

# Designing a Mobile Recommender System for Treatment Adherence Improvement among Hypertensives

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**Abstract**—Impelling the ambulatory hypertensive patients to stick to the prescribed treatment throughout a long term is a challenging problem. To address the problem, the personal monitoring system can be used providing the possibility both to gather various health state parameters and life style-related data and to intervene in case the patient does not stick to the appointed instructions. The subsystem related to health state monitoring have been presented in our previous work. In this paper, we introduce the recommender system intended to patient's behavior correction.

## I. INTRODUCTION

Hypertension disease is identified among the most common diseases and requires regular continuous treatment [1]. The patient treatment adherence can be supported with modern mobile information technology when health monitoring and disease therapy are performed regularly during everyday patient's activity [2]. Such procedures as long-term monitoring of electrocardiography (ECG) signals or blood pressure data are carried outside a hospital environment. The procedures are implemented as a recommendation service when monitoring provides data for constructing recommendations in the form of context-aware prescriptions, online advises, and other informational assistance in treatment adherence. An information service-oriented space is formed around the patient [3]. The space accompanies the mobile patient, accumulates information on patient's healthcare status by monitoring, provides this information to the doctor, and constructs online recommendations for the patient.

Long-term monitoring of medical and non-medical parameters is required to achieve treatment adherence. The joint observation of parameters obtained from the results of a survey or wearable devices allows us to assess the patient's current health status. The volume of obtained data is sufficiently large and heterogeneous, which requires special processing and analyzing methods [4]. A number of medical parameters can be obtained by analyzing these data. Further, it can be interpreted by a doctor manually or automatically with the help of digital recommender system. Parameters can characterize the work of the heart, physical activity, emotional state, etc. Joint processing of parameters shows the interrelations between them and assesses their compliance with established by doctor trajectory targets.

The main goal of the patient is to adhere to the prescribed treatment in a certain long period of time, using recommender

system. Since the treatment is sufficiently long, the digital recommender system should interact with the patient to control the achievement of the goals and, in cases of successes and failures, give recommendations. The approach for this digital informational assistance organizing is required, that would contain a model of medical data and additional non-medical information and a processing algorithm. As a result, the patient should receive recommendations in case of deviation from the treatment trajectory or successful achievement of the given goals.

Patients and health professional participants commented that patients would find wellness monitoring tools as not useful and potentially too complicated. At the same time, both participant groups agreed that wellness monitoring tools could act as a starting point from which health care providers and even older adult patients could build closer relationships through the deeper understanding of the patients history and assist with monitoring and providing recommendation [5].

The paper is organized as follows. Section II overviews some recent studies in mobile healthcare. Section III defines the problem of hypertensive patient treatment adherence and introduces our approach to solve this problem using mobile recommender system methods. We consider what prescriptions are typically provided by doctors to hypertensive patients and what related recommendations can be constructed based on mobile long-term monitoring. Section IV summarizes our previously developed solutions on collection and integration of medical-specific and non-medical information about a hypertensive patient for their use in the proposed design of mobile recommender system. Section V introduces our ontological model for semantic representation of the collected integrative information and its further use for recommendation construction. Section VI describes our design model of mobile recommender system that implements the above solutions on multi-source data collection, semantic representation, and recommendation construction. Finally, Section VII concludes the paper.

## II. RELATED WORK

Let us consider models and solutions, that enable development of the considered goal of the treatment adherence trajectory. Most of the discussed solutions have been elaborated in our previous work.

The IoT technology provides the opportunity to construct mobile health (m-Health) services based on long-term mobile monitoring of patient's medical parameters outside the hospital environment, e.g., see recent reviews in [3], [6]. Our previous work [7] discusses the approach to collection and integration of heterogeneous multi-source data based on ontology modeling methods. In particular, an ontological model for survey questionnaires is presented in [8]. The feasibility of this approach is experimentally studied in [9] for the case of personalized mobile assistance services in healthcare emergency situations. Existing IoT-solutions for m-Health monitoring and the Smart-M3 platform for smart spaces are efficient for development of mobile services constructed within a smart space that accompanies the patient during her/his everyday activity.

The applicability of ontology modeling methods in knowledge-based systems is discussed in [10]. Examples of ontology-based system developments can be found in various domains, including medicine and healthcare, industry and business, cultural and social applications. Ontologies are used in design and development of knowledge-based systems as well as a full-fledged component during the system operation. In particular, work [11] consider an ontological model for merging medical data that further are used for providing treatment advices. Several ontologies are developed where each ontology provides a representation model for a particular data set and for linking the data with other data sets and derived knowledge. As the key property, the model increases the coherence of data in traditional medical information systems.

Paper [12] considers a fog-assisted system for monitoring patients with acute illnesses. It guides us to develop healthcare solutions with more intelligent and prediction capabilities both for daily life. Healthcare is becoming increasingly difficult to manage due to insufficient and less effective healthcare services to meet the increasing demands of rising aging population with chronic diseases. The transition from the traditional clinic-centric treatment to patient-centric healthcare is discussed in [13]. All participating entities—such as hospital, patient, and service—become seamlessly connected to each other, independently on physical location.

The problem of intelligent (or smart) personal assistance is a straightforward consequence of the mobile monitoring opportunity [14]. In particular, such collected information as the patient location, heart rate, and fall detection can be used for decision-making in emergency alarms and first aid support [15]. Work [16] considers a mobile monitoring system that provides such recommendations for the patients as taking measures through sensors or recommendation to improve their eating habits and workout routines. Review [17] analyzes IoT healthcare monitoring applications where data mining and machine learning methods are used in self-care and clinical support scenarios. Article [18] applies machine learning methods for predicting epileptic seizures from Electroencephalograms (EEG) signals and for constructing recommendations on prevention of the seizure by medication.

Compared with the above studies, this paper applies the integration of data from various sources represented in the form of ontologies. The integrative vision on these multi-source data and their semantic relations forms a base for construction of recommendations to hypertensive patient treatment adherence

and leads to personalized treatment adherence trajectory for the patient.

### III. RECOMMENDATION PROBLEM

In hypertension, the aim is at constructing the treatment adherence trajectory for the patient. The aim is achieved based on own efforts and with the help of a recommender system. Doctors can prescribe the patient to lowering blood pressure, to regulate physical activity, to regulate the diet and consumption of alcohol, etc. Complex performance of tasks determines the degree of achievement of the goal. A large number of factors influencing the behavior of the patient must be taken into account to provide recommendations. Examples include the individual blood pressure norm, the reaction to the change in atmospheric temperature. Typically, the doctor defines the following tasks for hypertension patients.

- 1) Quality control of antihypertensive therapy:
  - blood pressure control,
  - regulating the intake of medication,
  - making a decision on an emergency visit to a doctor.
- 2) Correction of additional risk factors:
  - weight loss,
  - regulation of physical activity,
  - rejection of bad habits (smoking).
- 3) Ensuring the implementation of the principles of proper nutrition:
  - regulation of the food regime,
  - quality of food,
  - alcohol consumption.
- 4) Providing a rational mode of rest, positive mood:
  - regulation of emotional state,
  - regulation of sleep quality.
- 5) Analysis of the dependencies of the main parameters of the assessment of the state of health from various factors with a view to changing the treatment regimen:
  - determination of the presence of meteosensitivity based on recording the blood pressure, heart rate, variability, plotting weather dependencies (temperature, atmospheric pressure, magnetic storms, etc.),
  - establishing the dependence of parameters (blood pressure, heart rate, etc.) on the quality of sleep,
  - some others.

The required treatment adherence is achieved by applying doctor's prescriptions. Nevertheless, in practice only about half of people with high blood pressure have their condition under control. Therefore, it is required to observe and control the patient's performance of the prescriptions with the help of recommendations. Using medical standards and additional clinical studies, doctors have identified a set of recommendations in the long-term monitoring of patients for behavior change within the management system of a patient with hypertension. Also for an individual patient, a doctor can describe personal recommendations, e.g., when the individual rate of some parameter is inconsistent with the generally accepted one.

TABLE I. RECOMMENDATIONS IN PATIENT TREATMENT ADHERENCE

Recommendation Type	Recommendation Form
Encouraging (praising, rewarding) or punishing.	Visual notes to study and follow.
Providing instruction (e.g., on medication).	Showing personal achievements. Notification to the doctor.
Motivating (e.g., for particular activity or behavior).	Showing the progress and prediction of near success.
Warning on violation of the trajectory or alarming on risk situation prediction.	Alarm-like note delivery to the patient and/or doctor.

Recommendations can be divided by prescription into several classes. Diets recommendations determine goals for nutrition normalizing, for example, reducing the fat content of foods, salt content, and others. Lifestyle recommendations include recommendations on the distribution of physical activity, normalization of sleep, etc. On the other hand, some recommendations are addressed to the information system, and not to the user, for example, perform additional measurements using connected wearable devices. Initially, specific recommendations are formulated by doctor. As an additional opportunity the patient’s progress schedule is provided for self-examination with some periodicity to increase the effectiveness of therapy and treatment adherence. Recommendations to the patient are classified and related with the recommendations in Table I.

It is important how and how much the patient uses the recommender system. So the initial user needs more help for correct execution of tasks. Advanced users need more to encourage their actions. Such a patient needs to see his progress, which motivates him to the following achievements. An competent user needs fewer hints or reminders for the timely execution of actions. In some cases, if the user clearly performs the tasks, the recommender system cannot send anything at all. And the user at the failure stage needs additional confirmation of the need to follow the instructions of the recommender system. Such assistance can be provided not only by the recommender system, but also by the people who surround the patient, for example, relatives or friends.

In traditional recommender system, user preferences are derived from ratings and utilized to predict the users rating on new items, but they cannot completely full the purpose of health recommendation. Recommender system in medicine need to provide a simple interaction, empowerment through explanations of the proposed recommendations, and safety against harmful recommendations, considering identifying patient needs. This will allow patients to trust the system, as well as an accurate and correct presentation of medical and non-medical knowledge and processes important for doctors and experts [19].

IV. DATA SOURCES

Context-aware information about the patient should be known to achieve the prescriptions and tasks. If the patient is observed in the hospital, all data is measured and stored centrally. In the case when the patient is observed remotely, it is necessary to determine what data the patient can collect independently.

The survey of products and their components provides information about the content of proteins, fats, carbohydrates.

Glycemic index, the nutrients ratio diagram by the product or ingredient name from daily food intake are determined. Also, data on the frequency and time of meals is entered in the survey mode, the regime can be established and / or entered after a fact. The control of drug administration occurs by means of survey too. Data on names, doses and time of intake can be recorded only once, then the fact of intake is noted. If necessary, taking medications regime can be edited. Answers on the facts of anxiety, panic attacks can be obtained by assessing the emotional state through a mood survey on different scales [20]. Other well-being data, facts of dizziness, nausea, etc. also the patient writes through a survey. Sleep quality surveys are conducted to describe night regime: insomnia, waking up at night, snore, cough, feeling cold or fever, bad dreams, drowsiness during the day, etc.

The next input data requires less patient involvement. Wearable devices are used to receive them, most often they have a wireless interface (Bluetooth, WiFi), so the user only needs to connect the device, then the data is transferred to the recommender system in an automatic mode. Weight, blood pressure, body temperature are made manually in the absence of connection via bluetooth. Indicators changes dynamics diagram is built on the basis of these data, trends are also being built. One of their main parameters is the ECG, which is measured by a monitor at the doctor’s request or for a long time. The data based on the RR-intervals form the heart rate variability conclusion, QRS width and other parameters.

The level of physical activity for the whole day or in a certain period can be measured using an accelerometer built into the smartphone or smart clock , which counts the number of steps. The pulse measured by the pulsmeter is also used to determine the sleep phases: deep, superficial periods. Also for this purpose the position of the body is checked based on the average number of movements of the limbs of the person. Its other application is the fall definition, when a vertical component of accelerometer sharp change occurs.

The next data type do not refer directly to the patient, it describes the environmental context: atmospheric temperature, pressure, precipitation, etc. The data is transmitted from the weather site, when analyzing the complex of parameters obtained over a long period of time. Thus, it is possible to obtain a correlation (dependence / meteorological sensitivity) with a certain weather.

To achieve each task, Table II shows examples of data sources needed to accomplish prescriptions. The model of data integration from various sources assumes the receipt of the following data. It includes a description of the heterogeneous data corpus as well as the connection between them.

V. ONTOLOGICAL MODEL

Set of data sources is described by an ontological model of data integration from various sources [7], which includes a survey ontology [8] , measurement ontology [4], joint patient’s adherence ontology [2]. Due to this, the associations between the different sources are established and can be used for their joint analysis. These data form the basis of the recommendation. Each parameter individually already carries information about human health, but their comprehensive processing gives more complete picture of the patient’s health.

TABLE II. EXAMPLES OF DATA SOURCE USAGE TO PRESCRIPTION

Prescription	Survey	Devices	Context
Quality control of antihypertensive therapy	survey about medicinal preparations, doses and time of reception	blood pressure from the tonometer	GPS-coordinates from the sensor
Correction of additional risk factors	survey about symptoms	number of steps, the position of the body in space from the accelerometer fitness tracker	temperature, atmospheric pressure from sensors
Ensuring the implementation of the principles of proper nutrition	survey about frequency and time of meals	weight from the weighing-machine with the possibility of data transfer	-
Providing a rational mode of rest, positive mood	survey about the emotional state	pulse, ECG signal received from the monitor	Noise level, air pollution

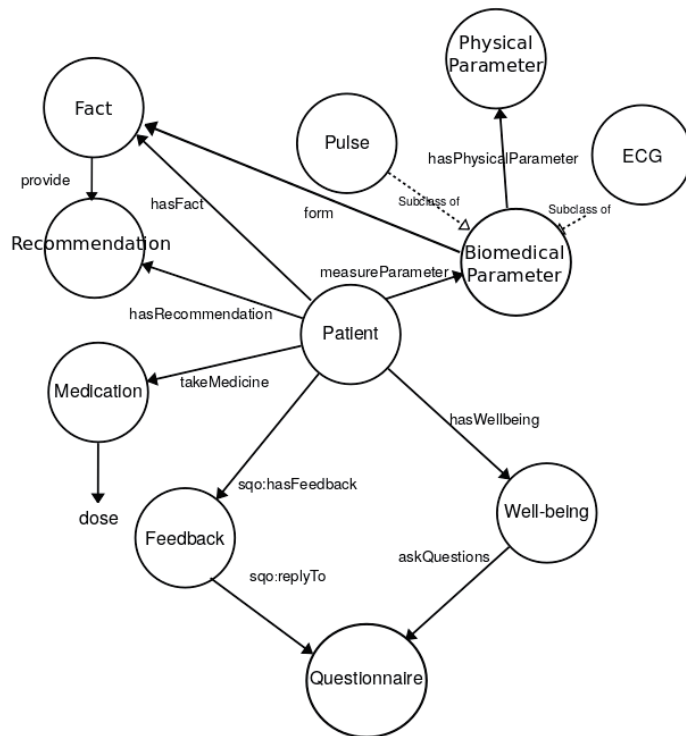


Fig. 1. Fragment of joint patient's adherence ontology

For the purpose, new fragment of the ontology is introduced, as it shown at Fig. 1. Several parameters are combined into one fact. The corresponding object is contained in the ontology and is called "Fact". The fact describes the condition or action, may be as medical as non-medical. For example, a fact can describe a symptom and be associated with an object of symptoms ontology [21]. The fact may reflect the performance of some action, be an indicator of its performance, skip or partial execution, show was it successful or negative action. The fact can also characterize a certain period of time.

Facts are associated with the concepts of own or third-party ontologies that classify them. For example, a patient's diagnosis can be linked to the corresponding object of the disease ontology [22]. A set of complaints may correspond to

some symptom from the symptoms ontology [21].

Further, the fact is related to a recommendation or set of recommendations, ontological object is named "Recommendation". With the help of such recommendations, the patient's treatment trajectory is adjusted. Each recommendation can be classified according to ontology of behavior change taxonomy technology (BCTT) [23]. This ontology was designed to standardize approaches of measures for behavior changes to increase the effectiveness. It contains more than 26 varieties of behavior changes methods that can be used to characterize and classify actions. For example, method No. 1 "Goals and planning" offers the following types of actions: action planning, behavioral contract, commitment, discrepancy between current behavior and goal, goal setting, problem solving etc. Good reliability (85%) was observed, which indicates that these instructions and definitions can reliably be applied to much more detailed descriptions of interventions.

Link between fact and recommendation is formed at the stage of creating an ontology by a researcher doctor, when he introduces a new individual of recommendation, he also indicates class of BCTT ontology that this recommendation applies. In the managing a patient with hypertension subject area, the ontology of the behavior change taxonomy technology can be applied to the classification of specific recommendations. For example, if the blood pressure rises to 150/90, the recommender system should recommend to take the medicine, and if the blood pressure increases above 170/100, call an ambulance.

Summing up, the ontology contains a presentation of medical and non-medical parameters derived from heterogeneous sources, facts that combine parameters by some classification and recommendations that describe the necessary actions on the part of the patient. All these ontological objects are interconnected and represent a semantic network that has to be processed to ensure the fulfillment of tasks for adherence to treatment.

VI. RECOMMENDATION CONSTRUCTION SCHEME

The recommendation construction scheme is based on the ontological model and includes the selection of priority recommendations, as Fig. 2 shows. Examples of recommendation construction in accordance with the scheme are presented in Table III.

TABLE III. EXAMPLES OF RECOMMENDATION CONSTRUCTION

Ex.	Step1	Step2	Step3
1	Blood pressure: 130/80	The entered parameters correspond to the targets	To praise: "The goal is reached"
2	Steps number per day, but the norm is still not achieved	The number of steps is growing, but the norm is still not achieved	Motivate: the person is on the right track, the target is close
3	The percentage of salt by different meals	More salt intake was detected	To give instruction: to reduce the use of a particular product, or to refuse it altogether
4	Scores on the depression scale	The number of points on psychic tension scale is borderline	To warn: to pay attention to it
5	Mean values of blood pressure, regime of medication intake	Charts of mean values of blood pressure, regime of medication intake	To praise and motivate in case of positive results

Initially, the data come from surveys and wearable devices (monitoring). These semistructured, unprocessed data have no evaluation characteristics. On Step 1 the process of computing meaningful medical and non-medical parameters is performed. The parameters aggregate the raw data into interpretable problem domain information. Based on the ontology, response objects extracted from survey represent either text written by the user, or answer numbers, in the case of close-ended questions. Objects bases on data obtained from wearable devices are formed using mathematical algorithms (e.g., statistical methods, data mining).

In our previous work, the fast and reliable algorithm of R peak and QRS complexes detection in digital ECG recordings based on joint application of Teager energy operator and level crossing sampling have been proposed [24], [25]. This algorithm offers the opportunity to process the ECG recordings directly on mobile device of the patient without negative impact on the battery life and, therefore, encouraging user mobility. From the other hand, on-site ECG analysis makes it possible to obtain a number of ECG features continuously, among them the following ECG parameters are monitored: 1) heart rhythm disturbances such as arterial fibrillation, premature ventricular contraction and others; 2) heart blocks; 3) heart rate; 4) P wave duration; 5) P wave amplitude; 6) P wave morphology, in particular, two-phase shape; 7) PQ interval duration; 8) QT dispersion; 9) Q width; 10) R amplitude; 11) S amplitude; 12) QRS width; 13) QT duration; 14) T wave amplitude; 15) T wave alternation; 16) T wave width and “T peak-to-end” parameter; 17) ST elevation; 18) ST decrease; 19) rhythm turbulence; 20) heart rate variability.

The survey ontology [8] also allows to link responses to objects that characterize types of questions. Other medical parameters can also be described in the survey form. As

well as non-medical parameters, they can be analyzed for trends building. Since a large amount of heterogeneous data does not need to be stored in a common semantic space, some calculations can be made directly by the agent to their receiving.

On Step 2, facts formed under a certain condition are discovered. Such a fact indicates the need of a priority recommendation. Condition checking considers one or more parameters. The absence of these parameters is also subject to check. In this case, the first option is characterized as a positive fact, and the second is characterized as a negative one. On the other hand, the absence of a certain parameter, for example, smoking, is considered positive, and its presence is negative.

The condition can check the amount of skipping or the execution of a parameter for the specified time. For example, you need to measure blood pressure between 12:00 and 13:00. Fact 1: measurement was successful, therefore recommended to praise. Fact 2: measurement is missed, it is reminded to fulfill it. If the parameter characterizes physical activity, power or sleep, then the condition checks the volume of parameter’s execution. Then the condition checks the parameter according to the characteristic: the norm is fulfilled, not reached or exceeded.

Conditions can be described using the ontology or with the help of production rules. Recommendation process in ontological terms is not enough to express real-world application scenarios. For example, deriving new and implicit knowledge from ontologies is efficiently done through rule-based reasoning. This kind of rules is represented in the form “IF condition DO reaction”. For representing this form with OWL language [26]. Another form to express description logic is based on a declarative formalism—a language—for defining concepts in multiple hierarchies/taxonomies [27].

The fact is associated with recommendation objects that are classified according to the BCTT ontology. The recommendation can be related to several facts, and vice versa. In this case, the most prioritized recommendation is given to the patient. Additional recommendations can also be attached to the main recommendation.

On Step 3, the ontology provides an information representation model in the form of a semantic network [7]. In semantic network  $G = (V, L)$ , the set  $V$  consists of objects (parameters, facts, and other instances of classes define in the ontology), whereas the set  $L$  consists of links  $(v, w)$  that represent particular semantic relations between objects  $v, w \in V$ . Possible types of relations are also defined in the ontology. Then semantic data mining methods are used to analyze this semantic network and construct recommendations based on searching appropriate information and selecting the most interesting facts to provide to the patient. In particular, the selected facts create the content for the recommendation forms (see the forms in Table I in Section III above).

The selection is reduced to the ranking problem, which can be used in various smart spaces applications [28]. Basically, a rank value  $r_v \geq 0$  can be associated with any object  $u \in V$ . We consider three techniques for this kind of ranking.

First, the local ranking when  $r_v$  is computed based on the informational content of  $v$  and/or its neighbors in the semantic

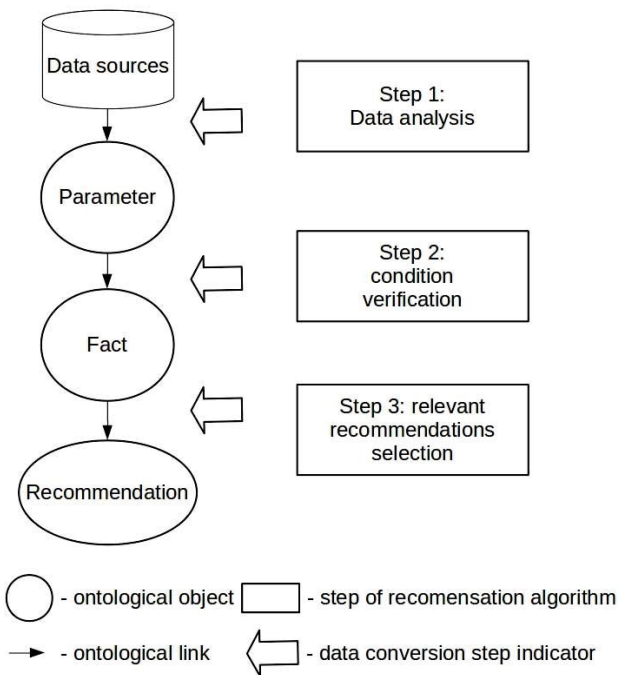


Fig. 2. Recommendation construction scheme

network. In particular, a recommendation is constructed from the most ranked objects.

Second, the rank  $r_v(u) = \rho(u, v)$  reflects semantic distance between the given object  $u$  and all other objects  $v$ . That is,  $u$  is selected by some condition on Step 2 and then a recommendation is constructed from the semantically closest objects (semantic neighborhood).

Third, the global linkage structure of  $N$  is used for computing the ranks, similarly as it happens in the PageRank algorithm for web pages. Given a semantic network  $G$ , ranks  $r_v$  for all  $v \in V$  are computed iteratively starting from some initial values  $r_v^{(0)}$ :

$$r_v^{(i+1)} = \alpha \sum_{\forall w: v \rightarrow w} p_{vw} r_w^{(i)} + (1 - \alpha) \pi_v,$$

where  $v \rightarrow w$  is a link in  $G$ ,  $p_{vw}$  is the weight of the link,  $\alpha$  is the damping factor denoting the probability of following the link structure, and  $\pi$  is a personalization vector of damping factors for all objects.

This scheme of providing recommendations is applicable for various stored diseases, in particular we have given examples of recommendations for patients suffering from hypertension. It is planned to use this scheme to build intelligent agents of mobile recommender system to ensure adherence to the treatment trajectory.

## VII. CONCLUSION

This paper proposed the designing a mobile recommender system addressing the problem of the low adherence to the treatment among ambulatory hypertensive patients and for the decreasing of hypertension-related risk. Model of joint patient's adherence combines data from the various data sources which gives an opportunity for for health and lifestyle-related data gathering, and joint analysis to provide recommendations. We propose the adherence assessment method based on recommendation services, thus the patient can be motivated to adhere to treatment, to praise in case of successful achievement of tasks or to warn about the consequences of harmful behavior. This, in turn, leads to improve adherence to the treatment among the patients and, as a consequence, decreases the chances of the hypertension-related complications, including the risk of sudden cardiac death.

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