Negative Information Measurement at AI Edge: A New Perspective for Mental Health Monitoring

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This work was supported by the China National Natural Science Foundation (No. 61802138, No. 61802139). This research is supported by the Shenzhen Institute of Artificial Intelligence and Robotics for Society (AIRS). This work is also supported by the Technology Innovation Project of Hubei Province of China under Grant (No. 2019AHB061).

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1533-5399/2022/01-ART62 $15.00
https://doi.org/10.1145/3471902

The outbreak of the corona virus disease 2019 (COVID-19) has caused serious harm to people's physical and mental health. Due to the serious situation of the epidemic, a lot of negative energy information increases people's psychological burden. However, effective interventions against mental health problems are not in abundance. To address such challenges, in this article, we propose the concept of negative information to describe information that has a negative impact on people's mental health. To achieve the measurement of negative information, the level of mental health inversely measures the degree of negative information. Specifically, we design a system to measure the negative information used to monitor the mental health state of the user under the impact of negative information. The cognition of mental health is realized based on the intelligent algorithm deployed on the edge cloud, and the needs of users can be responded to in real time in practical applications. Finally, we use real collected dataset to verify the influence of negative information. The experiments show that the system can achieve negative information measurement and provide an effective countermeasure for solving mental health problems during a pandemic situation.

CCS Concepts: • **Applied computing** → **Health informatics**; *Law, social and behavioral sciences*; • **Mathematics of computing** → *Information theory*; Mathematical analysis;

Additional Key Words and Phrases: Negative information, mental health, cognitive computing, edge cloud

ACM Reference format:
Min Chen, Ke Shen, Rui Wang, Yiming Miao, Yingying Jiang, Kai Hwang, Yixue Hao, Guangming Tao, Long Hu, and Zhongchun Liu. 2022. Negative Information Measurement at AI Edge: A New Perspective for Mental Health Monitoring. *ACM Trans. Internet Technol.* 22, 3, Article 62 (January 2022), 16 pages.
https://doi.org/10.1145/3471902

1 INTRODUCTION

The corona virus disease 2019 (COVID-19) induced pneumonia outbreak has seriously endangered the health and lives of people, changing day-to-day lifestyle and production routines greatly. The rapid development of social networking services and new media have expanded the channels of information communication and, with the rapid development and the ceaseless increase of reported coronavirus cases, a massive amount of information is produced and spread, including the daily increase of infected cases, scarcity in medical resources, and numerous exaggerated news and rumors that influence the life of people in different ways. Simultaneously, some researchers have shown that the outbreak and prevalence of COVID-19 have caused a large number of people's emotional distress and mental problems, among which the common feature is the occurrence of depression and anxiety, and even the increase in the prevalence rate [1, 2].

There are many incentives, including gender, region, emotional relief methods, network use time, the influence of people around [3]. One of the most important incentives is that to obtain external information normally, people in a state of social distance or home isolation are more likely to contact high **information and communication technology (ICT)** when they are alone. Previous studies have shown that the increase of ICT use frequency will aggravate the occurrence of mental health problems such as anxiety and depression [4, 5]. In this article, a new concept, negative information, namely, false, unreal, bad, and harmful information or news, is proposed and can cause harm to people's physical or mental health. In the context of the COVID-19 epidemic, the increase in the frequency of social media usage means that people are exposed to more negative information. A large number of negative information will aggravate the transmission of negative energy, such as social events caused by the epidemic situation, uncertain news, and inflammatory emotions [6, 7].

Thus, it is reasonable to conclude that negative information might change the mental status of people and lead to nervousness, anxiety, and so on. Abnormal mental status may severely impair the life, work, and study of people and even cause depression, anxiety, and other mental disorders, which can further lead to substantial adverse consequences on their health. According to World Health Organization statistics, nearly 4.4% of the global population suffers from depression, while another 3.6% from anxiety disorder [8]. Mental disorders have become a significant public health problem and important factors impairing the physical and psychological health of people [9]. However, most of the studies on psychological health and mental disorders are focusing on ways to improve the therapeutic schedules and approaches, while little attention is given on factors leading to mental disorders.

Nowadays, there are many researches on psychological intervention under the COVID-19 epidemic [10, 11], including the release of psychological crisis intervention procedures for public health emergencies and online psychological counseling services for the public. Meanwhile, some institutions have conducted the management and control of public opinion and information, increasing social support. However, due to the sudden outbreak of the epidemic, the formulation of psychological intervention measures is still imperfect, and it is urgent to establish more intelligent and rapid response guidelines [12, 13]. One of the key elements to achieve this goal is to explore the underlying causes of mental disorders. However, due to the difference in people's living environment, education level, and tolerance to information, it is difficult to construct a standard to measure negative information. In this article, we focus on exploring the impact of negative information on mental health. By measuring the negative information received by people, it is possible to predict mental health. At the same time, through the evaluation of mental health, the negative degree of negative information is obtained. It is expected to provide more reference and support for psychological intervention.

To judge the relationship between the negative information and mental health, we need to carry out real-time and comprehensive monitoring of the population. In addition to requiring the public to actively report personal information and fill in the questionnaire [14, 15], collecting users' multimodal data through non-interference intelligent devices can ease the public's tension in a more comfortable way. In addition, after deep fusion and analysis based on health big data, how to feed back the results to public in a more intuitive way and monitor their mental state changes in the interaction process can provide strong support for the improvement of psychological intervention measures, which is also a challenging problem.

To address these challenges, we investigate the relation between negative information and the psychological health of people from a new direction. The effects on the mental state of people after receiving negative information were analyzed with the use of wearable devices. The data collected from smart phones and comfortable smart wearable devices, giving information on physical signs, personal characteristics, behavior characteristics, and other multi-modal data of the user, were then roughly processed on the edge cloud and finally offloaded to remote cloud training and study for vital-sign and behavioral modeling. Thus, the main contributions of this article include:

- The concept of negative information was first proposed and the potential connection between negative information and mental health was used to give a measure of negative information. This discovery will be of great significance to the prevention and intervention of mental illness.
- The multi-level system architecture was designed for mental health monitoring. By uploading the multi-modal data collected by the wearable device to the server on the edge cloud, the cognition of the health condition is realized based on the artificial intelligence algorithm.
- An experimental platform was set up to verify the proposed theory. The experiments were performed from two aspects, including group and individual. During the period of the COVID-19, people accepting negative information under the epidemic are more likely to have mental problems.

The remaining parts of this article are arranged as follows: Related work is reviewed in Section 2, the structure of the mental health monitoring system is described in detail in Section 3, modeling analysis is presented in Section 4, applications of the system are illustrated in Section 5, a testbed to confirm the effects of the aforementioned system is set up in Section 6, and the conclusion is presented in Section 7.

2 RELATED WORK

This section introduces the related work of cognitive information and focuses on the research ideas of negative information. At the same time, the monitoring methods of mental health status are summarized.

2.1 Polarity of Cognitive Information

In this age of Internet, the data size of information is exploding and the popularity of mobile internet devices such as mobile phones, computers, tablets, and the emergence of new media are bringing massive information to everyone every day. People have constant access in a world relying on interlinked information, but different people may be influenced by such information to different extents and in different aspects. In other words, the same piece of information can be beneficial to one individual, but harmful to another. Chen et al. [16] presented the concept of *polarity of cognitive information*, that is, polarities can be found in a piece of information and positive information shows positive effects when is delivered and interlinked with people, while negative information has negative impact. For example, an encouraging word will make people energetic, which is a sign of positive polarity, while some information related to gambling and violence on the Internet will make people addicted, showing a negative polarity. Therefore, considering the polarity of information is of critical importance.

2.2 Methods for Monitoring Mental Health Status

In early days, mental health checks were mostly conducted by ways of questionnaire and face-to-face diagnosis. In recent years, with the rapid development of big data, cloud computing, **artificial intelligence (AI)**, and other related technology, medical services have evolved considerably and mental health can be analyzed at any time and place. Monitoring methods currently available for mental health and mental state can be roughly classified into the following types:

Monitoring based on mobile devices. Mental health monitoring relying on mobile devices can be further classified into two types: active data and passive data. Active data refers to data actively recorded by the user through mobile devices that record the mental health state of the user on a daily basis. Passive data refers to objective data collected by the devices, such as voices and social networking, without active recording by the user. In Reference [17], the author designed a SNAPSHOT research to study the pressure and mental health reported by college students in their daily life. Every student needed to complete the questionnaire on pressure and mental health and actively report the data by uploading the electronic diary on a daily basis. Mental health was classified through the received data and high accuracy could be obtained.

In another research described in Reference [18], the authors collected objective data recorded by the smart phones of bipolar disorder patients and healthy individuals to analyze usage of smart phones. The experimental results showed the correlation between bipolar disorder symptoms and smart phone data, and the authors made classification for affected disorder patients and healthy individuals based on mobile phone data. Although actively reported data shows effects in alleviating the symptoms of mental disorders, many patients might refuse or forget to record, and their active report may be affected by memory bias and emotional fluctuation. Collection of potential objective data through mobile phones is easier [19], making passive data collection for mental health monitoring using mobile devices an easier task. Cho et al. [20] collected two years' worth of objective data of 55 patients with mental disorder using mobile phones and wearable devices and monitored the occurrence of mental disorders with machine learning algorithms. However, this method is designed for the purpose of improving prognosis of patients and the effects on other groups of people are unknown.

Monitoring based on questionnaire and interview dataset. In several existing research centers, databases refer to recorded interview records. Zhang et al. [21] proposed a multi-modal in-depth learning framework using **bipolar affective disorder (BDC)** corpus and E-DAIC as the database. This corpus consisted of semi-clinical interviews and used machine learning algorithms to process texts, voice bands, and other multi-modal characteristics and finally realized analysis and detection of mental disorders.

Monitoring based on social networks. The popularity of social networks and the emergence of social networking **applications (APPs)** make it possible to monitor the mental health state of people through social networking. Dubey et al. [22] presented a machine learning framework where data of journal files on social networking was used to monitor mental problems like internet addiction. Shen et al. [23] built a dataset by collecting social media data from Twitter and presented a model to detect depression patients on Twitter. However, this method was hardly applicable on other applications in view of the great pressure on detection work and the low probability of depression patients updating their moments.

Mental health monitoring methods in early days focused more on the accuracy rate of health state monitoring based on existing symptoms and results. In the present study, while accuracy is still considered, we particularly focus on the reasons leading to changes in mental state from the view of negative information.

3 SYSTEM ARCHITECTURE OF MENTAL HEATH MONITORING

The measurement of negative information needs to be achieved through the evaluation of mental health. In this section, we introduce the multi-level system architecture in detail, which includes the data collection layer, the data processing layer, and the result feedback layer, as shown in Figure 1. The data collection layer consists of two important components: wearable devices and mobile phone, the data processing layer is equipped with algorithms in edge cloud and remote cloud to analyze collected data, while the result feedback layer reported the analysis result of the system and suggested countermeasures.

3.1 Data Collection Layer

To detect changes in the user's mental state as precisely as possible, it is necessary to acquire data from multiple layers and multiple dimensions. The data in this study was acquired from three sources: physical signs, personal characteristics, and behavioral characteristics. Changes in the physical signs of the users are acquired through smart phones and wearable devices. The wearable devices used in the study consisted of smart bracelets and smart clothes, which are designed with advanced technology to avoid causing the user discomfort and resistance monitor indexes including **electrocardiogram (ECG)**, blood pressure, body temperature, and **respiration (RSP)** signals.

Moreover, social characteristics refer to changes in the facial expressions and voice of the user, comments, forwarding, messages, and other text data generated by the user, after getting the information. Cameras and intelligent voice assistant are equipped in the smart devices to capture changes in facial expressions and voice emotions of the user. Text data are collected through mobile phone applications. For the purpose of privacy protection, the user is able to decide whether to upload the log data and only clips of the voice records reflecting changes in mental state are kept

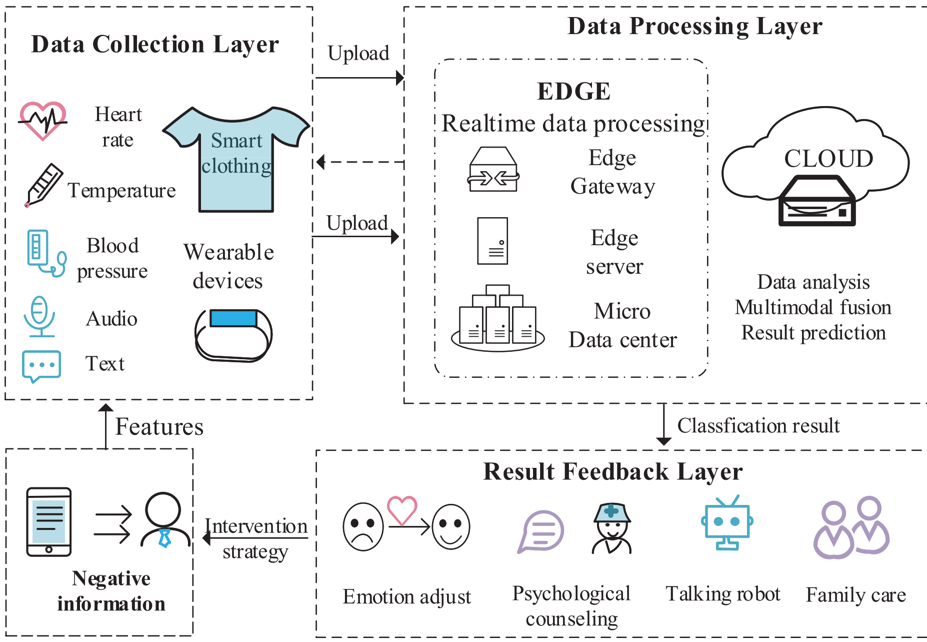

Fig. 1. Multi-level system architecture of mental health monitoring.

in the system. Behavioral characteristics refer to changes in the sleeping status and frequency of social activities of the user. The sleep quality and movements of the user are recorded by wearable devices, and the use frequency of mobile phones and the frequency of chatting on social networking applications are recorded as well.

3.2 Data Processing Layer

For the purpose of minimizing delay and enhancing interpretation, the data is sorted and screened at first level on the edge cloud. It will greatly help to detect valuable information from massive data. For example, blurry pictures and voice files with loud noises are deleted and the data is pre-processed. Then, the data is offloaded to the remote cloud for further training and study. The remote cloud provides services such as data storing, cleaning, and analyzing. Powerful machine learning algorithms are arranged at the cloud end to integrate and treat each mode of data. Additionally, a model is set up to analyze the mental health state under the impact of negative information for all-round and continuous mental health monitoring.

3.3 Result Feedback Layer

The result feedback layer monitored physiological and mental health data, available to the user so they could keep informed about their mental health state, take preventive measures, and seek medical assistance. The reporting mechanism consisted of the real-time presentation of results, regulation and intervention on mental state, the provision of medical advice, and so on. Adjustments can be made to the system in time based on the interaction with the user, and user experience can be optimized by seeking for the mode of adjustment better suited for them through long-term study.

4 SYSTEM MODEL FOR MENTAL HEALTH CLASSIFICATION AND MONITOR

In this section, we establish a model to monitor the mental health state based on acquired data and make comprehensive analysis on responses toward negative information. We classify the collected data into physical signs, social characteristics, and temporal-spatial behavior pattern data and process separately.

4.1 Features Extraction

4.1.1 Physical Signs. Physical signs such as ECG and RSP signals were acquired via wearable devices over long periods of time. Acquired data could be enlarged and filtered and the data exceeding normal medical range should be discarded. For instance, heart rate below 50 beats per minute were abandoned. Physical signs such as heart rate can vary considerably between different people, even in normal status. The focus of this study was the change in physical signs. Therefore, the signs were normalized. After preprocessing, we extracted typical statistical features for ECG and RSP [24], including the mean value $\overline{r}_{mean}$, the standard deviation σ_r, the max value max_r, the min value min_r, the range between max and min values $range_r$, first-order difference $diff_1$, second-order difference $diff_2$, the details are as follows

$$\overline{r}_{mean} = \frac{1}{N}\sum_{i=1}^{N} r_i, \tag{1}$$

$$\sigma_r = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(r_i - \overline{r}_{mean})^2}, \tag{2}$$

$$diff_1 = \frac{1}{N-1}\sum_{i=1}^{N-1} |r_{i+1} - r_i|, \tag{3}$$

$$diff_2 = \frac{1}{N-2}\sum_{i=1}^{N-2} |r_{i+2} - r_i|, \tag{4}$$

where r_i is the physical data, and N is the total dimension of the vector. For different physical signals, we use feature fusion to process, apply normalization method to unify dimension, and use **principal component analysis (PCA)** to reduce dimension of features. Moreover, these features are input into the **k-nearest neighbors (KNN)** model for classification, and the output of the model is y.

4.1.2 Social Characteristics. Social characteristics were derived from voice and text fragments considering that the data collection process did not cause too much interference to the user's daily life. For the purpose of privacy, information related to social characteristics was uploaded every 24 hours with consent of the user.

Voice data. Research has proved that mental disease leads to obvious changes in the voice characteristics of people [26]. For the purpose of privacy, only the part of voice data reflecting changes in mental state was stored in clips. The open-source tool openSMILE [27] was used to extract voice characteristics, and the voice data was segmented in 25 ms clips. Low-order descriptors (Mel-Frequency Ceptral Coefficients, MFCC, etc.) of each frame were calculated and later integrated and go through dimensionality reduction to get the final eigenvectors.

Text data. Text data were derived from the comments and messages from the user when they see or forward a piece of information. In view of the strong subjectivity and the irregular arrangements of words in this text form, preprocessing on the text data was conducted first, including the processing of participles, stop words, and so on, and emotion icons that cannot be identified and modal particles having no sense were eliminated. Characteristics extraction was conducted based on Doc2vec [28], which is the expansion of Word2vec, while Word2vec was used to convert the text corpus into word vectors. Doc2vec combined paragraph vectors and context words or averaged them to predict the next word. This method can train word vectors and sentence vectors as well. The semantics are extracted, while word order is also considered.

By using the early fusion strategy, the feature vectors corresponding to audio and text data are concatenated together to obtain multi-modal features. We used the **long short-term memory (LSTM)** model based on the attention mechanism to classify the mental health status. The attention mechanism could make the model pay more attention to the important part of the input data [29]. The output of the LSTM model is λ_i, w is the parameter vector of attention mechanism, and the weight of attention mechanism α_i can be obtained through the formula:

$$\alpha_i = \frac{exp(w^T \lambda_i)}{\sum_{t=1}^{T} exp(w^T \lambda_t)}, \tag{5}$$

where w^T represents the transpose matrix of w. The output of the attention layer is:

$$v = \sum_{i=1}^{T} \alpha_i \lambda_i, \tag{6}$$

where T is the number of time slices that need to be calculated in the attention layer. Then splice the output of attention layer with the output of LSTM as V, and input it into softmax to get the result of mental health status classification [30]:

$$y^* = P(s|V, W, b) = softmax(W \cdot V + b), \tag{7}$$

where y^* is the output result, representing the probability of being assigned to each class, s is the category, W is the weight matrix of fully connected layer, and b is the bias factor.

4.1.3 Temporal-spatial Behavior Pattern. Behavioral pattern is of great significance to the evaluation of individual mental health. As a supplement to physical data and social data, on the one hand, behavioral pattern is an in-depth manifestation of physical signs, such as the interaction between sleep status and physical signs would also affect mental state. Insomnia is also a mental disorder [31]. Thus, in this article, we first consider the user's sleep status. The sleep situation can be roughly estimated via the mobile phone sensor, while both the duration and quality of sleep can be estimated based on power consumption, screen unlocking, and ambient light. The get-up time, the go-to-bed time, and the sleep duration were calculated to measure changes in sleep quality. The sleep data can also be obtained by accessing the smart bracelet to make further analysis.

On the other hand, the behavior pattern is the embodiment of individual comprehensive index, which greatly reflects the mental status. Thus, we consider the user's activity pattern. The study showed that when mental status changed, so did the range and frequency of outdoor activities [32]. For example, many people with depression are reluctant to contact with the outside world and stay at home for a long time. It is necessary to count the activities of individuals, including location, time, and activities. It can be found that the behavior patterns of sleep and individual activities are carried out under the guidance of space-time dimension. Therefore, it is necessary to establish the individual behavior model under the space-time dimension. The specific introduction is as follows:

First, for the sleep state, we set the sleep time series of user U under time period T as $Sleep_T^u = \{t_1 : \alpha_1; t_2 : \alpha_2; \cdots ; t_m : \alpha_m\}$, where t represents the timestamp of user u during sleep, and α represents the sleep state, specifically expressed as α = {DeepSleep, LightSleep, RapidEyeMovementSleep, BodyMovement}. Using the data of sleep state under different timestamps, first, the grey theory was used to extract the sleep trend $gm^T(t)$ within a small time range [33], then the LSTM was used to model the local deviation part in each time unit at a small scale to obtain the features $lstm^T(t)$ [34], finally, the evaluation model of sleep status can be obtained:

$$\mathcal{B}_{sleep}(\alpha) = gm^T(t) + lstm^T(t). \tag{8}$$

Second, for the activity pattern, we set the activity time series of user u under time period T as $Activity^u_{T,L} = \{t_1, l_1 : \beta_1; t_2, l_2 : \beta_2; \cdots ; t_m, l_m : \beta_m\}$, where t and l represent the time and location of user u during the activity, and β represents the sleep state, specifically expressed as β = {Exercise, Work, Study, Entertainment}. The probability of each activity P_i can be obtained by using the approximate inference method under different time and location [35], and then the evaluation model of activity pattern can be obtained:

$$\mathcal{B}_{activity}(\beta) = \sum_{i=1}^{m} ln(P(\beta_i|t_i, l_i)). \tag{9}$$

Finally, we fused the results of the sleep state and activity pattern assessment model, and obtained the fusion model of the behavioral pattern and mental state associated with different weight parameters ω under the space-time trajectory:

$$\mathcal{B}_{fusion} = \omega_1 \cdot \mathcal{B}_{sleep} + \omega_2 \cdot \mathcal{B}_{activity}. \tag{10}$$

4.2 Multi-modal Fusion

After each mode was processed separately, multi-mode fusion was performed at last. Decision fusion was adopted for weighted computation of the results of each class, and the final results were obtained [36]. The product of the probability of each class and the weight coefficient $Rate_i$ under each mode was calculated and summed to obtain the score of the class after modal fusion. Finally, the class with highest scores was used as the final predicted result. *Class* is the result vector, and $Class_1, Class_2, \ldots, Class_p$ are its components. And *Result* depends on the maximum value among classes.

$$Class = y \cdot Rate_1 + y^* \cdot Rate_2 + \mathcal{B}_{fusion} \cdot Rate_3 \tag{11}$$

$$Result = argmax(Class_1, Class_2, \ldots, Class_p) \tag{12}$$

4.3 Experience Feedback Model

According to Figure 2, the result of evaluating the overall mental state of the user can be obtained after the fusion of multi-modal data. Then the system will adjust the mental state according to the user's situation evaluated on the different modal data and conduct intervention treatment. In the process of intervening users, some new intervention modes can be developed according to the feedback of users on physical signs, social characteristics, and behavioral characteristics.

The reinforcement learning is used to develop the optimal intervention strategy for users. The details are shown in Algorithm 1. In each round of intervention, R is the reward that is the result of multi-modal fusion when the action A is executed, *Action* (A) represents different intervention modes, including {*exercise*, *entertainment*, *CBT treatment*, *hospitalization*, *psychotherapy* }. The value of *State* (S) is in $\{Class_1, Class_2, \ldots, Class_p\}$, which is the user's mental state category. In the input of the algorithm, σ, ϵ, *epoch* and γ are the setting parameters. The algorithm is the feedback adjustment mechanism for user mental intervention. The terminal state of intervention is the mental state reaches the normal level, and an episode is stopped. In the last, the algorithm will return the corresponding intervention model for users according to different states based on strategy π. In the training process of algorithm, the user's existing state and intervention information are used to obtain intervention actions in different states. After completing training, a state-action

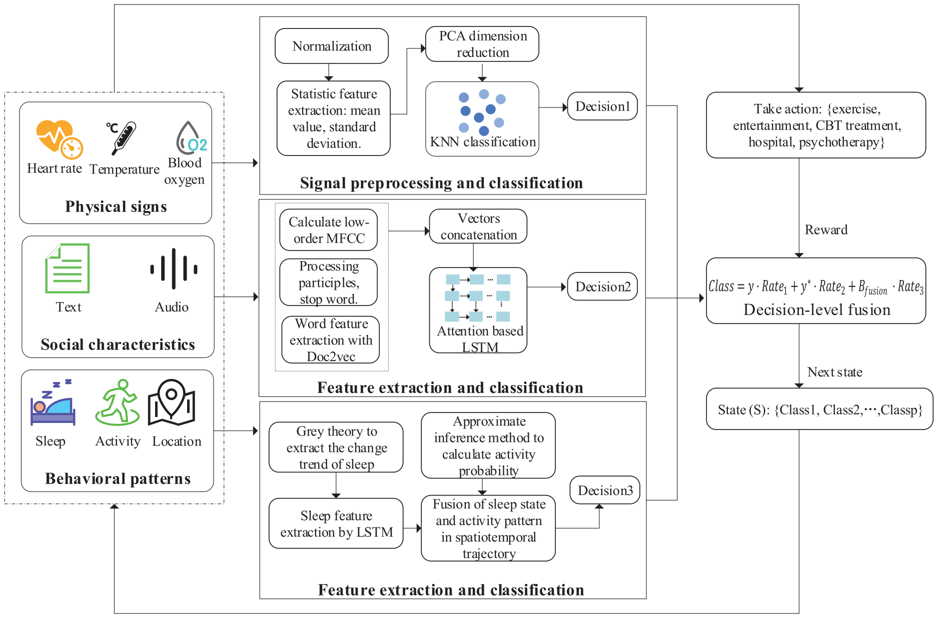

Fig. 2. Algorithm model based on multi-modal data for mental health cognition.

ALGORITHM 1: Dynamic intervention algorithm based on reinforcement learning

Input: Intervention step size $\sigma \in (0, 1]$, greedy value $\epsilon > 0$, epoch *Epoch*, discount factor γ.
Output: Intervention strategy π.

Initialize $Q(s, a)$ for all $s \in State$, $a \in Action$.
for *Epoch* **do**
  Initialize S
  while S is not terminal **do**
    $Q(S, A) \leftarrow Q(S, A) + \sigma[R + \gamma max_a Q(S', a) - Q(S, A)]$
    $S \leftarrow S'$
return Mapping from Q value to strategy π.

table is obtained and it can be utilized to intervention for the user. The algorithm could be adjusted dynamically based on the states of the users. Therefore, it can greatly help users to improve mental health.

5 APPLICATION SCENARIOS OF THE SYSTEM

The correlation between negative information and mental health of different groups of people was analyzed in this section, and four systematic applications for different groups of users were presented, including medical staff in pandemic conditions, regular citizens in pandemic conditions, teenagers with network addiction, and office workers under pressure, as shown in Figure 3.

Medical staff in pandemic. The prevalence of COVID-19 has brought considerable challenge to the work of medical staff. Exposed in negative information for long times, such as the increased number of reported cases, the shortage of medical resources, the great risk of being infected, and the long-term care for patients with severe disease, panic, and pain, can cause psychic trauma to

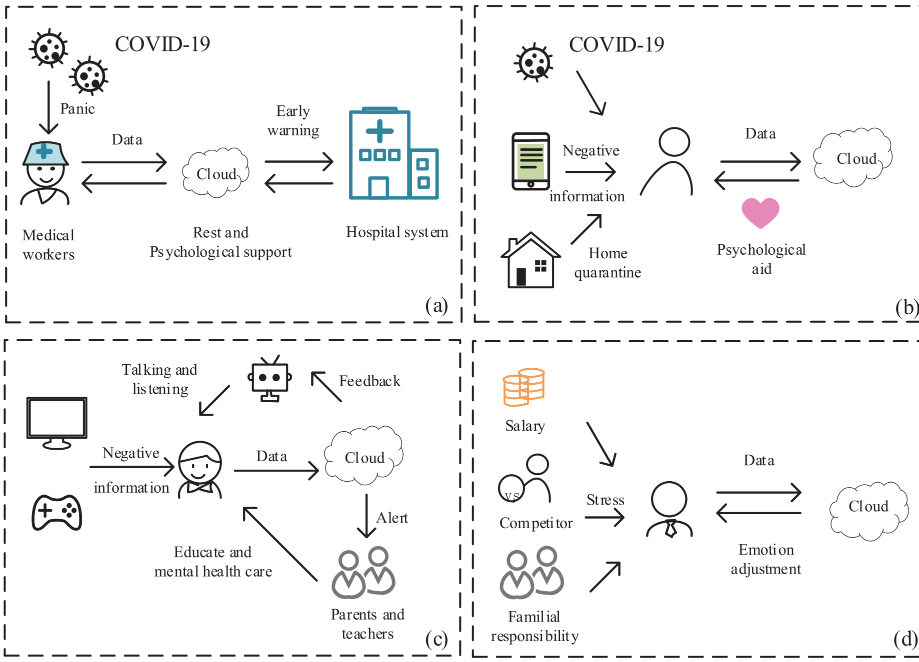

Fig. 3. Application scenarios of the system.

medical staff [1]. Our system can be used to monitor the mental health status of medical staff and be merged into the scheduling system of the hospital to make timely and reasonable adjustments whenever medical staff with poor health state is identified, as shown in Figure 3(a).

Regular citizens in pandemic. The outbreak of COVID-19 has caused sharp increase to the panic and mental health pressure of the public. Additionally, rumors and false news released on social media have caused anxiety, difficulty to fall asleep, and suspicion of illness to the public. Going out to see a doctor in this condition might be risky to certain extent. After collecting information from the user through wearable devices, our system can estimate the mental health of people and provide medical advice and psychological adjustments in time to the public, via network as shown in Figure 3(b).

Teenagers with network addiction. The Internet not only provides positive information, but also brings a lot of negative information. Some of the game designers constantly release negative information in the game, contributing to addictive behavior. Results of addictive behavior include loss of desire to study that leads to lower performance at school, decreased desire to pursue life goals, self-doubt, feelings of inferiority, depression, and anxiety [37]. Wearable devices that record only their mental state can be provided to teenagers with network addiction. If any abnormality is identified, then teachers and parents can be notified to provide psychological guidance. Teenagers can often resist the care of their parents, therefore, an emotional robot provided by the system will aid in communication, listen to their troubles, and pacify them in time, as shown in Figure 3(c).

Office workers under pressure. Pressure and rapid rhythm are common features of modern life. Difficult schooling of kids, comparison among colleagues, low pay, and difficult promotions are some of the concerns in the daily life of an office worker. All are considered negative information, and long-term exposure may lead to mental illness. However, people having mental disorders might delay or refuse medical assistance, due to the stigma that mental illness carries within society and thus miss the opportunity for early interference. The system described in this article can help identify mental disorders early, and emotional adjustment can be provided to people with slight mental disorders to relieve their worries, while medical advice can be recommended for those with severe mental disorders, as shown in Figure 3(d).

6 EXPERIMENT EVALUATION

To further study the correlation between negative information and psychological health and mental disorders, we design two experiments. The impact of negative information brought by the pandemic on the mental state of people is analyzed in the first experiment by collection 15,000 pieces of mental health data from the JingDong Health platform. The second experiment focused on individual and set up a platform for people in the pandemic. Volunteers were recruited and wearable devices were used to collect changes of each index under the stimulation of negative information with the permission of all volunteers.

6.1 Group Perspective

The data collected from the public are used to verify the harm of negative information for mental health to realize the measurement of the degree of negative information. During the COVID-19 epidemic, 15,000 pieces of data were collected through the distribution of mental health evaluation questionnaires on the JingDong Health platform. In the process of questionnaire collection, since the users will be rewarded by filling in the questionnaire to attract users to carry out psychological evaluation, the authenticity of the questionnaire can be guaranteed. At the same time, 15,000 pieces of data cover the group of different genders, ages, occupations, education levels, and regions, which meet the high coverage conditions of group. Therefore, the dataset can be used to carry experiment.

We collected questionnaires on health problems of the public that cover depression screening, generalized anxiety disorder, insomnia severity index, event impact of event scale, and so on, through the JingDong Health platform. People who have never had mental disorders or health problems before the pandemic were selected, and the correlation between negative information and mental health was investigated.

The depression situation of people who always read news during the pandemic period is depicted in Figure 4. The PHQ-9 questionnaire is used to evaluate depression, in which the severity of depression is divided into four levels. The evaluation result of questionnaire is expressed as score. The division standard $0 \leq score \leq 4$ means no depression, $5 < score \leq 9$ means having depressive symptoms, $10 < score \leq 14$ means significant depressive symptoms, and $15 < score \leq 27$ means severe depression. These people expressed in the questionnaire that the more information they received, the more probable they would be negatively impacted. The news they read might include false content or content expressing the severity of the pandemic and thus worsened the panic of the reader. It can be seen that almost half of the people showed depression symptoms, which indicated that negative information might have adverse impact on the mental health of people. According to the results of the PHQ-9 scale and the degree to which people accept negative information, the measurement of negative information through the mapping relationship is realized.

Figure 5 shows that the mental health state of questionnaire samples who answered "Have the following persons been diagnosed with infected cases so far?" and people who have families, friends, classmates/colleagues, or neighbors living in the same residential quarters being identified as infected are classified as people having infected cases nearby. These people were expected to be more impacted by negative information. People having identified cases nearby had higher frequency of worries including that more than 50% of people worried about being infected, 20% of people have difficulty falling asleep and intense emotional fluctuation, and 10% of people often

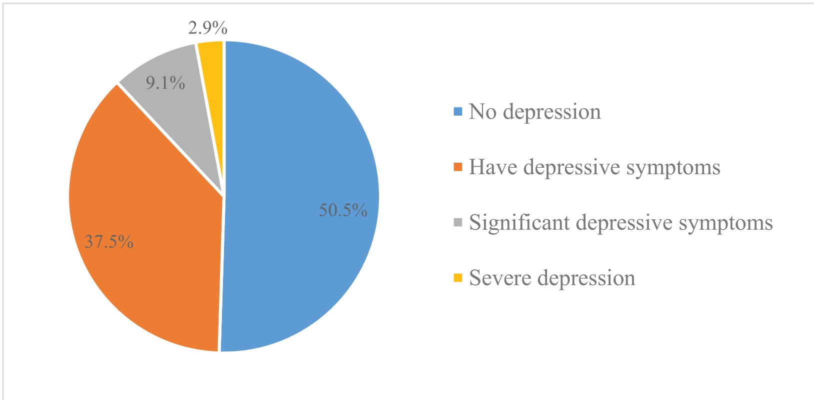

Fig. 4. The depression situation of people who always read news.

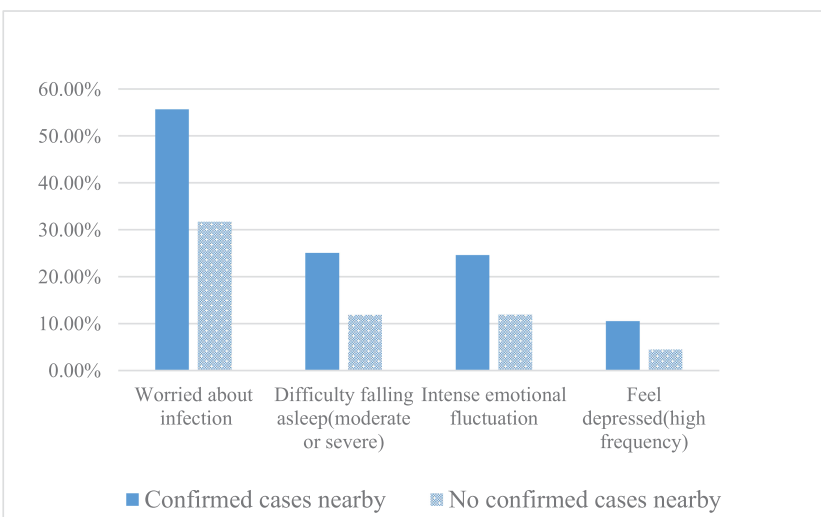

Fig. 5. The mental health state of users.

felt depression, and so on, when compared to those having no reported infected cases nearby. It also indicates that negative information may lead to abnormal changes in the psychological health and mental state of people.

6.2 Individual Perspective

For the purpose of verifying the impact of negative information from the point of view of individuals, an experimental platform for regular citizens in the pandemic was set up, as proposed in Section 5. The smart wearable devices described in the system used smart clothing in [38] and data including electrocardiogram, blood pressure, voice, texts, and sports information of the user were collected via smart clothes and smart phones. The cloud platform provided storage of historic data and data analysis for the system, Langchao's big-data appliance is used, with the reporting of analysis results realized by a mobile phone application.

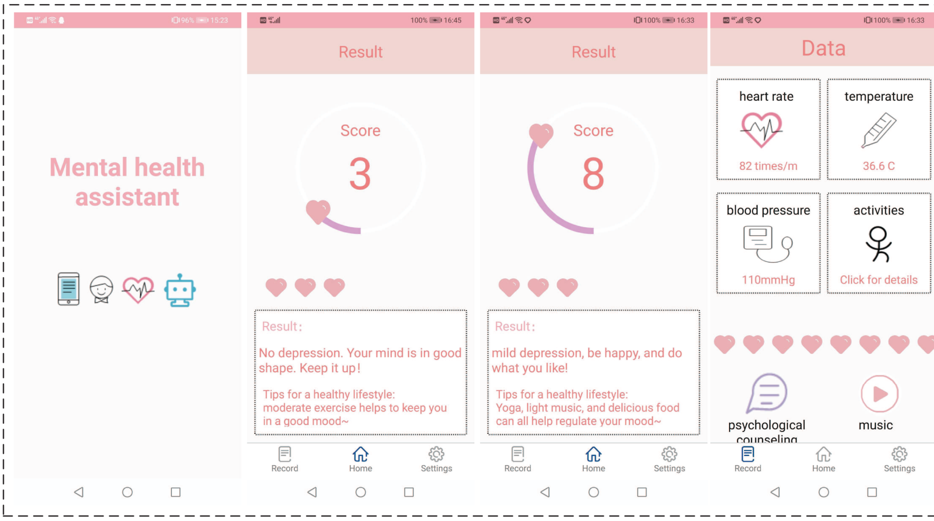

Fig. 6. User interface of the mobile phone application.

The pandemic caused the incidence rate of mental disorders to sharply rise. As the most common mental disorder, depression needs attention urgently. We investigated the PHQ-9 to reflect the severity level of depression. PHQ-9 shows great accuracy rate on the prediction of depression, making it extensively applicable [39]. Based on the PHQ-9 score, we divided the results into five categories as category labels, namely, no depression, mild depression, moderate depression, moderately severe depression, and severe depression. According to the different results, we put forward corresponding suggestions for psychological intervention.

We recruited a volunteer to take the test. After getting full consent of the volunteer and following the instructions of a psychiatrist, negative information was presented to the volunteer. The volunteer put on smart clothes and downloaded our auxiliary app in his mobile phone to acquire data and check the result. The interface of the mobile phone is shown in the Figure 6. When the volunteer was exposed to negative information for a long time, referring to long-term active and passive reception of negative information, the volunteer showed slight discomfort, which further points to the adverse impacts of negative information on psychological health. Therefore, in daily life, actively avoiding continuously refreshing all kinds of news information can relieve mental stress to a certain extent.

7 CONCLUSIONS AND FUTURE WORK

A novel concept of negative information is proposed to represent information that is harmful to people's mental health. To measure the negative information, the harm degree of the negative information is obtained through the negative information's impact on the human's mental health. Therefore, a mental health monitoring system was constructed to collect health data using wearable devices. At the same time, different models based on deep learning have been established for different modal data, which are deployed on the edge cloud to achieve real-time mental health intelligent cognition. In response to the impact of the COVID-19 epidemic on people's physical and mental health, four applications of the system among different people in the pandemic and in daily life were given. Finally, the impact of negative information on mental health and the feasibility and effectiveness of the system was tested through two experiments from group perspective and individual perspective. It is concluded that the degree of negative information can be measured through people's mental health. Meanwhile, the part of the mental health also can be dependent on the degree of negative information that people receive.

In the future, more work will be done on the measurement of negative information. On the one hand, the cognition of mental health can be realized through the processing of multi-modal data to present a more accurate degree of negative information. On the other hand, it is necessary to consider the response speed of the user's real-time interaction with the system to improve the user's quality of experience.

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Received October 2020; revised March 2021; accepted June 2021