

Digital Object Identifier 10.1109/ACCESS.2020.DOI

MEMO Box: Health Assistant for Depression with Medicine Carrier and Exercise Adjustment Driven by Edge Computing

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ABSTRACT According to the report by the World Health Organization, depression, as the leading disabling disease in the world, has aroused widespread social concern. However, the shortage of medical and nursing staff in psychiatry conflicts with the rising nursing needs of depressed patients. First, depression is a chronic mental illness, its cure course is relatively long, and stable drug treatment and healthy living habits are keys to the curing process. Second, the disease feature where depression patients have stronger emotional needs and more sensitive mental states is ignored in existing health monitoring systems. In consideration of the above two aspects, a health management assistant is proposed in this paper, called MEMO box system, that focuses on emotion and with smart medicine box as carrier. Specifically, the MEMO box system is composed of electronic medicine box and smart applications on mobile device, and electronic medicine box can collect the multi-mode data of patients, including their medication behaviors, daily activities, physical exercise data, and so on, which provide data basis for the health assistant. Emotion recognition and exercise recommend algorithms are deployed in the edge cloud, which can quickly respond to health service requests from patients. With the cooperation of hardware and software in this system, patients are urged to take medicines on time to effectively control their conditions, and emotion cognition and exercise adjustment recommendation can be realized for depression patients, thus providing patients with empathic sports recommendations.

INDEX TERMS Health assistant; Electronic medical prescription; Emotion cognition; Edge Computing

I. INTRODUCTION

ACCORDING to the report on World Health Organization [1], the incidence rate of chronic diseases has accelerated in recent years, which has brought great negative impact on social health and national economy [2]. In particular, mental illness is spreading throughout the whole society. And depressive disorder is characterized by high prevalence rate, high recurrence rate and high disability rate. According to the latest data released by World Health Organization [3], the global prevalence rate of depression is about 4.4%, with 322 million people suffering from depression. Depression

has become the leading cause of disability worldwide.

Thus, in the era of Internet of things (IoT) and artificial intelligence (AI), how to use intelligent algorithm, wearable technology and big data to solve the disorder of social mental health is a hot topic in the computer field and biomedical field. Hamad et al. proposed a novel scalable hybrid model that combines Bidirectional Gated Recurrent Units (BGRU) and Convolutional Neural Networks (CNNs) to detect depressed users on social media [4]. Li et al. focused on the role of different aspects of EEG and proposed a computer-aided detection system using CNNs. However, in addition

to focusing on the diagnosis and detection of depression, the demand for medical care of depression is also growing. And with improvement in living standards and the increasing awareness of social health care [5], [6], the medical service industry is transforming from “treatment service” to “health service”. The quality of health care services directly affects health state of patients. But unfortunately, the health services industry is in the situation where there is a severe shortage of personnel and unbalanced distribution of medical resources. Moreover, different from general chronic diseases, depression patients not only need physical health care, but also psychological emotional care [7]–[9], which put forward higher requirements for health care system for depression.

In addition, health care services for mental diseases should also consider the quality of the system to pay attention to the experience of patients. The medical framework of cloud computing has the problems of high cost and high latency. Edge computing reduces cloud computing load and service delay by configuring computing and storage capabilities at edge nodes [10]–[13]. Health care based on edge cloud can greatly reduce the cost of medical information, and make patients enjoy high-quality health care services in the remote. Moreover, through edge caching, user experience could be effectively improved while network load would significantly decreased [14]. Based on the above discussion, for the health care system of depression patients, we have the following considerations:

- **Inclusive care with medicine box.** Depression is an internal mood disorder that requires long-term health management. Patients should stick to regular medication to maintain a stable mood, which is the basis of cure of the disease. The health monitoring system with medicine box as carrier has the function of medication management naturally. Such a system can provide effective treatment management for depression patients at an affordable cost.
- **Emotion inferring for assisting nursing.** In consideration of depression patients as special people, the patients are emotionally fragile, and they are more in need of understanding in nursing. Deep learning technology is used to realize emotion recognition, thus to deeply understand the inner world of patients, so as to improve the efficiency of nursing with emotion cognition.
- **Efficient medical service response.** As a computing infrastructure, edge computing can place medical applications, computing and storage resources closer to patients. Edge computing infrastructure reduces reliance on remote centralized servers, which means hospitals and clinics will get more flexible services through the internet. This is particularly important for the condition that the amount of patient data is increase continuously.

Therefore, in view of analysis on above difficulties and requirements for health care system, and in combination with IoT [15], [16], Artificial Intelligence(AI) [17]–[19], edge computing [20], [21] and medical & health technology, a

health and emotion management assistant for depression patients is proposed, called MEMO box system. The “MEMO” therein means “Medicine”, “Emotion” and “Memory”, and it expressed three health care goals for depression patients. “Medicine”: establish a health assistant with medicine box as core device, and assist doctors in diagnosis with the help of big medical data; “Emotion”: conduct special emotional cognition for depression patients with mood disorders, to provide health services that truly understand the patient; “Memory”: it stands for an ongoing record of the patient’s health. In the process of accompanying patients, the health assistant understands patients more and more, and it accompanies to actively spend the recovery period together. To achieve this goal, The design of MEMO box system (termed as MEMO-system) consists of the medicine box and the mobile phone API, and the software and hardware are bound for real-time association.

In summary, the main contributions of this paper are as follows:

- 1) This paper proposes a health management system with medicine carrier for depression, the MEMO-system. MEMO-system combines edge computing and intelligent devices with mobile terminals and medical cloud to consist a continuous health detection medical system.
- 2) This paper introduces intelligent algorithms in MEMO-system, including emotion recognition model based on a deep network architecture and health recommendation mechanism with reinforcement learning theory.
- 3) This paper develops a testbed of MEMO-system. The components of the whole system are introduced in detail including hardware design and software design.

The rest of this paper is organized as follows: Section II summarizes relevant works of AI technology and edge computing designed in mental health field. Section III provides an architecture chart of the MEMO-system and introduces the composition and functions of each part in detail. In Section IV, we introduce algorithm model used in the paper; Section V builds a testbed of MEMO-system and verifies the validity of the system; Section VI summarizes this paper.

II. RELATED WORK

In this section, we will discuss closely related literature, and they are of guiding significance for our researches in this paper.

A. HEALTH ASSISTANT SOLUTION FOR MENTAL HEALTH

There are a lot of researches on healthcare works, but most of it is on throughput of chronic diseases [22]. And healthcare systems and programs that really focuses on mental illness have only begun to gain attention to recent years. C. Ernesting et al. [23] proposed health apps to modify and to manage health behaviors. To do this, they analyzed the correlation between application experiments and actual health behavior. In addition, researchers pay more and more attention

to the mental health needs of patients [22], [24]–[26] and psychodynamic in treatment has a great influence on the rehabilitation of the patient. In the study [27], a common tool for health information is established to measure patients' attitudes to self-care and treatment, thereinto, quantity of health knowledge, dosage of pills taken, and educational background are made as evaluation indicators. Božidara et al. [28] proposed a real-time management system for physical activity and mental stress through wristbands and smart-phones. This system designed activity recognition algorithm and psychological stress detection algorithm, aiming to train machine learning model based on user data.

Furthermore, there are several studies focusing on managing user health with their fragmented data [29]. A grass-roots approach is adopted by T. Gun et al. [30], and they proposed an intelligent health diagnosis technique that exploits automatically generated ontology and Web-based personal health record services. Literature [31] used software development for mobile phones to develop a simple interface that allows users to learn about their physical and mental state. They required them to wear a specially designed wristband in order to realize health detection of users. However, these researchers only realized the physical and psychological detection of users, but does not provide further help for users with these detection results reversely. And wearing wristband is unsuitable for use for specific situations such as hospitals and maintenance centers and will produce a sense of oppression to the user. Especially for depression patients, they are more sensitive and pay more attention to protect their diseases condition.

B. AI FOR DEPRESSION DETECTION

For general chronic diseases, they have significant clinical standards and is mainly based on physiological measurement. But different from these diseases, the diagnosis of mental illness depends on specific self-investigation report, in which information about the patient's mental level is obtained, such as personality characteristics and emotional state. With the development of the Internet, there are more and more data related to mental health status. It is a hot research to improve our understanding of mental health status by using big data and deep learning technology.

Specifically, text information on social media is an important form of users to share with the outside world. Through keyword extraction, word2vec model, text classifier to achieve the risk detection of depression. Chun et al. created a depression dictionary for automatically collecting data of depressive and non-depressive users and detected users with depressive tendency on Instagram [32]. And detecting depression based on audio and video data is also a way of assisting diagnosis. Niu et al. introduced a deep model, Depression AudioNet, which encodes depression-related features in the vocal tract and provides a more comprehensive audio representation [33]. And Zhu et al. studied the problem of automatic diagnosis of depression and proposed a new approach to predict the Beck Depression Inventory II (BDI-

II) values from video data based on the deep networks [34]. In addition, many scholars use deep network framework and mathematical analysis methods to explore the special characteristics of depression in brain signal [35], [36] and genetic engineering [37]. However, according to the above introduction, most existing studies focus on user behavior performance to detect whether a user suffers from depression or any mental illness. They ignore the psychological state of patients, and do not consider to detect their emotion. In this way, the emotion and depression of patients with depression can not be related to achieve empathy psychological intervention, which can not really meet the treatment needs of patients with depression.

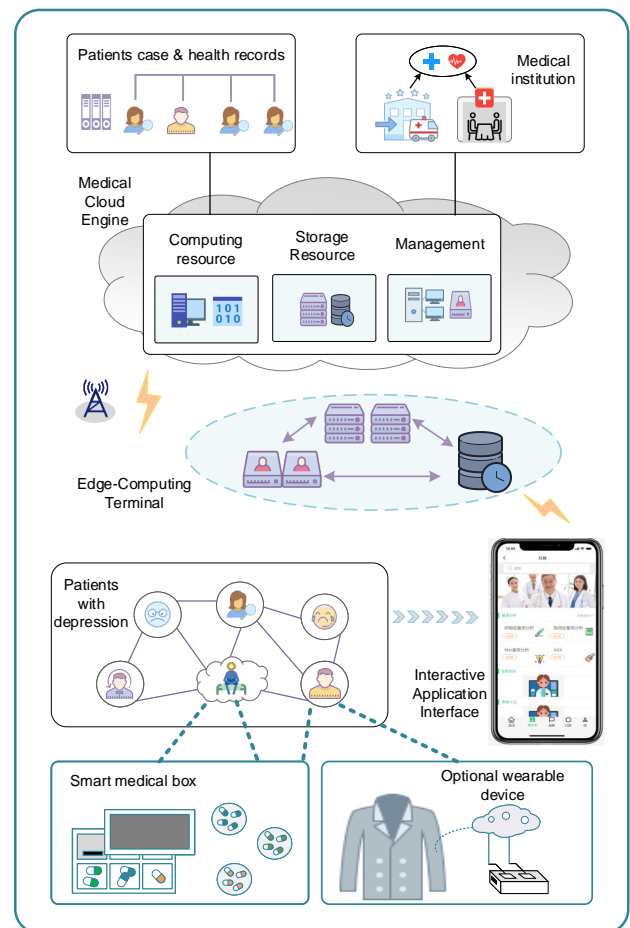


FIGURE 1 : The architecture of MEMO box system.

Therefore, in combination with analysis and discussion on relevant studies, we present MEMO-system, a health management assistant with medicine box as core device, that pays comprehensive attention to physical and mental health of depression patients. This system will focus on depression patients, and it realizes low-cost health detection and emotion inferring for patients through users' fragmented behavioral data. And it provides personalized health recommendations. In addition, combined with AI technology, we will use deep learning algorithm to predict the risk and emotional state of

users, and apply the results of depression and emotion detection to the health and exercise recommendation mechanism of users.

III. MEMO BOX SYSTEM ARCHITECTURE

To realize intelligent emotional cognition and medication supervision of the health system, the MEMO-system should have smart medicine box and intelligent deep learning algorithms. And edge computing is introduced to remotely configure and manage medical cloud resources to provide low-latency and secure network infrastructure. In addition, smart clothes are introduced into the health assistant system as an optional hardware device to collect physiological data of depression patients. In this section, we present the MEMO-system architecture, as shown in Fig.1, mainly including five components.

A. SMART MEDICAL CARRIER

Smart medicine box is made as the core of hardware processing in the system to realize collection, recording, transmission and processing for patients' behavior data and environmental data, thus it is the basic equipment for establishing patients' health management files. Compared with traditional electronic medicine box, the medicine box designed for depression patients in this paper is multi-functional, and it supports environment perception function; in the hope of providing recommendations on more healthy activity and lifestyle for depression patients. Medicine-box mainly includes two modules: medicine module and ambient module, which provide patients with medication monitoring and environment monitoring function respectively.

B. INTERACTIVE APPLICATION INTERFACE

Interactive application interface is actually the software application of MEMO-system, that is an important interface to realize interaction with patients, it mainly refers to API that matches medicine box. The hardware and software of MEMO-system work together to provide patients with functions such as medicine preparation, medication reminding, exercise records and personalized health recommendations. This API mainly shows the patient the historical medication record, the movement condition and so on. In addition to enabling the recording of data, a variety of light-weight intelligent algorithms are also deployed in the API, thus to provide personalized treatment advice and guidance for depression patients. The medicine box is linked to the software to urge patients with depression to take the medicine on time, effectively helping patients develop good medication habits and actively get recovery.

C. EDGE-COMPUTING TERMINAL

Edge computing terminal is a proximity computing model, which relies on the nearby medical centers in the community to provide services. Local edge computing sites can alleviate the pressure of medical services caused by the dispersion of medical resources, and enable doctors to quickly access

users' information to make wise medical decisions, which may be life and death. In cloud transmission, a part of simple data processing is carried out by edge nodes, which can reduce the data flow from the device to the cloud. Edge computing can maintain the basic care and health detection of patients in the temporary collapse of data center or internal network.

D. MEDICAL CLOUD ENGINE

The medical cloud engine is the controlling and storage center of the MEMO-system. Medical Cloud Engine uses cloud computing technology to provide storage and computing resources. The virtualization of computing resources will realize the supply of on-demand resources and provide a configurable resource operation environment for users. And Virtual storage technology, support large amounts of data can be written in parallel at the same time. Based on intelligent medical cloud engine our system provides patients with emotional detection, disease warning, health recommendation and other functions through the API, where a variety of artificial intelligence algorithms are applied to analyze patient data in-depth and provide patients with temperature interactions.

E. OPTIONAL WEARABLE DEVICE

The health status of depression patients is not only reflected in medication behavior, the emotional state and physiological data of patients are also important indicators to reflect illness state of patients. Smart clothes are a good choice for monitoring physiological data of patients [38]–[40]. Micro-sensors are embedded in the textile clothing, and smart clothes have advantages such as data collection without interference, accurate physiological detection, and comfortable wearing experience. Smart clothes, as optional wearable device, pay attention to physiological health of patients and perceive physiological data of patients. These physiological data will be used as supplementary information to analyze health status of depression patients.

The various micro-sensors in the smart clothes transmit original signals to data processing module, which is responsible for receiving and processing the data collected by sensors. In the connectionless state, the processed data remains in the local storage module. Data will be sent to Me-API via communication module when accessible. In addition, charging module will power each module in service. Finally, Me-API will upload the patient data to cloud for analysis and storage.

IV. METHODS OF MEMO-SYSTEM

A. BEHAVIOR-ASSOCIATED EMOTION INFERRING

The emotion recognition model is based on EEG signals of the patient. The emotional characteristics [41] of signals in each EEG channel are utilized in this paper, in addition, the emotional correlation between the signals in different channels is also taken into consideration. For single-channel EEG signals, the differential entropy of signal in each channel is

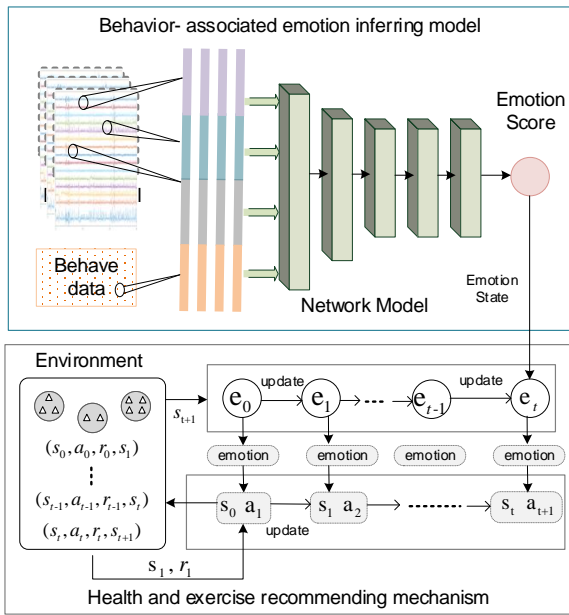


FIGURE 2 : The method model of MEMO-system.

extracted in this paper as feature which is the input in single-channel CNN model; MWRN network is used to mine the features of local regions between channels. The details are as follows.

First, it is assumed that the number of channels for EEG signals of a patient is N . The EEG signal in one channel is divided into P sub-signals with length of Q , then $x_p = \{x_{p,q}\}_{q=1}^{q=Q}$ stands for the p^{th} sub-signal. It is assumed that time window is τ , then the trajectory vector for the n^{th} channel is $x_n(t) = \{x_{n,t}, x_{n,t+(q-1)\tau}\}, n = 1, \dots, P; t = 1, \dots, N$. Therefore, the incidence matrix R in size of $N \times N$ is described as below:

$$R_{i,j}^{x_n}(\sigma) = \theta(\sigma - \|x_n(i) - x_n(j)\|) \quad (1)$$

$$i = 1, \dots, N; j = 1, \dots, N$$

Thereinto, ε is an adjustable threshold, and behavior trajectory vectors are pairwise. For example, x_{n1} and x_{n2} . Therefore, the combined recurrence rate of this RP can be expressed as:

$$CR(x_{n1}, x_{n2}) = \frac{1}{N^2} \sum_{i,j=1}^N R_{i,j}^{x_{n1}}(\sigma) R_{i,j}^{x_{n2}}(\sigma) \quad (2)$$

CR is a matrix in size of $P \times P$ for multidimensional behavior data. Take the data of the patient in each dimension as a node, and determine the weight between sub-signals with associated indicators, thus an MWRN can be constructed. The network matrix formed by the synchronous index contains the relationship information between data in different dimensions, which will be used as input of CNNs model.

The above data can be used to infer the emotions of patients. In the early stage, the emotions of a patient can be obtained through remarks of the doctor on the patient every

day, and these emotions will be made as emotional label to train model parameters. Therefore, emotion Inferring model is supervised learning. The well trained emotion Inferring model will be used to infer the score of the patient's emotional state.

In addition, although depression is a mental illness, but psychological state often has corresponding mapping in behavior. Abnormal behavior often occurs during a seizure. For individual patients, there may be significant differences between episodes of depression and episodes of calm. For example, there are two patients, Bob and Alice, who are in recurrence period of depression. They may prefer to stay at home and cut back on socializing; however, in normal period, Bob and Alice may be just like everybody else, and their medication and social behaviors are normal. However, different patients have different behaviors in recurrence period. For example, Bob is only depressed and more dependent on antidepressants, and he took too many medicines; however, the symptoms of Alice caused extreme depression, she is not able to have normal consciousness for treatment, and she often forgot to take medicine. The emotion inferring model for patients is based on description of medication behavior and exercise behavior. Thereinto, medication behavior includes data such as time of medication, frequency of medication and on-time rate of medication. Exercise behavior includes total daily exercise time, step number in exercise, and etc. Therefore, MEMO-system also takes records of the patient's exercise and medication behavior as auxiliary information to recognize emotions.

B. HEALTH AND EXERCISE RECOMMENDING MECHANISM

With the development of society, we are facing a serious exercise deficit disorder which can cause health crisis. According to sports psychology [41], sports behavior can exert a huge impact on psychology state of humans. The schemes of recommended traditional systems focus on users emotions, however, sports behaviors are also important due to the emotional sensitivity of depression patients [42]. Therefore, exercise factors will be introduced into our health assistant system, and reinforced learning model is adopted to find out the recommended strategy that maximizes cumulative reward value, thus to provide personalized health guidance and advice to patients.

It is assumed that s stands for state space of reinforced learning, s_t stands for the patient's exercise behavior and current emotional state; a stands for motion space of reinforced learning, a_t stands for the health information recommended to the patient by the system at time t . r_t stands for the reward value after execution of motion a_t . s_{t+1} means new state of the patient after execution of motion a_t , γ is discount factor with value range of $[0-1]$. Our goal is that the patient obtains the best possible emotional state, i.e.:



FIGURE 3 : The prototype design of MEMO-system.

$$\begin{aligned}
 Q * (s, a) &= r_{t+1} + \gamma \max_{a_{t+1}}(r_{t+2}) + \gamma^2 \max_{a_{t+2}}(r_{t+3}) \\
 &+ \dots + \gamma^n \max_{a_{t+n-1}}(r_{t+n}) \\
 &= r_{t+1} + \gamma \max_{a_{t+1}} Q * (s_{t+1}, a_{t+1})
 \end{aligned}
 \tag{3}$$

First, initialize neural network model, and input past behavior, emotion and exercise information of the patient into neural network for training. This health assistant pushes each kind of health advice including exercise plan, after a period of time, the patient’s emotional state after receiving the advice will be detected; the more positive emotional state will get higher reward value, and vice versa. The different kinds of health advice are the whole set of actions, the action that can lead to maximum value function will be selected each time. When the moment has passed, constantly give the best possible action at next moment as per input information renewed by the user.

In order to get a better estimated value, a little “disturbance” is usually added. In this paper, one action is selected uniformly and randomly with probability ϵ from all actions, and the optimal action given by current strategy is selected with probability of $[1 - \epsilon]$. The process of inputting data to obtain next-step suggestion is the process of reinforced learning. In current state, input user data, and action suggestion will be given to the user. After the user takes this action, sequence (s_t, a_t, r_t, s_{t+1}) will be produced. Then, provide the best possible health advice to the patient as per emotional state predicted according to current state.

V. TESTBED AND EXPERIMENT

According to the design idea of hardware and software in Section IV, the prototype of MEMO-system has been established. In this section, we introduce the details of the prototype system and analysis service function. In addition, in order to verify the reliability and effectiveness of the system,

we also discuss the calculation delay and transmission delay with the increase of the number of users.

A. TESTBED SET-UP

The above-mentioned testbed is mainly composed of smart medicine box, wearable device and application software, as shown in Fig. 3. The details are described below.

Smart Medicine box Design: Fig.3 (a) shows the hardware design of medicine carrier. These include control chips, core board, and so on; the external function mainly includes communication module, key module, reminding module and so on. As for medicine module, it can be divided into two parts: medicine chamber and charging capsule. The medicine chamber includes core controller, bus, circuit and various micro-sensors, and it is responsible for realizing functions related to medicine box. the single chip of the system is CC2540, which integrates micro-controller, host terminal and application on a single element. it includes radio frequency receiver and 8051 micro-controllers, and it supports single-mode low-power Bluetooth communication. As a charging container, charging capsule is not fixed in medicine chamber. Each capsule can be separated from medicine chamber, making it easy to charge and take medicine. The control treatment of medicine box is placed in medicine chamber.

Optional Wearable Device Design: Specially, smart clothes include clothes themselves, micro sensors, and interaction modules, as shown in Fig.3 (b). In consideration of mental sensitivity of depression patients, clothes made of elastic cotton fabric are adopted, they are more comfortable and close-fitting. Secondly, the micro sensor transmits the physiological indicators collected to data processing module through flexible textile electrode: NTC thermistor sensor under armpit of the clothes is used to record body temperature; an ECG sensor placed in left atrium of the garment measures the patient’s ECG signals; a blood oxygen sensor was placed on right cuff of the garment, and principles of optics are

adopted to measure oxygen concentration in the patient's blood. The suit also includes an electrode cap which consists of multiple electrodes, and each electrode picks up signals from a channel in the cortex.

Application Software Design: To realize high-interactive service interface, this paper designs an application, called Me-API. The software is developed on platform of Android 4.0 system, while the background system is deployed on lightweight server of Alibaba Cloud. Fig.3 (c) is the service interface of Me-API. Me-API application is an important interface for interaction between medical carrier and patients, including functions such as displaying medication record, searching for medicine box, step count and social data statistics. Based on these data, management and analysis on health status, exercise behavior and emotions of patients will be conducted by MB, thus to provide them with personalized health advice and guidance.

B. FUNCTION ANALYSIS

We analyze the function of the prototype platform of MEMO-system.

First of all, the two functions of software Me-API will be described in detail: (1) Multi-dimensional behavioral archives: as depression is a chronic mental illness, it is of great significance to establish a sheet of behavioral statements of depression patients. Me-API will record the patient's medication data, exercise behavior and physiological indicators, and feedback them to the patient regularly in the form of statements, which can not only help the patient review historical treatment status, but also assist the doctor to diagnose and treat the patient. (2) Immersive health recommendations: Me-API will synthesize the patients' medication behavior and exercise behavior to infer the patient's emotional state. In addition, the physiological indicators of patients from smart clothes will also be used as supplementary data to assist the intelligent algorithm in Me-API to make emotional decisions. Me-API will then provide immersive health advices to the patient based on the patients' mood and current environment.

Secondly, the system composed of software Me-API and electronic medicine box also has the functions of traditional smart medicine box, including easy medicine charging, medication reminding, medication recording, alarm to take medicine, and etc. Specifically, a medication plan has been set up by the patient in advance in API of the terminal device. When it is the prescribed time, the LED indicator light in the medicine chamber will flicker intermittently to remind the patient to take medicine in time. Principle of infrared detection is used by photoelectric sensor in the chamber to judge whether the patient has taken the medicine. If the patient has taken the medicine, medication record will be transmitted to mobile phone terminal by communication module in medicine chamber, thus the function of medication recording is completed. In addition, alarm to take medicine is sent out by mobile phone terminal; thereinto, "strategy to the nearest" is adopted to locate the position of electronic medicine box, the position of mobile phone during the last

communication between the mobile phone and the medicine box is taken as the current position of the electronic medicine box. If the mobile phone terminal and the medicine box have been in disconnection state, then, in a fixed period of time, comparison will be made between the position of the mobile phone terminal and that of the medicine box, thus to send out alarm to take medicine.

C. PERFORMANCE EVALUATION

Based on the prototype of the MEMO-system, we recruited a group of depression patients to test the system. They installed Me-API application on their phones. Each volunteer (depression patients) needs to manually input the medication plan into the drug management of Me-API, and put the drugs that need to be taken into the medicine box. In addition, each volunteer can choose whether to wear the smart clothes we provide.

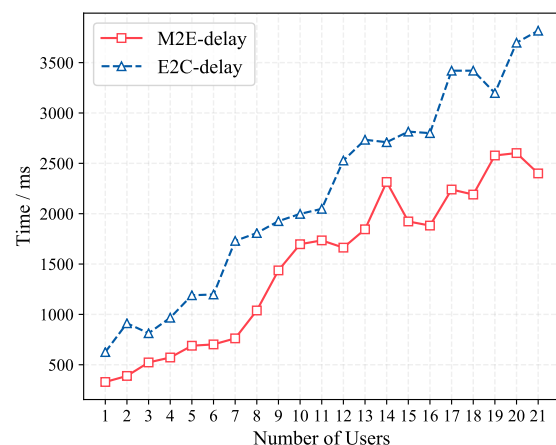
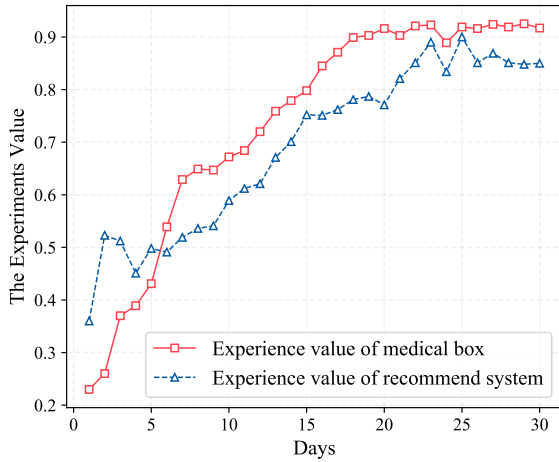


FIGURE 4 : The time delay of the MEMO-system with users numbers.

First of all, in order to evaluate the reliability and effectiveness of the system, we test the service delay of the MEMO-system, as shown in Fig.4. The system delay includes two parts: M2E-delay denotes the transmission delay of me API and edge computing terminal, and E2M-delay denotes the transmission delay of edge computing terminal and medical cloud engine. As can be seen from the figure, M2E-delay and E2M-delay increase with the number of users. Due to the increase of users, edge computing terminal needs to analyze the multi-user server requests, and use the algorithm to determine which user requests have the highest priority and respond to them fastest. Medical cloud engine also needs to execute deployed AI algorithms for many times, including emotion analysis model, health exercise recommendation algorithm, etc., so the delay is gradually increasing. In addition, when these computing models are idle in the medical cloud, the recent data will be used as training data to retrain the model in the cloud. The longer the time is, the more data are collected, so the recognition accuracy of the algorithm will be higher.



FIGURES : The experience value of the MEMO-system with users numbers.

$$e_{medical}^i = 1 - (num_{reminder}^i \div num_{total}^i) \quad (4)$$

In addition, this paper makes statistics on the experience of volunteers using the medical box and recommended system every day, and calculates an average experience value of daily use, as shown in the Fig.5. The experience value of medical box (i.e. $e_{medical}$) is calculated as follows: $e_{medical}^i = 1 - (num_{reminder}^i \div num_{total}^i)$ (see eq.4). $num_{reminder}^i$ denotes the number of times he was reminded to take medicine of the i^{th} user, num_{total} denotes the total number of times the medication needs to be taken of the i^{th} user. N denotes the number of users, $N = 21$. And $E_{medical}$ represents the average experience value on the medical box (see eq.5). The higher the value of $E_{medical}$, the higher the consciousness of patients in taking medicine. And according to the subjective evaluation of the patients, they score the recommended content of each memo box system, that is the experience value of recommend system, i.e. $E_{recommend}$ (see eq.5). As can be seen from the figure, at the beginning, with the increase of user's time of using the system, the experience value of medical box gradually increases. In other words, the system reminds users less and less to take medicine. After users use the system for a period of time, the experience value of medical box tends to be stable. The experimental results also prove that medical box can effectively promote users to develop good medication habits. For the curve of the experience value of the recommendation system, the longer users use the system, the more satisfied they are with the recommended content. The main reason is that with the interaction with users, the system is more and more aware of users, and the recommended content is more and more accurate, that shows that our system has good user stickiness.

$$\begin{aligned} E_{medical} &= \frac{1}{N} \sum_{i=1}^N e_{medical}^i \\ E_{recommend} &= \frac{1}{N} \sum_{i=1}^N e_{recommend}^i \end{aligned} \quad (5)$$

VI. CONCLUSION

In this paper, a health care assistant with electronic medicine box as carrier and in allusion to depression patients is proposed. The system includes electronic medicine boxes, optional smart clothes and corresponding software applications, called as Me-API. The electronic medicine box can collect a variety of data such as medication and environment of depression patients, Me-API software and electronic medicine box work together to provide patients with services such as medication reminding, exercise record and health recommendations. In this paper, the hardware and software design of the system are introduced in detail, a testbed platform has been established, corresponding electronic medicine box, smart clothes and Me-API application have been developed, to verify the feasibility of the system.

VII. ACKNOWLEDGMENT

The authors extend their appreciation to the Deputyship for Research & Innovation, "Ministry of Education" in Saudi Arabia for funding this research work through the project number IFKSURG-1436-023. This research is also supported by the Shenzhen Institute of Artificial Intelligence and Robotics for Society (AIRS).

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