Integration of Transtheoretical model with wellness Big Data for healthy behavior assessment to adoption

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***Abstract*—Innovative wellness gadgets are the products of convergence of science and technology in this dynamic digital era. It has not been possible before to provide just-in-time intervention to avoid unhealthy behavior. The change in behavior requires the understanding of the behavior theories and then practical implementation of the stages. Transtheoretical model supports to identify the stage of human behavior and the transition for improvement. Behavior analysis is performed through unbiased recording of actions in term of big data. Just-in-time coaching is provided to motivate the users, stage-wise to adopt the healthy behavior without any big deviation.**

***Keywords*—Persuasive technologies, big data, transtheoretical model, personalized coaching, wellness , healthy behavior adoption.**

I. Introduction

The user awareness about personal wellness has been revolutionized in past few years which is mainly due to the proliferation of smart gadgets and tons of health applications available on mobile app stores. Currently, immense computational power, cheap storage space and miniaturized electronic components have revolutionized the domain of medical care and wellbeing. It allows customers to continuously monitor their behavior and gain information from the collected data collected [1]. The variety of data collected by wellness applications exploits the built-in sensors like proximity and light sensors, gyroscope, accelerometer, and magnetometer. This data is then used for setting and achieving certain user centric milestones like weight loss, exercise, and women's health during pregnancy. The data related to user activities and health, triggers a new wave of realization where it is believed that just-in-time personalized indication prevent the unhealthy behavior [2].

The traditional evaluation of the behavior change depends on the interviews, surveys, observations, and log diaries. Usually, existing studies use interviews and surveys to monitor and get feedback from the subjects regarding the change and improvement in behavior [3]. It is a very tedious task, too much depends on human memory and sometimes have intentional and unintentional biasness. We have proposed a transtheoraetical model based method to induce healthy behavior through coaching and perform evaluation of different stages using activities log, stored in big data through persuasive technologies.

A. Big Data of Wellness from IoT

Big data techniques have the potential to manage the data that is generated at a high velocity, in large volume, and variety by multiple health devices and wearable embedded health sensors [4]. The analysis of big data supports to identify the key health identifiers and suitable interventions for healthier behavior.

The emerging Internet of Things (IoT) trend provides comprehensions relation between health, wellbeing and environment by generating large data [5] and can act as channels or interface for intelligent interaction to the user.

B. Persuasive Technologies

In computer science, persuasive technologies mainly focuse to adopt healthy behavior for leading healthy lifestyle [6]. These technologies change human behavior in an organized way without causing pressure and burden to user. The pattern of human behaviors defines the lifestyle and characterizes the human personality. So lifestyle is a product of choices and adaptation requires transformation in choices to adopt the healthy lifestyle. However, adopting new lifestyle is quite challenging as well as requires lot of patience. People desire healthy lifestyle, yet physical inactivity and poor dietary habits are increasing and leading to serious health issues [6].

C. Mining Minds Platform

The Mining Minds (MM) platform provides comprehensive personalized solution to the users using state of the art technologies [2]. It is a layered architecture of data, information, knowledge and services. Data curation layer collects data from variety of sources such as multimodal sensors, social networking sites, wearables, and audio/video streams to acquire knowledge and generate personalized services. The acquired heterogeneous data is semantically linked to the user identity and mapped to an ontological representation. Data from multimodal sensors are curated in big data to extract low level context information and high level context information such as behavior modeling and context recognition [8]. The context information and life-log creation based on personalized data are performed in the information curation layer. To extract knowledge and provide services to the end users; low level data from data curation, and contextual information from information curation layer are processed using state of the art techniques in knowledge curation and service curation layers [2].

II. Transtheoretical model of Behavior interventions

The Transtheoretical Model (TTM) is the widely used model for health-related behavior interventions [7]. The model consists of five stages that are usually followed by an individual which progressing through behavior modification.

A. Precontemplation (Not Ready)

An individual at this stage is not able to foresee the impact of his/her current behaviors. The lack of knowledge does not allow him/her to think about the action towards behavior improvement in near future.

B. Contemplation (Getting Ready)

The individual at contemplation stage understands the pros and cons of the change in behavior and intends to changes in near future. The tradeoff between benefits and costs may create confusion and cause behavioral procrastination.

C. Preparation (Ready for action)

Prepared individuals are ready to take action immediately. They have understood the pros of the behavioral change and want to take action.

D. Action

The individual has made recommended changes in lifestyle from recent past duration. The recommendations have been observed from the recorded action as observable behaviors. The criteria for observable actions depends on the scientific accounting of the intensity of action i.e. number of cigarettes per day.

E. Maintenance

The individual works to manage the acquired modification and avoiding the relapse. The change process is very less frequent. The confidence level increases incrementally as individual gains trust that changed action is continued.

III. Proposed Methodology

A. Behavior Stages Classification

We consider the BMI, activity level and daily calorie intake to classify the individual into different behavioral stages. The relationship between transtheoretical stages and the above mentioned attributes are shown in Table 1.

Table 1. Transtheoretical Model Stages Mapping

Sr. No	Transtheoretical Model Mapping		
	TTM Stages	***Definition***	***Strategy***
1	Precontemplation	Unaware of sedentary, unhealthy dietary , and obesity lifestyle	Review the impact of unhealthy lifestyle on physical and mental health
2	Contemplation	Considering change to avoid unhealthy behavior	Awareness of factors of sedentary, unhealthy dietary behavior
3	Preparation	Planning to adopt healthy behavior	Identify factors to avoid unhealthy behavior
4	Action	Involving in healthy behavior activities	Adopt active physical activities and healthy dietary habits
5	Maintenance	Keep managing the adopted lifestyle	Establish plans to avoid relapse and focuses on lifestyle goals

B. Activity log from Big Data

Behavioral data can be obtained through interviews, surveys, log and observations. We choose the log to obtain the unbiased information of daily physical activities and dietary habits through our well established Mining Minds Platform [8]. The platform provides the mobile application that is used to record the physical activity and food intake information. These log supports to calculate the bouts of sedentary behaviors as well as consumptions of the calories per day. According to the healthcare guidelines body mass index (BMI), activities and diet are categorised on the basis of ranges as shown in Table 2.

Table 2. Physical Behavior Focused Feature with range

Sr. No	Physical Behavior Features		
	Focused Features	***Attributes***	***Values***
1	Physical Activity	Sedentary	PA <150 mins/week
		Light Exercise	180 >PA >=150 mins/week
		Vigorous Exercise	PA>=300 mins/week
2	Diet	Low	Cals <1800 (per day)
		Normal	Cal between 1800 to 2500 (per day)
		High	Cal >2500 (per day)
3	Body Mass Index	Under weight	BMI<18
		Normal	BMI between 18.5 to 24.9
		Over Weight	BMI between 25.9 to 29.9
		Obese	BMI>30

C. Stage identification of User

Behavior data is gathered by our ongoing project of Mining Minds platform [8]. The platform supports to capture the human physical and dietary activities using multiple sensors. The log is maintained for analyzing the pattern of activities and generates recommendations. We use the log to identify the behavior stage of user and provide just-in-time personalized education and coaching derived by expert to adopt healthy behavior. The process of transtheoretical behavior stages identification, from the user log is shown in Fig. 1.

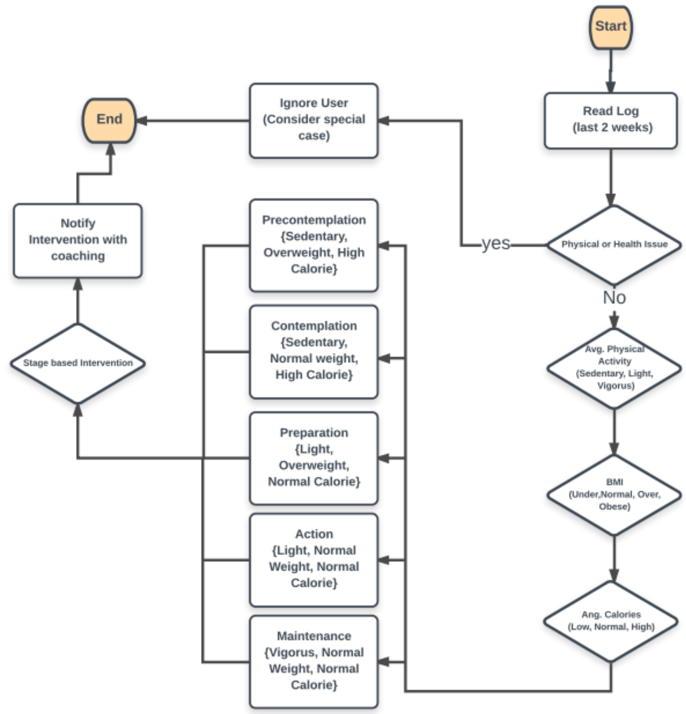

Figure 1. Behavior Stage Classification Process

IV. EVALUATION AND RESULTS

We have recruited 33 volunteers and they were guided to use Mining Minds platform to record their activities through mobile application that helped them to visualize the log of the activities on daily and weekly basis. At initial stage we gathered the log of two weeks to identify the transtheoretical behavior stages of our volunteers and then conduct interview regarding their intention and information relating to healthy lifestyle.

Our proposed system identified the behavior stage of volunteers on the basis 2 weeks' data of the physical activities performed and the calories intake. After that our mining minds platform provided coaching regarding the prolonged sedentary activities and unhealthy dietary habits to the respective user. The user of precontemplation stage got the educational information, contemplation stage users got the motivational information, preparation and action stage users got the indication and alarming personalized alerts, and the maintenance stage users got the goal enhancing messages. These messages were

Figure 2. Behavior Stage Transition Chart

managed and maintained by nutritionist and experts. The platform recorded the feedback regarding the improvement and efficacy of knowledge and suggestion provided to the users. After 5 weeks of just-in-time coaching there was a one week of observation for the transition of behavior stage and the results are shown in Fig. 2. We have to ignore data of three volunteers because they left in middle of experiment. It was observed from the collected data of activities and feedback that there were 23 volunteers whose transtheoretical model stages had improved.

V. CONCLUSION

We have utilized the big data generated by persuasive technologies for the assessment of behavior stages and provide just-in-time personalized coaching for the adoption of healthy behavior. The result shows that overall 76.66% behavior stage transition is there. In future we want to extend this work for the addicted habits of smoking and drinking.

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