SOCIAL IMPACT ANALYSIS BY SMART PHONE VOICE

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Abstract. *We have previously reported on the use of voice analysis technologies to assess stress and depression levels. In this study, we used data from a smartphone application called MIMOSYS (Mind Monitoring System), which uses this technology, to see if we could show the impact of incidents such as earthquakes and pandemics on the mental health of the general public. In the case of the Kumamoto Earthquake, we found there were regional differences in its impact on people's mental health. In addition, we found that, during the coronavirus (COVID-19) pandemic, people actually felt more stressed about restrictions related to self-isolation than from fear of the pandemic itself. The study suggested that, if this technology were to be used more widely, it could, potentially, enable better policymaking and target regions that need assistance when such an incident occurs.*

Keywords: Kumamoto earthquakes, Covid-19 pandemic, social psychological impact, voice biomarker, smartphone application

1. INTRODUCTION

Recently, interest has been growing in research using speech as a biomarker [1, 2]. This type of research has become possible due to the development of computers, that is, the vast improvement in computers' processing speed. For example, with regard to input devices, the paper tape used for data entry in the 1960s has been replaced by keyboards, mice, touch panels and, more recently, voice input. Smartphones, now used by most people, have more computing power than former supercomputers, and voice-operated devices like smart speakers are becoming commonplace. In other words, it has become extremely easy to capture and analyse speech. In medicine, the interest in speech biomarker research is growing because it is a way to potentially provide doctors with objective indicators in domains where they have to rely too heavily on their subjective judgment.

We have already published a number of studies on technologies for assessing stress and depression levels in the human voice [3-7]. In brief, using a technology by AGI, Inc. Japan called Sensibility Technology (ST), a speaker's emotions can be inferred

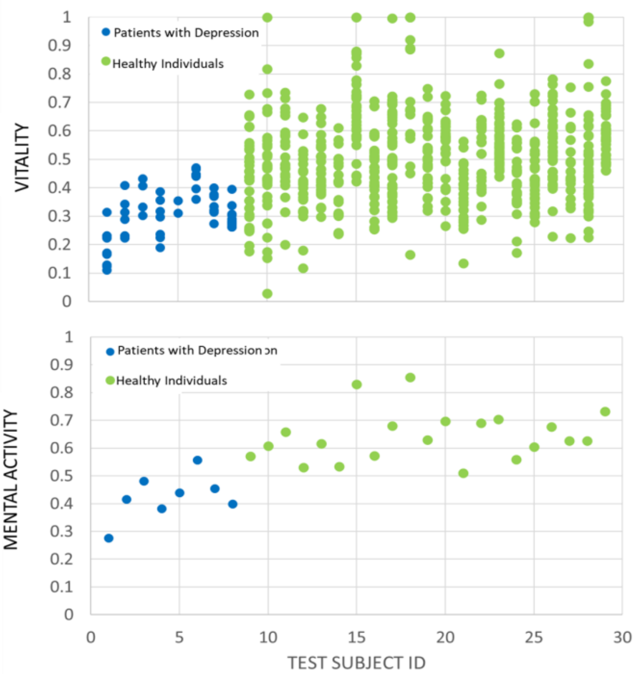

Fig. 1: Vitality and mental activity: Healthy individuals vs. patients with depression [9]

The vertical columns show multiple measurements for the same subject. In healthy individuals (in green), vitality fluctuated significantly. In patients with depression (in blue), fluctuations were smaller and they never exceeded 0.5. Mental activity, which takes into account the two-week vitality mean and variation, can be used to easily identify patients with depression.

from their voice. First, ST assesses the levels of four emotional components, namely, joy, sorrow, anger, and calmness, as well as the level of excitement in the person's voice. Using these emotional levels, a "vitality index" is calculated from the balance between joy and sorrow and the balance between calmness and excitement. In addition, a "mental activity index" is calculated from the mean and variation in vitality levels over two weeks [8]. As the results in the graphs in Fig. 1 show, the less energetic, that is, the more stressed the participants, the lower their mental activity level [9]. This technology is already used in the Mind Monitoring System (MIMOSYS), a smartphone application developed by PST, Inc. Japan, which is publicly available and can be used globally. In Japan, cloud services using it for corporate health management have been developed and it is preinstalled on some smartphones.

MIMOSYS is most commonly used to monitor mental health. It raises user awareness of their mental states, facilitating behavioural change [10]. An advantage of using voice in this way is that, because it is non-invasive, continuous monitoring is possible. In addition, data sharing allows for remote monitoring. That is, in cases in which self-monitoring does not result in behavioural change, others can intervene to assist [11]. Fig. 2 shows an example of a person who ended up in a crisis as stress due to personal problems mounted, until professionals intervened to help the person out of their crisis.

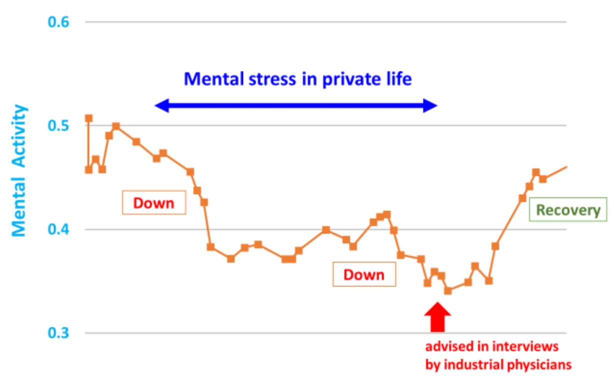

Fig. 2: Monitoring mental health using MIMOSYS: An example [11]

Although prominent declines were seen in mental activity during a period of personal stress, the activity level returned to normal after interventions by an occupational physician.

Another use of MIMOSYS is to screen for mental health conditions. As already mentioned, using the voice makes the screening process simple and non-invasive. As a result, it could be used in large populations. In addition, because the indicators derived are objective, they are free of reporting bias (i.e., participants consciously responding to health-related questions selectively resulting in an underreporting of symptoms) seen in assessments using a questionnaire (Fig. 3). However, although a single voice analysis by MIMOSYS has about the same sensitivity as a commonly used questionnaire, its specificity is low, resulting in many false positives (Table 1). This can be overcome by analysing two weeks of speech data, but the issue remains when the application is used for screening.

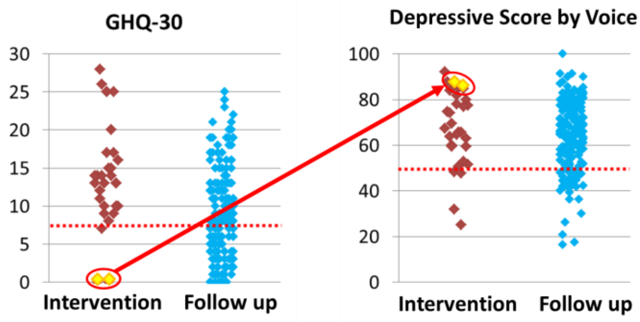

Fig. 3: A comparison of GHQ-30 (a self-administered questionnaire) scores and voice analysis scores for depression

Of the individuals found to be in need of medication or counselling (the intervention group) based on interviews, two had scores on the self-administered GHQ-30 that suggested reporting bias. Voice analysis was able to rate their conditions as severe. However, of the participants thought to be in need of follow-up treatment (the follow-up group), voice analysis rated more of them as being depressed than the questionnaire (16th World Congress of Psychiatry presentation materials).

Table 1: A comparison of GHQ-30 scores and voice analysis scores for depression

Voice Analysis		Medication & Counseling		
		+	-	
Score	50<=	26	162	188
	50>	3	34	37
		29	196	

Sensitivity: 0.897, Specificity: 0.173

GHQ=30		Medication & Counseling		
		+	-	
Score	7<=	27	123	188
	7>	2	73	37
		29	196	

Sensitivity: 0.931, Specificity: 0.372

While both voice analysis and the GHQ-30 demonstrated good sensitivity, voice analysis demonstrated poorer specificity (16th World Congress of Psychiatry presentation materials).

The third way MIMOSYS can be used is to determine the effectiveness of an intervention [12]. Fig. 4 compares the effectiveness of a stress resilience programme over time for participants who followed the programme for 13 days or more with those who dropped out by day 12. Participants in a state of good mental health at the start did not experience any benefit from the programme, so lost motivation and

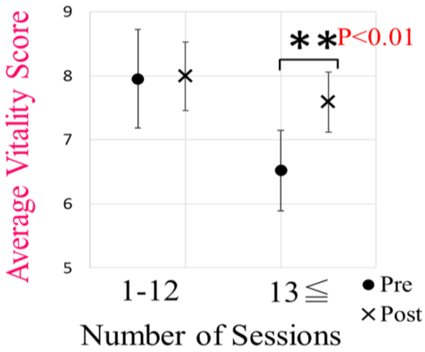

Fig. 4: Intervention effectiveness evaluation using MIMOSYS [8]

The effectiveness of a stress resilience programme was compared for the two groups using MIMOSYS. Individuals who had dropped out of the 50-session programme by the 12th session, had high vitality scores to start with and no change in those scores when they dropped out. Individuals continuing for 13 or more sessions had low scores at the start and an improvement was seen due to the intervention.

dropped out. However, those who were stressed to begin with did feel some benefit and continued with the programme, and consequently their mental state improved.

In the same way that the effect of an intervention on mental health can be shown, it should therefore be possible to find out how much of an impact a stressful event has on people. Thus, the purpose of this study was to investigate the emotional impact of disasters on people, using data from a publicly available smartphone application.

2. DATA COLLECTION

The voice data were collected and analysed by MIMOSYS, which was installed on individuals' smartphones. When a call was made, only the user's voice was recorded and when the call was completed, the data were automatically analysed and the results anonymously saved on the phone and either on a server owned by the University of Tokyo or by PST, Inc. The voice data on the phone were deleted immediately after analysis. The data saved on the servers were associated with a number unique to each phone that could not be used to identify the phone's owner.

2.1. The Kumamoto Earthquake

On 14 April 2016, an area in western Japan centred in the Kumamoto Prefecture experienced a very unusual series of earthquakes. During the first two days, there were three consecutive earthquakes with magnitudes of 6 or more and a total of 20 earthquakes with magnitudes of 5 or more over six days following the first earthquake on 14 April. The study period was divided into three five-day periods: the five days prior to the earthquakes (P0), the five days after the earthquakes started (P1), and the five days of smaller aftershocks that followed (P2) (Fig. 5).

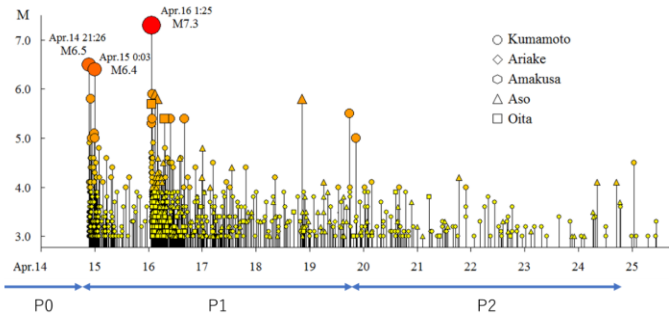

Fig. 5: The Kumamoto Earthquake: Time, scale, regional distribution

During the first two days, three earthquakes of magnitude 6 occurred in succession. Overall, for the six days starting on 14 April 2016, 20 earthquakes of magnitude 5 or more occurred. Chart is based on
https://www.jma.go.jp/jma/indexe.html (
https://commons.wikimedia.org/w/index.php?curid=48378131)

The sample consisted of 236 of the 3,125 MIMOSYS users who had made one or more calls during at least two of the three periods. Those users were grouped into nine geographical areas for the analysis. In Fig. 6, the area in red was the epicentre and the areas in orange were near the epicentre. The rest of the areas are shown in yellow except for the area in blue which was the region devastated five years previously by the Great East Japan Earthquake.

Because users of the application were concentrated in metropolitan regions, the number of participants in other regions was small. However, characteristic trends for each region were evident. In the disaster area near the epicentre (in red), vitality and mental activity levels fell during the period of severe seismic activity (P1) and then recovered somewhat afterward (P2). The magnitude of the impact of the earthquakes on mental health was evident. In regions adjacent to the disaster area, depression gradually increased. The fact that the epicentre moved every time there was another earthquake may have increased people's anxiety about becoming the next victims. In the other regions, no significant changes related to the timing of the earthquakes were found. However, in the region that was affected by the Great East Japan Earthquake five years before, changes were found that differed from all the other regions. Without having conducted any further investigation, we could

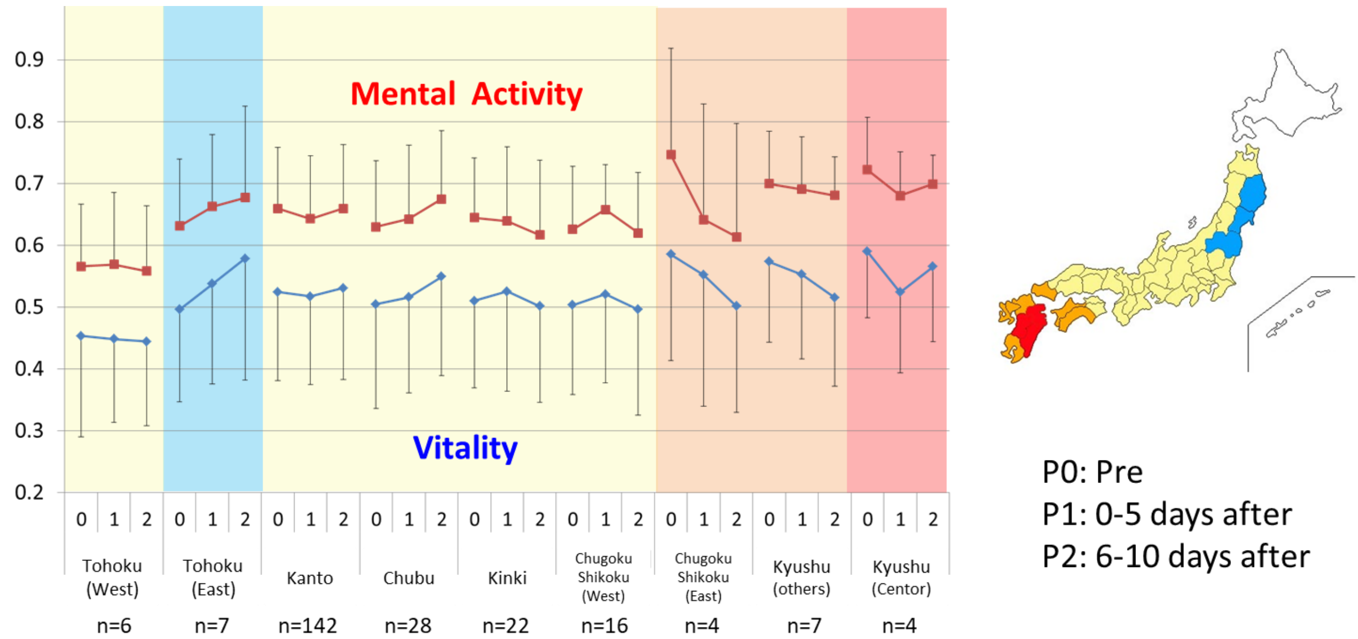

Fig. 6: Kumamoto Earthquake: Changes in vitality and mental activity by region [10]

In the disaster area near the epicentre (red), vitality and mental activity levels fell significantly during the severe seismic activity and recovered somewhat afterward. In regions near the disaster area (orange), depression gradually increased. In the other regions (yellow), no significant changes related to the timing of the earthquakes were found. However, in the region that was victim to the Great East Japan Earthquake (blue) five years before, changes were found that differed from all the other regions.

only speculate that this difference could be indicative of responses related to post traumatic stress disorder (PTSD) or other psychological conditions.

2.2. The COVID-19 pandemic

Although the spread of the coronavirus (COVID-19) pandemic appears to have peaked in some countries as of this writing, with 130,000 new infections being reported daily [13], and with no sign of the pandemic coming to an end. In addition, many countries that had reopened their economies once new infections seemed to be under control are now seeing a second wave of infections.

With no effective cure or vaccine available, treatment is centred on controlling symptoms in order to save lives. In the early stages of the pandemic, countries in the midst of the epidemic took preventative measures that kept people from coming into close contact with others by locking down cities and having everyone stay home, and going out only when necessary. However, now, the process of reopening economies and resuming life is gradually accelerating. To make that possible, people are asked to practice social distancing in an attempt to reduce actual contact with others. These measures have made people feel isolated and brought economies to a standstill. As a result, life has become hard for many due to a loss of employment or reduced income. Various authoritative bodies, including the World Health Organisation (WHO), have drawn attention to the need to care for one's own and others' mental health [14].

Unfortunately, there is no clear answer to the question: "How much impact has the pandemic had on people's mental health?" Of course, some evidence of the impact has come to light, albeit gradually. For example, a Chinese study found that nearly half of the healthcare professionals caring for patients with COVID-19 complained of depressive symptoms [15]. In addition, Rogers et al. performed a review and meta analysis of studies of psychiatric conditions in patients with COVID-19 [16]. However, as far as we could establish, there have been no studies looking at objective indicators of mental health for an entire society. Thus, we performed a study based on data collected through MIMOSYS to find out how stressed a sample of Japanese were due to Japan's self-isolation measures [17].

For the present study, the study period was from 1 January to 6 June 2020. Of the 5,246 users of the application in Japan, 126 users of android OS smartphones that continuously performed the automatic voice analysis during calls were selected for the sample. Of those, we only selected the analysis results when at least three call analyses were performed in a two-week period. As a result, the study's analysis was based on 8,669 call analyses for 90 users. In addition, weekly means and standard errors for the overall sample were calculated from the weekly means for each individual.

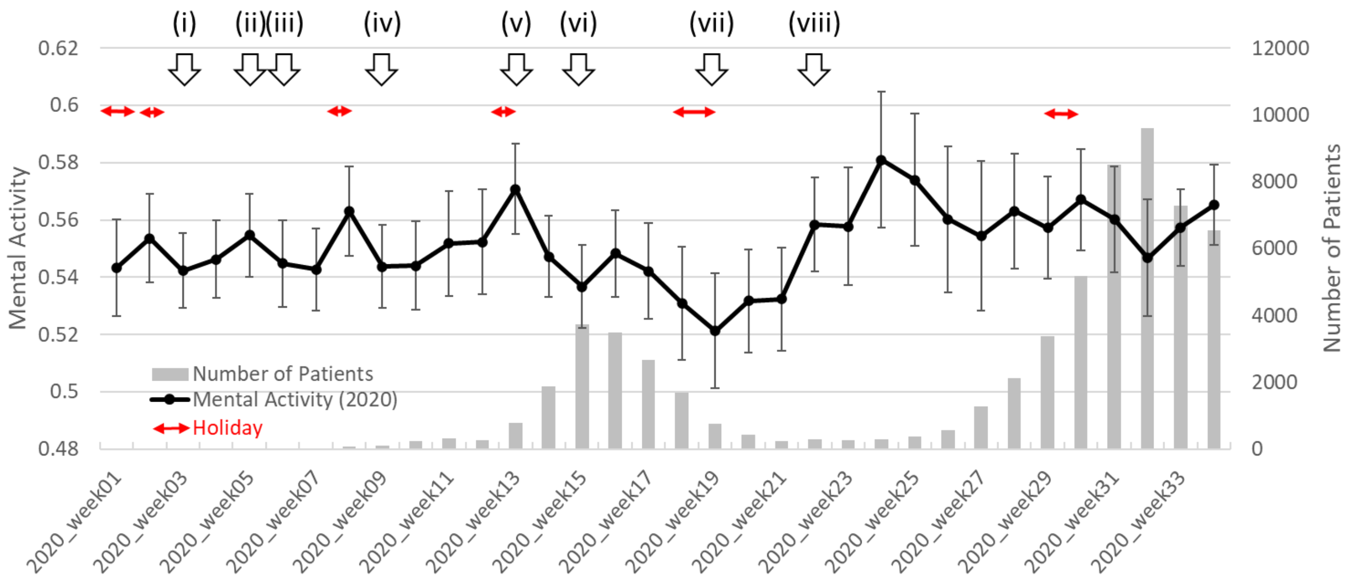

Fig 7.: Change in voice stress mental health indicator due to COVID-19 pandemic

The graph shows the weekly means and their standard errors. The gray background represents the period of outing restrictions. (i) First case of infection reported in Japan. (ii) Charter plane brings 206 Japanese back from Wuhan. (iii) The WHO declares a public health emergency; the quarantine of the Diamond Princess cruise ship begins. (iv) Elementary, middle, and high schools closed. (v) The governor of Tokyo mentions lockdown. (vi) State of emergency declared (voluntary isolation at home). (vii) State of emergency extended. (viii) State of emergency lifted.

There was no clear correlation between the number of patients reported and mental activity,

Reviced form [17]

Fig 7. shows the trends in mental activity over the 23 weeks of the study period. Although there were short-term declines due to several pandemic related events, the steepest declines were related to the state of emergency which mandated voluntary self-isolation at home. Specifically, events that coincided with moderate temporary declines in mental activity were: (i) the first case of infection being reported in Japan; (iii) the WHO declaring a state of emergency and the Diamond Princess cruise ship being put under quarantine; and (iv) the closing of elementary, middle, and high schools. However, mental activity started declining continuously starting with (v) the governor of Tokyo announcing a lockdown, and then the decline accelerated with (vi) the declaration of a state of emergency (voluntary self-isolation at home). Subsequently, when (vii) the state of emergency was extended, mental activity began to recover; and, when (viii) the state of emergency was lifted, it returned to normal levels. A potential explanation for this could be that, when the state of emergency was extended, it was done with a clear end date. The general public may have responded more negatively to open-ended restrictions that directly affected them than to fear of the pandemic. Then, when a clear deadline for the restrictions to be lifted was announced, their mental activity, based on greater optimism, was able to return to normal.

3. ETHICAL CONSIDERATIONS

This study was conducted with the approval of the Ethics in Research Committee of the University of Tokyo School of Medicine and in compliance with the MIMOSYS user agreement and the privacy policy of the developer (PST, Inc.). The need to obtain informed consent from the owners of the phones was waived.”

4. DISCUSSION

In this study, we presented a method for using voice analysis to assess the impact of major incidents, such as earthquakes and pandemics, on the mental health of the general public. A limitation of this study was that the sample may have been too small to eliminate the effects of personal biases in the participants . The use of larger samples in future studies should allow for more representative assessments of the impact of such incidents on the entire country or a specific region. That could enable better policymaking and better identification of regions that need assistance when such an incident occurs.

On the other hand, in order to expand the collection of this kind of data, the reality is that barriers protecting personal information would need to be negotiated. In fact, from the perspective of the need to protect personal information, the automatic recording of conversations has recently been disabled on android phones. For the same reason, this was already true for iPhones. This was an issue given that our research to date has shown that the application usage rate falls significantly when conversations cannot be recorded automatically and the user has to open the application to record conversations manually. Going forward, it appears there will be a need to look into this mechanism or other means to run the application continuously.

5. CONCLUSION

This study presented a method for assessing the impact of incidents such as earthquakes and pandemics on the mental health of the general public using voice analysis. Although the potential for personal bias in the results was not eliminated due to the small sample size, the study was able to adequately demonstrate the viability of this approach.

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