – "Exoskeleton_TweetIDs_Set2.txt" available on a local storage.
4. If the file upload is successful, the Hydrator app will show the total number of Tweet I.D.s present in the file. For this file - "Exoskeleton_TweetIDs_Set2.txt", the app would show the Number of Tweet I.D.s as 19,415.
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 I.D.s. During the hydration process, the progress indicator would increase, indicating the number of Tweet I.D.s that have been successfully hydrated and the number of Tweet I.D.s 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. 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 the detailed information about the tweets, which would include the text of

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the tweet, user I.D., user name, retweet count, language, tweet URL, source, and other public information related to the tweet.

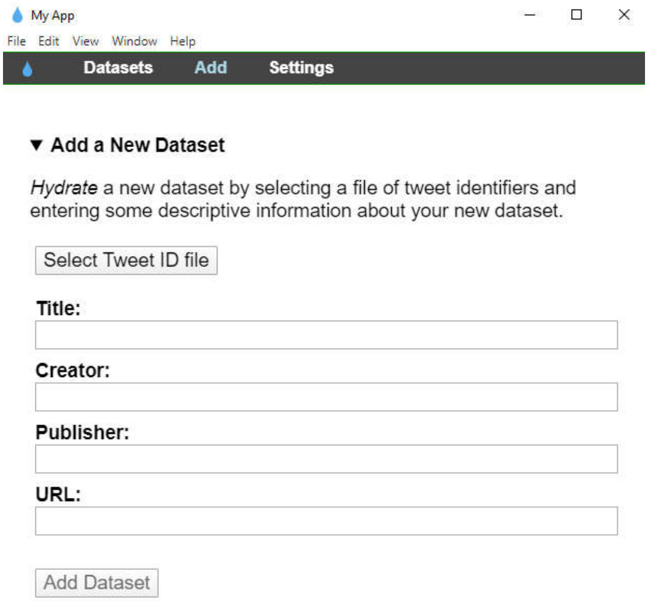

Figure 1. Screenshot from the Hydrator app for the dataset upload step.

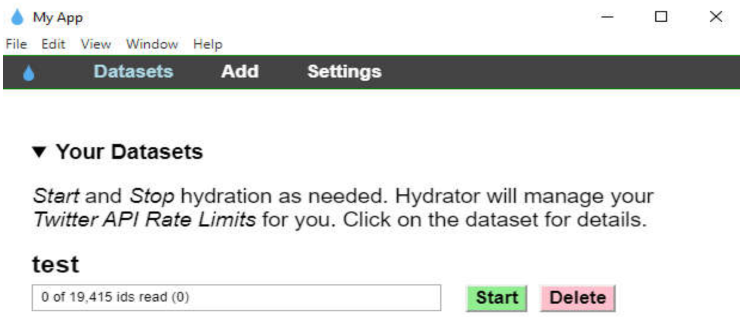

Figure 2. Screenshot from the Hydrator app for the dataset processing step.

Even though the above steps are discussed in the context of using the "Exoskeleton_TweetIDs_Set2.txt" file from the dataset, the same steps can be repeated for hydrating all the other dataset files. However, it is to be noted that Hydrator functions by connecting with the Twitter API and in compliance with the Twitter API rate limits [59]. So, when the app reaches the 15-minute or 3-hour or any similar usage limit, hydrating any additional dataset files might not be possible in that 15-minute or 3-hour or a similar usage criteria/window. Table 3 shows a random selection of 10 tweets (only the tweet text is shown for clarity of representation) from this dataset that were hydrated using the Hydrator application. Even though all the 138,585 Tweet I.D.s (from all the 7 dataset files) were successfully hydrated by repeating all the steps mentioned above, only a list of 10 tweets is shown here to avoid presenting a very long table comprising 138,585 rows.

Table 3. A random collection of the Tweet text of 10 Tweet I.D.s from this dataset that were hydrated using Hydrator.

Tweet No.	Text of the Tweet
Tweet #1	Disabled children walk again with life-changing robotic exoskeleton. #excellence #innovation
Tweet #2	This exoskeleton from Trexo Robotics lets disabled children walk again - truly changing lives! Trexo Robotics
Tweet #3	A brain-controlled exoskeleton just let a quadraplegic man walk again #future #futurism #technology #innovation #leadership #education #entrepreneurship #management https://311institute.com/a-brain-controlled-exoskeleton-lets-a-quadraplegic-walk-again/
Tweet #4	Tomorrow @aalborguni will present a biomechanical investigation of a passive upper extremity #exoskeleton for manual material handling - a common activity associated with the development of work-related musculoskeletal disorders.
Tweet #5	Nice knee exoskeleton design, intended to assist people with cerebral palsy: untethered, 20 Nm peak torque, 22 Hz bandwidth, 1.7 kg total mass, 5% torque tracking error, 70 dB audio noise. @SainanZhang1, @ProfHaoSu, and colleagues: https://arxiv.org/pdf/2101.00289.pdf
Tweet #6	China recently revealed another type of military-use exoskeleton suit that is powered and can carry ammunition after a previous type of non-powered exoskeleton suit was introduced in 2020. More suits for different purposes will emerge, analysts predict. https://globaltimes.cn/page/202101/1212636.shtml
Tweet #7	$RWLK - is a pioneer in the robotic exoskeleton market, making robotic machines that leverage a series of advanced motors to enable disabled persons with spinal injuries to walk again - https://finance.yahoo.com/news/robot-revolution-spark-15x-rally-143024351.html
Tweet #8	Japanese startup Archelis has designed a wearable exoskeleton leg to assist factory workers whose jobs require them to stand for hours in one place
Tweet #9	WATCH: This exoskeleton lets you 'sit' while standing. It straps to the legs and disperses the wearer's bodyweight
Tweet #10	Researchers at @NIST have developed a new measurement method to test whether an #exoskeleton and the person wearing it are moving smoothly and in harmony. #wearablerobotics #3Dprinting https://tectales.com/bionics-robotics/exoskeleton-research-marches-forward.html

4. Potential Applications and Research Directions

This comprehensive dataset that consists of Tweet I.D.s of 138,585 tweets about exoskeletons that were posted over a 5-year period from May 21, 2017, to May 21, 2022, is expected to have multiple interdisciplinary applications related to the advancement of research, innovation, and discovery in the field of exoskeleton technology. Some of these applications could include interpretation and analysis of the degree and trends of user interests, perspectives, opinions, reviews, attitudes, feedback, engagement, acceptance, buying behavior, and satisfaction, related to different exoskeletons used by diverse users for different use cases. To further support the same, based on a comprehensive review of emerging works in the fields of Big Data, Data Mining, Natural Language Processing, Information Retrieval, Pattern Recognition, and Artificial Intelligence that may be applied to relevant Twitter data for advancing research, innovation, and discovery the field of exoskeleton research, a total of 100 Research Questions (R.Q.'s) are presented for researchers to study, analyze, evaluate, ideate, and investigate based on this dataset. These R.Q.'s are presented as follows:

RQ1. Sentiment analysis [68] of these tweets would help to identify the positive, negative, and neutral sentiments associated with these conversations about exoskeletons on Twitter.

RQ2. Deep learning may be used to identify the emotional state of the users in terms of the basic emotional responses - fear, anger, joy, sadness, disgust, and surprise [69], at the time of posting of these respective tweets.

RQ3. Aspect-based sentiment analysis, along with tokenization and lemmatization of these tweets [70], may be performed to identify the specific aspects or subject matters related to exoskeletons to which certain specific sentiments or emotional responses are associated.

RQ4. Studying the trends in tweet counts [71] and the associated sentiments and emotional responses to detect any correlations between the two.
RQ5. Studying the word count of each of these tweets [72] to determine if any correlation exists between the word count and the associated sentiments and emotional responses towards different exoskeleton products.
RQ6. Investigating whether the number of replies or retweets of a tweet [73] posted by a company to share the news about a new kind of exoskeleton, could have a correlation with the influence and follower metrics of the company's Twitter profile.
RQ7. Detecting popular tweets [74] related to exoskeletons and studying the subject matters and aspects mentioned in those tweets by performing tokenization and lemmatization.
RQ8. Detecting sarcasm [75] related to exoskeletons and studying for any correlation of sarcasm with the sentiment or emotional response associated with the respective tweets.
RQ9. Identifying the commonly used hashtags associated with tweets related to exoskeletons and detecting the sentiment related to these respective hashtags [76].
RQ10. Analyzing the tweets made by users of exoskeletons to detect the diverse user personas [78] and their associated perspectives, experiences, opinions, and feedback about exoskeletons.
RQ11. Studying trending discussions [79] on Twitter related to exoskeletons and using machine learning to detect these trends in real-time.
RQ12. Studying the trends in sentiments and emotional responses [80] associated with exoskeletons to track if there is any correlation of the same with the trends in exoskeleton sales or its market potential.
RQ13. Investigating for any interdependence between tweets about specific exoskeleton products and sales of those specific exoskeleton products.
RQ14. Performing topic modeling [81] of these respective tweets to interpret the associated communication as news, recommendation, discussion, feedback, perspective, opinion, etc., related to different kinds of exoskeletons.
RQ15. Investigating retweeting patterns of tweets [82] to determine the interest in certain topics related to exoskeletons, expressed in the respective tweets.
RQ16. Studying the tweeting patterns and content of the tweets by various companies or manufacturers of exoskeletons to understand their audience management methodologies which include targeting different audiences, concealing subjects, and maintaining authenticity [83].
RQ17. Detecting the Point of Interest (P.O.I.) of a tweet [84], which presents high-level location information about a place, to understand the location-specific opinions, perspectives, or attitudes of the public towards exoskeleton technology.
RQ18. Developing a personalized tweet recommendation system [85] that would present the latest developments in exoskeleton technology, including exoskeletons available for purchase to potential user groups, which may include the elderly, disabled, handicapped, etc.
RQ19. Performing a case study on different kinds of machine learning classifiers [86] to develop sentiment analysis approaches [87] to deduce the best machine learning classifier in terms of performance characteristics for sentiment analysis of tweets related to exoskeleton technology.
RQ20. Performing semantic analysis of the content of each tweet as per the methodology discussed in [88] to determine if any political leaders have influenced the sale or public opinion or perspectives towards a specific kind of exoskeleton.
RQ21. Analysis of tweets to determine the emergence of exoskeletons [89] in different fields such as healthcare and medicine.
RQ22. Studying the mentions of exoskeleton companies in tweets to determine the patterns of customer engagement [90] with each of these companies.

RQ23. Investigating tweets to determine the global [91] and region-specific [92] reason/drive centered around purchase or use of specific exoskeletons.
RQ24. Development of a tweet ranking model to present important tweets [93] to potential end-users or customers of exoskeletons based on their specific needs or interests.
RQ25. Determining how official accounts on Twitter play a role in the propagation and correction of online rumors related to exoskeletons in different geographic locations [94].
RQ26. Studying the semantics of the tweets to determine how user diversities such as gender differences [95,96] may impact the tweeting patterns and content of tweets centered around exoskeletons, including their usage and needs.
RQ27. Performing content value analysis [97] of tweets to filter the most relevant and least relevant tweets [98] involving exoskeletons.
RQ28. Developing an approach to determine the audience size [99] of any potential tweet related to a specific exoskeleton that might be helpful for the consumer outreach of exoskeleton companies and manufacturers.
RQ29. Application of the gratification theory [100] on these tweets to deduce the factors that gratify users related to different use-cases of exoskeletons.
RQ30. Performing a study on the tweets to investigate the role of news organizations, including regional media, local media, national media, and broadcast news agencies, in the dissemination of the latest developments [101] in the field of exoskeleton technology.
RQ31. Determining the occupation of potential end-users of exoskeletons from their tweets [102], which may be helpful for companies and/or manufacturers to develop or improvise exoskeletons to better assist these end-users in their respective professions.
RQ32. Implementation of the TCV-Rank summarization technique for generating online summaries and historical summaries related to tweets [103] about exoskeletons posted from different geographic regions.
RQ33. Implementation of the TURank (Twitter User Rank) algorithm [104] to find authoritative Twitter users who post tweets related to exoskeletons.
RQ34. Studying the trends of entity linking [105] in tweets about upcoming exoskeletons for different use-cases.
RQ35. Investigating the impact of following clusters of exoskeleton users or exoskeleton companies [106] on the ideologies of the Twitter user(s) over exoskeletons.
RQ36. Analysis of the tweets centered around specific hashtags [107] related to exoskeletons, to analyze the tweeting trends and replies related to these hashtags.
RQ37. Implementation of the HybridSeg approach [108] to find the optimal segmentation of tweets related to exoskeletons for improving segmentation quality as well as for exploring applications of this approach for named entity recognition.
RQ38. Interpretation of the use of Twitter by companies or organizations in the exoskeleton industry to examine brand attributes (both product-related and non-product-related) and their relation to Twitter's key engagement features (Reply, Retweet, Favorite) [109].
RQ39. Development of an approach by application of the Latent Dirichlet Allocation (LDA) model as proposed in [110] to deduce the information credibility related to exoskeleton-based tweets originating from different sources.
RQ40. Studying tweets to detect and predict any potential conspiracy theories [111,112] related to emerging developments in the field of exoskeletons or any specific exoskeleton-based product.
RQ41. Implementation of the Tweet2Vec method [113] for learning tweet embeddings using character-level CNN-LSTM encoder-decoder for efficient categorization of tweets centered around exoskeleton technologies in general or related to any specific exoskeleton technology.

RQ42. Implementation of the Self-Exciting Point Process Model for Predicting Tweet Popularity (SEISMIC) model [114] to predict the popularity of tweets related to exoskeletons.
RQ43. Studying the geographic diffusion patterns in terms of random, local, and information brokerage of the information contained in a specific tweet [115] related to exoskeletons and their diverse use cases.
RQ44. Performing tweet wikification [116] to identify different concepts mentioned in a tweet to link these concepts to existing concepts about exoskeletons present in a knowledge base, such as Wikipedia.
RQ45. Detecting spam accounts [117] and social spam [118] on Twitter that may be the source of spam related to exoskeleton-based information expressed in tweets.
RQ46. Development of an approach similar to the work in [119] for detection of complaints related to specific exoskeleton technologies.
RQ47. Predicting the cost [120, 121] of planned and expected developments in existing exoskeletons based on drawing insights from the tweets about these developments.
RQ48. Application of the approach proposed in [122] to detect the patterns of emojis present in information-based tweets about exoskeletons for the analysis of the relationships between plain texts and emojis usage in such tweets.
RQ49. Tracking and investigating the usage of multiple emojis expressed in the tweets related to different use cases of exoskeletons for investigating the associated sentiment [123,124], performing tweet classification [125], user verification [126], irony detection [127], and trust modeling [128].
RQ50. Detection of fake users [128] who post fake news [130] about exoskeletons on Twitter.
RQ51. Investigating the effect of tweeting about research papers [131] on exoskeletons on the downloads and citations of these respective papers.
RQ52. Determining the social identities [132] of diverse users of exoskeletons based on the content and context of their tweets.
RQ53. Studying the relevance of a tweet [133] about a specific exoskeleton based on the hyperlinked documents in the same.
RQ54. Investigating how exoskeleton companies and/or manufacturers use tagging [134] on Twitter for audience engagement and retention.
RQ55. Performing stance detection [135] towards exoskeletons by analyzing the tweets posted by its users.
RQ56. Interpretation of satire [136] in the context of tweets about new and upcoming exoskeleton technologies.
RQ57. Predicting the age of existing users or potential users of exoskeletons from their tweets [137] to personalize the exoskeletons as per the age-specific needs.
RQ58. Investigating the selective attention over different entities expressed in any tweet pertaining to exoskeletons, as per the methodology proposed in [138].
RQ59. Studying the paradigms of readability in tweets posted by users of exoskeletons to interpret the degrees of engagement [139].
RQ60. Deducing the best time to tweet [140] any information related to exoskeletons which might be helpful for the sales and marketing team of exoskeleton companies and/or manufacturers.
RQ61. Tracking repliers and retweeters of tweets about improvisations in existing exoskeletons posted by exoskeleton companies to detect degrees of intimacy with the target audience.
RQ62. Detecting the number of tweets [142] related to exoskeletons from a geographic area that could be helpful to understand the associated needs or public perceptions of a specific exoskeleton-based technology available or marketed in that area.
RQ63. Analyzing the multimodal factors that are associated with the retweet of any tweet [143] communicating news about exoskeletons.

RQ64. Using the concept of knowledge graphs for tweet summarization for effectiveness in obtaining useful information [144] related to exoskeleton technologies on Twitter.
RQ65. Recommendation of specific hashtags [145] related to exoskeletons to Twitter users who could be potential users of exoskeletons.
RQ66. Performing contextualization of tweets [146] related to exoskeletons based on hashtags performance prediction and multi-document summarization.
RQ67. Assigning value to tweets related to specific use cases of exoskeletons based on the approach proposed in [147] to compute the worth of the underlining tweets.
RQ68. Deducing the number of followers of exoskeleton companies from their tweets [148] to determine their customer base.
RQ69. Studying tweets for detection of suggestions and classifications of suggestions [149] related to existing and/or emerging technologies associated with exoskeletons.
RQ70. Studying tweets to interpret any forms of discrimination [150] faced by existing or potential users of exoskeletons.
RQ71. Implementation of the iFACT framework [151] on tweets associated with exoskeletons to identify, assess, and evaluate the underlying factual information mentioned in the tweets.
RQ72. Implementation of the SEDTWik framework [152] for segment-based detection of any kinds of events from tweets that focus on use of exoskeletons by diverse user groups.
RQ73. Developing an approach as per [153] for followee recommendation to existing and/or potential users of exoskeletons based on topic extraction and sentiment analysis from exoskeleton-based tweets.
RQ74. Studying tweets for detecting stress levels and reasons for stress [154] in current or potential users of exoskeletons.
RQ75. Detecting if any tweet about exoskeletons posted by exoskeleton companies can be classified as a "regrettable" tweet [155], so that these companies may delete the tweet to reduce chances of any potential damage to their reputation.
RQ76. Interpreting diverse activities related to exoskeleton use cases by studying the associated tweets [156] and mapping these activities on pleasure and arousal dimensions using cognitive computing principles.
RQ77. Studying tweets posted by users of exoskeletons to monitor their mental health [157].
RQ78. Detecting deception (both positive and negative deception) from tweets [158] about the use of exoskeletons by specific user groups.
RQ79. Tracking happiness associated with exoskeleton usage in different cities [159] based on studying tweets related to exoskeletons originating from these cities.
RQ80. Identification of hate speech and abusive language in tweets [160] made by unsatisfied customers of exoskeletons.
RQ81. Developing an approach as per [161] to filter out relevant tweets comprising of latest breaking news in the context of exoskeletons.
RQ82. Extracting information from tweets related to exoskeletons to interpret the multimodal forms of purchase intentions [162] in potential users.
RQ83. Inferring shared interests [163] related to exoskeletons based on studying the tweets of both its current and potential users.
RQ84. Modeling public mood in different geographic regions [164] towards new advances in exoskeletons based on semantic analysis of the tweets originating from these respective regions.
RQ85. Implementation of the Categorical Topic Model [165] for extracting categorical topics and emerging issues about exoskeletons from tweets.
RQ86. Using classification approaches to deduce inundation levels [166] in the context of use case scenarios of different exoskeletons by different user groups.

RQ87. Studying the tweets to interpret bias and degrees of the same [167] towards using exoskeletons by potential user groups.
RQ88. Detection, classification, and ranking of trending topics [168] related to conversations about exoskeletons on Twitter.
RQ89. Analyzing tweets related to exoskeletons sold by any specific company to study and predict the changes in that specific company's stock price based on the tweeting patterns [169,170].
RQ90. Performing user characterization [171] from the tweeting patterns of any potential user to develop user personas for personalization of exoskeletons.
RQ91. Studying tweets posted by users of exoskeleton technologies to detect and analyze their feedback and suggestions [172] for possible improvements in the exoskeletons used by these respective users.
RQ92. Application of the Similarity Learning Algorithm (SiLA) as proposed in [173] to identify popular tweets related to current and emerging exoskeletons and their use cases.
RQ93. Implementation of the approach proposed in [174] to study patterns of tweets related to exoskeletons to detect tweets that represent "extreme behavior" on social media.
RQ94. Classifying tweets about specific use cases of exoskeletons as "alarming" and "reassuring" [175] to investigate the views of different user groups.
RQ95. Performing semantic analysis of tweets posted by new users of exoskeletons to detect instances of euphoria or delusion [176] in the context of the use cases mentioned in the underlining tweets.
RQ96. Detecting obesity from tweets [177] made by users of exoskeletons and investigating any potential correlations between obesity and exoskeleton usage.
RQ97. Classifying potential user groups of exoskeletons into communities [178] based on studying their needs expressed in their tweets for development of specific exoskeletons to meet these community-based needs.
RQ98. Estimating demographic information of exoskeleton users from their tweets [179] to interpret any variation of use cases based on user diversity.
RQ99. Studying the tweets to deduce the perceptions [180] of exoskeletons users about different exoskeleton companies to interpret their buying behavior.
RQ100. Analyzing the tweets to track misinformation and trends in the same [181] about upcoming or existing exoskeletons.

5. Conclusions

The exoskeleton technology has been rapidly advancing in the last few years on account of its multitude of applications and diverse use-cases in assisted living, military, healthcare, firefighting, and industry 4.0. The exoskeleton market is projected to increase by multiple times of its current value within the next two years.

Therefore, it is crucial to study the trends of user interest, views, opinions, perspectives, attitudes, acceptance, feedback, acceptance, buying behavior, and satisfaction, towards exoskeletons, for which the availability of Big Data of conversations about exoskeletons is necessary. In today's Internet of Everything era, the use of social media platforms has skyrocketed in the recent past as social media platforms provide a sense of "community" where people develop "virtual" relationships and converse on diverse topics which includes emerging technologies such as exoskeletons. Twitter, popular amongst users of all age groups, is the second most visited social platform, and its popularity has constantly been increasing in the last few years. Researchers from different disciplines have worked on developing datasets by mining this Big Data of Twitter to record, study, interpret, and analyze conversations on Twitter related to different emerging technologies, topics, applications, matters of global concern, diseases, viruses, events, disasters, and so on; which shows the immense potential, relevance, importance, and applicability of mining of Twitter Big Data.

Even though there have several advances in the field of exoskeleton research in the last decade and a half, no prior in this field or in the field of social media research has focused on the development of a dataset of conversations on Twitter related to exoskeletons. The work presented in this paper addresses this research challenge. It presents an open-access dataset of 138,585 Tweet I.D.s corresponding to 138,585 Tweets about exoskeletons posted on Twitter for a period of 5-years from May 21, 2017, to May 21, 2022. To add, based on a comprehensive review of 108 recent works in the fields of Big Data, Natural Language Processing, Information Retrieval, Data Mining, Pattern Recognition, and Artificial Intelligence that may be applied to relevant Twitter data for advancing the field of exoskeleton research, this paper presents 100 Research Questions for researchers to investigate, analyze, ideate, and explore by using this dataset. Future work would involve investigating these research questions and developing new ones to advance research and development in this field.

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Data Availability Statement: This work resulted in the creation of an open-access dataset which is available at https://dx.doi.org/10.21227/r5mv-ax79, as per the CC BY 4.0 License.

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References

1. Olar, M.-L.; Leba, M.; Risteiu, M. Exoskeleton - Wearable Devices. Literature Review. *MATEC Web Conf.* **2021**, *342*, 05005, doi:10.1051/matecconf/202134205005.
2. Yang, C.-J.; Zhang, J.-F.; Chen, Y.; Dong, Y.-M.; Zhang, Y. A Review of Exoskeleton-Type Systems and Their Key Technologies. *Proc Inst Mech Eng Part C* **2008**, *222*, 1599–1612, doi:10.1243/09544062jmes936.
3. Palazzi, E.; Luzi, L.; Dimo, E.; Calanca, A. An Affordable Upper-Limb Exoskeleton Concept for Rehabilitation Applications. *Technologies (Basel)* **2022**, *10*, 22, doi:10.3390/technologies10010022.
4. Laubscher, C.A.; Goo, A.; Farris, R.J.; Sawicki, J.T. Hybrid Impedance-Sliding Mode Switching Control of the Indego Explorer Lower-Limb Exoskeleton in Able-Bodied Walking. *J. Intell. Robot. Syst.* **2022**, *104*, doi:10.1007/s10846-022-01583-7.
5. Sarkisian, S.V.; Ishmael, M.K.; Lenzi, T. Self-Aligning Mechanism Improves Comfort and Performance with a Powered Knee Exoskeleton. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2021**, *29*, 629–640, doi:10.1109/TNSRE.2021.3064463.
6. van der Have, A.; Rossini, M.; Rodriguez-Guerrero, C.; Van Rossom, S.; Jonkers, I. The Exo4Work Shoulder Exoskeleton Effectively Reduces Muscle and Joint Loading during Simulated Occupational Tasks above Shoulder Height. *Appl. Ergon.* **2022**, *103*, 103800, doi:10.1016/j.apergo.2022.103800.
7. Zahedi, A.; Wang, Y.; Martinez-Hernandez, U.; Zhang, D. A Wearable Elbow Exoskeleton for Tremor Suppression Equipped with Rotational Semi-Active Actuator. *Mech. Syst. Signal Process.* **2021**, *157*, 107674, doi:10.1016/j.ymssp.2021.107674.
8. Peng, X.; Acosta-Sojo, Y.; Wu, M.I.; Stirling, L. Actuation Timing Perception of a Powered Ankle Exoskeleton and Its Associated Ankle Angle Changes during Walking. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2022**, *30*, 869–877, doi:10.1109/TNSRE.2022.3162213.
9. Liu, H.; Zeng, B.; Liu, X.; Zhu, X.; Song, H. Detection of Human Lifting State Based on Long Short-Term Memory for Wearable Waist Exoskeleton. In *Lecture Notes in Electrical Engineering*; Springer Singapore: Singapore, 2022; pp. 301–310.
10. Ishmael, M.K.; Archangeli, D.; Lenzi, T. A Powered Hip Exoskeleton with High Torque Density for Walking, Running, and Stair Ascent. *IEEE ASME Trans. Mechatron.* **2022**, 1–12, doi:10.1109/tmech.2022.3159506.
11. Garosi, E.; Mazloumi, A.; Jafari, A.H.; Keihani, A.; Shamsipour, M.; Kordi, R.; Kazemi, Z. Design and Ergonomic Assessment of a Passive Head/Neck Supporting Exoskeleton for Overhead Work Use. *Appl. Ergon.* **2022**, *101*, 103699, doi:10.1016/j.apergo.2022.103699.
12. Song, J.; Zhu, A.; Tu, Y.; Zou, J. Multijoint Passive Elastic Spine Exoskeleton for Stoop Lifting Assistance. *Int. J. Adv. Robot. Syst.* **2021**, *18*, 172988142110620, doi:10.1177/17298814211062033.
13. Dragusanu, M.; Iqbal, M.Z.; Baldi, T.L.; Prattichizzo, D.; Malvezzi, M. Design, Development, and Control of a Hand/Wrist Exoskeleton for Rehabilitation and Training. *IEEE Trans. Robot.* **2022**, 1–17, doi:10.1109/TRO.2022.3172510.
14. Athira; Oommen, R.M. Advancements in Robotic Exoskeleton. In Proceedings of the 2018 International Conference on Circuits and Systems in Digital Enterprise Technology (ICCSDET); IEEE, 2018; pp. 1–3.

15. Li, G.; Cheng, L.; Sun, N. Design, Manipulability Analysis and Optimization of an Index Finger Exoskeleton for Stroke Rehabilitation. *Mech. Mach. Theory* **2022**, *167*, 104526, doi:10.1016/j.mechmachtheory.2021.104526.
16. Guntara, A.; Rahyussalim, A.J. The Uses of Lower Limb Exoskeleton, Functional Electrical Stimulation, and Future Improvements for Leg Paralysis Management – A Systematic Review. In Proceedings of the Proceedings of the 5th International Symposium of Biomedical Engineering (ISBE) 2020; A.I.P. Publishing, 2021.
17. Thamsuwan, O.; Milosavljevic, S.; Srinivasan, D.; Trask, C. Potential Exoskeleton Uses for Reducing Low Back Muscular Activity during Farm Tasks. *Am. J. Ind. Med.* **2020**, *63*, 1017–1028, doi:10.1002/ajim.23180.
18. Kumar, V.; Hote, Y.V.; Jain, S. Review of Exoskeleton: History, Design and Control. In Proceedings of the 2019 3rd International Conference on Recent Developments in Control, Automation & Power Engineering (RDCAPE); IEEE, 2019; pp. 677–682.
19. Coren, M.J. Robot Exoskeletons Are Finally Here, and They're Nothing like the Suits from Iron Man Available online: https://qz.com/971741/robot-exoskeletons-are-finally-here-and-theyre-nothing-like-the-suits-from-iron-man/ (accessed on 26 May 2022).
20. Global Market Insights; Inc Exoskeleton Market Worth $3.4bn by 2024: Global Market Insights, Inc Available online: https://www.globenewswire.com/en/news-release/2017/08/30/1104254/0/en/Exoskeleton-Market-worth-3-4bn-by-2024-Global-Market-Insights-Inc.html (accessed on 26 May 2022).
21. Farias da Costa, V.C.; Oliveira, L.; de Souza, J. Internet of Everything (IoE) Taxonomies: A Survey and a Novel Knowledge-Based Taxonomy. *Sensors (Basel)* **2021**, *21*, 568, doi:10.3390/s21020568.
22. Radetić-Paić, M.; Boljunčić, V. The Causes of I.C.T. Use Which Increase Time Spent on the Internet by Secondary School Students and Affect Exposure to Bullying from Other Students. *Econ. Res.-Ekon. Istraž.* **2021**, 1–9, doi:10.1080/1331677x.2021.1982746.
23. Pan, Y.-C.; Chiu, Y.-C.; Lin, Y.-H. Systematic Review and Meta-Analysis of Epidemiology of Internet Addiction. *Neurosci. Biobehav. Rev.* **2020**, *118*, 612–622, doi:10.1016/j.neubiorev.2020.08.013.
24. 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.
25. Gruzd, A.; Haythornthwaite, C. Enabling Community through Social Media. *J. Med. Internet Res.* **2013**, *15*, e248, doi:10.2196/jmir.2796.
26. Shepherd, A.; Sanders, C.; Doyle, M.; Shaw, J. Using Social Media for Support and Feedback by Mental Health Service Users: Thematic Analysis of a Twitter Conversation. *BMC Psychiatry* **2015**, *15*, 29, doi:10.1186/s12888-015-0408-y.
27. Kavada, A. Social Media as Conversation: A Manifesto. *Soc. Media Soc.* **2015**, *1*, 205630511558079, doi:10.1177/2056305115580793.
28. Goldberg, S.C. The Promise and Pitfalls of Online' Conversations.' *Roy. Inst. Philos. Suppl.* **2021**, *89*, 177–193, doi:10.1017/s1358246121000023.
29. Ramnarain, Y.; K Govender, K. Social Media Browsing and Consumer Behaviour: Exploring the Youth Market. *Afr. J. Bus. Manag.* **2013**, *7*, 1885–1893, doi:10.5897/ajbm12.1195.
30. Javed Awan, M.; Shafry Mohd Rahim, M.; Nobanee, H.; Munawar, A.; Yasin, A.; Mohd Zain Azlanmz, A. Social Media and Stock Market Prediction: A Big Data Approach. *Comput. mater. contin.* **2021**, *67*, 2569–2583, doi:10.32604/cmc.2021.014253.
31. Pezzuti, T.; Leonhardt, J.M.; Warren, C. Certainty in Language Increases Consumer Engagement on Social Media. *J. Interact. Mark.* **2021**, *53*, 32–46, doi:10.1016/j.intmar.2020.06.005.
32. Wang, L.; Lee, J.H. The Impact of K-Beauty Social Media Influencers, Sponsorship, and Product Exposure on Consumer Acceptance of New Products. *Fashion Text.* **2021**, *8*, doi:10.1186/s40691-020-00239-0.
33. Varghese, M.S.; Agrawal, M.M. Impact of Social Media on Consumer Buying Behavior. *Saudi j. bus. manag. stud.* **2021**, *6*, 51–55, doi:10.36348/sjbms.2021.v06i03.001.
34. Majeed, M.; Asare, C.; Fatawu, A.; Abubakari, A. An Analysis of the Effects of Customer Satisfaction and Engagement on Social Media on Repurchase Intention in the Hospitality Industry. *Cogent bus. manag.* **2022**, *9*, doi:10.1080/23311975.2022.2028331.
35. 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.
36. Gruzd, A.; Wellman, B.; Takhteyev, Y. Imagining Twitter as an Imagined Community. *Am. Behav. Sci.* **2011**, *55*, 1294–1318, doi:10.1177/0002764211409378.
37. Aslam, S. Twitter by the Numbers (2022): Stats, Demographics & Fun Facts. *Omnicoreagency.com* 2022.
38. 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 A.C.M. Conference on Recommender Systems (RecSys 2013); 2013.
39. Banda, J.M.; Tekumalla, R.; Wang, G.; Yu, J.; Liu, T.; Ding, Y.; Chowell, G. A Large-Scale COVID-19 Twitter Chatter Dataset for Open Scientific Research -- an International Collaboration. *ArXiv* **2020**, *2*, 315–324, doi:10.3390/epidemiologia2030024.
40. Chen, E.; Deb, A.; Ferrara, E. #Election2020: The First Public Twitter Dataset on the 2020 U.S. Presidential Election. *J. Comput. Soc. Sci.* **2022**, *5*, 1–18, doi:10.1007/s42001-021-00117-9.
41. 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.

42. 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; A.C.M. Press: New York, New York, U.S.A., 2014.
43. Meng, L.; Dong, Z.S. Natural Hazards Twitter Dataset. *arXiv [cs.SI]* **2020**, doi:10.48550/ARXIV.2004.14456.
44. Salem, M.S.; Ismail, S.S.; Aref, M. Personality Traits for Egyptian Twitter Users Dataset. In Proceedings of the Proceedings of the 2019 8th International Conference on Software and Information Engineering; A.C.M.: New York, NY, U.S.A., 2019.
45. 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, U.S.A., 2020; pp. 215–221.
46. Tekumalla, R.; Banda, J.M. A Large-Scale Twitter Dataset for Drug Safety Applications Mined from Publicly Existing Resources. *arXiv [cs. I.R.]* **2020**, doi:10.48550/ARXIV.2003.13900.
47. 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.
48. Febriana, T.; Budiarto, A. Twitter Dataset for Hate Speech and Cyberbullying Detection in Indonesian Language. In Proceedings of the 2019 International Conference on Information Management and Technology (ICIMTech); IEEE, 2019; Vol. 1, pp. 379–382.
49. 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.
50. Schroeder, D.; Schaal, F.; Filkukova, P.; Pogorelov, K.; Langguth, J. WICO Graph: A Labeled Dataset of Twitter Subgraphs Based on Conspiracy Theory and 5G-Corona Misinformation Tweets. In Proceedings of the Proceedings of the 13th International Conference on Agents and Artificial Intelligence; SCITEPRESS - Science and Technology Publications, 2021.
51. Stemmer, M.; Parmet, Y.; Ravid, G. What Are IBD Patients Talking about on Twitter? In *I.C.T. for Health, Accessibility and Wellbeing*; Springer International Publishing: Cham, 2021; pp. 206–220 ISBN 9783030942083.
52. Warren, E. Strengthening Research through Data Sharing. *N. Engl. J. Med.* **2016**, *375*, 401–403, doi:10.1056/NEJMp1607282.
53. Fecher, B.; Friesike, S.; Hebing, M. What Drives Academic Data Sharing? *PLoS One* **2015**, *10*, e0118053, doi:10.1371/journal.pone.0118053.
54. Logan, J.A.R.; Hart, S.A.; Schatschneider, C. Data Sharing in Education Science. *AERA Open* **2021**, *7*, 233285842110064, doi:10.1177/23328584211006475.
55. Privacy Policy Available online: https://twitter.com/en/privacy/previous/version_15 (accessed on 27 May 2022).
56. Developer Agreement and Policy Available online: https://developer.twitter.com/en/developer-terms/agreement-and-policy (accessed on 27 May 2022).
57. RapidMiner GmbH Search Twitter - RapidMiner Documentation Available online: https://docs.rapidminer.com/latest/studio/operators/data_access/applications/twitter/search_twitter.html (accessed on 27 May 2022).
58. 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; A.C.M. Press: New York, New York, U.S.A., 2006.
59. Rate Limits: Standard v1.1 Available online: https://developer.twitter.com/en/docs/twitter-api/v1/rate-limits (accessed on 27 May 2022).
60. Using Standard Search Available online: https://developer.twitter.com/en/docs/twitter-api/v1/tweets/search/guides/standard-operators (accessed on 27 May 2022).
61. 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.
62. Lamsal, R. Hydrating Tweet I.D.s Available online: https://theneuralblog.com/hydrating-tweet-ids/ (accessed on 27 May 2022).
63. Bramus!, P. by Accessing a Tweet Using Only Its ID (and without the Twitter API) Available online: https://www.bram.us/2017/11/22/accessing-a-tweet-using-only-its-id-and-without-the-twitter-api/ (accessed on 27 May 2022).
64. Hydrator Available online: https://github.com/DocNow/hydrator (accessed on 27 May 2022).
65. Tekumalla, R.; Banda, J.M. Social Media Mining Toolkit (SMMT). *Genomics Inform.* **2020**, *18*, e16, doi:10.5808/GI.2020.18.2.e16.
66. Twarc Available online: https://github.com/DocNow/twarc (accessed on 27 May 2022).
67. Hydrator Versions Available online: https://github.com/DocNow/hydrator/releases (accessed on 27 May 2022).
68. 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.
69. Gu, S.; Wang, F.; Patel, N.P.; Bourgeois, J.A.; Huang, J.H. A Model for Basic Emotions Using Observations of Behavior in Drosophila. *Front. Psychol.* **2019**, *10*, 781, doi:10.3389/fpsyg.2019.00781.
70. Do, H.H.; Prasad, P.W.C.; Maag, A.; Alsadoon, A. Deep Learning for Aspect-Based Sentiment Analysis: A Comparative Review. *Expert Syst. Appl.* **2019**, *118*, 272–299, doi:10.1016/j.eswa.2018.10.003.
71. Asur, S.; Huberman, B.A.; Szabo, G.; Wang, C. Trends in Social Media: Persistence and Decay. *SSRN Electron. J.* **2011**, *5*, 434–437, doi:10.2139/ssrn.1755748.

72. Fouad, M.M.; Mahany, A.; Aljohani, N.; Abbasi, R.A.; Hassan, S.-U. ArWordVec: Efficient Word Embedding Models for Arabic Tweets. *Soft Comput.* **2020**, *24*, 8061–8068, doi:10.1007/s00500-019-04153-6.
73. Chen, G.M. Tweet This: A Uses and Gratifications Perspective on How Active Twitter Use Gratifies a Need to Connect with Others. *Comput. Human Behav.* **2011**, *27*, 755–762, doi:10.1016/j.chb.2010.10.023.
74. 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 - W.W.W. '11; A.C.M. Press: New York, New York, U.S.A., 2011.
75. Rajadesingan, A.; Zafarani, R.; Liu, H. Sarcasm Detection on Twitter: A Behavioral Modeling Approach. In Proceedings of the Proceedings of the Eighth A.C.M. International Conference on Web Search and Data Mining - WSDM '15; A.C.M. Press: New York, New York, U.S.A., 2015.
76. Wang, X.; Wei, F.; Liu, X.; Zhou, M.; Zhang, M. Topic Sentiment Analysis in Twitter: A Graph-Based Hashtag Sentiment Classification Approach. In Proceedings of the Proceedings of the 20th A.C.M. international conference on Information and knowledge management - CIKM '11; A.C.M. Press: New York, New York, U.S.A., 2011.
77. Li, J.; Galley, M.; Brockett, C.; Spithourakis, G.P.; Gao, J.; Dolan, B. A Persona-Based Neural Conversation Model. *arXiv [cs.CL]* **2016**, doi:10.48550/ARXIV.1603.06155.
78. Aiello, L.M.; Petkos, G.; Martin, C.; Corney, D.; Papadopoulos, S.; Skraba, R.; Goker, A.; Kompatsiaris, I.; Jaimes, A. Sensing Trending Topics in Twitter. *IEEE Trans. Multimedia* **2013**, *15*, 1268–1282, doi:10.1109/tmm.2013.2265080.
79. Lee, K.; Palsetia, D.; Narayanan, R.; Patwary, M.M.A.; Agrawal, A.; Choudhary, A. Twitter Trending Topic Classification. In Proceedings of the 2011 IEEE 11th International Conference on Data Mining Workshops; IEEE, 2011; pp. 251–258.
80. Munjal, P.; Narula, M.; Kumar, S.; Banati, H. Twitter Sentiments Based Suggestive Framework to Predict Trends. *J. Stat. Manag. Syst.* **2018**, *21*, 685–693, doi:10.1080/09720510.2018.1475079.
81. 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.
82. 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.
83. Marwick, A.E.; Boyd, D. I Tweet Honestly, I Tweet Passionately: Twitter Users, Context Collapse, and the Imagined Audience. *New Media Soc.* **2011**, *13*, 114–133, doi:10.1177/1461444810365313.
84. Li, W.; Serdyukov, P.; de Vries, A.P.; Eickhoff, C.; Larson, M. The Where in the Tweet. In Proceedings of the Proceedings of the 20th A.C.M. international conference on Information and knowledge management - CIKM '11; A.C.M. Press: New York, New York, U.S.A., 2011.
85. Chen, K.; Chen, T.; Zheng, G.; Jin, O.; Yao, E.; Yu, Y. Collaborative Personalized Tweet Recommendation. In Proceedings of the Proceedings of the 35th international ACM SIGIR conference on Research and development in information retrieval - SIGIR '12; A.C.M. Press: New York, New York, U.S.A., 2012.
86. Ray, S. A Quick Review of Machine Learning Algorithms. In Proceedings of the 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon); IEEE, 2019; pp. 35–39.
87. da Silva, N.F.F.; Hruschka, E.R.; Hruschka, E.R., Jr Tweet Sentiment Analysis with Classifier Ensembles. *Decis. Support Syst.* **2014**, *66*, 170–179, doi:10.1016/j.dss.2014.07.003.
88. Kreis, R. The "Tweet Politics" of President Trump. *J. Lang. Polit.* **2017**, *16*, 607–618, doi:10.1075/jlp.17032.kre.
89. Myslín, M.; Zhu, S.-H.; Chapman, W.; Conway, M. Using Twitter to Examine Smoking Behavior and Perceptions of Emerging Tobacco Products. *J. Med. Internet Res.* **2013**, *15*, e174, doi:10.2196/jmir.2534.
90. Wigley, S.; Lewis, B.K. Rules of Engagement: Practice What You Tweet. *Public Relat. Rev.* **2012**, *38*, 165–167, doi:10.1016/j.pubrev.2011.08.020.
91. Liu, I.L.B.; Cheung, C.M.K.; Lee, M.K.O. Understanding Twitter Usage: What Drive People Continue to Tweet. **2010**.
92. Cheng, Z.; Caverlee, J.; Lee, K. You Are Where You Tweet: A Content-Based Approach to Geo-Locating Twitter Users. In Proceedings of the Proceedings of the 19th A.C.M. international conference on Information and knowledge management - CIKM '10; A.C.M. Press: New York, New York, U.S.A., 2010.
93. Uysal, I.; Croft, W.B. User Oriented Tweet Ranking: A Filtering Approach to Microblogs. In Proceedings of the Proceedings of the 20th A.C.M. international conference on Information and knowledge management - CIKM '11; A.C.M. Press: New York, New York, U.S.A., 2011.
94. Andrews, C.A.; Fichet, E.S.; Ding, Y.; Spiro, E.S.; Starbird, K. Keeping up with the Tweet-Dashians: The Impact of `official-Accounts on Online Rumoring. In Proceedings of the Proceedings of the 19th A.C.M. Conference on Computer-Supported Cooperative Work & Social Computing - CSCW '16; A.C.M. Press: New York, New York, U.S.A., 2016.
95. Pujazon-Zazik, M.; Park, M.J. To Tweet, or Not to Tweet: Gender Differences and Potential Positive and Negative Health Outcomes of Adolescents' Social Internet Use. *Am. J. Mens. Health* **2010**, *4*, 77–85, doi:10.1177/1557988309360819.
96. Merler, M.; Cao, L.; Smith, J.R. You Are What You Tweet…pic! Gender Prediction Based on Semantic Analysis of Social Media Images. In Proceedings of the 2015 IEEE International Conference on Multimedia and Expo (ICME); IEEE, 2015; pp. 1–6.
97. André, P.; Bernstein, M.; Luther, K. Who Gives a Tweet?: Evaluating Microblog Content Value. In Proceedings of the Proceedings of the A.C.M. 2012 conference on Computer Supported Cooperative Work - CSCW '12; A.C.M. Press: New York, New York, U.S.A., 2012.
98. Tao, K.; Abel, F.; Hauff, C.; Houben, G.-J. What Makes a Tweet Relevant for a Topic? Available online: https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.309.8507&rep=rep1&type=pdf (accessed on 27 May 2022).

99. Kupavskii, A.; Umnov, A.; Gusev, G.; Serdyukov, P. Predicting the Audience Size of a Tweet. *ICWSM* **2013**, *7*, 693–696.
100. Han, S.; Min, J.; Lee, H. Antecedents of Social Presence and Gratification of Social Connection Needs in S.N.S.: A Study of Twitter Users and Their Mobile and Non-Mobile Usage. *Int. J. Inf. Manage.* **2015**, *35*, 459–471, doi:10.1016/j.ijinfomgt.2015.04.004.
101. Armstrong, C.L.; Gao, F. Now Tweet This: How News Organizations Use Twitter. *Electron. news* **2010**, *4*, 218–235, doi:10.1177/1931243110389457.
102. Hu, T.; Xiao, H.; Nguyen, T.-V.T.; Luo, J. What the Language You Tweet Says about Your Occupation. *arXiv [cs. C.Y.]* 2017.
103. Shou, L.; Wang, Z.; Chen, K.; Chen, G. Sumblr: Continuous Summarization of Evolving Tweet Streams. In Proceedings of the Proceedings of the 36th international ACM SIGIR conference on Research and development in information retrieval; A.C.M.: New York, NY, U.S.A., 2013.
104. Yamaguchi, Y.; Takahashi, T.; Amagasa, T.; Kitagawa, H. TURank: Twitter User Ranking Based on User-Tweet Graph Analysis. In *Web Information Systems Engineering – WISE 2010*; Springer Berlin Heidelberg: Berlin, Heidelberg, 2010; pp. 240–253 ISBN 9783642176159.
105. Guo, S.; Chang, M.-W.; Kıcıman, E. To Link or Not to Link? A Study on End-to-End Tweet Entity Linking Available online: https://aclanthology.org/N13-1122.pdf (accessed on 27 May 2022).
106. Himelboim, I.; McCreery, S.; Smith, M. Birds of a Feather Tweet Together: Integrating Network and Content Analyses to Examine Cross-Ideology Exposure on Twitter. *J. Comput. Mediat. Commun.* **2013**, *18*, 40–60, doi:10.1111/jcc4.12001.
107. Bruns, A. How Long Is a Tweet? Mapping Dynamic Conversation Networks Ontwitterusing Gawk and Gephi. *Inf. Commun. Soc.* **2012**, *15*, 1323–1351, doi:10.1080/1369118x.2011.635214.
108. Li, C.; Sun, A.; Weng, J.; He, Q. Tweet Segmentation and Its Application to Named Entity Recognition. *IEEE Trans. Knowl. Data Eng.* **2015**, *27*, 558–570, doi:10.1109/tkde.2014.2327042.
109. Parganas, P.; Anagnostopoulos, C.; Chadwick, S.' You'Ll Never Tweet Alone': Managing Sports Brands through Social Media. *J. Brand Manag.* **2015**, *22*, 551–568, doi:10.1057/bm.2015.32.
110. 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 - W.W.W. '15 Companion; A.C.M. Press: New York, New York, U.S.A., 2015.
111. Stephens, M. A Geospatial Infodemic: Mapping Twitter Conspiracy Theories of COVID-19. *Dialogues Hum. Geogr.* **2020**, *10*, 276–281, doi:10.1177/2043820620935683.
112. Fong, A.; Roozenbeek, J.; Goldwert, D.; Rathje, S.; van der Linden, S. The Language of Conspiracy: A Psychological Analysis of Speech Used by Conspiracy Theorists and Their Followers on Twitter. *Group Process. Intergroup Relat.* **2021**, *24*, 606–623, doi:10.1177/1368430220987596.
113. Vosoughi, S.; Vijayaraghavan, P.; Roy, D. Tweet2Vec: Learning Tweet Embeddings Using Character-Level CNN-LSTM Encoder-Decoder. In Proceedings of the Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval; A.C.M.: New York, NY, U.S.A., 2016.
114. Zhao, Q.; Erdogdu, M.A.; He, H.Y.; Rajaraman, A.; Leskovec, J. SEISMIC: A Self-Exciting Point Process Model for Predicting Tweet Popularity. In Proceedings of the Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '15; A.C.M. Press: New York, New York, U.S.A., 2015.
115. van Liere, D. How Far Does a Tweet Travel?: Information Brokers in the Twitterverse. In Proceedings of the Proceedings of the International Workshop on Modeling Social Media - M.S.M. '10; A.C.M. Press: New York, New York, U.S.A., 2010.
116. Huang, H.; Cao, Y.; Huang, X.; Ji, H.; Lin, C.-Y. Collective Tweet Wikification Based on Semi-Supervised Graph Regularization. In Proceedings of the Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers); Association for Computational Linguistics: Stroudsburg, PA, U.S.A., 2014.
117. Alom, Z.; Carminati, B.; Ferrari, E. Detecting Spam Accounts on Twitter. In Proceedings of the 2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM); IEEE, 2018; pp. 1191–1198.
118. Wang, B.; Zubiaga, A.; Liakata, M.; Procter, R. Making the Most of Tweet-Inherent Features for Social Spam Detection on Twitter. *arXiv [cs. I.R.]* **2015**, doi:10.48550/ARXIV.1503.07405.
119. Purwarianti, A.; Andhika, A.; Wicaksono, A.F.; Afif, I.; Ferdian, F. InaNLP: Indonesia Natural Language Processing Toolkit, Case Study: Complaint Tweet Classification. In Proceedings of the 2016 International Conference On Advanced Informatics: Concepts, Theory And Application (ICAICTA); IEEE, 2016; pp. 1–5.
120. Pant, D.R.; Neupane, P.; Poudel, A.; Pokhrel, A.K.; Lama, B.K. Recurrent Neural Network Based Bitcoin Price Prediction by Twitter Sentiment Analysis. In Proceedings of the 2018 IEEE 3rd International Conference on Computing, Communication and Security (ICCCS); IEEE, 2018; pp. 128–132.
121. Jain, A.; Tripathi, S.; Dwivedi, H.D.; Saxena, P. Forecasting Price of Cryptocurrencies Using Tweets Sentiment Analysis. In Proceedings of the 2018 Eleventh International Conference on Contemporary Computing (IC3); IEEE, 2018; pp. 1–7.
122. 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 A.C.M. International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers; A.C.M.: New York, NY, U.S.A., 2018.
123. Tomihira, T.; Otsuka, A.; Yamashita, A.; Satoh, T. What Does Your Tweet Emotion Mean?: Neural Emoji Prediction for Sentiment Analysis. In Proceedings of the Proceedings of the 20th International Conference on Information Integration and Web-based Applications & Services - iiWAS2018; A.C.M. Press: New York, New York, U.S.A., 2018.

124. Bansal, B.; Srivastava, S. Lexicon-Based Twitter Sentiment Analysis for Vote Share Prediction Using Emoji and N-Gram Features. *Int. J. Web Based Communities* **2019**, *15*, 85, doi:10.1504/ijwbc.2019.098693.
125. Singh, A.; Blanco, E.; Jin, W. Incorporating Emoji Descriptions Improves Tweet Classification. In Proceedings of the Proceedings of the 2019 Conference of the North; Association for Computational Linguistics: Stroudsburg, PA, U.S.A., 2019; pp. 2096–2101.
126. Suman, C.; Saha, S.; Bhattacharyya, P.; Chaudhari, R.S. Emoji Helps! A Multi-Modal Siamese Architecture for Tweet User Verification. *Cognit. Comput.* **2021**, *13*, 261–276, doi:10.1007/s12559-020-09715-7.
127. Reyes, A.; Rosso, P.; Veale, T. A Multidimensional Approach for Detecting Irony in Twitter. *Lang. Resour. Eval.* **2013**, *47*, 239–268, doi:10.1007/s10579-012-9196-x.
128. Mendoza, M.; Poblete, B.; Castillo, C. Twitter under Crisis: Can We Trust What We RT? In Proceedings of the Proceedings of the First Workshop on Social Media Analytics - SOMA '10; A.C.M. Press: New York, New York, U.S.A., 2010.
129. Ersahin, B.; Aktas, O.; Kilinc, D.; Akyol, C. Twitter Fake Account Detection. In Proceedings of the 2017 International Conference on Computer Science and Engineering (UBMK); IEEE, 2017; pp. 388–392.
130. Saez-Trumper, D. Fake Tweet Buster: A Webtool to Identify Users Promoting Fake News Ontwitter. In Proceedings of the Proceedings of the 25th A.C.M. conference on Hypertext and social media; A.C.M.: New York, NY, U.S.A., 2014.
131. Tonia, T.; Van Oyen, H.; Berger, A.; Schindler, C.; Künzli, N. If I Tweet Will You Cite? The Effect of Social Media Exposure of Articles on Downloads and Citations. *Int. J. Public Health* **2016**, *61*, 513–520, doi:10.1007/s00038-016-0831-y.
132. Huang, B.; Carley, K.M. Discover Your Social Identity from What You Tweet: A Content Based Approach. In *Lecture Notes in Social Networks*; Springer International Publishing: Cham, 2020; pp. 23–37 ISBN 9783030426989.
133. McCreadie, R.; Macdonald, C. Relevance in Microblogs: Enhancing Tweet Retrieval Using Hyperlinked Documents. In Proceedings of the Proceedings of the 10th Conference on Open Research Areas in Information Retrieval; LE CENTRE DE HAUTES ETUDES INTERNATIONALES D'INFORMATIQUE DOCUMENTAIRE: Paris, F.R.A., 2013; pp. 189–196.
134. Haugh, B.R.; Watkins, B. Tag Me, Tweet Me If You Want to Reach Me: An Investigation into How Sports Fans Use Social Media. *Int. J. Sport Communication* **2016**, *9*, 278–293, doi:10.1123/ijsc.2016-0044.
135. Darwish, K.; Stefanov, P.; Aupetit, M.; Nakov, P. Unsupervised User Stance Detection on Twitter. *arXiv [cs.SI]* 2019, 141–152.
136. 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.
137. Pandya, A.; Oussalah, M.; Monachesi, P.; Kostakos, P. On the Use of Distributed Semantics of Tweet Metadata for User Age Prediction. *Future Gener. Comput. Syst.* **2020**, *102*, 437–452, doi:10.1016/j.future.2019.08.018.
138. Ran, C.; Shen, W.; Wang, J. An Attention Factor Graph Model for Tweet Entity Linking. In Proceedings of the Proceedings of the 2018 World Wide Web Conference on World Wide Web - W.W.W. '18; A.C.M. Press: New York, New York, U.S.A., 2018.
139. Davis, S.W.; Horváth, C.; Gretry, A.; Belei, N. Say What? How the Interplay of Tweet Readability and Brand Hedonism Affects Consumer Engagement. *J. Bus. Res.* **2019**, *100*, 150–164, doi:10.1016/j.jbusres.2019.01.071.
140. Al Abdullatif, A.M.; Alsoghayer, R.A.; AlMajhad, E.M. An Algorithm to Find the Best Time to Tweet. In Proceedings of the International Conference on Computer Vision and Image Analysis Applications; IEEE, 2015; pp. 1–13.
141. Yuan, N.J.; Zhong, Y.; Zhang, F.; Xie, X.; Lin, C.-Y.; Rui, Y. Who Will Reply to/Retweet This Tweet?: The Dynamics of Intimacy from Online Social Interactions. In Proceedings of the Proceedings of the Ninth A.C.M. International Conference on Web Search and Data Mining; A.C.M.: New York, NY, U.S.A., 2016.
142. Wei, H.; Zhou, H.; Sankaranarayanan, J.; Sengupta, S.; Samet, H. Residual Convolutional LSTM for Tweet Count Prediction. In Proceedings of the Companion of the The Web Conference 2018 on The Web Conference 2018 - W.W.W. '18; A.C.M. Press: New York, New York, U.S.A., 2018.
143. Lee, M.; Kim, H.; Kim, O. Why Do People Retweet a Tweet?: Altruistic, Egoistic, and Reciprocity Motivations for Retweeting. *Psychologia* **2015**, *58*, 189–201, doi:10.2117/psysoc.2015.189.
144. Kim, T.-Y.; Kim, J.; Lee, J.; Lee, J.-H. A Tweet Summarization Method Based on a Keyword Graph. In Proceedings of the Proceedings of the 8th International Conference on Ubiquitous Information Management and Communication - ICUIMC '14; A.C.M. Press: New York, New York, U.S.A., 2014.
145. Jeon, M.; Jun, S.; Hwang, E. Hashtag Recommendation Based on User Tweet and Hashtag Classification on Twitter. In *Web-Age Information Management*; Springer International Publishing: Cham, 2014; pp. 325–336 ISBN 9783319115375.
146. Deveaud, R.; Boudin, F. Effective Tweet Contextualization with Hashtags Performance Prediction and Multi-Document Summarization. In Proceedings of the INitiative for the Evaluation of XML Retrieval (INEX); 2013.
147. Yan, J.L.S.; Kaziunas, E. What Is a Tweet Worth?: Measuring the Value of Social Media for an Academic Institution. In Proceedings of the Proceedings of the 2012 iConference on - iConference '12; A.C.M. Press: New York, New York, U.S.A., 2012.
148. Klotz, C.; Ross, A.; Clark, E.; Martell, C. Tweet! – And I Can Tell How Many Followers You Have. In *Advances in Intelligent Systems and Computing*; Springer International Publishing: Cham, 2014; pp. 245–253 ISBN 9783319065373.
149. Dong, L.; Wei, F.; Duan, Y.; Liu, X.; Zhou, M.; Xu, K. The Automated Acquisition of Suggestions from Tweets. In Proceedings of the Twenty-Seventh AAAI Conference on Artificial Intelligence; 2013.
150. Yuan, S.; Wu, X.; Xiang, Y. A Two Phase Deep Learning Model for Identifying Discrimination from Tweets Available online: http://www.csce.uark.edu/~xintaowu/publ/edbt16p.pdf (accessed on 27 May 2022).

151. Lim, W.Y.; Lee, M.L.; Hsu, W. IFACT: An Interactive Framework to Assess Claims from Tweets. In Proceedings of the Proceedings of the 2017 A.C.M. on Conference on Information and Knowledge Management; A.C.M.: New York, NY, U.S.A., 2017.
152. Morabia, K.; Bhanu Murthy, N.L.; Malapati, A.; Samant, S. SEDTWik: Segmentation-Based Event Detection from Tweets Using Wikipedia. In Proceedings of the Proceedings of the 2019 Conference of the North; Association for Computational Linguistics: Stroudsburg, PA, U.S.A., 2019; pp. 77–85.
153. Yamamoto, Y.; Kumamoto, T.; Nadamoto, A. Followee Recommendation Based on Topic Extraction and Sentiment Analysis from Tweets. In Proceedings of the Proceedings of the 17th International Conference on Information Integration and Web-based Applications & Services; A.C.M.: New York, NY, U.S.A., 2015.
154. Kvtkn, P.; Ramakrishnudu, T. A Novel Method for Detecting Psychological Stress at Tweet Level Using Neighborhood Tweets. *J. King Saud Univ. - Comput. Inf. Sci.* **2021**, doi:10.1016/j.jksuci.2021.08.015.
155. Zhou, L.; Wang, W.; Chen, K. Identifying Regrettable Messages from Tweets. In Proceedings of the Proceedings of the 24th International Conference on World Wide Web - W.W.W. '15 Companion; A.C.M. Press: New York, New York, U.S.A., 2015.
156. Jussila, J.; Madhala, P. Cognitive Computing Approaches for Human Activity Recognition from Tweets—A Case Study of Twitter Marketing Campaign. In *Research & Innovation Forum 2019*; Springer International Publishing: Cham, 2019; pp. 153–170 ISBN 9783030308087.
157. McClellan, C.; Ali, M.M.; Mutter, R.; Kroutil, L.; Landwehr, J. Using Social Media to Monitor Mental Health Discussions − Evidence from Twitter. *J. Am. Med. Inform. Assoc.* **2017**, *24*, 496–502, doi:10.1093/jamia/ocw133.
158. 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.
159. Pauken, B.; Pradyumn, M.; Tabrizi, N. Tracking Happiness of Different U.S. Cities from Tweets. In *Big Data – BigData 2018*; Springer International Publishing: Cham, 2018; pp. 140–148 ISBN 9783319943008.
160. Ibrohim, M.O.; Budi, I. Multi-Label Hate Speech and Abusive Language Detection in Indonesian Twitter. In Proceedings of the Proceedings of the Third Workshop on Abusive Language Online; Association for Computational Linguistics: Stroudsburg, PA, U.S.A., 2019; pp. 46–57.
161. Sankaranarayanan, J.; Samet, H.; Teitler, B.E.; Lieberman, M.D.; Sperling, J. TwitterStand: News in Tweets. In Proceedings of the Proceedings of the 17th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems - G.I.S. '09; A.C.M. Press: New York, New York, U.S.A., 2009.
162. Haque, R.; Hasanuzzaman, M.; Ramadurai, A.; Way, A. Mining Purchase Intent in Twitter. *Comput. sist.* **2019**, *23*, 871–881, doi:10.13053/cys-23-3-3254.
163. Chaloulos, K. Inferring Shared Interests from Tweets Available online: https://pub.tik.ee.ethz.ch/students/2011-FS/SA-2011-20.pdf (accessed on 27 May 2022).
164. Bollen, J.; Mao, H.; Pepe, A. Modeling Public Mood and Emotion: Twitter Sentiment and Socio-Economic Phenomena. *ICWSM* **2011**, *5*, 450–453.
165. 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.
166. Felicia Ilona, K.; Budi, I. Classification of Inundation Level Using Tweets in Indonesian Language. In Proceedings of the 2021 10th International Conference on Software and Computer Applications; A.C.M.: New York, NY, U.S.A., 2021.
167. Tankard, E.; Flowers, C.; Li, J.; Rawat, D.B. Toward Bias Analysis Using Tweets and Natural Language Processing. In Proceedings of the 2021 IEEE 18th Annual Consumer Communications & Networking Conference (CCNC); IEEE, 2021; pp. 1–3.
168. Umakanth, N.; Santhi, S. Classification and Ranking of Trending Topics in Twitter Using Tweets Text. *J. Crit. Rev.* **2020**, *7*, doi:10.31838/jcr.07.04.171.
169. Garcia-Lopez, F.J.; Batyrshin, I.; Gelbukh, A. Analysis of Relationships between Tweets and Stock Market Trends. *J. Intell. Fuzzy Syst.* **2018**, *34*, 3337–3347, doi:10.3233/jifs-169515.
170. Liew, J.K.-S. Do Tweet Sentiments Still Predict the Stock Market? *SSRN Electron. J.* **2016**, doi:10.2139/ssrn.2820269.
171. 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; A.C.M. Press: New York, New York, U.S.A., 2018.
172. Balusamy, B.; Murali, T.; Thangavelu, A.; Krishna, P.V. A Multi-Level Text Classifier for Feedback Analysis Using Tweets to Enhance Product Performance. *Int. j. electron. mark. retail.* **2015**, *6*, 315, doi:10.1504/ijemr.2015.073455.
173. Ahmed, H.; Razzaq, M.A.; Qamar, A.M. Prediction of Popular Tweets Using Similarity Learning. In Proceedings of the 2013 IEEE 9th International Conference on Emerging Technologies (ICET); IEEE, 2013; pp. 1–6.
174. Sharif; Mumtaz; Shafiq; Riaz; Ali; Husnain; Choi An Empirical Approach for Extreme Behavior Identification through Tweets Using Machine Learning. *Appl. Sci. (Basel)* **2019**, *9*, 3723, doi:10.3390/app9183723.
175. Vemprala, N.; Akello, P.; Valecha, R.; Rao, H.R. An Exploratory Analysis of Alarming and Reassuring Messages in Twitterverse during the Coronavirus Epidemic. In Proceedings of the AMCIS 2020 Proceedings; 2020.
176. Akpojivi, U. Euphoria and Delusion of Digital Activism: Case Study of #ZumaMustFall. In *Advances in Social Networking and Online Communities*; I.G.I. Global: Hershey, PA, 2018; pp. 179–202 ISBN 9781522528548.

177. Anwar, M.; Yuan, Z. Linking Obesity and Tweets. In *Smart Health*; Springer International Publishing: Cham, 2016; pp. 254–266 ISBN 9783319291741.
178. Silva, W.; Santana, Á.; Lobato, F.; Pinheiro, M. A Methodology for Community Detection in Twitter. In Proceedings of the Proceedings of the International Conference on Web Intelligence - W.I. '17; A.C.M. Press: New York, New York, U.S.A., 2017.
179. 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.
180. Culotta, A.; Cutler, J. Mining Brand Perceptions from Twitter Social Networks. *Mark. sci.* **2016**, *35*, 343–362, doi:10.1287/mksc.2015.0968.
181. Jain, S.; Sharma, V.; Kaushal, R. Towards Automated Real-Time Detection of Misinformation on Twitter. In Proceedings of the 2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI); IEEE, 2016; pp. 2015–2020.