Digital Information Seeking and Sharing Behaviour During the COVID-19 Pandemic in Pakistan

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Abstract. Studies on digital interaction in emergent users' population are rare. We analyse the electronic data generated by users from Pakistan on Google Search Engine and WhatsApp to understand their information-seeking behaviour during the first wave of the Covid-19 pandemic. We study how the Pakistani public developed their understanding about the disease, (its origin, cures, and preventive measures to name a few) through digital media. Understanding this *information seeking behaviour* will allow corrective actions to be taken by health policy-makers to better inform the public in future health crises through electronic media, as well as the digital media platforms and search engines to address misinformation among the users in the emergent markets.

Keywords: Digital information · Covid-19 · Google trends · WhatsApp · Misinformation

1 Introduction

The first wave of COVID-19 pandemic tested the health care systems and economies around the world. A key point noted in Pakistan was the lack of understanding about the causes, symptoms, and preventive measures of COVID-19. That frequently led to lax attitude towards social distancing protocols [45] or widespread adoption of pseudo-medicinal remedies that are known be ineffective or to have dangerous side effects [8].

In October 2020, Gallup Pakistan released a survey report that described the public's behaviour on COVID-19, just before the increase in the number of new infections during second wave in Pakistan. According to that report, almost 75% of the population thought that COVID-19 was under control and the need for continued precautions was no longer necessary. Whereas, nearly 70% of the

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public thought that the threat of the SARS-CoV-2 virus was exaggerated, 46% consider COVID-19 as a foreign conspiracy, and 45% public thought that it was a laboratory-made virus. Hence, according to the survey, the public underestimated the threat posed by this disease and many even considered it unreal [1]. Conveying correct medical information to the public is extremely important in a country like Pakistan with limited medical resources, and the high prevalence of pseudo-medicine and quackery in order to ensure that the information seekers have been provided with correct and reliable information. The aim of this paper is to understand how the Pakistani public developed its understanding of this disease, its origin, cures, and preventive measures. Understanding this *information seeking behaviour* will allow corrective actions to be taken by health policymakers to better inform the public for possible future waves of this pandemic, especially through electronic channels.

2 Relevant Literature

Online search trends can be very helpful in digital surveillance and prediction of an infectious disease. Relative search volume regarding COVID-19 increased during the early period of the pandemic and there was a positive correlation between daily new cases and relative search volume [22,42]. A study found a strong correlation between COVID-19 related Google trends and daily new cases in the US, with R value around 0.80 [26]. Similarly, a sharp hike in Google trends happened in searches related to COVID-19 after the detection of the first case in Taiwan [23]. This strong correlation between the daily confirmed cases and related Google search trends worldwide can be used to predict the trends of outbreak [4,26]. The rapid increase in web searches on COVID-19 and related topics also created an infodemic like situation and caused the worldwide spread of misinformation on disease [5,35,36]. Effective strategies are needed by governments and public health organizations to better manage such infodemic and strengthen the public awareness on the outbreak [22]. Educating the public to use websites of official public health forums can be helpful in this regard [21]. Social media played a key role in propagating health-related misconceptions and poses a big challenge to practitioners and policymakers [20]. The main reason for this challenge is that many people are not clear about the relationship between science, policy-making and media [34], and they tend to rely more on nonscientific but more definitive advice. For example, misinformation circulating during the 2014 Ebola outbreak challenged the efforts of health workers to control the epidemic [11]. Even in countries like Germany, Italy, US and UK, social media movements incited people to resist getting measles vaccination [12,17]. Similarly, another study analysed 2691 tweets about the treatments and preventive measures of gynecologic cancer and found 30% of them to contain misinformation [10]. While another study found that 40% of links shared on health-related forums contained fake news and were shared more than $450,000$ times between 2012–2017 [44]. Psychological and cognitive biases greatly influence how we react in a pandemic. People anticipated that the SARS-CoV2 virus cases would grow linearly, and they underestimated the possibility of an exponential growth [14]. This lack of understanding and failure of public health messaging had disastrous results even in developed countries [37]. Conspiracy theories and myths pose another serious threat to public health and affect the behavioural responses of people [31] that can dangerously affect the situation in a pandemic. Pseudo-medicinal information and conspiracy theories about COVID-19 circulated through social media traveled faster than the virus itself [15]. Many websites containing unproven claims about COVID-19 are widely visited by the public. They also shared on social media sometimes due to naivety and surprisingly sometimes intentionally to share inaccurate information [32]. This lack of accurate health information on COVID-19 also severely affected the psychological condition of the general public during the pandemic [43].

Google search trends, search queries, and social media debates can be used to analyse the public interests on a specific topic. This data can be specifically helpful during international crises and epidemics. A few studies tried to predict the spread of epidemics in a specific geographical location by performing analysis on search engine queries and Google trends in that region [18,33,39]. Search query analysis also showed that the public immediately started searching about the pandemic but they started searching for prevention and protection e.g. social distancing in the initial stages of the COVID-19 pandemic [6]. Similarly, studies indicated that social media can also be a useful way for early detection of epidemics [25,40].

3 Methodology

In this section we will present our methodology to understand the digital information seeking behaviour of Pakistani users during the first wave of COVID-19. Pakistani users are considered an emergent users group when it comes to technology use [7,24]. Although digital information can take many forms like text, images, and videos, we focused on analysing text data due to ease of availability and simplicity of analysis. There is a plethora of literature on studying the spread of information or misinformation in text based digital data on online social networking sites such as Twitter [27,38]. However, we took an alternative route and chose the following two other sources of digital information:

1. We studied how information was searched on **Google search engine** for COVID-19 related searches through Google Trends related to pseudo-medicinal information on COVID-19. We then compared these search trends with real world circumstances like changing government SoPS, the number of cases, and number of deaths etc., to understand the information trajectory in Pakistan during the COVID-19 crises.
2. WhatsApp is a popular way of communication in Pakistan. According to a mobile ranking forum, WhatsApp is the second most used mobile application in the country. Owing to the popularity of this communication medium, we identified a public **WhatsApp group** focused on COVID-19. We then exported the conversations in the form of textual data from that group. In an

automated way, we replaced all names and phone numbers with unique identifiers and we then stored the data as a *.csv* file with the following columns: Time and *Date, User Identifier, Text Message*. We then analysed the data to understand the mood and content of the messages.

We selected keywords so the data can be mined more easily. It was obvious to use corona, covid etc., but it was not clear which pseudo-medicinal treatment we should use as keywords.

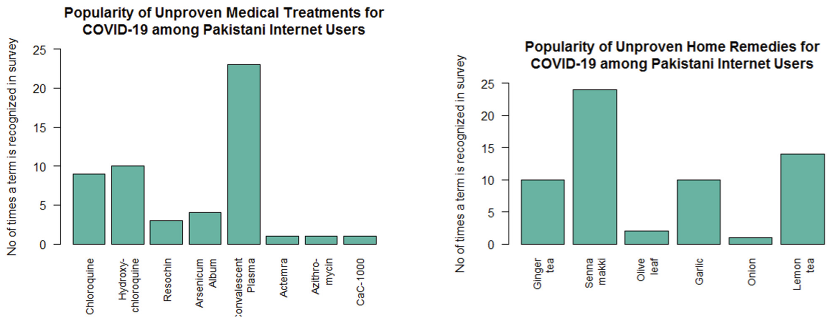
3.1 Pseudo-medicinal Treatments

We observed the following non-scientific treatments of COVID-19 were popular on social media platforms during the first wave of the pandemic in Pakistan:

1. **Herbs and Spices** such as garlic, ginger tea, lemon tea, olive leaf and senna makki (a laxative). Albeit some of these are harmless, *senna makki*, being a laxative, can cause dehydration and in extreme cases deaths in patients.
2. **Homeopathic drugs** such as Arsenicum album received publicity as a powerful immunity booster and were thought to help in preventing COVID-19. While the drug by itself may not have any serious side effects but people consider themselves immune to COVID-19 and as consequence took lesser preventive measures.
3. **Medicines** such as Chloroquine (also marketed with brand name Resochin) and Hydroxychloroquine are antimalarial drugs that gained a lot of attention on social and traditional media without any solid scientific backing and sometimes can be dangerous. Further this medicine is also used for rheumatoid arthritis patients and over-the counter availability of this drug created a shortage in the market for the patient in need.
4. **Convalescent Plasma** therapy was a popular treatment in Pakistan[1] and worldwide including U.S. despite many concerns on its effectiveness and possible adverse effects in some cases [29].

The above list of unproven treatments of COVID-19 acted as keywords for our textual analysis. However, it was not clear whether the general Pakistani public was aware of those terms and hence used them for in their online search queries and conversations. We tried to confirm the suitability of using these keywords through a *small non-representative sample* of users. We electronically sent our consent form and questionnaire to potential participants and then proceeded with only those who indicated their consent electronically. The questionnaire listed misinformation on social media (as listed above) as keywords and asked the participant to tick the boxes which they recognized. The targeted population of this survey was the general Pakistani public and we tried to get the representation from different areas of the country. A total of 40 participants (18 Males and 22 Females) filled this online survey. The participants were geographically distributed in 19 locations around Pakistan from residents of small towns to those living in big cities.

[1] https://p.dw.com/p/3eeAj.



(a) Popularity of Unproven Medical Treatments for COVID-19 among Pakistani Internet Users.

(b) Popularity of Unproven Home Remedies for COVID-19 among Pakistani Internet Users.

Fig. 1. Popularity of Unproven treatments identified on different social and electronic media forums among Pakistani internet users. We can see that the most popular home treatment was Senna Makki, followed by Lemon Tea, Ginger Tea, and Garlic. On the other hand, plasma therapy was a very popular medicinal treatment followed by Hydroxychloroquine and Chloroquine

All home remedies identified by our research team were validated through this survey. As shown in Fig. 1(a), the most popular home treatment was Senna Makki, followed by Lemon Tea, Ginger Tea, and Garlic. Figure 1(b) shows the popularity of unproven medical treatments for COVID-19 in Pakistan, which shows that a lot of interest was shown by internet users in plasma therapy as a possible treatment for COVID-19 plasma therapy followed by Hydroxychloroquine and Chloroquine.

4 Analysis 1: Search Trends During COVID-19 Pandemic

We performed a systematic analysis to evaluate the relationship between Google search trends on various non-scientific treatments on pseudo-medicinal information and the changing situation of COVID-19 pandemic in Pakistan.

4.1 Dataset

Google Trends represents the popularity of a specific search term on Google during a specific duration. For a specific search term, Google Trends shows the daily relative popularity of the search term during this duration. It returns a number n ranging between 0 and 100, where $n = 100$ on the day when the search term was most popular and $n = 0$ when it was least popular. This allows the analysis of search interests of users in specific regions as well as around the globe. It also provides the comparison of search trends on multiple search terms by similarly normalizing them between 0 and 100. This allows us to compare the relative popularity of multiple search terms, giving us insight to public interests and concerns at a specific time.

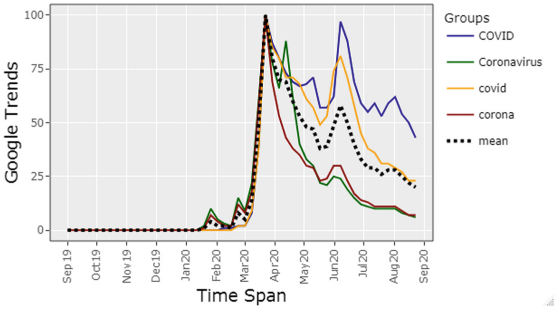
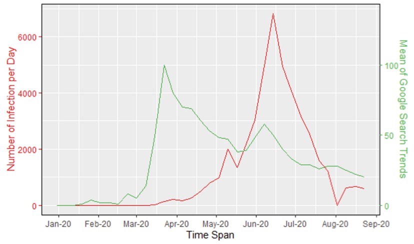


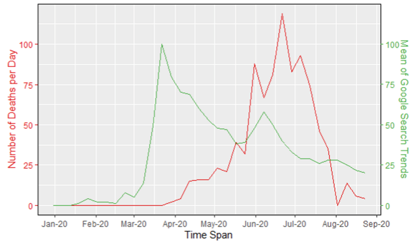
Fig. 2. Comparison of Google trends on Coronavirus search terms during pandemic in Pakistan. The dashed line shows the mean popularity of COVID-19 related searches.

We first performed a comparative analysis of Google Trends on different terms that can be alternatively used for searching details about COVID-19 in Pakistan. We choose 4 generic terms that are commonly used in Pakistan: COVID-19, Coronavirus, Covid, and Corona. As shown in Fig. 2, all these terms started to appear in Google Trends during the 3rd week of January 2020 and they all reached their peak in 3rd Week of March 2020. A sudden rise appeared in search trends during the second Week of March as the government implemented various spread control measures including nationwide lockdown. We also calculated their mean popularity on Google Trends and in the remainder of this paper, we will only use the mean of the various terms used to search for Coronavirus as shown in Fig. 2.

We also checked whether the quick spread of COVID-19 in the region and the rising number of infections and deaths resulted in increased searches in COVID-19 by the public. Here our assumption is that the increased number of searches indicate increased public concern about the pandemic. We explored this by comparing the day to day statistical data of COVID-19 cases in Pakistan with the popularity of COVID-19 searches using data from Google Trends. We computed the correlation of search popularity of COVID-19 searches with daily new infections and found that it has a value of just 0.27. Similarly, the correlation of popularity of COVID-19 searches with daily deaths came out to be 0.23. We can see that these are very small values, indicating that the search popularity was insignificantly influenced by the spread of the pandemic. Figure 3(a) shows how search popularity change with rising number of new infections and similarly Fig. 3(b) shows how search popularity change with daily deaths. It is surprising as well concerning that people seem to be searching very little even at the peak of the pandemic and it seems that Google searches about COVID-19 was



(a) Comparison of daily new COVID-19 infections and search popularity of Coronavirus situation.



(b) Comparison of daily new COVID-19 deaths and search popularity.

Fig. 3. A comparison of how internet search statistics about COVID-19 changed with changing number of infections and deaths.

fuelled more because of the initial total lack of knowledge about the virus and the resulting disease.

4.2 Search Interest Regarding Treatment and Prevention of COVID-19

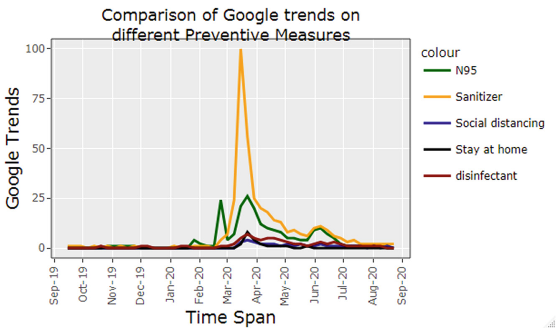


Fig. 4. Comparison of Google trends on preventive measures during Pandemic in Pakistan.

We also performed a comparative analysis of Google trends in Pakistan on different preventive measures suggested by WHO for COVID-19. We choose 5 popular terms that were commonly used in Pakistan: N95 mask, Sanitizer, Social distancing, stay at home, disinfectant. Figure 4 shows the comparison and it is clear that "Sanitizer" is clearly the most popular of these terms during the first wave of the pandemic in Pakistan. We used the top trending term "Sanitizer" for further analysis to evaluate the relationship between these trends and peaks of trends on different pseudo-medicinal information search terms.

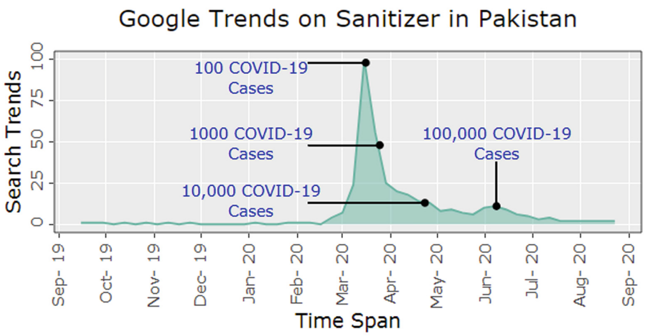


Fig. 5. Comparison of Google trends on Sanitizer during March-August 2020.

Figure 5 shows the pattern of how the popularity of the search term *sanitizer* varies over time. We can see that this search term experienced a sudden rise in popularity immediately after the first patient was detected, this was when the whole country was experiencing previously unknown levels of fear and uncertainty. At this time, many items essential for the pandemic like sanitizers, masks, and other hygiene related items experienced a sudden increase in demand. This was probably when the public was searching if sanitizers were available online or if they are available at cheaper price. However, very soon private businesses started to fill this newly created demand and as a result the search term "sanitizer" quickly dropped in popularity However, it still remained more popular than pre-pandemic time. We also investigated the Google Trends to check the popularity of "Chloroquine" and "Hydroxychloroquine" in Pakistan after Trump's endorsement of these drugs and found a pattern very similar to that in the US. As presented in Fig. 6, there was a sudden hike in Google searches on both medicinal terms in the last week of March, 2020 and they remain popular till 3rd week of April, 2020. This indicates that the backing of a popular personality drives the public interests and increases the trustworthiness of a piece of information.

In summary, the results presented suggests that people in Pakistan actively search COVID-19 related information during the early stages of the first wave of the outbreak but later the public interest seemed to have waned.

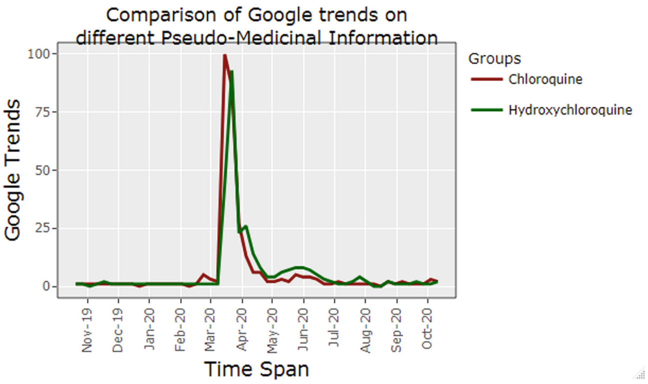


Fig. 6. Comparison of Google trends on Chloroquine and Hydroxychloroquine in Pakistan.

5 Analysis 2: WhatsApp Public Group Data

Now, we present an analysis of data from a public WhatsApp group and also explore the popularity of the pseudo-medicinal information in the discussions during the first wave of COVID-19.

After careful scrutiny, we focused on one public WhatsApp group specifically created in response to the COVID-19 pandemic called `Understanding COVID-19`. The group was created to understand the causes and potential cures of this novel disease and its members actively discussed various issues about the pandemic, especially in the start of the pandemic when limited information about this disease was available. The group was created in the middle of March 2020, when the number of daily infections and deaths started to grow. This group had 53 members, all of whom were Pakistani residents and most of them living in different major cities of Pakistan. Moreover, almost all members were literate and with basic healthcare knowledge and some of them were even medical doctors. The complete record of the WhatsApp group was exported till the 3rd week of August as a CSV file for text analysis in `R`. Since most of the discussion on this group was in English with Urdu being used only occasionally, the text analysis was done only on text messages in English. Careful pre-processing was performed to clean the data while making sure that important information was not lost.

The time series visualized in Fig. 7 represents the frequency of messages per day and the points indicate important events during the first wave of the COVID-19 pandemic in Pakistan. We can see in Fig. 7, the group remains mostly active between March and July 2020, the period when COVID-19 cases were at its peak. An increase in the number of messages in a day can be seen after two important events, the day the first patient died and the day when the national lockdown was initiated.

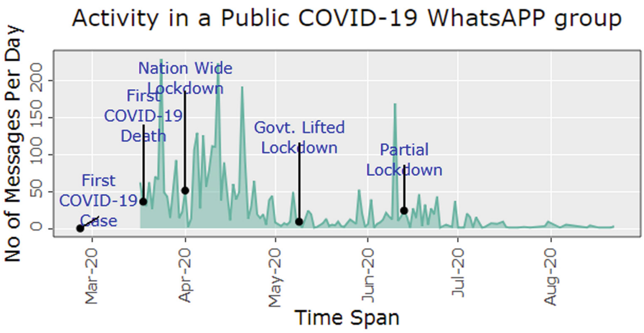


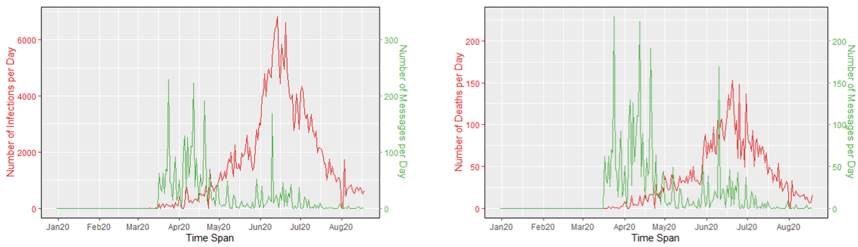
Fig. 7. A representation of message frequency per day in COVID-19 public group with important events in Pakistan. An increase in the number of messages in a day can be seen after two important events, the day the first patient died and the day with the national lock.

We then wanted to get an idea of the discussion in this WhatsApp group. We plotted a word cloud as it gives a good idea of the most frequent words used and hence the discussions between the group members. We performed the below pre-processing steps so our plot can be more meaningful.

- We converted all text to lower case.
- We removed all punctuation marks.
- We then performed stemming i.e. reduced all words to their root form.

These pre-processing steps were completed through the `stm` package of `R`. The most commonly used words in their discussions. The words show that there were discussions on patients, clinics, hospitals, medics, and also various possible treatments.

To check whether the number of infections/deaths was related to increase in discussions on the WhatsApp group, we first computed the correlation, which came out to be 0.0006 for daily new infections and −0.0135 for the daily new deaths respectively. It indicates that the discussion was not correlated at all with how fast the pandemic is spreading, in fact in case of new deaths it seems that in some cases higher number of deaths seem to have resulted in lower number of messages on the WhatsApp group. We hence compared how the time series of daily number of messages exchanged on the group changes the time series for the daily number of infections and daily number of deaths respectively. Figure 8(a) compares the number of messages per day with the number of new COVID-19 number of cases per day in Pakistan, while Fig. 8(b)compares it with daily deaths due to COVID-19. This patterns shows the concern of the public at the very start of the pandemic and as the number of infections and deaths increased. However, very soon with the increasing number of infections and deaths in Pakistan. It can be seen from both figures that the group was more active in earlier



(a) Comparison of WhatsApp group activity with daily infections in Pakistan.

(b) Comparison of WhatsApp group activity with daily deaths in Pakistan.

Fig. 8. Comparison of WhatsApp group activity with daily reported COVID-19 numbers in Pakistan. Please note that the peaks in Fig. 8(b) look larger because the number of deaths are significantly less than the number of infections. The 4 peaks in the WhatsApp messages count seem to influenced more by coverage in traditional news media and initial fear among the public.

phases of the COVID-19 (i.e., March-July 2020) and later the public seemed to be less concerned about the pandemic and possible dangers from it. The 4 peaks in the WhatsApp messages count seem to influenced more by coverage in traditional news media and initial fear among the public. More specifically, the first peak was around the time soon after the government implement country wide complete lockdown, the second peak came because there was a lot discussion about possible treatments and sharing individual experiences; the 3rd peak came because of there was a lot of discussion about psychological issues resulting from the pandemic and sharing views on how to cope with this new reality; while the 4th peak in mid June was because this was when the total number of infections in Pakistan crossed $100,000$.

We also explored communication related to the two anti-malarial drugs Chloroquine and Hydroxychloroquine, and found that both started to be discussed immediately after the endorsement of President Trump and Elon Musk. They remain in regular discussion till July 2020 as can be seen in Fig. 9. This was despite of the fatality reported on March 22, 2020 [28].

Lastly, we applied thematic analysis to extract main topics in the WhatsApp group. We started by applying an algorithmic technique called Latent Dirichlet Allocation but did not find the results to be satisfactory. As a result, we followed the 6-step process suggested by Braun and Clarke for thematic analysis [9]. We note here that *thematic analysis* studies are suited for studies that are of exploratory nature and to generate hypotheses that can be later tested from a representative sample. After initial scanning of the messages for getting a high-level idea of about the issues being discussed in this group, the first author went through each message and identified 11 categories labeling each message accordingly. This labeling was done to uncover the repeated patterns of behaviour i.e. *themes* in the data. The second author then reviewed this categorization by going through the file and reviewing 40% messages and their associated labels

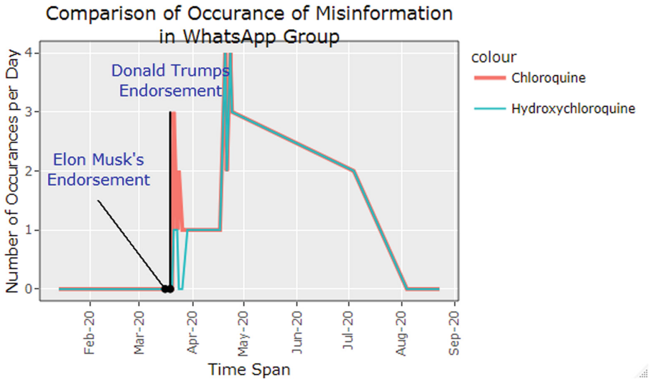


Fig. 9. Chloroquine and Hydroxychloroquine started being discussed immediately after the endorsement of the high profile personalities and remained in discussion till July 2020.

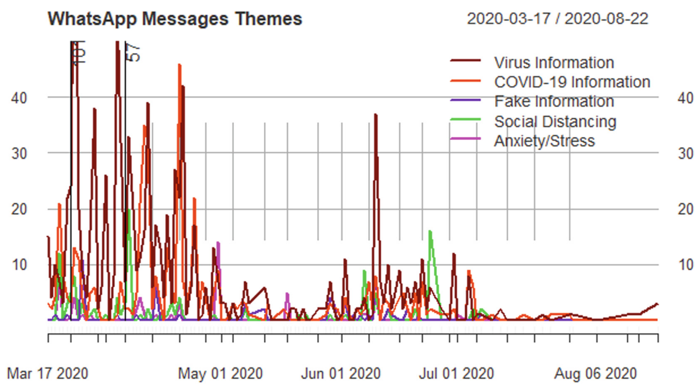


Fig. 10. Themes observed in the discussion on the public WhatsApp group. We can see that there was a lot of interest at the start of the pandemic and gradually interest reduced. Interestingly, we observed that all themes tend to be discussed more or less together with most of the discussion being focused on either information about the virus or information about the disease.

and suggested merging some categories and also recategorized some other messages. After this recategorization, we ended up with 6 categorizes. The categories and their brief explanation is given below:

1. **General Conversation:** General conversations messages such as hellos, goodbyes, greetings, etc.
2. **Virus Information:** Messages that sought and shared information about the SARS-CoV-2 virus, its origin, how it spreads etc.
3. **COVID-19 Information:** In this category, the participants discussed the disease its risks, possible treatments and shared information that can be helpful to the patients of COVID-19.

4. **Fake Information:** In this category, the participants discussed various fake or dubious treatments like plasma therapy. We also included messages that discussed or shared various conspiracy theories about the origin of the virus or the nature of the disease.
5. **Social Distancing:** Messages that discussed the importance of social distancing and masks etc. or expressed concern about the non-compliance of social distancing protocols.
6. **Anxiety/Stress:** Messages that discussed high levels of anxiety and stress due to the pandemic were categorized into this category. This category also included suggestions intended to help cope with these issues, including those of religious nature.

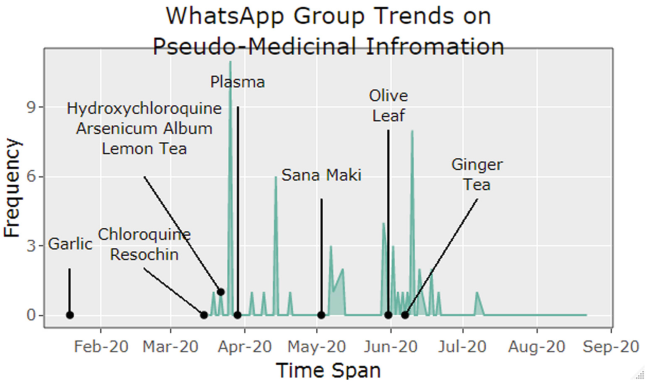


Fig. 11. The trend of how various fake information was discussed on the WhatsApp group. In this figure, the days when the search peak on Google trends was observed is labeled. Interestingly, we can see that the search peak corresponds very near to a peak in the WhatsApp discussion about some fake information.

The variation of these themes with time is shown in Fig. 10. We did not include the category of general conversation in the interest of clarity of the figure. Moreover, the plot does not show two very high peaks, but their values are written where the peak is truncated. We can see from the figure that discussions in this group started as soon as it was created and the initial discussions revolved around basic information about the virus, its origin, the disease, and social distancing other preventive measures. In about a week's time, the discussion also started to have significant messages on fake information and also anxiety/stress issues. A large number of messages were exchanged for about 2 months till about May 2020 and when the volume of messages in all themes dropped. However, all themes started being discussed again with renewed interest in the middle of June, but the level of interest was lesser than the initial weeks of the pandemic and it dropped to insignificant levels within a few weeks. Recall that mid-June was the time when the total number of infections in Pakistan crossed 100,000.

Interestingly, we observed that all themes tend to be discussed more or less together with most of the discussion being focused on either information about the virus or information about the disease.

We plotted the trend of how discussions on fake and pseudo-medicinal remedies identified in Sect. 3 varied with time. We can see from Fig. 11 that this discussion seems to be bursty and the peaks seem to fall very close to the time with the peak of pseudo-medicinal treatment on Google Trends. This indicates that both the WhatsApp discussion as well as the search peak seem to be related.

6 Conclusion

In this paper, we investigated the information-seeking behaviour of the Pakistani public during the first wave of the COVID-19 pandemic in Pakistan. We decided to focus on online resources and social media as they were a major source of health-related information during the COVID-19 pandemic. The major contributions of this paper are the following:

1. We investigated how the public searched the web for various COVID-19 related information as the pandemic progressed. We used data from Google Trends for this purpose. Interestingly, our analysis seems to indicate that although the number of infections and number of deaths due to COVID-19 was increasing, the general public was searching lesser for COVID-19 related information. Analysis of search trend of COVID-19 related treatments and prevention also indicated that search volume seems to be influenced more by external factors like Donald Trump and Elon Musk endorsing a drug; sanitizer not being available in the market, or the psychological effect and media coverage when the number of patients crossed 100, 000.
2. For a high-level semantic understanding about the information sought during the first wave, we analysed data from a public WhatsApp group that was created to share information about COVID-19. Similar to search trends, the group members shared more information during the early weeks of the pandemic and gradually the number of messages decreased despite the pandemic becoming more widespread. Like search trends, discussion in this group seemed to be sparked by external factors and associated media coverage. For example, a sudden increase in the volume of messages was observed when the COVID-19 patient died; when government-imposed countrywide complete lockdown; and when the number of infected persons crossed the 100, 000 threshold.

The results discussed in Sect. 4 and Sect. 5 seem to indicate that the public was very concerned at the start of the pandemic, however with time their level of concern gradually reduced. Their level of concern and interest then seem to rise occasionally when an event that they perceived as occurred. This seems to indicate habituation, here *habituation* is psychological behaviour found in all living things and it informally means the reduction of a particular response after repeated exposure of the same stimulus [19]. A number of studies have been conducted to establish the causality of repeated exposure of the same stimulus and resulting decrease in response [13,30]. In case our paper, the stimulus is the daily pandemic-related news that everyone heard or read at various places and the response was their level of concern and resulting online behaviour that we tried to observe. Habituation is also found to be *stimulus specific* [41], hence the response can be returned to previous levels when an individual who is already habituated to one stimulus is presented with a novel stimulus [16].

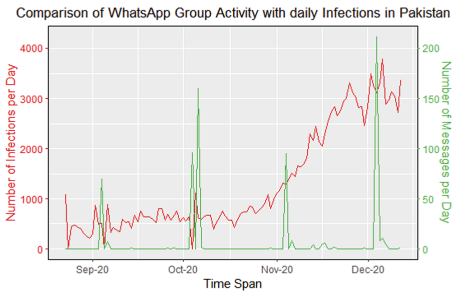


Fig. 12. Number of Messages on the Whatsapp group in the second wave compared to number of infections.

We conjecture that in the case of the COVID-19 pandemic, the public habituated after daily exposure of warnings and worrying news on traditional media as well as on social media. They were, however, ‘dishabituated’ when the stimulus changed, for example when news of the number of infections crossing $100,000$. We check this conjecture by plotting the number of messages exchanged on the WhatsApp group in the second wave as shown in Fig. 12. Note this plot only shows till December 2020 as the WhatsApp group was deactivated soon after it. We can see that very few messages were exchanged, however, the number of messages on the group experienced sudden and short peaks. On further investigating, they all seem to be a result of something unusual or different, explained as follows:

1. **First Peak:** (September 04, 2020) At this time, the public was concerned about the likely effect of government’s decision to open schools.
2. **Second Peak:** (October 06, 2020) A famous newspaper Dawn publishes a gloomy article [3] about second wave and how deadly it can be. There was a lot of discussion about this article.
3. **Third Peak:** (November 04, 2020) There was discussion about the news [2] that the government ruling out lockdown again.
4. **Fourth Peak:** (December 04, 2020) Clinical trials of the COVID-19 vaccine starts in Pakistan and it was discussed a lot in the group.

A similar pattern can be seen for the search results data from Google Trends (Fig. 6). The keywords chosen in Sect. 4 were very frequent from March 2020 till about July 2020 probably due to initial scare and confusion. After the initial scare, at the height of the first wave, they dropped to almost pre-pandemic times. Hence supporting our conjecture (Fig. 13).

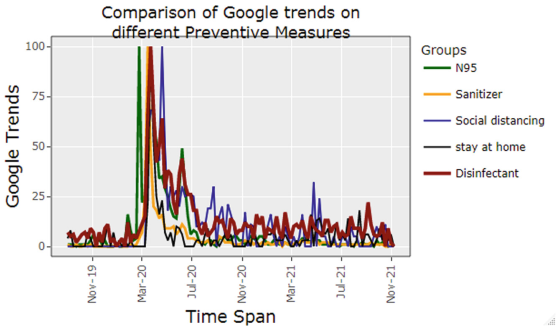


Fig. 13. Figure showing Google trends data of keywords selected in Sect. 4 were only very high from March 2020 till about July 2020 probably due to initial scare and lack of information.

Further work is needed to confirm whether there is a causal relationship between online activity and external factors. It also needs to be investigated how governments, health agencies, digital media platforms should communicate with the general public so habituation can either be avoided or reduced in future pandemics, specifically for the emergent user communities.

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