Personalized Eating Disorder Care on the Mobile Dietary and Emotional Diary System

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Eating disorders are complex medical and psychiatric illnesses that can have serious consequences for health, productivity, and personal relationships, and individuals' cognitive eating behavior often varies from one person to another. As a result, compared to a generic model considering profiles of several users, a personalized model can capture a user's cognitive eating behavior more accurately to predict their health status. In this work, we build a mobile dietary and emotional diary system with a weighted hybrid approach to model users' cognitive behavior analysis. Through an analysis of normal and abnormal dietary input and emotional state, this system is intended to provide an eating disorder healthcare service as a service in the cloud. By using dynamic performance-based weighting, we combine the predictions of a general model, a group model, and a personalized model. The initial experimental results are presented, and further research topics are discussed.

CCS Concepts: • **Information systems → Personalization**.

Additional Key Words and Phrases: personalized eating disorder care, adaptive modelling, mobile dietary, emotional diary system

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1 INTRODUCTION

There is a cognitive behavior work for eating disorder [9]. However, it provides no mobile IoT tracking mechanism and personalized care. Our prior work focused on treating eating disorders based on daily eating habits, and knowledge base [7]. However, it can be enhanced to have personalized eating disorder care.

Eating disorders, our primary focus, are real, complex medical and psychiatric illnesses that can seriously affect health, productivity, and relationships. Also, enabling eating disorders health care is one of the behavioral health care we need to take care of. The treatment strategy is determined by the severity of the illness and the specific eating disorder diagnosis, and cognitive-behavioral therapy and interpersonal therapy produce substantial and long-lasting changes. Pharmacological treatment often has a valuable role [2]. Therefore, our mobile dietary and emotional diary system for eating disorder care will provide a long-lasting tracking system by writing the diary from the patient and checking the facial emotions to analyze the cognitive-behavioral.

On the other hand, an E-health care system can collaborate with healthcare professionals, regulators, pharmacies, insurance companies, vendors, hospitals, and patients [10]. Also, E-health has many challenges, such as how medical and healthcare information is collected and stored, the lack of technologies, and the potential cost of digitizing existing processes and tasks. Since one of the significant challenges is to convert all medical and healthcare information to electronic format, we provide a healthcare system where patients and professionals can quickly write or update the information using a smartphone.

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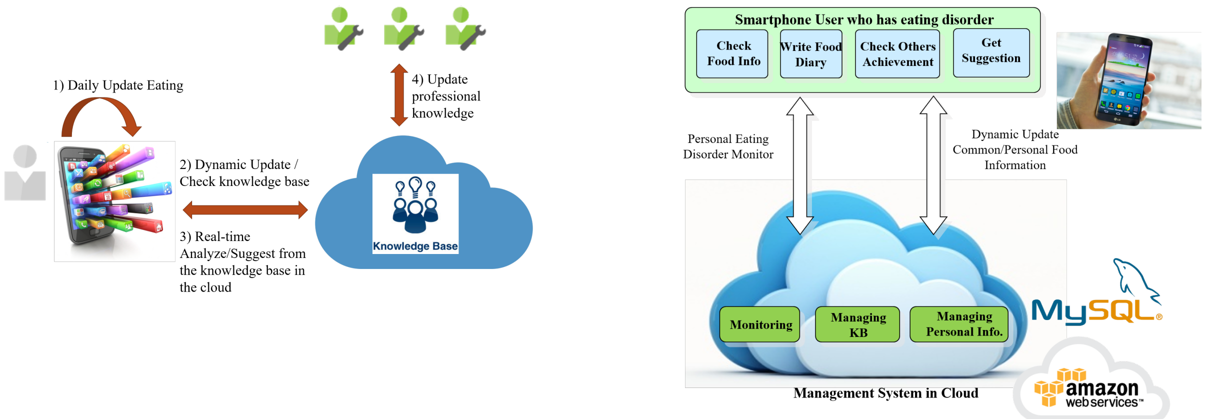


Fig. 1. Eating disorder diary system scenario (left) and eating disorder architecture on Android platform and MySQL database on the cloud environment (right).

In this paper, we explore healthcare services that could detect personalized eating disorders by (1) enabling eating disorders health care, (2) dynamic diet information by adaptive personalized modeling, (3) real-time diet diary system, and (4) emotion state recognition.

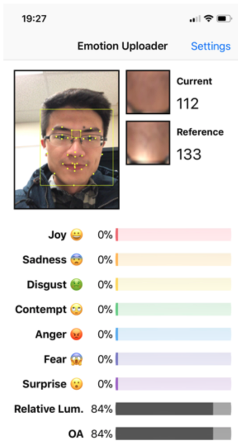
2 PERSONALIZED EATING DISORDER CARE

2.1 EATING DISORDER DIARY SYSTEM

For the mobile dietary system, the eating disorder diary system has three major parts: prevention, diagnosis, and treatment. Prevention aims to promote healthy development before the occurrence of eating disorders. It also intends early identification of an eating disorder before it is too late to treat. Children as young as ages 5–7 are aware of the cultural messages regarding body image and dieting. Internet and modern technologies provide new opportunities for prevention. Online programs have the potential to increase the use of prevention programs. The development and practice of prevention programs via online sources make it possible to reach a wide range of people at minimal cost. Such an approach can also make prevention programs to be sustainable. For prevention, we designed the professional suggestion part for individual patents by building communication platforms for sharing information.

The diagnostic workup typically includes complete medical and psychosocial history and follows a rational and formulaic approach to the diagnosis. Multiple medical conditions may be misdiagnosed as a primary psychiatric disorder, complicating or delaying treatment. These may synergistically affect conditions that mimic an eating disorder or a properly diagnosed eating disorder. This typically involves counseling, a proper diet, a normal amount of exercise, and reducing efforts to eliminate food. Hospitalization is occasionally needed. Medications may be used to help with some of the associated symptoms. At five years, about 70% of people with anorexia and 50% of people with bulimia recover. Recovery from binge eating disorder is less clear and estimated at 20% to 60%. These diagnoses and treatments can be solved by depression recognition, monitoring psychological status, machine learning to make better diagnoses, real-time diary systems, positive feedback to encourage healthier eating habits, and so on.

Figure 1 shows the eating disorder diary system scenario. Whenever the patient writes a diary to update the eating history, the system will dynamically update and check the knowledge base, which is located in the cloud database. Meanwhile, real-time analysis and suggestion mechanisms from the cloud knowledge base come to the



Input: D_i
for *Centroid* Φ_j *in all Centroids* **do**
  calculate the distance $d(D_i, \Phi_j)$
  if $(d(D_i, \Phi_j) == min)$ **then**
    $c(D_i) = \Phi_j$
  end
  add D_i into the data instances
  update the Φ_j
end
if $\Psi(c(D_i)) == e_1$ **then**
  return *completely normal event*
end
if $\Psi(c(D_i)) == e_2$ **then**
  return *normal event*
end
if $\Psi(c(D_i)) == e_3$ **then**
  return *slightly abnormal event*
end
if $\Psi(c(D_i)) == e_4$ **then**
  return *abnormal event*
end
Output:$\{\Phi_1, \Phi_2, \Phi_3, \Phi_4\}$

Define:
  clu, gen, per = group, general, personal models
  f^* = set of f-measures of each model
  day_usage = aggregate cognitive user behavior for the current day
  day_instances = diary instances current day
Input : x: a new instance of incoming diary
Output: *state*: attentiveness state
begin
  if *getday()* $\neq$ *current_day* **then**
    f^* = compute_models_performance(y_preds, y_true)
    clu = get_cluster(day_usage)
    w^* = update_weights(f^*) using [3]'s eq.3
    per = update_personalized_model(day_instances)
    reset f^*, day_usage and day_instances
    current_day = getday()
  $P_{gen}(y_i = 0) = gen(x_i)$
  $P_{clu}(y_i = 0) = clu(x_i)$
  $P_{per}(y_i = 0) = per(x_i)$
  $P(y_i = 0)$ = combine predictions using [3]'s eq.2
  if $P(y_i = 0) > 0.5$ **then**
    state = *inattentive*
  else
    state = *attentive*
  y_preds.add(model, state)
  return state
end

Fig. 2. User-interface of emotion diary app (left) algorithm for the procedure of detecting the event types (middle), an algorithm for adaptive modeling for personalized cognitive behavior (right).

smartphone's eating disorder diary system. On the other hand, all the patient's information will be provided to professionals for individual feedback. Figure 1 also explains the eating disorder diary architecture. On the smartphone side, there are four components: checking food information, writing a food diary, checking others' achievements, and getting professional suggestions for the mobile dietary app, which is implemented on the Android platform. These components are used to monitor the personal eating disorder as well as dynamically update the common and personal food information to the management system in the cloud. On the cloud server side, there are three components: monitoring, managing knowledge base, and managing personal information. All this information is implemented on the top of MySQL and Amazon Web Service cloud servers.

2.2 EMOTION STATE RECOGNIZING

The user's emotional information can be collected through the emotional diary system. The emotional diary system is a smartphone app implemented on the iOS platform, which utilizes the smartphone camera to detect the user's facial expressions. Human facial expression can be sensed and analyzed through "Affdex SDK", which is distributed as CocoaPod. "Affdex SDK" provides open-source API support for Swift projects to detect different emotional expressions such as joy, disgust, surprise, etc. [8]. Through the camera, the emotional diary system is able to localize the key facial landmarks and capture the user's facial expressions.

The emotional diary system can recognize the user's seven different emotional expressions. Each emotion is represented by a numerical value expressed in the progress bar. After the user confirms the most representative emotion, a detailed facial expression report will be generated and available for the user to read in Figure 2.

For this project, we are mainly interested in the three representative emotions: joy, disgust, and sadness, to detect the abnormal amount of calorie intake and track the care procedure for eating disorders.

Our emotional diary system architecture can be divided into three components interacting with each other. A mobile component (smartphones, personal computer) collects the user's emotions at different time stamps and uploads the emotions into Chronobot MySQL Database of a Mobile Slow Intelligence System [1]. Then, the eating disorder diagnosis component sends the request to the database to continuously monitor the emotions of each user. The emotional state can be one of the criteria for evaluating the caring procedure of an eating disorder.

2.3 ABNORMAL STATE MONITORING

Eating disorder care aims to identify the abnormal events in the data. The system uses the data-driven model to identify the three different events in the data: abnormal-event, almost-abnormal event, almost normal event, normal event, also denoted as e1, e2, e3, e4. The basic idea of abnormal event identification is to "customize" for each user. That is, the definition of the abnormal event can be automatically adjusted with respect to users.

In the system, the problem of identifying the abnormal events can be seen as the problem of clustering with three centroids (Φ1, Φ2, Φ3, Φ4). Each centroid is equivalent to a different type of event [5].

Definition 1: For the new data instance Di, the Euclidean distance between the data instance Di and the thΦ2), d(Di, Φ3); C(Di) is a cluster of the data instance Di: If C(Di) = Φ1, then Ψ(Di) = e1. If C(Di) = Φ2, then Ψ(Di) = e2. If C(Di) = Φ3, then Ψ(Di) = e3. If C(Di) = Φ4, then Ψ(Di) = e4.

The algorithm in Figure 2 's middle shows the process of the system detecting the abnormal event with the data instance Di as the input and the event types as the output. The study of the clustering is data-driven. However, during the initial phase of the system, identifying the centroid may be a problem due to the lack of data instances. We assume the initial three centroids are (μ-2σ, μ, μ+2σ), where μ = 2,200 calories, σ = 200 calories, following with the Gaussian distribution, based on the average amount of calories in taking on daily basis recommended by Dietary Guidelines Advisory Committee (DGAC). Clustering the new data instance Di with d dimensions and updating the new centroids of the cluster is implemented through the k-means algorithm illustrated in [7] Equation 1 and 2, which enables the definition of the abnormal event gradually adjusted to each user.

The attributes in the data instances consist of continuous values (e.g., calorie amount) and categorical values (e.g., emotions). The distance calculation between the Di and the centroids cannot be purely the calculation of Euclidean distance, which does not work well for categorical values. We separate the attributes of the data instance into two groups, ϵ and η, where ϵ is the set of attributes with continuous values and η is the set of attributes with categorical values. The difference between two ϵ: $\epsilon 1$ and $\epsilon 2$ can be simply calculated with distance function (e.g., Euclidean distance, city block, etc.). For η, the difference of the two η: $\eta 1$ and $\eta 2$ can be computed through a kernel function that calculates the dissimilarity scores between $\eta 1$ and $\eta 2$.

The λ is the normal distance calculation function, and κ is the kernel function used to measure the dissimilarities. The weights assigned to each distance measurement are the α and β. Using this approach, it can consider all attributes for the distance measurement while avoiding the inference caused by categorical values. Besides, the values of α and β can dynamically change and be learned through a continuous data stream collected from the user to detect the abnormalities better.

2.4 PERSONALIZED MODELLING

Accurately modeling user cognitive behavior requires different approaches at different stages [3, 4]. Rather than treating this issue as a model selection problem, we approach it by building a hybrid model that aims to integrate predictions from multiple models to be able to adapt to the situations mentioned above without relying solely on the amount of data available [6]. The algorithm in Figure 2's right describes how the adaptive model works.

3 EXPERIMENT AND RESULTS

The application was implemented on iOS and Android platforms to collect users' emotional states and dietary information. All the records were stored in the Chronobot MySQL database. We focus on identifying abnormal events with incoming data streams collected from the applications. From the Chronobot database, we can extract

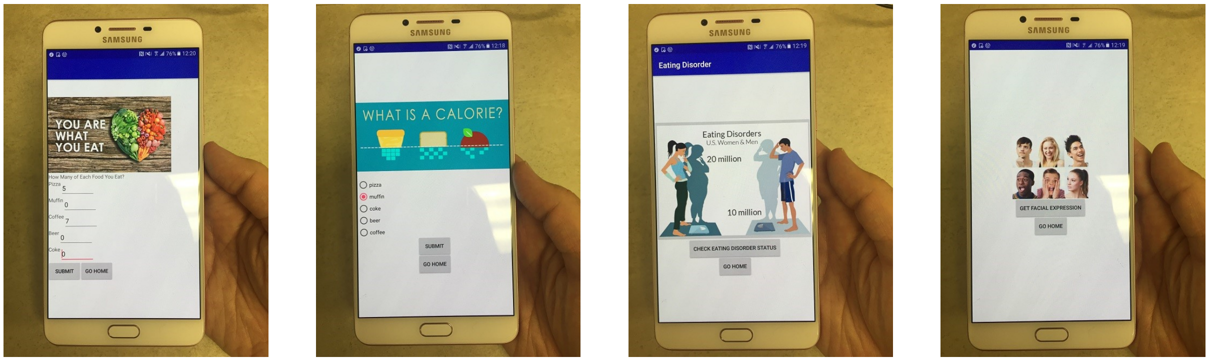


Fig. 3. Dietary System: updating dietary history (first), checking food information(second), checking eating disorder status(third), getting emotion status identification (fourth)

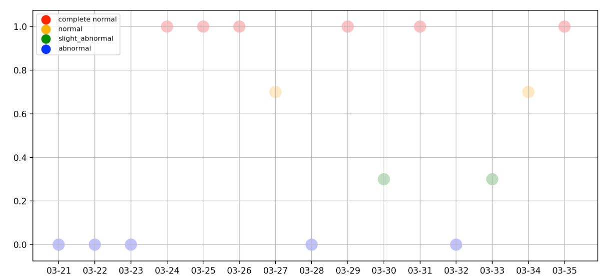


Fig. 4. Graph visualization of abnormal event identification

the total amount of calories taken on a daily basis, associating it with its corresponding emotional state. The total amount of calories and emotional state are the two criteria to evaluate the abnormality of the events.

Through the mobile dietary system on the top of the Android platform, we can upload our dietary history several times per day, check food information such as calories, check eating disorder status among normal / almost normal / almost abnormal/abnormal, and get emotion status identification which is extracted from iOS platform as shown in figure 3.

We conducted a user-study experiment for a period of 15 days with five different patients. During the experiment, we kept track of users' daily food consumption. We calculated the total calories taken based on the food types and amount while recording users' emotional expressions. Then, to better project the abnormalities of the events, we normalized the event abnormality values into the interval [0, 1] and classified the event based on its event abnormality values. The higher value indicates the higher degree of abnormality of the event.

The types of the event also map to different colors. Figure 4 is the different visualization of the types of events identified by our system. Event set abnormal-event, almost-abnormal event, almost normal event, normal event map to the color set (red, orange, green, blue) to let users and physicians know the abnormalities inside the data or evaluate the caring process of eating disorder. Figure 4 is a sample visualization of a patient over the testing period.

4 CONCLUSION AND FUTURE WORK

Eating disorders are real, complex medical and psychiatric illnesses that can seriously affect health, productivity, and personal relationships, and individuals may have different cognitive behaviors. We designed and implemented a mobile dietary and emotional diary system on the smartphone in order to detect personalized eating disorders based on patients' eating history and facial status detection. Through an analysis of normal and abnormal dietary input and emotional state and personalized adaptive modeling, this system is intended for providing eating disorder healthcare services. In the future, we can experiment with participants to understand how our system is effective. We can also build software engineering modeling with cloud architecture for the slow intelligence system and professional medical users' interface to collect recommendations. In the future, we also plan to increase the number of criteria that were used to determine the abnormalities of the event. For example, we could consider the patient's daily exercise and the types of food. Even though a patient's daily total calories are high, he/she has very active daily exercises, the system will still consider it normal. Although a patient's daily calories are low, the food he/she eats is mostly junk food, and then the system still considers it an abnormal event.

REFERENCES

[1] Shi-Kuo Chang, Wei Guo, Duncan Yung, ZiNan Zhang, HaoRan Zhang, and WenBin You. 2017. A Mobile TDR System for Smart Phones.

[2] Katherine A Halmi. 2005. The multimodal treatment of eating disorders. *World Psychiatry* 4, 2 (2005), 69.

[3] Pranut Jain, Rosta Farzan, and Adam J. Lee. 2019. Adaptive Modelling of Attentiveness to Messaging: A Hybrid Approach. In *Proceedings of the 27th ACM Conference on User Modeling, Adaptation and Personalization* (Larnaca, Cyprus) *(UMAP '19)*. Association for Computing Machinery, New York, NY, USA, 261–270. https://doi.org/10.1145/3320435.3320461

[4] Pranut Jain, Rosta Farzan, and Adam J. Lee. 2019. Are You There? Identifying Unavailability in Mobile Messaging. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI EA '19)*. Association for Computing Machinery, New York, NY, USA, 1–6. https://doi.org/10.1145/3290607.3312893

[5] Pranut Jain, Rosta Farzan, and Adam J Lee. 2021. Context-based Automated Responses of Unavailability in Mobile Messaging. *Computer Supported Cooperative Work (CSCW)* (2021), 1–43.

[6] Pranut Jain, Rosta Farzan, and Adam J. Lee. 2022. Laila is in a Meeting: Design and Evaluation of a Contextual Auto-Response Messaging Agent. In *Designing Interactive Systems Conference* (Virtual Event, Australia) *(DIS '22)*. Association for Computing Machinery, New York, NY, USA, 1457–1471. https://doi.org/10.1145/3532106.3533493

[7] InJung Kim, HanZhong Zheng, and Shi-Kuo Chang. 2018. A Mobile Dietary and Emotional Diary System for Eating Disorder Care on the Smart Phone.. In *DMSVIVA*. 65–70.

[8] Daniel McDuff, Abdelrahman Mahmoud, Mohammad Mavadati, May Amr, Jay Turcot, and Rana el Kaliouby. 2016. AFFDEX SDK: a cross-platform real-time multi-face expression recognition toolkit. In *Proceedings of the 2016 CHI conference extended abstracts on human factors in computing systems*. 3723–3726.

[9] P Södersten, C Bergh, M Leon, U Brodin, and M Zandian. 2017. Cognitive behavior therapy for eating disorders versus normalization of eating behavior. *Physiology & behavior* 174 (2017), 178–190.

[10] Upkar Varshney. 2009. *Pervasive healthcare computing: EMR/EHR, wireless and health monitoring.* Springer Science & Business Media.