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Enriching Remote Monitoring and Care Platforms with Personalized Recommendations to Enhance Gamification and Coaching

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Abstract. Patients' remote monitoring platforms can be enhanced with intelligent recommendations and gamification functionalities to support their adherence to care plans. The current paper aims to present a methodology for creating personalized recommendations, which can be used to improve patient remote monitoring and care platforms. The current pilot system design is aimed to support patients by providing recommendations for Sleep, Physical Activity, BMI, Blood sugar, Mental Health, Heart Health, and Chronic Obstructive Pulmonary Disease aspects. The users, through the application, can select the types of recommendations they are interested in. Thus, personalized recommendations based on data obtained by the patients' records anticipated to be a valuable and a safe approach for patient coaching. The paper discusses the main technical details and provides some initial results.

Keywords. Gamification, pHealth, recommendations, coaching, eHealth, IT systems, Rule-based Expert System, patient telemonitoring

1. Introduction

Health Information systems often include advanced features aimed to managing diseases and promoting healthy living. [1-3]. Meanwhile, the idea of intelligent patient coaching is also widely accepted in these systems because it can provide users with a more consistent, safer, and more reliable guidance through tailored information and recommendations [4,5]. Additionally, patients' remote monitoring and care can be also enhanced with gamification and functionalities, as recommendations, that support their adherence to care plans [6-8]. The current paper aims to present a methodology for

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creating personalized recommendations and coaching schemes, which can be used in patient remote monitoring and care platforms. The adoption of such technologies may contribute to higher patient engagement on the care plan as well as in a healthier lifestyle and better disease management.

2. Methods

The proposed recommendations' module aims to support patients in achieving a healthier lifestyle. The goal is to "educate" users to develop habits that will improve their daily life quality and their health status. At the same time, another goal is to make sure that these habits adhere to WHO and other relevant organizations' guidelines. [9,10]. The presented initial system is intended to support and educate patients by making recommendations for Sleep, Physical Activity, BMI, Blood sugar, Mental Health, Heart Health, and Chronic Obstructive Pulmonary Disease issues. The system functions as a ruled based "intelligent agent" [11-13], converting the user's data into guidelines for a improving their lifestyle. Domain-specific knowledge is required to model the "environment" where the agent will convert the user's data into recommendations. Furthermore, the need of a scoring mechanism is required in order to assess the user's data with the coordinated recommendations, additionally, the score is used by the *Credit* generator mechanism. A mechanism exploits the user's score to generate the *credits*, a points-like object that is used to enhance the gamification approach [14,15]. Using these *credits*, the user can reclaim some gaming benefits that the application provides. The integration of serious games (mental games and exergames) in the system, facilitates the development of additional Personal Health Record (PHR) data, which is subsequently utilized as an indication to evaluate the user's mental health and mobility. The *Intervention* mechanism inquires for the proper recommendation according to the user's score. This component produces the appropriate domain recommendation. Figure 1 illustrates the aforementioned flow.

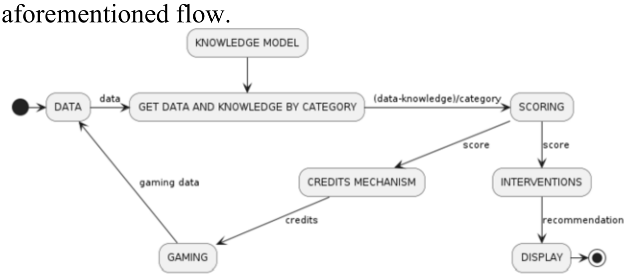


Figure 1. The recommendations flow in the system

2.1. Data Source

Personal Health Records (PHRs) are used as input for the recommendation module. The PHRs are collected by smart devices (mainly smart watches) via third-party applications, by Bluetooth devices or by user's manual input if the user has not any available interconnected devices for measurements like weight or blood-sugar. Furthermore, external data such as weather forecast can be used to make strong-evidence inferences on some recommendations, including those for patients with Chronic Obstructive Pulmonary Disease (COPD), or soft-evidence inferences on other recommendation types like physical activity recommendations.

2.2. Domain-specific knowledge

In Figure 1, the *KNOWLEDGE MODEL* represents the guidelines given by the World Health Organization, other National organizations such as the American Heart Association [9], other medical advisory organizations like Sleep Foundation [10], or individual healthcare physicians. For each domain, the KNOWLEDGE MODEL is encoded as a set of multivariate objects. A default knowledge has been stored in a structure in which each domain contains information about a goal, an acquisition technique, a reference period, and a condition. An example of how such a model could be represented in each domain is shown in Table 1. If needed, physicians can modify goals, periods, and conditions in every domain for each patient.

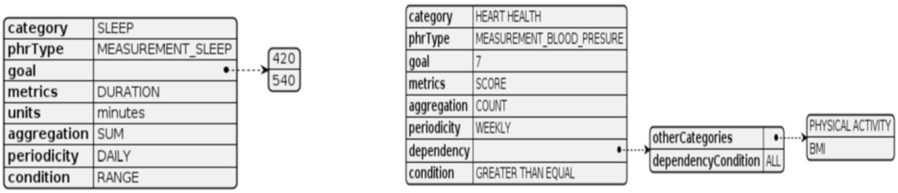
Table 1. Example of the encoded KNOWLEDGE MODEL

Category	Acquisition	Goal	Units	Reference Period	Condition
Sleep	smart watch	420 - 540	minutes	DAILLY	RANGE
Physical Activity	smart watch	150	minutes	WEEKLY	≥
BMI	weight	18.5 - 25	-	WEEKLY	RANGE
Blood Sugar	Sensor (Blood sugar)	100	mg/dL	DAILLY	≤
Mental Health	Games	2	-	DAILLY	≥
Heart Health	Physical activity, BMI		-	WEEKLY	-
COPD	Weather data, Physical activity	-	-	DAILLY	-

The *KNOWLEDGE MODEL* can generate complicated elements such as *Heart Health* and *COPD*, which are objects that rely on the success of other primitives such as *Physical activity*. The *KNOWLEDGE MODEL* is discussed in more detail in the subsequent section.

2.3. Modeling The Knowledge

The recommendation module is a mechanism which primary function is to encourage and alert the users in developing healthier habits. The *KNOWLEDGE MODEL* consists of rules. The representation of each rule is configured as shown in Figure 2. The category variable has the name of the recommendation domain (physical activity, sleep, BMI, and other). For some categories we only need some aggregation on the user's PHRs data and then to evaluate those data within the KNOWLEDGE MOLEL. *Physical activity*, *Sleep*, and *Blood sugar* are examples of such types. These types of categories are referred as *"Primitive"* types in the *KNOWLEDGE MODEL*. Other types, such as *Heart Health*, *COPD*, dependent on the success of some primitive types. These are called *Mixed* types in our *KNOWLEDGE MODEL*. Figure 2 also depicts instances of primitive and mixed elements where we know that (a) a daily sleep should be between 7 and 9 hours, and (b) for the *Heart health* element, a systematic blood pressure measurement and success in both physical activity and BMI assessments are necessary. The current object explicitly sets that the Primitive objects, PHYSICAL ACTIVITY and BMI should be accomplished. Additionally, it defines that an individual should perform at least 7 blood-pressure measurements in a week. A Physician may change the goals and dependencies to create new tailor-made rules (elements in the KNOWLEDGE BASE) based on the different patient's conditions.



(a) (b)

Figure 2. The structure of a Primitive element in the KNOWLEDGE MODEL (a), the structure of a Mixed element where the goal, metrics, aggregation and periodicity are optional (b).

2.4. Scoring - Recommendations - Credits

Based on the above, the state of each individual user is evaluated using their PHRs. For this purpose, firstly *Primitive* elements (such as Physical activity, Sleep) and then *Mixed* elements (such as *Heart health*) information is examined. As a result, a score based on the guidelines (rules) and the user's data is computed and forwarded to the subsequent processes, which involve the “credit construction” and “recommendation creation”. Three different levels of scoring are defined. The first level indicates that the goal was met. The second level indicates that a little more effort is required, and the third indicates that significant more effort is required by the patient. A recommendation is formulated and displayed on the user’s application screen based on the user’s score in each category. Furthermore, the credits earned can be used to play a variety of games through the app.

3. Results and Discussion

The application allows the users to select the types of recommendations according to their profile. Relevant recommendations based on their preferences are displayed on their application screen. Figure 3 illustrates the user settings (a) and the related recommendations (b).

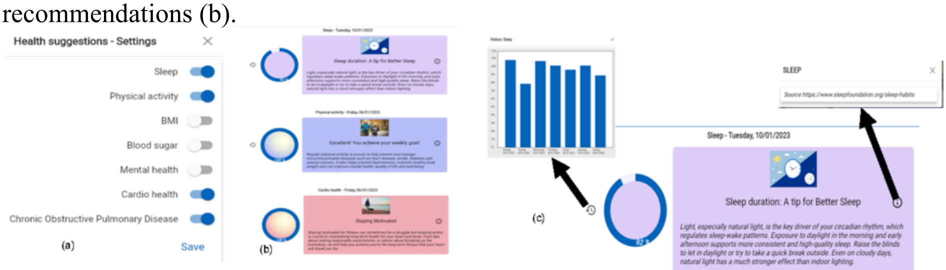


Figure 3. (a) The UI widget from which the user selects the categories. (b) Health recommendations in the user’s screen. (c) A snapshot from a recommendation card.

Each suggestion card has a unique color palette, based on the recommended category. The card includes an image relevant to the category, a title, and a message. In addition, a success indicator in the form of a “ring” appears. When the goal is reached, the ring appears to take a 3D shape (Figure 3 b). The user can view his status history for the given recommendation field as a graph by clicking a button on the interface. He can also find more about the source of the recommendation by clicking the information icon. Figure 3 (c) presents the recommendation card and its elements.

4. Conclusions

The proposed recommendations' tool can be applied in patient remote monitoring and care platforms to enhance gamification and the patients' coaching. Personalized recommendations based on data obtained by the patients' records seems to be a valuable and a safe approach for patient coaching. A limitation is that the system's knowledge field displays the key condition dependence factors. In fact, each condition may be dependent on more than the aspects reflected in the created model. To keep the approach simple for both the user and the inference process, we are currently excluded scenarios which have smoking, drinking, meals, nutritional value as factors. The proposed approach assessment by different types of patients is one of the future works of our research.

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