Identifying and Ranking Common COVID-19 Symptoms from Arabic Twitter

Eisa Alanazi, Abdulaziz Alashaikh, Sarah Alqurashi, Aued Alanazi

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Eisa Alanazi[1] PhD, MSc, BSc; Abdulaziz Alashaikh[2] BEng, MSc, PhD; Sarah Alqurashi[1] BSc; Aued Alanazi[1] BSc

[1]Center of Innovation and Development in Artificial Intelligence Umm Al-Qura University Makkah SA
[2]University of Jeddah Jeedah SA

Corresponding Author:
Eisa Alanazi PhD, MSc, BSc
Center of Innovation and Development in Artificial Intelligence
Umm Al-Qura University
Prince Sultan Road
Makkah
SA

Abstract

Background: Massive amount of covid-19 related data is generated everyday by Twitter users. Self-reports of covid-19 symptoms on Twitter can reveal a great deal about the disease and its prevalence in the community. In particular, self-reports can be used as a valuable resource to learn more about the common symptoms and whether their order of appearance differs among different groups in the community. With sufficient available data, this has the potential of developing a covid-19 risk- assessment system that is tailored toward specific group of people.

Objective: The aim of this study is to identify the most common symptoms reported by covid-19 patients in the Arabic language and order the symptoms appearance based on the collected data.

Methods: We search the Arabic content of Twitter for personal reports of covid-19 symptoms from March 1st to May 27th, 2020. We identify 463 Arabic users who tweeted testing positive for covid-19 and extract the symptoms they publicly associate with covid-19. Furthermore, we ask them directly through personal messages to opt in and rank the appearance of the first three symptoms they experienced right before (or after) diagnosed with covid-19. Finally, we track their Twitter timeline to identify additional symptoms that were mentioned within +-5 days from the day of tweeting having covid-19. In summary, a list of 270 covid-19 reports were collected and symptoms were (at least partially) ranked from early to late.

Results: The collected reports contained roughly 900 symptoms originated from 74% (n=201) male and 26% (n=69) female Twitter users. The majority (82%) of the tracked users were living in Saudi Arabia (46%) and Kuwait (36%). Furthermore, 13% (n=36) of the collected reports were asymptomatic. Out of the users with symptoms (n=234), 66% (n=180) provided a chronological order of appearance for at least three symptoms.

Fever 59% (n=139), Headache 43% (n=101), and Anosmia 39% (n=91) were found to be the top three symptoms mentioned by the reports. They count also for the top-3 common first symptoms in a way that 28% (n=65) said their covid journey started with a Fever, 15% (n=34) with a Headache and 12% (n=28) with Anosmia. Out of the Saudi symptomatic reported cases (n=110), the most common three symptoms were Fever 59% (n=65), Anosmia 42% (n=46), and Headache 38% (n=42).

Conclusions: This study demonstrates that Twitter is a valuable resource to analyze and identify COVID-19 early symptoms within the Arabic content of Twitter. It also suggests the possibility of developing a real-time covid-19 risk estimator based on the users' tweets.

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Eisa Alanazi, BSc MSc PhD;
Center of Innovation and Development in Artificial Intelligence
Umm Al-Qura University
Saudi Arabia

Abdulaziz Alashaikh BEng MSc PhD;
Department of Computer Engineering and Network
University of Jeddah
Saudi Arabia

Sarah Alqurashi BSc;
Center of Innovation and Development in Artificial Intelligence
Umm Al-Qura University
Saudi Arabia

Aued Alanazi BSc;
Center of Innovation and Development in Artificial Intelligence
Umm Al-Qura University
Saudi Arabia

Corresponding Author:
Eisa Alanazi, BSc MSc PhD
Center of Innovation and Development in Artificial Intelligence
Umm Al-Qura University
Makkah, 21421
Saudi Arabia
Email: eaanazi@uqu.edu.sa
Phone: 00966125270000
Fax: 00966125276697

Identifying and Ranking Common COVID-19 Symptoms from Arabic Twitter

Abstract

Background: A massive amount of COVID-19 related data is generated everyday by Twitter users. Self-reports of COVID-19 symptoms on Twitter can reveal a great deal about the disease and its prevalence in the community. In particular, self-reports can be used as a valuable resource to learn more about the common symptoms and whether their order of appearance differs among different groups in the community. With sufficient available data, this has the potential of developing a COVID-19 risk-assessment system that is tailored toward specific group of people.

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Conclusions:
This study identified the most common symptoms of COVID-19 from Arabic tweets. These symptoms can be further analyzed in clinical setting and may be incorporated in a real-time COVID-19 risk estimator based on the users' tweets.

Keywords:
Social networks analysis; Twitter; data mining; COVID-19; early symptoms; ranking; Arabic;

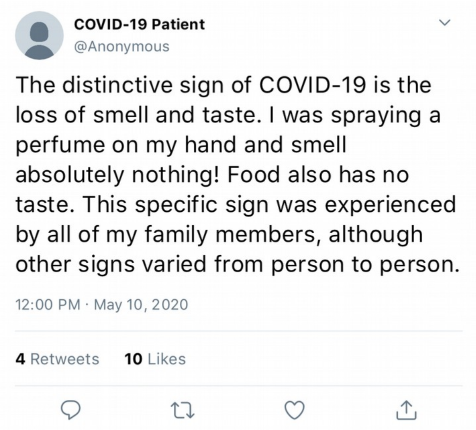
Introduction

The ongoing vigorous COVID-19 outbreak has shown a great impact on human health and well-being and radically enforced a rigorous change in societies lifestyle undermining their prosperity. Along with this catastrophe, we have witnessed a great effort from diverse research communities to study this disease in all its aspects.

In recent years, social networks have become an unignorable source of information where users expose and share ideas, opinions, thoughts, and experiences on a multitude of topics. Several researches have utilized the abundance of information offered by social platforms to conduct non-clinical medical research. For example, Twitter has been the source for data for many health and medical studies; such as surveillance and monitoring of Flu and Cancer timeline and distribution across the USA using Twitter [1], analyzing the spread of influenza in the UAE based on geo-tagged Arabic Tweets [2] and the surveillance and monitoring of Influenza in the UAE based on Arabic and English tweets [3]. Also, Twitter data has been utilized to identify symptoms and disease in Saudi Arabia using Twitter [4], and most recently, to analyze COVID-19 symptoms on Twitter [5] and analyze the chronological and geographical distribution of COVID-19 infected tweeters in the USA [6].

Twitter platform enables obtaining multiple features (such as age, sex, geo-location, … etc.) along with informative messages that using appropriate data mining and analysis techniques can potentially result in useful insights about a specific health condition [7]. Extracting common symptoms associated with a disease from publicly available data has the potential to control the spread of the disease and identify users at high risk. It also gives new insights that call for early intervention and control. For example, Figure 1 highlights the translation of a tweet (from Saudi Arabia) mentioning explicitly the loss of smell and taste as one distinctive symptom of COVID-19. Interestingly, the official COVID-19 questionnaire App in Saudi Arabia was updated on late May, 2020 to include the sudden loss of smell and taste as one risk indicator of having COVID-19[8]. Tracking COVID-19 symptoms in real-time from public data on Twitter could have shorten the gap.

Figure 1: A COVID-19 patient tweets about how the loss of smell and taste was the only common sign among all of her family members. The tweet is anonymized and translated to English.

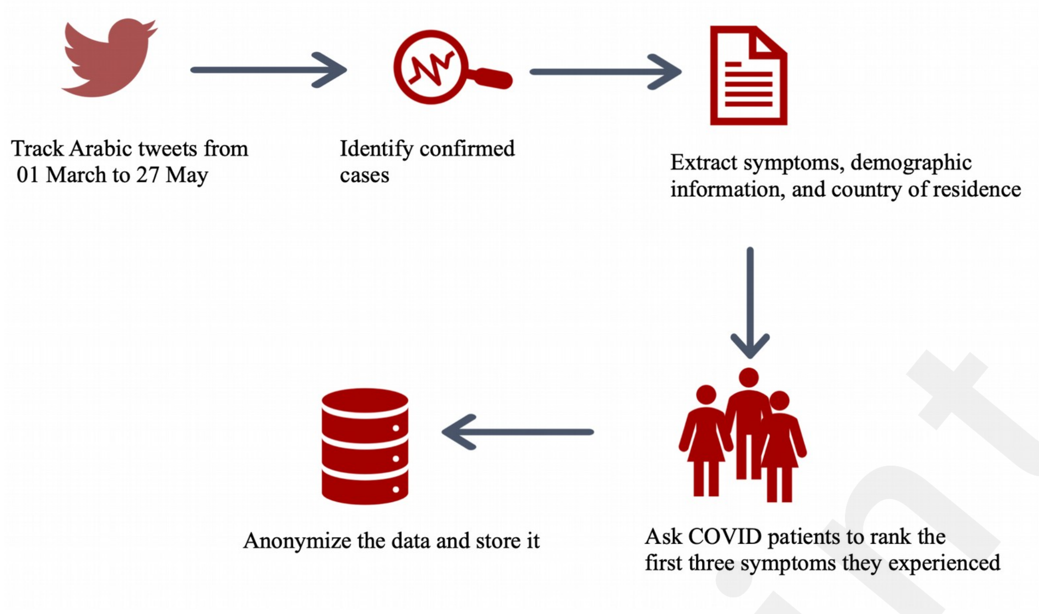


In this paper, we study COVID-19 symptoms as reported by Arabic tweeters. Initially, we shuffled Arabic tweets and searching for tweets with COVID-19 symptoms and also collected tweets for users who reported themselves infected through clinical test. In addition, we asked users who have been marked infected about the first three symptoms they had experienced via a voluntary survey template sent over private message.

Methods

Our method for data collection is outlined in Figure 2. First, we searched Twitter for personal reports of COVID-19 from March 1st, 2020 to May 27, 2020 using two Arabic keywords إصابتي and تشخيصي which translate~~s~~ roughly to *"I have been diagnosed"*. Suck keywords are likely to filter out reports that were not associated with a formal test result. An initial list of 463 users were collected and two independent freelancers were asked to further read users' timeline and extract symptoms that were explicitly mentioned to be related to COVID and their order of appearance, if mentioned. Additional information such as user gender, date of infection, and the country of residence were also collected. We assume the date of tweeting being COVID-19 positive is the date of infection in case no other information were available.

Figure 2: Data collection steps.



A final list of 270 COVID-19 users were identified amongst 80 were sharing their symptoms publicly. To further understand the chronological order of the symptoms, we asked through Twitter personal messages users to order the first three symptoms they experienced right before or after tested positive for COVID-19.

We recorded the symptoms from first to last based on the received responses and what is available publicly on the users' tweets. In case no order was given, an implicit order is assumed following the order of which the symptoms were mentioned by the user.

Tracking tweets containing specific keywords is simply not enough to have the big picture about the disease dynamics [9]. Many patients detailed their experience while infected, hence, knowing their health condition, sentiment, and tracking useful information may lead to a better understanding of the disease symptoms. In particular, we found tweets that were posted within ±5 days of infection date to contain valuable information about early symptoms, allowing us to process and rank the symptoms. As an example, Figure 3 highlights three tweets by three different COVID-19 patients that indirectly relate symptoms before or after diagnosed with COVID-19. For simplicity, we set a fake date (28 Apr, 2020) for all the three using the TweetGen service [10]. User..1 was tested positive on Apr 26 and tweeted on Apr 28 about the loss of smell. User..2 tested positive May 1st, three days after complaining about a headache. User..3 tested positive Apr 29th, one day after tweeting her wish to be able to taste the food.

Figure 3: Example of tweets collected within ±5 days of the user tweeting being COVID-19 positive

The example highlighted in Figure 3 demonstrates that mining twitter for COVID symptoms require more than a simple keyword search. In principle, the context of the tweet, narrated by a COVID-19 patient, is also important. Therefore, it is important to look not only the verbatim of the tweet but also to its context. To build a high-quality database of COVID symptoms based on Arabic tweets, we .have relied on manual symptoms extraction

Results

The majority of the cases were recorded in May (78%, n=210), followed by April (14%, n=39) and March (8%, n=21). This surge of May reports is understandable as most of world countries, let alone the Arabic speaking countries, witnessed a great increase in the number of confirmed cases. As for the demography, users from Saudi Arabia, Kuwait, and UAE constitute 85% of reports with Saudi Arabia being the largest cluster of reports (46%). The other countries (Egypt, Iraq, Bahrain, Qatar, UK, USA, Belgium, and Germany) together constitute the remaining 15%. Needless to say, some of the adopted strategies to prevent further spread of the virus (e.g., active screening by the Ministry of Health in Saudi Arabia [12]) may also helped in finding more reports in May compared to other months. We have witnessed this firsthand as some of the asymptomatic reports were mainly a result of early active screening.

The fact that almost half of the reports came from Saudi Arabia is not surprising as its one of the top countries participating on Twitter with more than 15 million users [13]. We have collected ~~almost~~ 893 symptoms from the 270 reports (as shown in Figure 4). The daily number of collected tweets is also highlighted in Figure 5.

Figure 4 indicates that most of the reported cases experience between 2 to 5 symptoms, whereas 13% of the reported cases were asymptomatic. Table 1 lists the frequency of each symptom ordered from the most prevalent symptom to the least. Only Fever experienced by more than 50% of the patients. The frequency of symptoms appears to be consistent across male and female patients (Corr. Coeff. =0.966). Further, Table 2 lists the top-8 first, second, and third symptoms. By top-8 first (respectively second or third), we mean the most common 8 symptoms appeared as the first (respectively second or third) symptom in the collected reports. Fever and headache were commonly the first reported symptoms. The top 4 symptoms that coincide with fever were headache (23.7%), cough (14.4%) anosmia (13.7%), and ageusia (12.2%). Other symptoms have relatively lower frequency with fever. In addition, Table 3 lists the top-8 common symptoms for Saudi Arabia and Kuwait which correspond for about 81.2 % of the reports. The symptoms have a Corr. Coeff. of 0.835 between the two countries.

Figure 4: Number of reports distributed by number of symptoms.

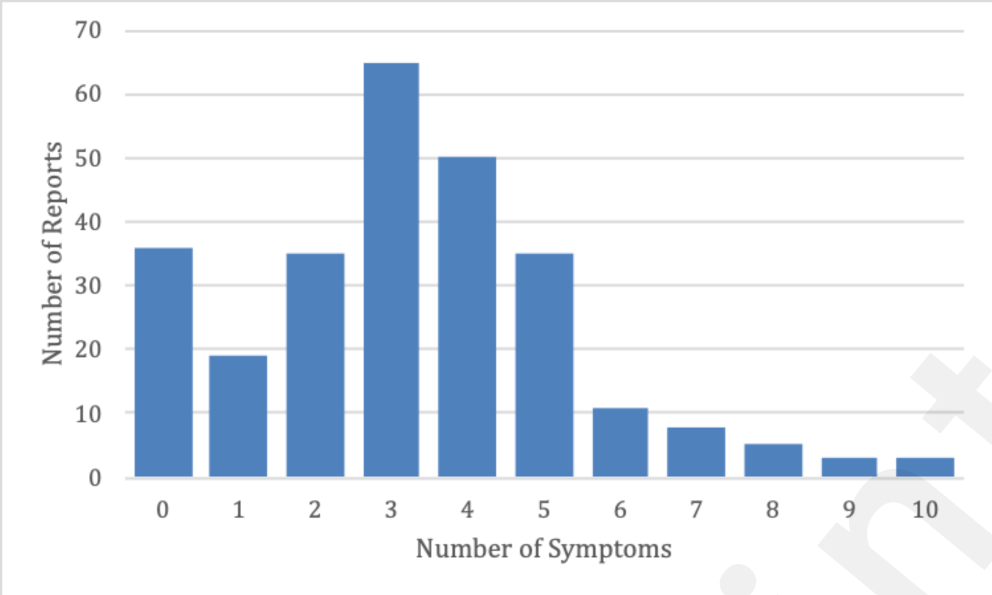


Figure 5: Number of daily collected reports from Twitter for March to May 2020

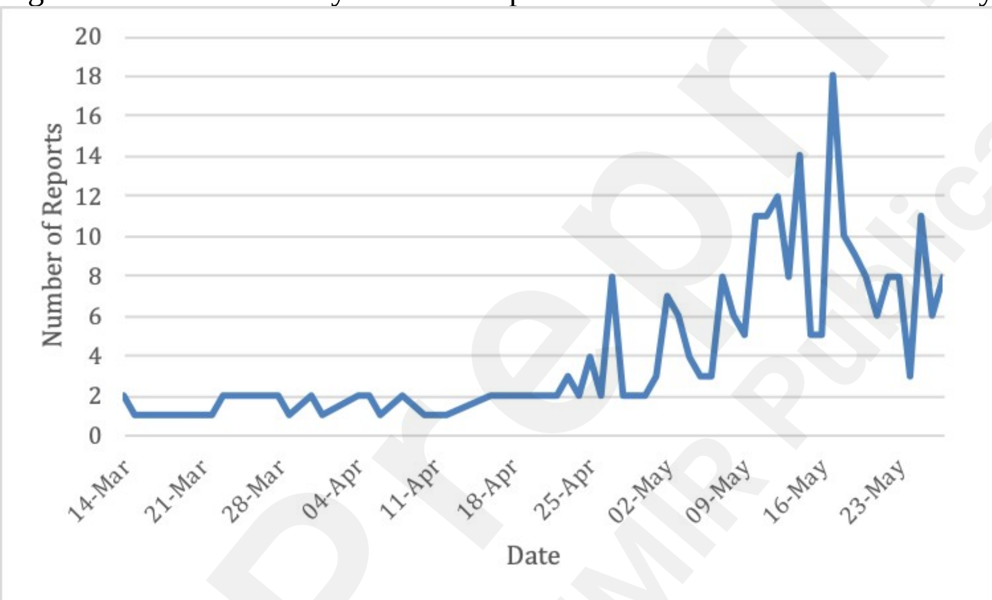


Table 1: Most common symptoms reported by the users

Symptom	All users n=234 (%)	Male n=171(%)	Female n=63 (%)
Fever	139 (59)	98 (57)	41(65)
Headache	101 (43)	68 (40)	33(52)
Anosmia	91 (39)	63 (37)	28(44)
Ageusia	72 (31)	51 (30)	21(33)
Fatigue	68 (29)	54 (32)	14(22)
Cough	62 (26)	48 (28)	14(22)
Sore Throat	42(18)	30 (18)	12(19)
Dyspnea	33(14)	26 (15)	7(11)
Diarrhea	27(12)	22(13)	5(8)
Runny Nose	23(10)	17 (10)	6(9)
Arthralgia	16(7)	10 (6)	6(9)
Chest Pain	15(6)	13(8)	2(3)

Back Pain	14(6)	11(6)	3(5)
Anorexia	14(6)	11(6)	3(5)
Body Ache	12(5)	8(5)	4(6)
Nausea	12(5)	8(5)	4(6)
Osteodynia	11(5)	8(5)	3(5)
Dry throat	9(4)	6(3)	3(5)
Myalgia	9(4)	7(4)	2(3)
Dizziness	8(3)	6(3)	2(3)
Chills	7(3)	5(3)	2(3)
Nasal Congestion	7(3)	4(2)	1(2)
Sinusitis	7(3)	3(2)	4(6)

Table 2: Top-8 first, second, and third symptoms reported by the users

First	**Second**	**Third**
Fever	Fever	Fever
Headache	Headache	Headache
Anosmia	Fatigue	Anosmia
Fatigue	Cough	Ageusia
Cough	Ageusia	Fatigue
Sore throat	Anosmia	Cough
Runny Nose	Sore Throat	Anorexia
Diarrhea	Arthralgia	Dyspnea

Table 3: Top-8 common symptoms for Saudi Arabia and Kuwait

Symptom	**Saudi, n=110 (%)**	**Kuwait, n=80 (%)**
Fever	65 (59)	45 (56)
Headache	42 (38)	38 (48)
Anosmia	46 (42)	21 (26)
Ageusia	36 (37)	19 (24)
Fatigue	31 (28)	19 (24)
Cough	21 (19)	19 (24)
Sore Throat	22 (20)	11 (14)
Dyspnea	14(13)	11 (14)

Discussion

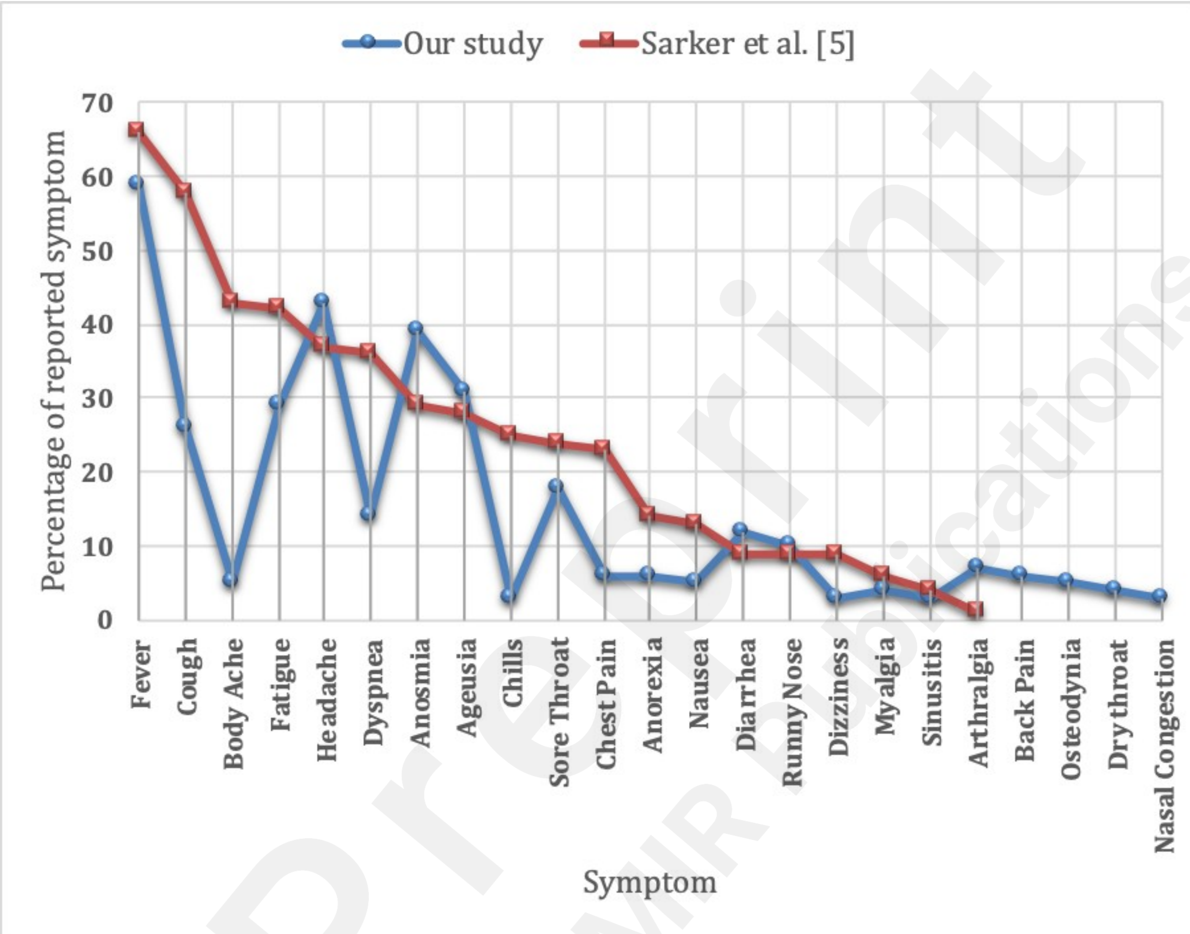
This work identified common COVID-19 symptoms from Arabic personal reports on Twitter. Such study complements other recent studies [5-6,9] that were focused on English tweets or specific demographic groups. This study was carried in a way to report not only the symptoms but their timeline as narrated by users. Social networks have become the de facto communication channel for a large number of people. Many individuals around the globe write, interact, or even just browse the content of the social networks countless times a day. Social networks have the property of being continuously updated by new information provided by other global citizens. As such, it is crucial to monitor their content to identify health issues [14-15]. One potential benefit of analyzing social networks is understanding COVID-19 symptoms and identifying people at high risk [7].

Anosmia being one of the top three reported symptoms, mentioned in 39% of the reports, was a surprising result in our study. Several tweets have complained about how long it lasts before they started to smell again. Our sample size is still relatively small to make any good judgement in this regard. However, recent clinical studies have reported finding Anosmia in 35.7% of the mild cases of COVID-19 which is relatively close to our estimation from Arabic tweets [16]. Indeed, the size of self-reports reflect the testing capacity in different countries. As of June 9, 2020, Saudi Arabia has done almost one million tests and Kuwait has roughly exceeded 350,000 tests [17].
It is worth noting that we found some users experienced weight loss due to COVID-19, as one user claimed losing 20kg due to the disease. Another interesting observation is that several users experienced what they describe as a short-term mild fever for couple of hours only. Quitting smoking was a positive outcome of COVID-19, per one user describing his journey. On the societal aspect, we were stunned by some users early April claiming to be positive for COVID-19, a claim that were appeared later on to be an April fool. These findings urge for further studies into how different communities react to a pandemic and how it affects their life. Moreover, Table 4 and Figure 6 compare symptoms prevalence of our study to the one provided by Sarker et al. [5]. A correlation coefficient of 0.72 was found between the percentages of symptoms appeared in both studies.

Table 4: Comparison of common symptoms reported by other studies.

Symptom	**Our study n=234 (%)**	**Sarker et al. [5] n=171(%)**
Fever	139 (59)	113 (66)
Headache	101 (43)	64 (37)
Anosmia	91 (39)	49 (29)
Ageusia	72 (31)	48 (28)
Fatigue	68 (29)	72 (42)
Cough	62 (26)	99 (58)
Sore Throat	42(18)	41 (24)
Dyspnea	33(14)	62 (36)
Diarrhea	27(12)	15 (9)
Runny Nose	23(10)	16 (9)
Arthralgia	16(7)	2(1)
Chest Pain	15(6)	39 (23)
Back Pain	14(6)	-
Anorexia	14(6)	23 (14)
Body Ache	12(5)	73(43)
Nausea	12(5)	19 (13)
Osteodynia	11(5)	-
Dry throat	9(4)	-
Myalgia	9(4)	10 (6)
Dizziness	8(3)	15 (9)
Chills	7(3)	43 (25)
Nasal Congestion	7(3)	-
Sinusitis	7(3)	7 (4)

Figure 6: A comparison between symptoms prevalence in our study and Serker et. al. [5] (Corr. Coeff. = 0.72)



Limitations

The reported cases from Egypt, the Arabic country with largest population, were inadequately representative. This could be attributed to factors such as the preferred social platform (e.g., Facebook), the dialect and use of local idioms.

Our study tracked two widely used keywords to identify Arabic COVID-19 patients on Twitter then manually extract symptoms. More complex keywords could reveal more interesting patterns about symptoms, and this brings the need to establish a comprehensive medical dictionary for different local Arabic dialect. The dictionary can be utilized when mining different health opinions and conditions from the Arabic content in social networks.

Our main motivation is to extract symptoms from users who are likely took the disease test and, hence, tweeted based on its result. In this study, we have not used other COVID-19 sources.

Specifically, studying the Arabic content of personal reports from both Facebook and Twitter will enrich the study.

The noticeable increase in May reports compared to other months show the importance of developing a real-time surveillance system based on the symptoms reported by the Arabic content of Twitter. It also suggests further studies into the information sharing behavior in different communities and across different demographic groups (i.e., users grouped by age, gender, geo-location, etc) [19]**.**

One interesting observation from our analysis is related to the gender distribution. As discussed above, almost only 25% of the collected reports came from female users. This could be due to many several reasons. One of the reasons could simply because there are more COVID-19 male Arabic patients than female ones. We are however not aware of any reliable source for such claim. Nevertheless, in Saudi Arabia, Male reported cases consistently outnumbered Female cases for April and May 2020 [20]. Further insights and studies are needed to investigate the gender differences in information sharing and analyze whether there is any notable difference in how male and female Arabic users disclose health information on social media.

In this work, we used Modern Standard Arabic (MSA) keywords to keywords to have a general view on the Arabic content in Twitter. It is, however, well-noted in the literature that many Arabic users write in their own local dialect in social media. Hence, it is helpful to consider not only keywords in the MSA form but also keywords that are tailored towards different Arabic dialects to better capture the Arabic COVID-19 symptoms tweets. This may explain why the cases from Egypt, the largest Arabic country with almost 100 million people, were under represented in this study. Furthermore, we believe that developing a multi-dialect COVID-19 Arabic dictionary and an NLP-based algorithm to detect, analyze Arabic tweets dataset is an important line of research during the coronavirus pandemic [18].

Privacy is one of the key issues that need to be addressed before utilizing social media for public health surveillance. Apart from the network privacy policy, there exists no global census on what to disclose when collecting health information from social media networks. Some attempts in the literature have suggested best practices to follow when collecting health information from Twitter [21]. Such practices include, among other things, avoiding both quoting directly from users' tweets and mentioning the users' IDs. Moreover, some social media sites have updated their privacy policy to further control the content re-distribution. For instance, the recent policy of Twitter allows re-distributing only the Tweets ID, but not their verbatim content to third parties [22]."

Conclusion

This study identified most common self-reported COVID-19 symptoms from Arabic tweets. The study showed that Fever, Headache, and Anosmia are the most common three symptoms experienced by users. Furthermore, we analyzed symptoms prevalence in the two largest clusters found in our database: Saudi Arabia and Kuwait.

Acknowledgements

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Authors' Contributions

Eisa Alanazi and Abdulaziz Alashaikh designed the study and wrote the manuscript. Sarah Alqurashi developed the social network analysis part and collected related tweets from the Twitter API. Aued Alanazi extracted and translated the symptoms from the collected personal reports to their scientific names. All authors approved the final version of the manuscript.

Conflicts of Interest

None declared

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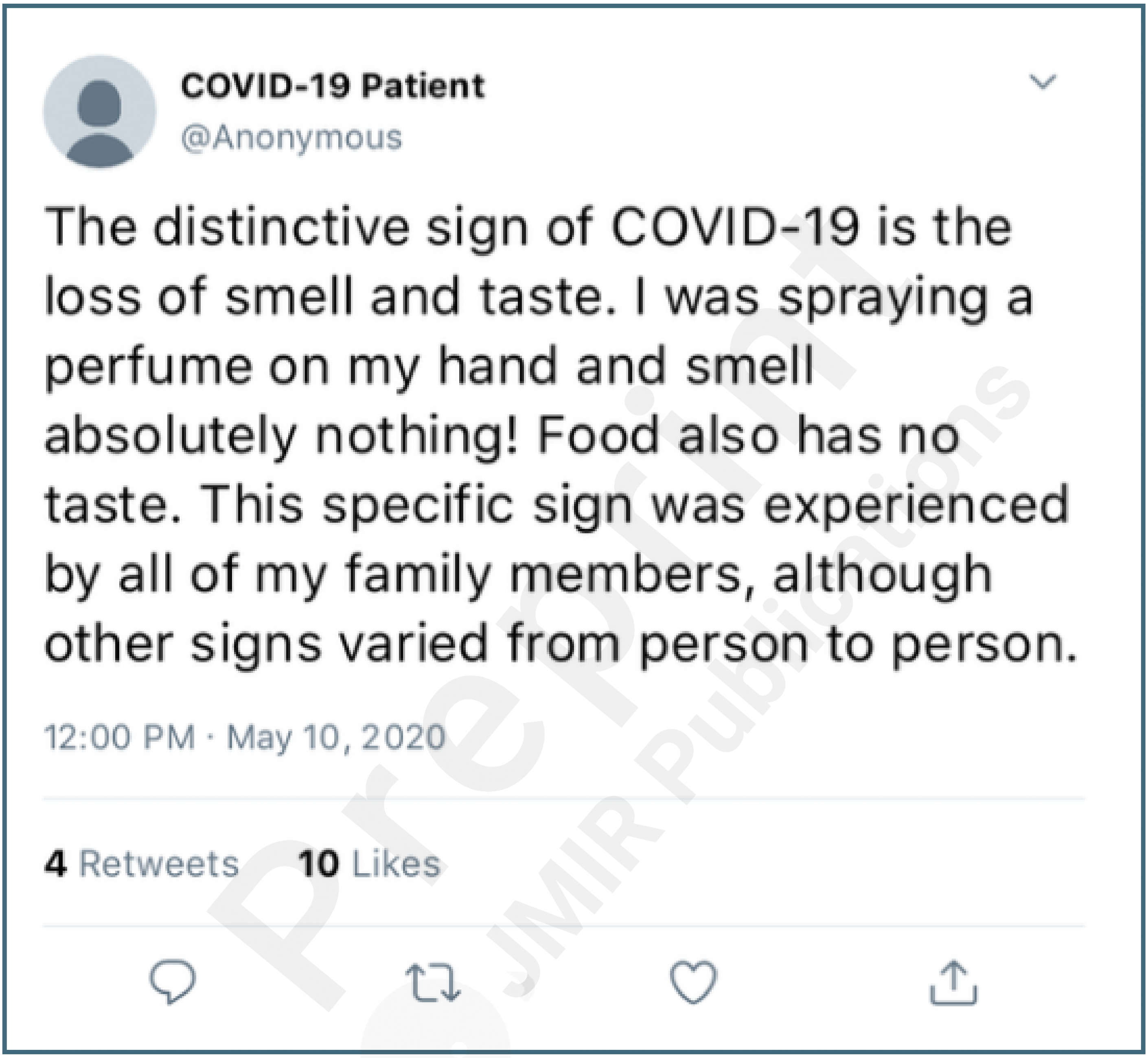
Abbreviations

API: application programming interface
COVID-19: coronavirus disease

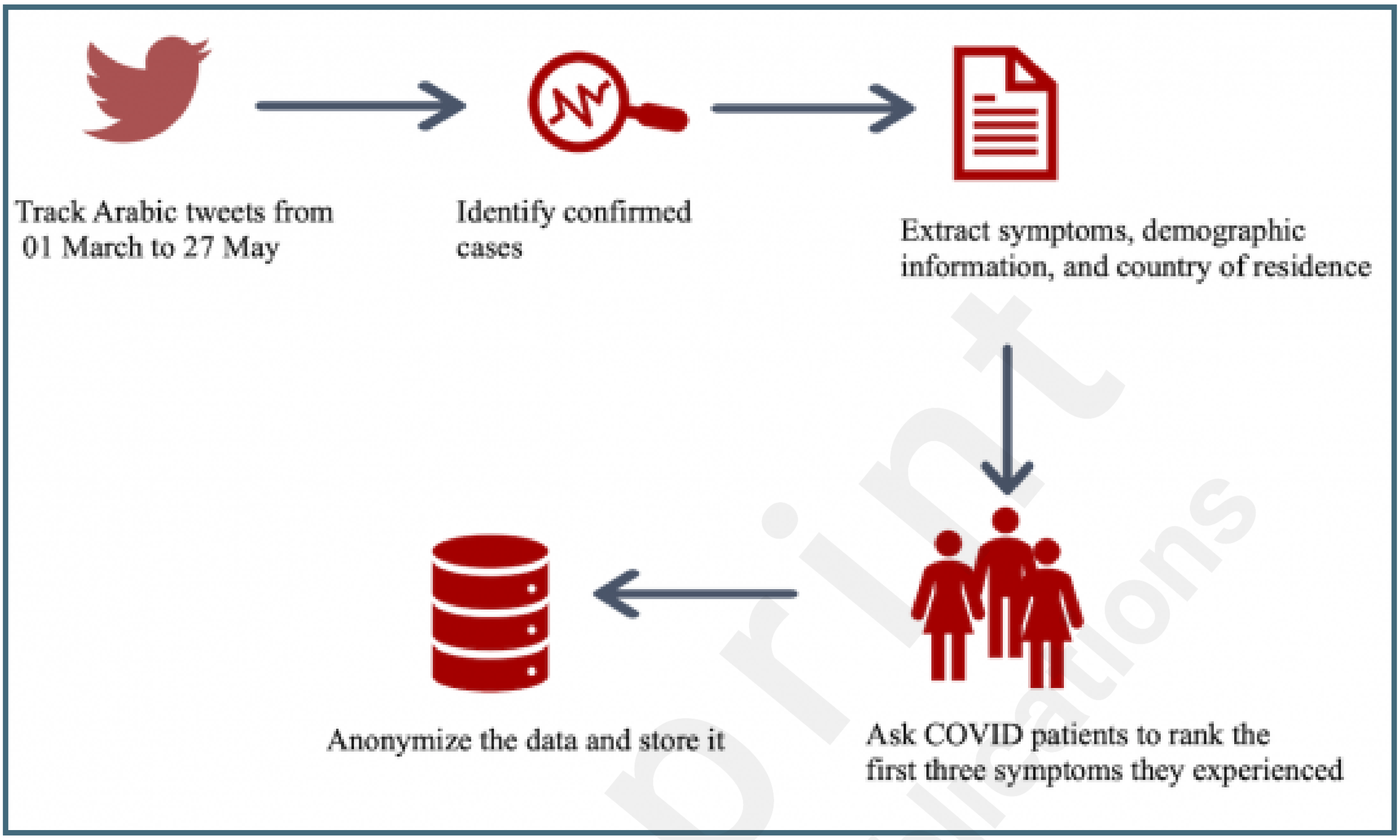
Supplementary Files

Figures

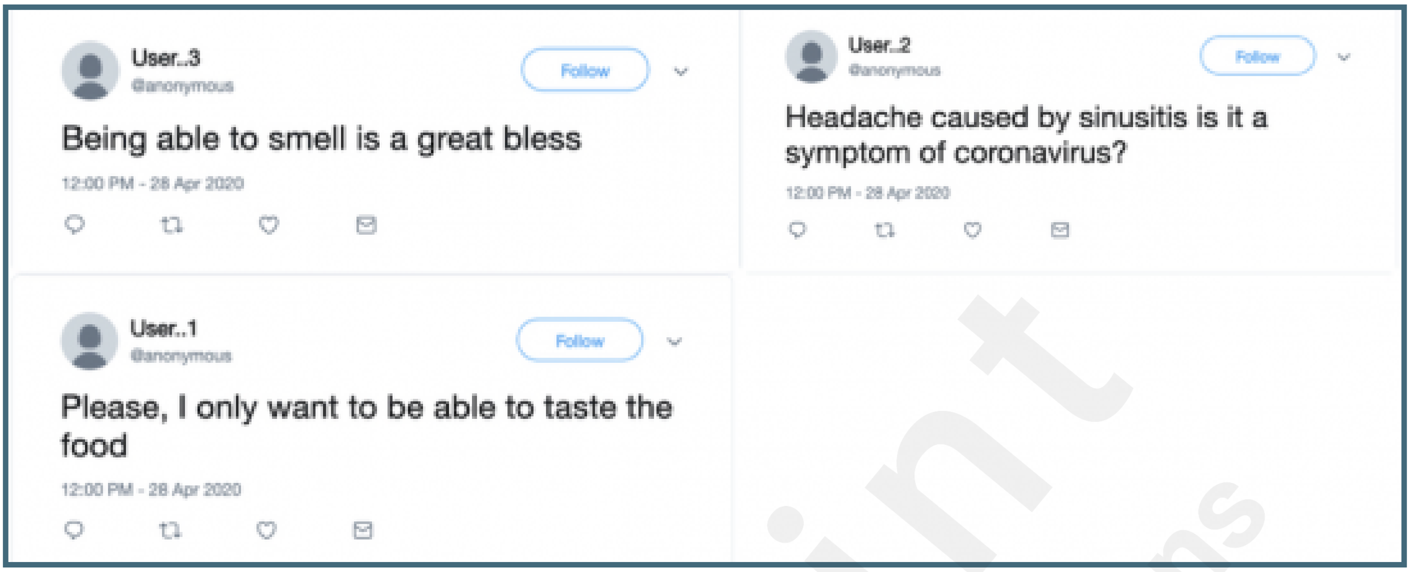
A COVID-19 patient tweets about how the loss of smell and taste was the only common sign among all of her family members. The tweet is anonymized and translated to English.



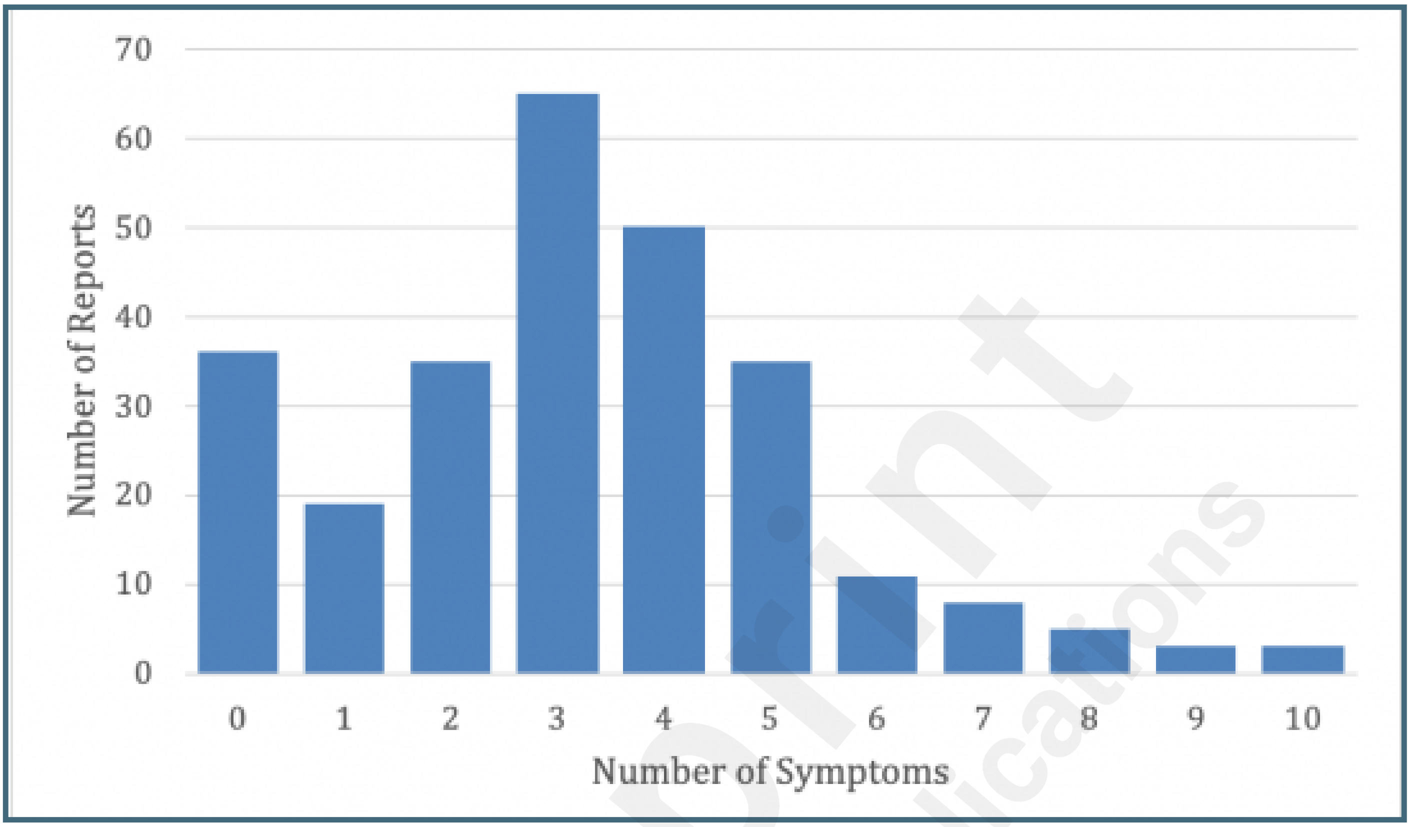
Data collection steps.



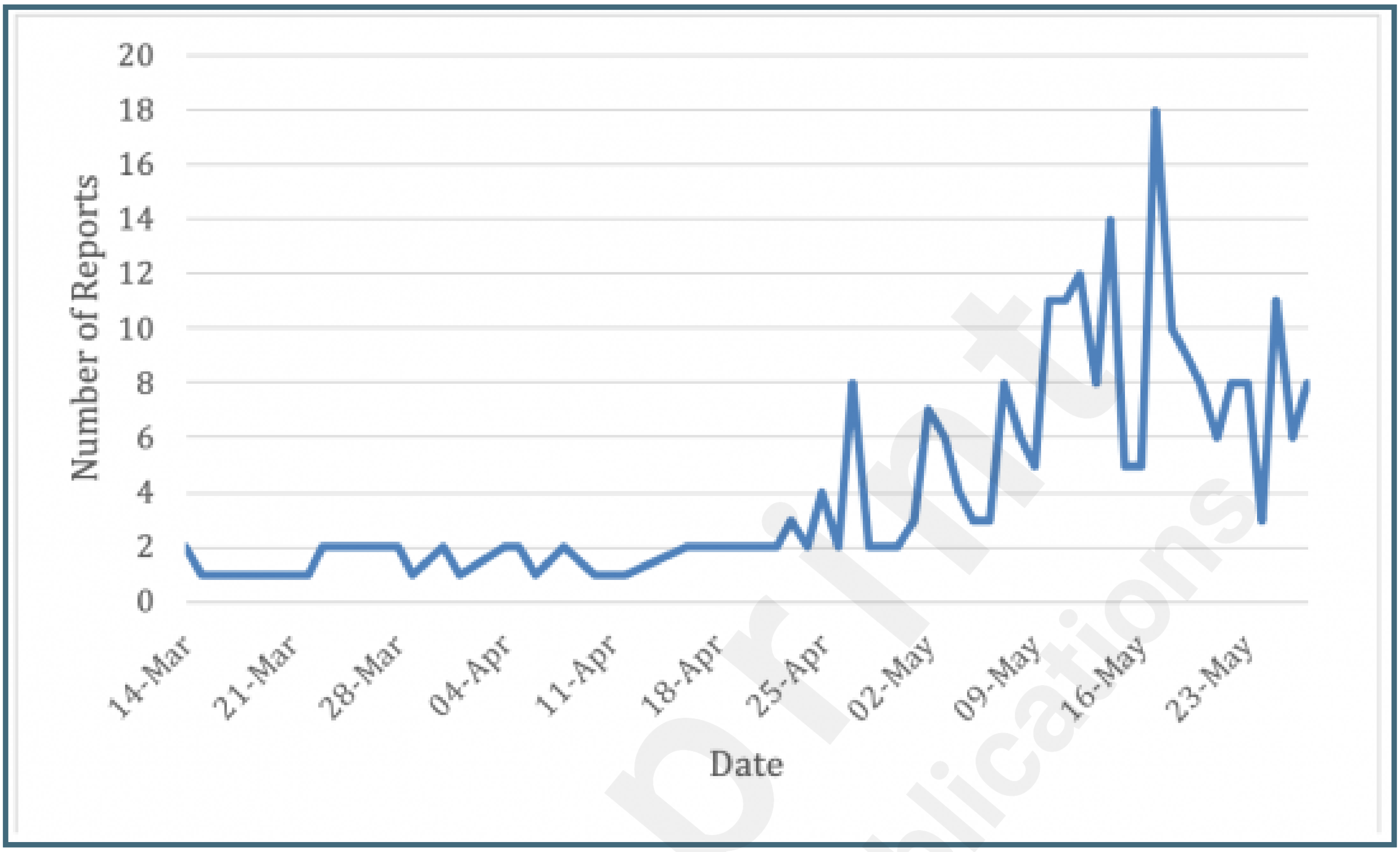
Example of tweets collected within ±5 days of the user tweeting being COVID-19 positive.



Number of reports distributed by number of symptoms.



Number of daily collected reports from Twitter for March to May 2020.



A comparison between symptoms prevalence in our study and Serker et. al. [5] (Corr. Coeff. = 0.72).