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Sentiment analysis of tweets in Saudi Arabia regarding governmental preventive measures to contain COVID-19

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Abstract

Background: Countries around the world are facing extraordinary challenges in implementing various measures to slow down the spread of the novel coronavirus (COVID-19). Guided by international recommendations, Saudi Arabia has implemented a series of infection control measures after the detection of the first confirmed case in the country. However, in order for these measures to be effective, public attitudes and compliance must be conducive as perceived risk is strongly associated with health behaviors. The primary objective of this study is to assess Saudis' attitudes towards COVID-19 preventive measures to guide future health communication content.

Methods: Naïve Bayes machine learning model was used to run Arabic sentiment analysis of Twitter posts through the Natural Language Toolkit (NLTK) library in Python. Tweets containing hashtags pertaining to seven public health measures imposed by the government were collected and analyzed.

Results: A total of 53,127 tweets were analyzed. All measures, except one, showed more positive tweets than negative. Measures that pertain to religious practices showed the most positive sentiment.

Discussion: Saudi Twitter users showed support and positive attitudes towards the infection control measures to combat COVID-19. It is postulated that this conducive public response is reflective of the overarching, longstanding popular confidence in the government. Religious notions may also play a positive role in preparing believers at times of crises. Findings of this study broadened our understanding to develop proper public health messages and promote health behaviors to control COVID-19.

Keywords: *Saudi Arabia; COVID-19; Sentiment Analysis; Twitter; Measures*

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Introduction

Countries around the world are facing extraordinary challenges in implementing various measures in to slow down the spread of the novel coronavirus (COVID-19) and to sustain their healthcare systems. A good illustration of these measures comes from China, which implemented home isolation of cases, home quarantine, social distancing, and closure of schools and universities in highly affected regions. These measures led to a decrease in R0, a measure of reproduction of new infections, to less than one and thus suppressed the local spread of the virus so far (Kucharski et al., 2020). A recent report published by the Imperial College's COVID-19 Response Team on March 16, 2020 showed that effective suppression of the virus spread found to be achievable by implementing policies that include population-wide social distancing combined with home isolation of cases and school and university closures (Ferguson et al., 2020).

Guided by such policies, the government of Saudi Arabia has implemented various public health measures after the detection of the first confirmed case on March 2nd, 2020. The following timeline reflects the series of measures that have been gradually implanted within the first two weeks, (Saudi Press Agency, 2020):

- March 5: temporary daily closures of the Great Mosque for sterilization purposes
- March 8: a temporary control of all traffic in and out of Qatif, where the majority of the first cases of COVID-19 were recorded
- March 8: schools and universities closure announced to start from the following day until further notice
- March 14: closure of all shopping malls, restaurants, coffee shops, and public parks with the exception of essential businesses, such as pharmacies and supermarkets
- March 15: all sport leagues and competitions suspended until further notice.

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- March 17: all congregational and weekly Friday prayers suspended across the Kingdom.
- March 23: Saudi Arabia announced a nationwide curfew for the next 21 days. Figure 1 illustrates the sequence of the events over time.

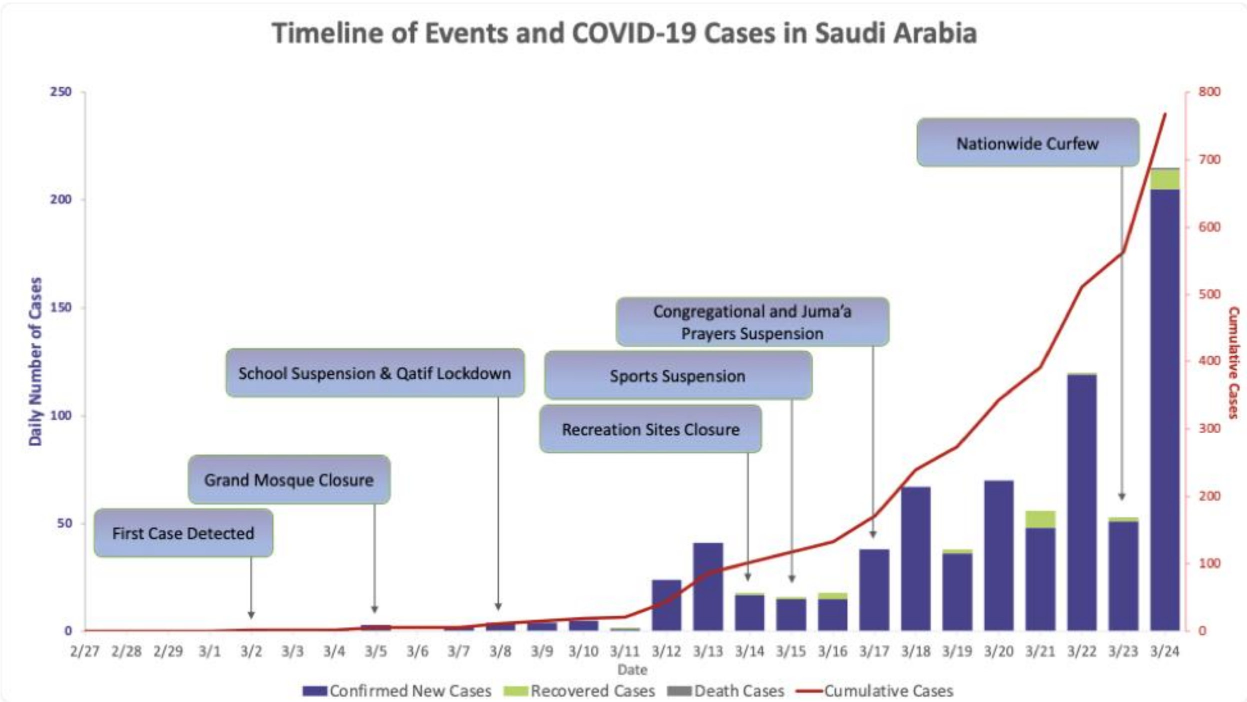

Figure 1. Timeline of events followed the detection of the first COVID-19 case in Saudi Arabia with daily and cumulative cases over time.

These unprecedented measures aimed to contain the spread of the disease while it is still in early stages. However, in order for these measures to be effective, they have to last for an extended period of time, probably until vaccines are available (Ferguson et al., 2020). This raises a unique challenge for countries on how to ensure adequate public awareness, continuous cooperation, and durable compliance. Notably, public attitudes towards preventive measures and the subsequent adoption of health behaviors are closely associated with perceived risk, a concept central to many health behavior theories. (Brewer et al., 2007). For instance, the Health Belief Model argues that the stronger people's perception of the severity of a health outcome and the higher their perceived susceptibility to acquiring that negative outcome, the more motivated they are to avoid it. (Janz &

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Becker, 1984). Therefore, assessing a community's perception of risk is essential to the development of health communication campaigns to promote public compliance. The success of public health interventions is likely to be partially explained by their ability to influence perceived risks which in turn can predict adoption of health behaviors.

Sentiment analysis can provide critical information about communities' risk perceptions. This novel computational approach analyzes textual data to interpret and classify public emotions towards any given issue (i.e., products, regulations, measures etc) (Pang & Lee, 2008). In the age of social media, sentiment analysis can efficiently analyze copious amounts of textual data, much of which is personal and can be freely accessed and analyzed. In fact, Twitter has been used extensively for public health surveillance, from monitoring and prediction to gauging public response (Jordan et al., 2018). Such technological advances have proven helpful in providing illuminating insights that can assist public health agencies and policymakers to improve their interventions by understanding public reaction.

The primary objective of this study is to assess Saudis' attitudes towards COVID-19 preventive measures through sentiment analysis of Twitter content.

Methods

The application of machine learning has flourished recently and been applied to tackle multiple challenges across the healthcare sector, including outbreak prediction. A commonly referenced definition of machine learning is that introduced by Mitchel (1997, p.2): "A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E." In this context, the task is to predict a Twitter user's sentiment based on their Tweets. Meanwhile, the experience is an Arabic corpus which the model learns from in order to provide the indicated task.

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Performance is measured based on the trained model's ability to accurately predict sentiment for a given Tweet text when compared to the correspondent correct sentiment labelled by a human. In a nutshell, a machine learning model is trained to map an input (Arabic text) to an output (positive or negative sentiment).

In order to develop a suitable machine learning model capable of processing Arabic semantics and drawing accurate conclusions, labelled data is needed. Given that the Arabic language contains over 100 million words, the labeled dataset must be sufficiently large. To pilot this model while avoiding the laborious work, we demonstrate the methodology using a labeled dataset of Arabic Tweets whose sentiment labels are based on emoji lexicons (Kaggle, 2019). It is important to note that Arabic is a challenging language with dialectic variations and morphological complexities that require careful preprocessing. In a systematic literature review of Arabic sentiment analysis, Ghallab and colleagues (2020) showed that the most common and effective Arabic text preprocessing techniques are stemming, normalization, tokenization, and stop-word removal; hence, these cleaning steps are adopted in the current study. Feature selection (i.e., what the model receives as input) is another step toward building an accurate and generalizable model. N-Grams (i.e., the sequence of n-words) is an established featuring engineering technique in computational linguistics that is found to be popular and effective in Arabic semantic analysis applications (Ghallab, Mohsen, & Ali, 2020; Silva, Goncalves, & Cunha, 2016). This approach allows for models to learn both the individual words and the semantic relationship between multiple words.

Supervised machine learning classification models are either probabilistic or non-probabilistic. Since the interest of this study is analyzing sentiment as a continuum while training only on two labels (positive and negative), probabilistic models are advantageous. These models

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allow for incorporating the uncertainty stemming out of the prior dataset distribution in contrast to the global or posterior distribution. In this proposal, Naïve Bayes was utilized as it is the most commonly probabilistic supervised learning classification model used in Arabic sentiment analysis (Ghallab et al., 2020). The aforementioned Arabic sentiment dataset (Kaggle, 2019) was split into 47,000 and 11,000 Tweets for training and testing, respectively. Note that both splits are balanced (i.e., 50% positive and 50% negative Tweets). Using a 1-Gram Naïve Bayes model, testing results showed accuracy, precision, recall, and F-score of 0.89, 0.92, 0.86, and 0.89, respectively. Given this excellent performance, this model was used to evaluate public sentiments towards the events and government actions associated with COVID-19 in Saudi Arabia.

Seven major preventive measures implemented by the Saudi government within the first two weeks of the 1st COVID-19 case in Saudi Arabia were determined. The corresponding dates of the announcement of these measurements were identified. To analyze the Saudi public sentiment towards these preventive measures, Twitter platform was utilized. For each event, tweet search was done with three major inclusion criteria: 1) tweets with relevant hashtags; 2) tweets published within Saudi geographical borders as indicated by user IP address ; and 3) tweets posted within the first 48 hours following the event with a maximum limit of 20,000 tweets per event. Of these tweets, only those whose predicted probability (positive or negative) was above 90% were preserved in order to enhance the confidence level of the sentiment analysis results. Python 3.6 was the programming language of choice, where the Natural Language Toolkit (NLTK) library was used to facilitate tweet preprocessing and model training (Python.org, 2016). Word clouds were generated for each event based on word occurrence frequency. Non-Arabic words, corresponding hashtags that were used for tweet search, and stop words (e.g., “is” and “the”) were

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filtered out. WordCloud (Mueller, 2019) was used to visualize the major content of the tweets for each of the seven preventive measures.

Initially, a total of 20,000 random tweets by users in Saudi Arabia published in February 2020 were extracted before the detection of the first case of COVID-19 in the country. Analysis of these tweets was performed to serve as a baseline before the series of the events took place so the results of this study could be compared.

Results

Table 1 shows a summary of the results. A total of 9,924 tweets were collected within the 48-hour period from the announcement of the Grand Mosque closure. After the exclusion of 6,358 neutral or uncertain tweets (confidence accuracy less than 90%), 2,736 (76.72%) of the remaining tweets were positive and 830 (23.28%) were negative.

Using a similar method, a total of 8,189 tweets were collected for the announcement of Qatif lockdown. After the exclusion of 5,943 neutral or uncertain tweets, 1,418 (63.13%) of the remaining tweets were positive and 828 (36.87%) tweets were negative.

This process was performed again for the hashtags pertaining to the closure of schools and universities. A total of 20,000 tweets were collected after the announcement of this preventive measure. After the exclusion of 12,900 neutral or uncertain tweets, 5,365 (75.56%) of the remaining tweets were found to be positive and the other 1,735 (24.44%) tweets were negative.

The analysis was repeated again for shopping malls, parks, and restaurants closure measures. A total of 4,592 tweets were collected. After the exclusion of 3,372 neutral or uncertain tweets, 601 (49.26%) of the remaining tweets were positive and the other 619 (50.74%) were negative.

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When the process was performed again for the sports competition suspension hashtags, a total of 3,233 tweets were initially collected. After the exclusion of 2,207 neutral or uncertain tweets, 718 (69.98%) of the remaining tweets were positive and the other 308 (30.02%) were negative.

Similarly, the analysis was repeated for the congregational and weekly Friday prayers suspension measure. A total of 2,594 tweets were collected. After the exclusion of 1,479 neutral or uncertain tweets, 943 (84.57%) of the remaining tweets were positive and the other 172 (15.43%) were negative.

Finally, the analysis was repeated for the nationwide curfew measure. A total of 24,595 tweets were collected. After the exclusion of 20,041 neutral or uncertain tweets, 3,017 (66.25%) of the remaining tweets were positive and the other 1,537 (33.75%) were negative.

Figure 2 illustrates these findings. Additionally, Figure 3 and Table 2 show the tweet content for each preventive measure to visualize the most frequent vocabularies used.

Table 1

The Preventive Health Measures, Corresponding Hashtags, and Counts for Tweet Sentiments

Preventive Measure	Hashtags	Total Tweets	Positive Tweets	Negative Tweets
Grand Mosque closure	#الحرم_المكي #منظر_الحرم #اغلاق_الحرم	3,566	2,736 (76.72%)	830 (23.28%)
Qatif lockdown	#القطيف #القطيف_تحت_الحجر_الصحي #القطيف_في_قلوبنا #القطيف_منطقة_موبؤة	2,246	1,418 (63.13%)	828 (36.87%)
School and university closure	#تعليق_الدراسة	7,100	5,365 (75.56%)	1,735 (24.44%)

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Shopping malls, parks and restaurants closure	#اغلاق_المولات #إغلاق_الحدائق #إغلاق_المجمعات_التجارية #اغلاق_المولات_في_السعوديه #اغلاق_المطاعم	1,220	601 (49.26%)	619 (50.74%)
Sports competition suspension	#ايقاف_الدوري #تعليق_النشاط_الرياضي	1,026	718 (69.98%)	308 (30.02%)
Congregational and weekly Friday prayers suspension	#ايقاف_الصلاة_بالمسجد #إيقاف_صلاة_الجمعة_والجماعة	1,115	943 (84.57%)	172 (15.43%)
Nationwide curfew	#الحجر_المنزلي #الحظر_اليوم_الثاني #الحظر_الكامل #كلنا_مسؤول	4,554	3,017 (66.25%)	1,537 (33.75%)

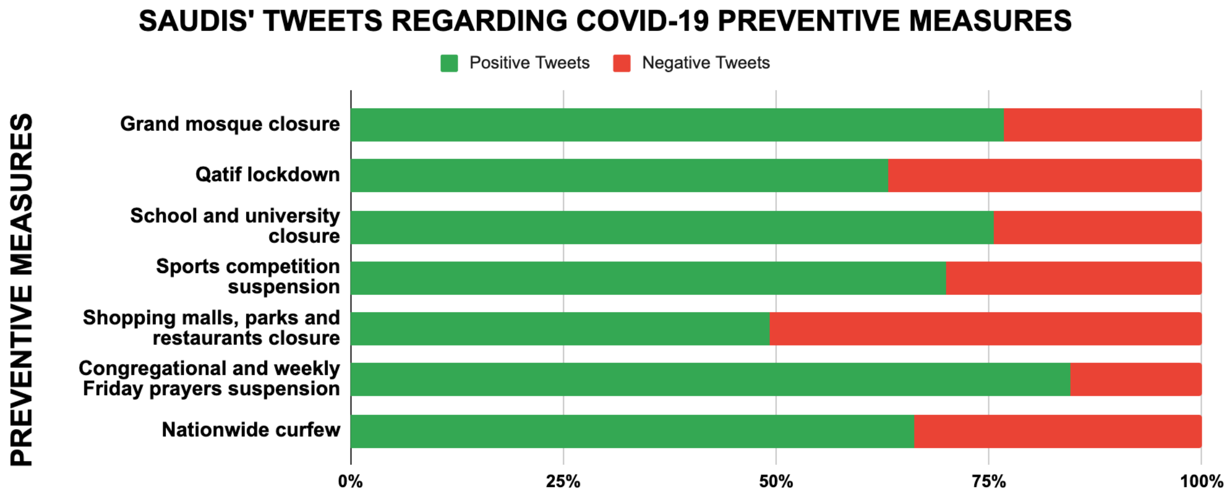

Figure 2. Illustration of sentiment analysis of Saudis towards COVID-19 preventive measures.

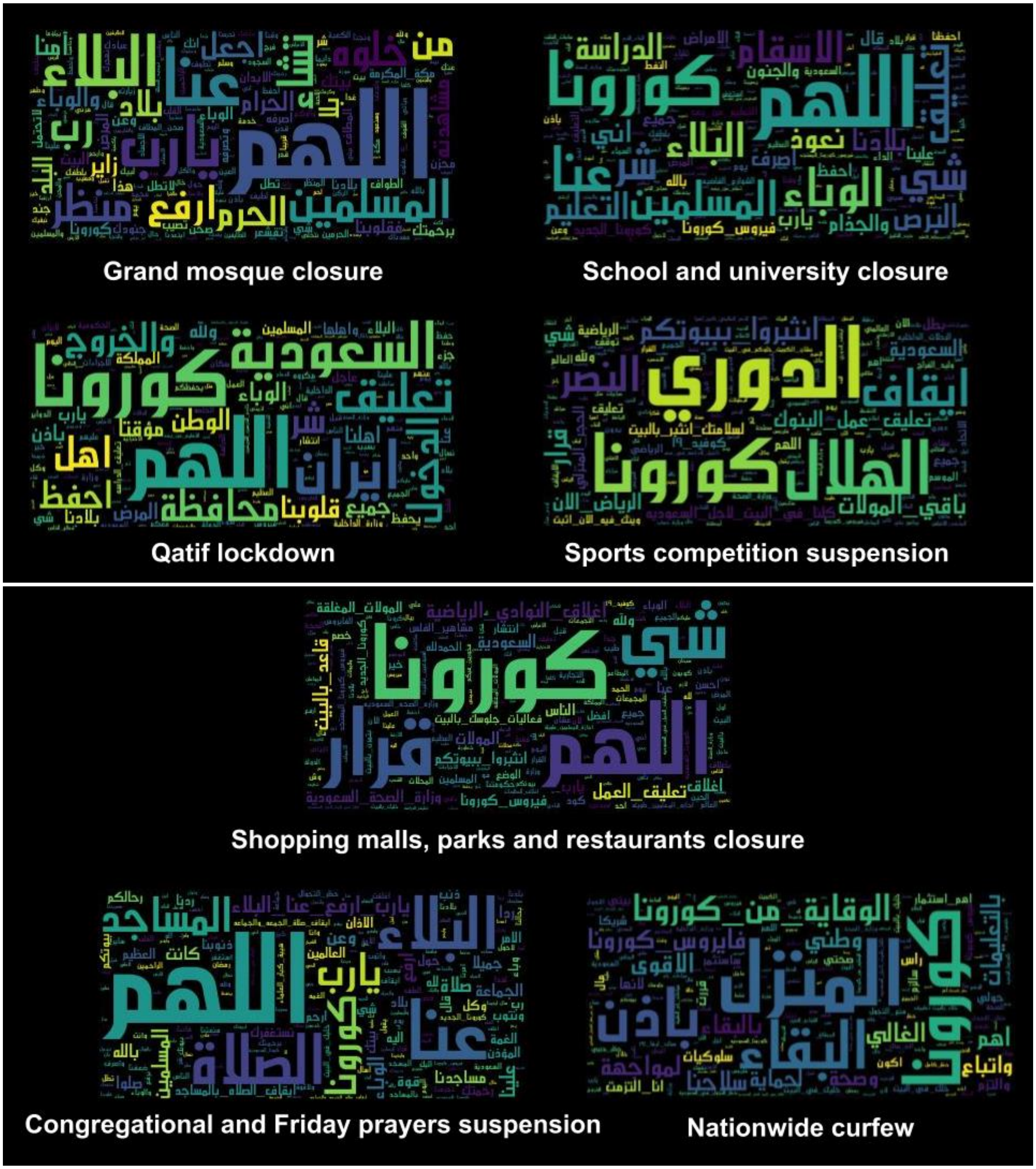

Figure 3. Illustration of words clouds for each preventive measure.

Table 2

Summary of the Five Most Frequent Words Mentioned in Tweets Regarding each Measure

Preventive Measure	Most Frequent Words
Grand mosque closure	Oh God; The affliction; About us; Lord; Muslims
Qatif lockdown	Corona; Oh God; Saudi Arabia; Iran; Suspension
School and university closure	Oh God; Corona; About us; The epidemic; Muslims
Shopping malls, parks and restaurants closure	Corona; Oh God; Ordinance; Something; Staying home
Sports competition suspension	The League; Corona; Al-Hilal FC (Soccer team); Suspension; Al-Nassr FC (Soccer team)
Congregational and weekly Friday prayers suspension	Oh God; About us; Prayer; The affliction; Mosques
Nationwide curfew	Corona; Home; With permission; Stay; Corona prevention

Discussion

Since the detection of the first case of COVID-19 in December 2019 in Wuhan, China, this novel virus has caused a major international crisis. The spread and severity of cases across the world urged the WHO to classify COVID-19 as a pandemic infection. In the absence of effective vaccines, countries around the world rushed to implement a variety of preventive measures to contain the spread of the virus and, therefore, prevent the total collapse of their healthcare systems.

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Saudi Arabia announced the first case of COVID-19 on March 2nd, 2020. This event provoked a series of preventive measures that were implemented within the first two weeks. Successful infection control strategies require firm public cooperation and durable compliance. Thus, it is very important to evaluate public perception of risk and attitudes as predictors of adoption of these preventive measures and to develop health communication interventions.

The initial analysis of tweets from February 2020, prior to the detection of any case in Saudi Arabia, showed more negative tweets 2,879 (57%) than positive tweets 2,174 (43%). Interestingly, analysis of tweets about all the preventive measures showed more positive tweets versus negative tweets, except for shopping malls, parks, and restaurant closure. Among all the categories that showed higher positive tweets compared to negative ones, The Grand Mosque closure and suspension of congregational and weekly Friday prayers categories have the highest positive tweet percentages after exclusion of neutral/uncertain categories. Due to the religious nature of these events, it was notable that most of the tweets contained supplications, which could explain the relatively higher percentages of positive tweets compared to other measures.

One possible explanation of the overall positivity of tweets regarding preventive measures is that people in Saudi Arabia may have overall trust and confidence in their government, perhaps due to the patriarchal nature of governance and the longstanding allegiance between the people and the ruling monarch. This trust is further strengthened by the swift, proactive governmental approach in the implementation of necessary preventive measures, which includes not only protecting the people inside the country but also citizens abroad who have been reported to be evacuated and treated with utmost hospitality (CNN, 2020). In addition to these intimate gestures, Islamic faith plays a crucial role in believers' perceptions of any affliction (Koenig & Shohaib, 2014), especially in highly religious societies such as Saudi Arabia (Al Ahwal, Al Zaben, Sehlo,

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Khalifa, & Koenig, 2016). One of the major Islamic tenets is that every individual will endure many trials of hardships in order to validate the sincerity of their faith. This concept is emphasized on many occasions in the Holy Quran and in prophetic narratives. Fate and predestination is another notion in Islam that has a great influence on believers' perception at the time of crises. According to Islamic teachings, life affairs are predestined by God. These religious notions could explain the excessive use of supplications in tweets in general, which are mostly classified as positive tweets in sentiment analysis.

However, the overwhelmingly positive sentiment found in this study could be an artificial effect. It could be that people are reluctant to publicly voice their negative opinions, as doing so might be considered offensive to the efforts that have been implemented to control this devastating pandemic. The Saudi culture is collectivist in nature, and any transgression that threatens social cohesion might stigmatize the offenders. At times of public health emergencies, cultural assumptions have a significant impact on how a community reacts and mobilizes its resources to strengthen its control over the emerging challenges. This applies to institutions and individuals alike (Raich, Lorenzoni, Stummer, & Nöhammer, 2017). Consequently, the dominating positive sentiment found in this study might be overestimated due to social desirability bias. Future anonymous, private survey research could provide a more accurate assessment of public attitudes.

This study emphasizes the significance of assessing public risk perceptions and overall attitudes as an antecedent to effective public health interventions. Several seminal theories in health behaviors link risk perceptions to adoption of preventive behaviors. For instance, the Protection Motivation Theory postulates that perceived severity and vulnerability promote health motivation (Rogers, 1975). Future studies can include objective measurements, such as traffic data, to assess the actual alteration of behavior towards the preventive measures and how this correlates with sentiment analysis.

The findings of this study should be considered with its limitations. The accuracy of sentiment analysis is inherently limited by its ability to capture linguistic nuances and contexts. To mitigate this challenge, qualitative assessments of the textual results from Twitter search was done frequently to ensure the relevance of the data. Secondly, sample tweet selection was based on specific hashtags and limited to a specified timeframe. In Twitter, not all tweets contain hashtags, as many users prefer to share their thoughts without adding one. Such tweets were not captured in our analysis. This might have constricted our sample. However, thousands of tweets were still extracted and analyzed as shown in Table 1. Finally, the Twitter population might not be completely representative of the entire population. Although, Saudi Arabia has one of the highest social media penetrations in the world (Stata, 2020), which suggests that samples using Twitter might reflect the true population to a considerable extent.

Sentiment analysis, or opinion mining, is an effective tool and a novel method to assess public attitudes and engagement with crucial health measures. Pandemics, such as the emergent COVID-19, present a chaotic and rapidly evolving challenge that necessitates close monitoring of how people perceive the imminent risk and how they are responding to guidelines and policies. Such assessments are necessary for the development of appropriate communication content that can address potential concerns and strengthen compliance. Overall, the findings of this study suggest that Saudis are supportive of the public health measures to contain the viral spread of COVID-19.

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