Pandemic Response and Crisis Informatics: An Imperative for Public Health Messaging

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***Abstract*—The focus of this research is to examine the usage patterns exhibited by users of online search engines in the midst of COVID-19. We aim to understand how the queries are structured and their timing on the various platforms that citizens are using to check the availability of Personal Protective Equipment (PPE) since the outbreak of the COVID-19 public health crisis. Understanding and analyzing peak volume for information platforms is critical, especially for public health policy, with a mind toward crisis informatics. In this study, we collect all the data of users querying data from Face Mask Map (FMM), a real-time application which displays the inventory status for all stores selling PPE. This data is from the point at which the public health crisis became widely known to the time at which PPE availability saturated the market. As COVID-19 continues to proliferate and affect people around the globe, official organizations such as Department of Health and World Health Organization (WHO) utilize Web or Social Media (Facebook or Twitter) to announce up-to-date news, e.g. daily confirmed cases or in order to update policy regarding resource management. We then correlate the significant announcements from public health officials, specifically published by Ministry of Health and Welfare (MoHW) in Taiwan, that are concerning usage and distribution of PPE. We find that the temporal dynamics of aggregated users behavior are consistent with the events. For the practitioner of disaster management, it is critical to be able to identify when the public will consistently react to public health announcements for the purpose of ensuring proper supply distribution and avoid misallocation. It is our hope that the study can help to build an effective online disaster preparedness information system, in the consideration of computing and public psychology, to better respond to disaster with a greater corpus of data.**

***Index Terms*—COVID-19, Disaster Preparedness System, User Behavior, Crisis Informatics**

I. Introduction

According to the status report maintained by the WHO, Taiwan has been recognized for a relatively low number of confirmed COVID-19 cases. This is attributed to its better adoption of data analytics in the pursuit of precise and efficient contact tracing, as well as supplies management, and surveillance of those requiring quarantine [1]. In particular, the use of the application Face Masks Map (FMM), which represents a collaboration by the Taiwanese hacking community and the Taiwanese national public health authorities, has been attributed as one of the most critical components in Taiwan's effort to fight COVID-19. This application works to give citizens better situational awareness regarding the inventory status of PPE, in particular masks, for every store. This information sharing by authorities helps to build the multi-trust bridge between the public and authorities [2]. The app has been recognized for its good design practices, as well as its clear consideration of crisis informatics fundamentals. These elements help to mitigate irrational behaviors often displayed by the public in the face of an epidemic such as panic-buying and stockpiling. While face masks have been categorized as one of the key materials in epidemic containment [3], there is relatively less research and investigation that has been conducted in order to understand the behavior and actions of people in the midst of pandemics.

The temporal view of disaster progression can be a useful lens to consider our research. To that end, we roughly divide the COVID-19 crisis into several distinct stages as follows: At the very first stage, COVID-19 was regarded as a local infectious disease in Wuhan, China. However, with the interconnected nature of the world, and the intransigence of Chinese officials to be forthcoming with accurate data regarding the nature of this pandemic, we quickly moved on to stage 2. Stage 2 represents known spread to other continents, primarily Western Europe and North America. The first confirmed case in Europe was regarded as a critical event since it had potential to cause panic and the resulting policies of lockdown in an attempt to limit spread. Before major disaster strikes, it is critical to build a robust and reliable crisis informatics platform. This paper introduces FMM detail and presents a multi-aspects data analytics for the system. In particular, we are interested in these two research questions. RQ1. In the event of pandemic events, does the mask rationing efforts affect the total number of query to face masks? More specifically, can we deduce a strong correlation, or even a causality. RQ2. Which type of users will be more likely to use FMM?

The rest of the paper is organized as follows. Section II outlines the related interdisciplinary works on various directions toward disaster management and impact for online society such as Twitter. Section III describes timeline and user aggregated data for public resource query platform, which was created and maintained by the collaboration with public health authorities and the local hacker community. We present the correlation study between critical events of COVID-19 in Taiwan and users query temporal patterns to Face Mask

The data for this paper is provided by g0v community.

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Map in Section IV. Section V further discusses the source and the medium in order to understand where they mostly access FMM. Finally, we offer our conclusion and public policy considerations in Section VI.

II. Background and Related Work

Disaster research has a long history with a wide range of sociological studies, which have been conducted during different phases of hazardous events [4]. For example, Green [5] and Constable [6] investigate the moral and legal principles of dramatic outbreaks of looting behavior in New Orleans after Hurricane Katrina in 2005. Shibuya and Tanaka examine how the used-car market was impacted during the great eastern Japan earthquake and tsunami of 2011 [7]. They found that the demand of cheaper used cars and cars with carrying capacity increased after disaster. Moreover, Bonanno et al. [8] and Vlahov et al. [9] focus on behavioral and psychological impacts following the September 11, 2001 attacks in New York, for instance, increased use of alcohol and marijuana.

Crisis informatics is a multidisciplinary research area where social and behavioral studies are conducted using Information and Communication Technology (ICT) for disaster research [10]. With social media being one of the major means of communication, many prior works have shown that social media provides valuable information and insights at every stage of a disaster. Shibuya and Tanaka [11] demonstrate there were correlations between expressed social media sentiment and social-economic recovery posted for the great eastern Japan earthquake and tsunami of 2011. This could be important for officials to understand where to focus their efforts in order to be most helpful to citizens. Sreenivasulu and Sridevi [12] indicate that the frequency of hashtags and the position of the earthquake keyword on Twitter were the most important features in detecting target events during the Nepal earthquake and landslide in 2015. This technique, in conjunction with the information we are presenting could be extrapolated to help identify epicenters of activity that need addressed by public health officials.

Due to the severity of the COVID-19 pandemic, many researchers are focused on this as an area of research. There is an attempt by some researchers to utilize big data analytics in an attempt to curb the outbreak and mitigate potential side effects from the epidemic. Dewhurst et al. [15] suggests the use of epidemiology words on social media may be useful in forecasting later disease cases. Chen et al. [1] applied traveling guides, GPS in buses, credit card transactions, the electronic toll collection system on the national freeway and the mobile phone position system to perform smart contact tracing for persons in contact with the Diamond Princess cruise ship COVID-19 passengers who disembarked at Keelung Harbor in Taiwan for a one day tour. Gharavi et al. [16] discovered there was a temporal lag of from five to nineteen days between the rising number of symptom-reported tweets and officially-reported confirmed positive cases. Shiera et al. [17] exploit Google searches and Tweets which gave an accurate estimation of COVID-19 cases three days before public health officials released confirmed case numbers. In contrast, our focus is studying and predicting the temporal dynamics of users on social media platforms in the context of a disaster preparedness system based on the official announcements and their affect on PPE acquisition and distribution.

III. Resource Query Platform and User Data Description

When a public health crisis strikes, a crisis informatics system is critical to (1) inform the policy response by public health officials, (2) disseminate information and instructions to the public and provide situational awareness, this in turn acts to (3) reduce public panic. In this section, we describe an interactive face mask supply tracking system and the online user data we collect.

A. Face Mask Map

In the early stage of COVID-19 spread (January February in 2020), people were flocking to supermarkets and pharmacies in order to stockpile as many critical supplies as possible. At the same time, a large influx of calls were directed to the stores to enquire as to the stock status of any PPE, e.g. hand sanitizer, gloves, and face masks. This prompted Howard Wu, a freelancer from GoodIdeas Studio[1], to build a platform in the beginning of Feb. 2020, **FMM**, in order to help the public understand the availability of PPE based on geolocation. Figure 1 illustrates the primary three components: (1) Geolocation identifier, (2) Connector to MoHW, and (3) Google Analytics.

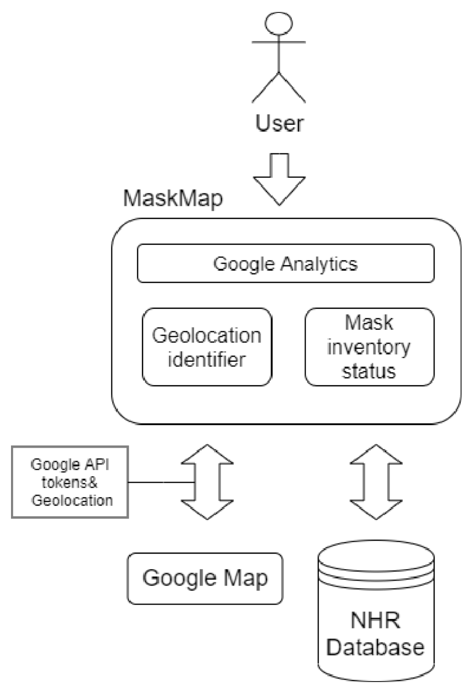

Fig. 1. Face Mask Map System Overview

[1]https://goodideas-studio.com/

- *Geolocation identifier*: An user may choose to input an address manually or allow FMM to access their device location. After identifying the user's location, the system will display inventory status for nearby stores, which has been maintained by an authoritative database.
- *Connector to Authority Database*: The primary problem is how to access the stock status for every drug store or supermarket, even though they do not belong to the same enterprise. FMM Version 1.0 utilizes a unique crowdsourcing mechanism – users will report the availability for their local store. However, for the consideration of completeness and authenticity, authority later then requires every store to report their inventory status to MoHW and then allow API access with permission.
- *Google Analytics*: Google Analytics makes website owner to analyze visitors activity and network traffic on the website much easier. It tracks all of its data by a Google Analytics tracking code that we install on our website. This code is a small snippet of Javascript, which runs in viewers web browser when they visit the website.

FMM will display the inventory status from nearby stores with the following colored bar: gray (no mask or not reported), pink (20 percent or less), yellow (20 to 50 percent) and green (sufficient), based on geolocation identifier, simultaneously, every query activity will be recorded by Google Analytics. With the support and development from authority and software engineer community, there are many similar online tools, offering face mask information in Taiwan after the global outbreaks of COVID-19. Yet, FMM is the first and most popular one.

B. User Session Data Description

The first local confirmed COVID-19 case was a 55-year female engaged in trade between China and Taiwan at the end of January, 2020 [2]. Hence, in this research, we focus on analyzing the temporal pattern of audiences for active 3-month FMM, from February 1 to May 1, with a toal of 183533 users. The formal definition of necessary terms will be described as follows:

- User: An user U in Google Analytics includes a combination of random numbers and timestamp. Sometimes it is also called client id, which was assigned by Google to each device which users engage FMM. Therefore, two users may reflect the same real person behind the screen if she uses two distinct devices.
- Session: A session $U^i_{s_j}$ is a group of event records for an user U^i in a given time period (30 minutes). Accordingly, if an user had an activity on FMM on 12:30 am, any additional activities such as re-search, click, zoom out and in occurred in the following 30 minutes will be considered as the same session. However, the session will expire if (1) there does not have any activity for 30 consecutive minutes or (2) at midnight.

[2]https://www.cdc.gov.tw/En

- Overview of Sessions in specific duration: The report somehow reflects how many users send a request to FMM to enquire current inventory status nearby.
- Number of Sessions per User $|U^i_{s_n}|$: The metric represents the temporal pattern for a particular user U^i, whether she tends to perform a query in the morning or evening. We are able to speculate the relationship or causality between one's buying and enquiring behavior since it's presumably natural to query the platform before intending to buy face masks.

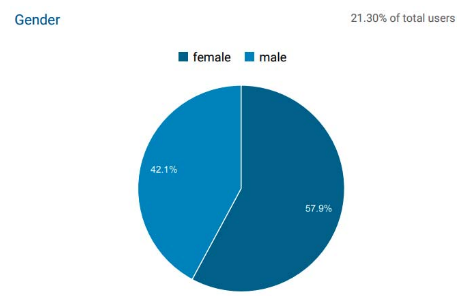

Fig. 2. Gender Pie Chart for Users

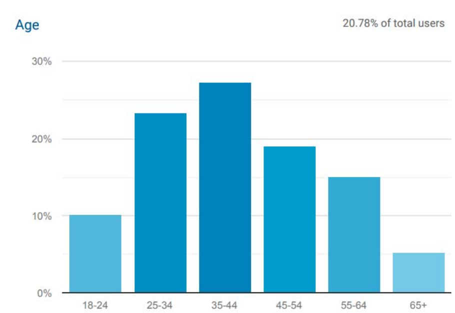

Fig. 3. Age Bar Chart for Users

Figure 2 and 3 shows the age and gender distribution for users between Feb 1 to May 1, which includes 21.3% and 20.78% of all users respectively, the reason we cannot calculate all users is that Google cannot identify some users detail if they choose not to disclose it. According to our data, females are more likely to utilize FMM to ascertain the inventory status (57.9%) compared to males (42.1%). Additionally those aged 35-44 are the group that query Face Mask Map at the greatest rate. Overall, we see that the main audience for crisis informatics is middle age and female. This may be partially explained by the Technology Acceptance Model [18] [19].

IV. Correlation Between Critical Events and Online Users Behavior

A. Pandemic Event

The public usually relies on the official announcements from public health officials in order to understand the extent of a public health emergency, and contextualize their individual response to the situation. . For example in the case of COVID-19, WHO updates an online dashboard daily showing the current situation broken down by country. In Taiwan, *https://covid19.mohw.gov.tw/* is the official domain utilized by public health officials for disclosing current pandemic information. A disaster news dashboard is usually composed of a series of events. These range from international breaking news, such as a new COVID-19 outbreak in Beijing, to relevant domestic matters. Although we are able to identify events using social media mining and natural language processing techniques [20], the events published by public health officials were considered in order to measure the correlation with aggregated users behavior for its credibility. In this work, we identify the events from the above URL satisfying the following conditions: (1) with the label *material preparation* (2) including the hashtag: Face Masks (3) Manually checked by at least two authors to clarify that the target influence would be a substantial number of citizens, e.g. children's face masks buying policy change. We listed all 9 identified events as the following:

1) **E1** (2020-02-06): Name-Based Mask Distribution System1.0 on board, people need to hold their health insurance cards (HIC) to purchase at pharmacies. Add diversion here.
2) **E2** (2020-02-20): One can purchase 4 child face masks within 7 days given a child HIC.
3) **E3** (2020-02-27): Adjust the distribution method of children's masks (1) Each person can hold up to 3 childrens's HIC (2) HIC are not subject to the diversion restriction based on the last number of Social Security Number.
4) **E4** (2020-03-05): The purchase of adult masks increased to 3 pieces, meanwhile, children masks 5 pieces, all in 7 days.
5) **E5** (2020-03-12): Name-Based Mask Distribution System 2.0 on board. Pre-Order online and pick-up in-store (pharmacies) were allowed based on SSN through MoHW application.
6) **E6** (2020-03-19): Purchase date was not restricted by the last number of SSN.
7) **E7** (2020-04-09): Adjust the purchase cycle and quantity of masks, 9 for adults and 10 for children every 14 days. In addition, cancel all odd and even number split restrictions.
8) **E8** (2020-04-13): Masks requisition and export ban has been extended to the end of June.
9) **E9** (2020-04-22): Name-Based Mask Distribution System 3.0 on board, one is able to pre-order at every domestic convenience store.

B. MacroQuery Temporal Peak

After identifying related events on MoHW website, we turn our attention to determine the temporal peak within a 90-day interval. We then define a time series $T = \{(t_1, x_1), (t_2, x_2), ...(t_n, x_n)\}$, as x_i represents the total number of sessions on t_i. According to the session refresh policy on Google Analytics, we set the length of t_i is 24-hour, from 12:00 am to 11:59 pm.

We then adopt the method proposed by Schneider [21] to detect the significant peak in our dataset. A candidate peak needs to satisfy the following condition:

- Greater than yesterday and tomorrow: $\forall i = 2, 3, ..., n-1$, if t_i represents when the peak occurs, then it satisfies that $x_i > x_{i-1} \wedge x_i > x_{i+1}$.
- Greater than an absolute threshold ϵ: To avoid the scenario where the peak detected is merely a local maximum, we consider that a daily value for candidate should exceed a threshold, which is 10000 in this work.
- Greater than the average of week: To measure the significant peak in a time series, we also consider that a peak $x_i > \bar{x}$, where $\bar{x}$ is the arithmetical mean value of a consecutive array nearby (t_i, x_i). Next we set the length of array is $n = 7$, representing a week period.

$$\bar{x} = \frac{1}{n} \times (x_{i-5} + x_{i-4} + ... + x_i + x_{i+1}), \qquad (1)$$

One key question here is why we set the period between $i-5$ to $i+1$, instead of $i-6$ to i. Assume an event E occurs on t_E, which will bring out the increase of total sessions on x_{E+k}, where k is the reaction time window. We hypothesize that a news requires a day to disseminate, hence we calculate the average between $i-5$ to $i+1$, where i is the significant peak and t_{i-1} or t_i is the tipping point.

C. Result

We define the function $E(t)$ as the exact time that event E occurs. If the public was impacted by a critical event E on $E(t) = t_i$ propagated by both traditional and social media, we should speculate that there will be a peak p_{occur} occurred on $t_{(i)}$ or $t_{(i+1)}$, assuming that the reaction time window for an event E is roughly a day. We then assume that the p_{occur} was correlated and may be attributed by E.

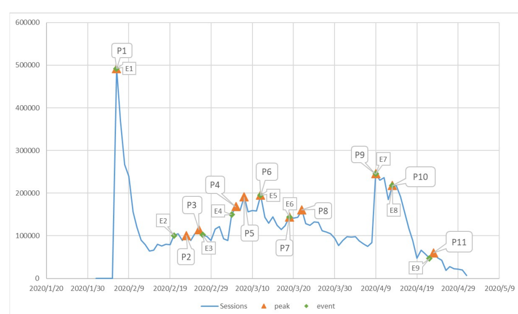

Fig. 4. Timeline of Traffic to Face Mask Map and Related Events

Figure 4 illustrates and visualizes the occurrence of identified events and temporal peak for users query activities toward FMM. Among 11 detected temporal peak labelled in Section IV-B, we argue that 7 peaks (64%) can be precisely correlated to an event we identified from the MoHW authority dashboard, which proves the public query or even the behavior of purchases made by the public, especially the temporal peak, are highly correlated to the policy and guiding principles given by public health officials. The most obvious peak occurred on February 6, corresponding to Name-Based Mask Distribution System 1.0[3] was just on board, meaning that the first significant wave of buying panic will come when both COVID-19 just started and the authority announce the face mask control policy. The second significant peak was on April 9, when the Taiwanese government changed the policy from 3 masks per 7 days to 9 masks every 14 days.

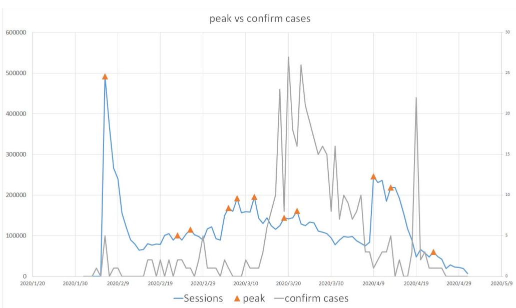

Fig. 5. Timeline of Traffic to Face Mask Map and Domestic Confirmed Cases

We also examine the temporal dynamics between # of sessions and # of domestic confirmed cases. Intuitively, the public tend to enquire the inventory status after noticing # of confirmed cases increases. However, as Figure 5 shows, there is no obvious correlation between two lines (correlation coefficient $\rho \approx 0.0594$), indicating that the public just enquired and bought face masks no matter the severity.

V. Discussion for Users Composition

After examining the gathering enquiring behavior during COVID-19, we turn our attention to how crisis informatics system be accessed. In specific, we are interested in the following questions: What is the best channel for broadcasting the information regarding supplements when disaster occurs? What kind of devices do they prefer to use? These information can facilitate the disaster infrastructure maintenance and management.

A. Channel

As Figure 6 shown, most people (86%) utilize smartphone to access FMM, indicating the public usually rely on mobile communication to enquire and receive information other than traditional desktop. On the other hand, Figure 7 shows that the distribution how face mask map have been explored. The top 4 channels are: Referral (52.16%), Organic Search (29.37%), Direct Access (15.69%) and Social Media Platform (2.73%). In specific, according to the definition by Google Analytics, *Referral* traffic is the reporting visits coming from sources outside of Google Search engine, e.g. the authority website or other media site (CNN, BBC). Second, *Organic Search* is when one use any keywords (mask, face mask, *etc.*) to search or after entering the relative keyword that some websites popup. Third, *Direct Search* means that users enter website URL address to visit, usually with bookmarks or saved URLs. Finally, Social Media platforms such as Facebook or Twitter have also acted as essential role regarding disaster management.

[3]https://www.nhi.gov.tw/english/Content_List.aspx?n=022B9D97EF66C076

TABLE I
Top Source & Medium Description

Source / Medium	Users	Sessions	Avg. Session Duration
mask.pdis.nat.gov.tw / Referral	2,055,130 (48.32%)	4,833,341 (46.12%)	00:02:31
google / Organic	1,198,021 (28.17%)	3,585,029 (34.21%)	00:02:58
(direct) / Direct	659,984 (15.52%)	1,494,743 (14.26%)	00:02:45
m.facebook.com / Referral	97,665 (2.30%)	118,749 (1.13%)	00:01:10
yahoo / Organic	35,798 (0.84%)	77,449 (0.74%)	00:02:34

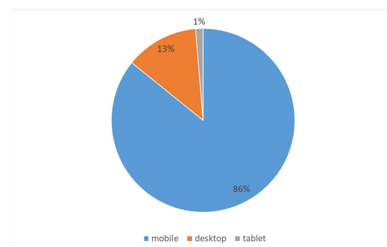

Fig. 6. Pie Chart for Device Usage in terms of FMM

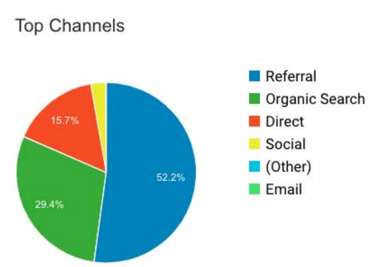

Fig. 7. Pie Chart for Multiple Channels in terms of FMM

B. Acquisition

Table I summarizes top 5 sources, # fo users, # of session and average session duration for the coming audiences of FMM. Obviously, the governmental domain (*https://mask.pdis.nat.gov.tw/*) holds about an half of traffic. This website introduces and reveals all registered collaboration services between MoHM and hacker communities. In other words, when disaster just started, it is extremely neccesary to

Social Networks Platform	Sessions	Avg. Session Duration
Facebook	137,132 (87.99%)	01:20
Line	15826 (10.15%)	03:04
Twitter	776 (0.5%)	01:05
Youtube	644 (0.41%)	01:04

create a corresponding platform since people will trust and rely on it. Accordingly, some people utilize Search Engine (Google and Yahoo) to search related information. 15.52% users directly access to the platform either with saved bookmarks or mobile apps. Finally, Facebook is also a channel that small portion of people will use to link to FMM. However, we can obviously observe that people referred from Facebook stay shorter (1 minute and 10 seconds) than users from other channels (greater than 2 minutes), indicating that Social Media Users requires instant and partial rather than detail but complete information. Among all users utilize Social Media Platforms as a channel to access crisis informatics system, as Table V-B shown, Facebook and Line dominate the social media usage regarding Face Mask information in Taiwan. Compared with the research report on daily usage of social media [22], Youtube, Facebook and Line are the top 3 platforms in Taiwan. However, during disaster, the characteristic of Youtube is not capable for broadcasting crisis information. Instead, Facebook and Line provide more short message and Interactivity. We also observe that the duration of Line users (3 minutes and 4 seconds) is signficantly longer than others (below 1 and an half minute), indicating the point-to-point communication provide detail and careful information, comparing with broadcasting browsing methods, such as Facebook public pages.

VI. Conclusion

This study introduces a model for a crisis informatics system, informed by our work with public health officials and the hacker communities. The result of this collaboration has been considered as a critical component in fighting COVID-19 in Taiwan. Secondly, our study also suggests that the users query peak for appropriate PPE was able to be detected. This gives us a predictive power previously lacking, since the trends usually occurred after the official announcement for face masks policy change, indicating people are afraid of the lack of supplies when official public health policy is distributed, creating a fear of missing out among citizens. Source and Medium have also been studied, which suggests that people rely on Official website, search engine, and social media to obtain information in the midst of crisis. This disparate source of information for citizens can be alleviated with the introduction and development of a robust crisis informatics system. Our work contributes academically to understanding how simple measures can positively impact a society's resiliency to a pandemic, specifically exploring this in the context of PPE preparedness in Taiwan.

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