

Intelligent Support for Clinical Processes Based on Automaton Approach

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Abstract—A lot of systems that support various aspects of e-health are presented on the market and in the literature (a brief overview is provided in the next section). But, as the analysis shows and practice confirms, among them there are no systems that fully satisfy the standardization and personalization limitations and many other requirements. This paper proposes the development of clinical decision support systems based on automata approach. The specifics of the solution is demonstrated on the real clinical process of management of patients with stable coronary artery disease and high-grade ventricular arrhythmia. The data storage specifics with obtaining and presenting the medical contraindications is shown, allowing to isolate, store and process the conflicting clinical information. The effectiveness of the proposed system in comparison with existing approaches is introduced.

I. INTRODUCTION

The worldwide trend towards e-health has brought the rapid development of information systems to support its various aspects. In particular, the development of e-health is declared as one of the key areas of the National Healthcare project for 2018–2024 in Russia. Within the framework of an extensive set of tasks in this area, the Ministry of Health of the Russian Federation highlights the creation of clinical decision support systems (CDSS) for doctors in the form of “... a desktop as a clinical protocol that suggests algorithms for further actions - in terms of tactical treatment (what needs to be done and how to manage it), and an additional examination” [1]. Among the huge contradictory set of constraints that the CDSS should satisfy, the key ones are the following:

- Standardization. CDSS must comply with the framework standards adopted in healthcare, including terms of terminology, and at the same time adapt to the specific standards of the hospital. For example, currently in the medical institutions of the Russian Federation different information standards are used (including 13606 / OpenEHR Archetypes [2] and Health Level 7 [3]), which differ not only in the data model, but even in terminology;
- Personalization. CDSS should provide the doctor at each decision-making with the opportunity to take into account the specific features of a particular patient, including individual reactions to drugs and other potential contraindications.

Given these limitations, it is possible to formulate conceptual requirements for the architectural solution of the CDSS:

- (R1). Flexible interaction with the complex and multi-connected structure of medical data as a whole, while changes in the data structure should as low as possible affect the application program code;
- (R2). Flexible structure of requests, organized, as a rule, according to the scenario type;
- (R3). Extensibility in accordance with newly emerging classes of tasks specific to a particular patient.
- (R4). Built-in procedures for execution control of doctor’s decisions.

A lot of systems that support various aspects of e-health are presented on the market and in the literature (a brief overview is provided in the next section). But, as the analysis shows and practice confirms, among them there are no systems that fully satisfy the requirements and limitations formulated above. This article proposes a solution for the development of such systems based on the automata approach [4].

II. BACKGROUND AND RELATED WORKS

A. Terminology used

The choice of the conceptual and terminological base in many respects determines the effectiveness of any medical information system, including CDSS. In this work, we rely on the terminology of the ISO “Medical Informatics” system of standards, in particular, on the standard [5], which defines the following concepts:

- clinical process (CP) – medical process that covers all the actions of health care providers;
- health state (HS) – physical and mental functions, body structure, personality factors, activity, participation and environmental aspects as components of the subject’s health; the clinical process considers individual clinical health states;
- clinical symptoms (health condition, HC) – observable or potentially observable aspects of the current state of health;
- clinical activity (healthcare activity, HA) – activity aimed directly or indirectly at improving or maintaining a state of health; it may consist of several components;

– clinical fact (healthcare matter, HM) – a fact that is defined by one of the subjects of the clinical process as related to the health of the patient.

The advantage of this terms system is that, on the one hand, it is easily interpreted by a doctor, and on the other hand, it can be adequately translated into the concepts of an information system. The technique of such a transition is

illustrated in this paper within the example of a clinical process of managing stable coronary artery disease and high-grade ventricular arrhythmias. The process scheme [6] is shown in Fig. 1. The choice of this process has been made due to its high demand in clinical practice: according to recent studies [6–8], such patients constitute the most numerous risk group in predicting sudden cardiac death.

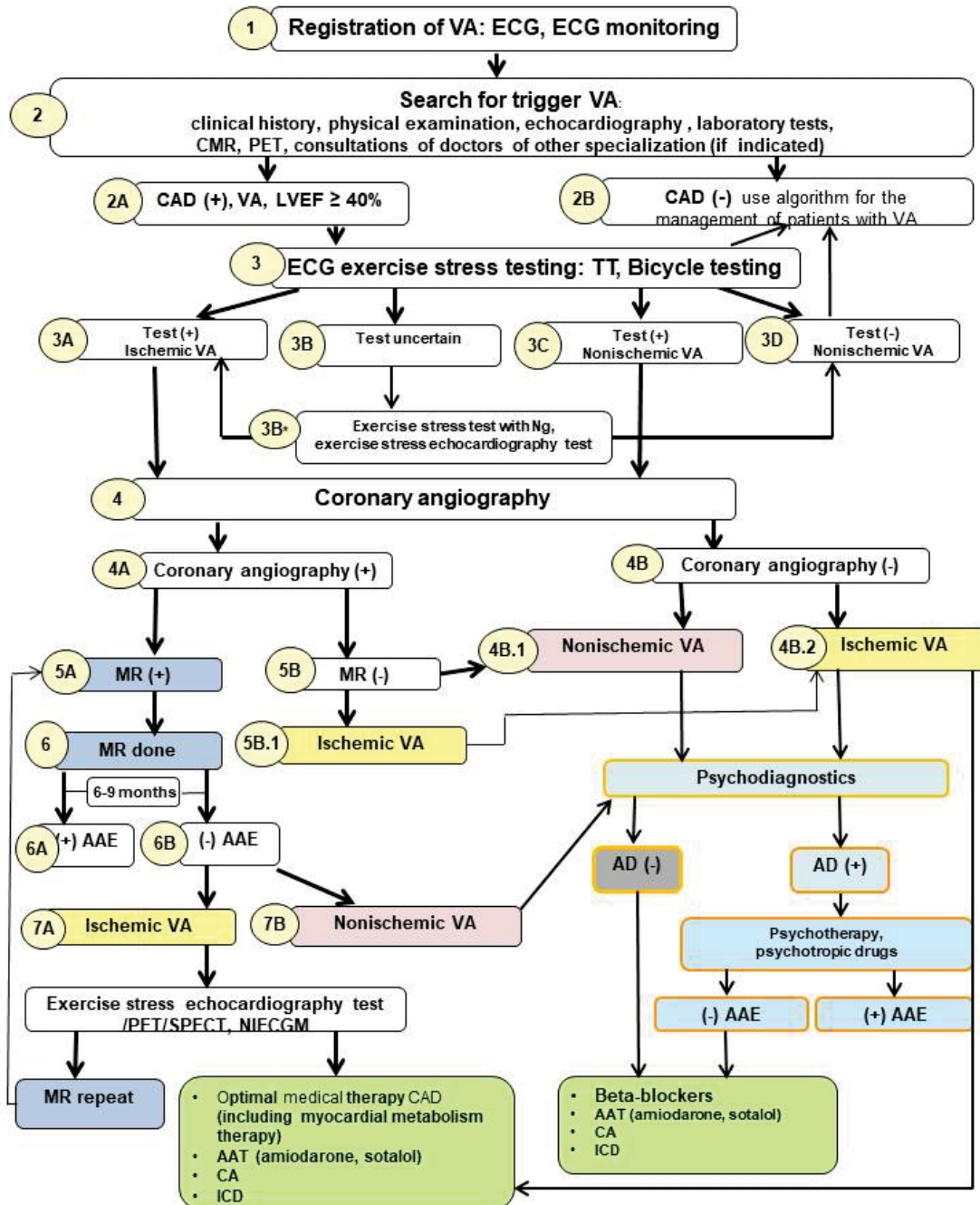


Fig. 1. Fig 1. The original form of scheme for the management of patients with stable coronary artery disease and high-grade ventricular arrhythmias: AAE – Antiarrhythmic effect; AD – Anxiety disorder; CMR – Cardiac magnetic resonance; CA – Catheter ablation; CAD – Coronary artery disease; ECG – Electrocardiogram; ICD – Implantable cardioverter defibrillator; LVEF – Left ventricular ejection fraction; MR – Myocardial revascularization; Ng – Nitroglycerin; NIECGI – Noninvasive electrocardiographic mapping; PET – Positron emission tomography; SPECT – Single-photon emission computed tomography; TT- Treadmill test; VA – Ventricular arrhythmia

B. Conceptual approaches to building CDSS as a means for support of clinical processes

CDSS are the primary tool for providing intelligent support for clinical processes. Meanwhile the definitions of CDSS given in various literature [9–12] are far more broad. For example, the official source [13] determines CDSS as a system providing clinicians with knowledge, intelligently filtered or presented at appropriate times, to enhance health and health care.

Accordingly, these definitions cover a wide variety of health care support systems that have been announced as projects or are already on the market (see reviews [10–12], [14], [15]). A detailed analysis showed that most of these systems individually or in combination implement the following functionality: support for individual diagnostic procedures (for example, automated analysis of radiographs, CT and MRI images); statistical evaluation of indicators and access to medical calculators; reference functions (for example, checking drug compatibility, structured access to medical information); recording of indicators during remote monitoring of patients; manual recording of assignments (during treatment in the clinic). However, in the available literature concerning CDSS realization, we were unable to find the function of prompting the algorithms of the doctor's actions during the clinical process, that is, in the form of maintenance of the clinical protocol execution, as stated in [1].

In accordance with the broad interpretation of the concept of CDSS, the literature presents a variety of requirements for CDSS. Most often, authors don't go beyond the lists of very high-level requirements for functionality and architecture [9, 16–19]. Quite often, requirements for the usability of the interface are also formulated. For instance, In [20] the models for building CDSS based on XML Web services according to the normative sections of the HL7 standard are specified. Here the requirements concerning the simplicity and functional completeness of the service interface are accented.

As the analysis of literary sources has shown, the personalization and standardization of CDSS as stated in [1] are not yet formulated as separate requirements. Standardization is often understood as the need to include CDSS in the general information support system of a particular medical institution [Ball, Berner], while the problem of adapting CDSS to various medical standards is not considered.

Insufficient attention in existing CDSS is given to personalization. A review of solutions in the field of medical information systems shows that they seek to combine various aspects of the clinical process and to form and then to maintain a single process for certain groups of patients. For example, in [21], a system of multilateral support for a typical surgical process is proposed, and in [22], [23] the patients are grouped during the treatment process depending on the type of help they received earlier. On the other hand, systems like [24], that are aimed at personalizing the diagnostic process, are usually strictly adapted to a narrow disease and do not provide the necessary variability in making medical decisions.

A significant role in the personalization of the clinical process is played by possible contradictions between the

various types of medical measures offered to the patient, which, even at the decision-making stage, is one of the tasks of the CDSS. For example, the prescribed medication can worsen the course of another disease that the patient suffers (HA–CP contradiction), may be contraindicated in connection with some medical history parameters (HA–HS contradiction), or may enter into undesirable interactions with other medicines that the patient is taking (HA–HA contradiction). To identify such contradictions, two approaches are proposed below.

The first approach is based on combining all available information about contraindications into a single database, to which the doctor must independently form queries [25–27]. Obviously, such an integrated base becomes very “heavy”, the corresponding systems are proprietary (see examples in [26]), doctors cannot make changes to them and hardly master them in practice.

Lightweight solutions are offered as the second approach to identify inconsistencies in a particular patient or disease [28–30]. For example, in [29], an ontological approach was used, namely linking terms of interest (names of drugs and diagnoses) with proprietary or third-party ontologies and forming a SPARQL query to search for drugs that can interact. Authors [31–33] use systems of production rules or logical expressions. The disadvantage of such systems is that they are created manually for a specific task and do not allow scaling.

C. Approaches to building CDSS architecture

The variety of tasks solved by specific CDSSs corresponds to the variety of applied architectural solutions [34]. However, the vast majority of CDSSs are built as knowledge-based systems and should have such components as a data repository, an inference engine, and a user interface in its structure [9], [16], [19]. As the literature analysis showed, the main differences in architectural solutions for CDSS are related to the implementation of the first two entities, namely the data repository and inference engine.

The literature presents various approaches to organizing the storage of data used in the CDSS. Most often they are very generalized, based either on data typing or on modules structure, and their direct use in the design of the CDSS architecture is difficult. For example, in [16] the following common structure of modules is provided for storing medical data in CDSS: clinical data repository, clinical process database, clinical rules database, knowledge database. At the same time, in the CDSS reference model according to [19] only data types are declared, namely: clinical practice data, unstructured data, outcomes data, clinical guidelines and standards, as well as knowledge extracted from knowledge bases.

On the other hand, much attention is paid to the organization of medical data storage in general, i.e. building medical data warehouse schemas (see reviews [35–37]). Different sets of requirements for storing medical information are formulated in them, of which in relation to the problems of our article we can distinguish the following:

- (SR1) heterogeneous data integration;
- (SR2) temporary data changes accounting;
- (SR3) knowledge evolution and source evolution accounting;
- (SR4) possibility of independent work and ease of connection to other medical systems.

It is easy to see that the first three correspond to the requirement of personalization, and the last – to the standardization requirement [1] (see Introduction).

Various architectural solutions have been proposed for their implementation. In terms of the conceptual data model, entity-relationship model [38], ontology model [39] and dimensional-fact model [40] are distinguished. In order to store temporal data changes it is proposed to use specialized architectures [41]. Finally, in terms of the approach to the design of the medical data warehouse, the proposed solutions according to [35] can be divided into four types: relational [42], dimensional [43], anchor [44], data vault [45], [46], each of which has its own peculiar properties. For example, the anchor and data vault models are specifically designed to create a flexible database where information is stored, but this needs much time to make changes both in structure and content; the dimensional models based on facts, more organically describe “best-known practices” and typical medical cases [35]. The data vault model allows the user to introduce the concept of early and late data binding, i.e. to split data into relatively stable being bounded early, and volatile data that should be bound late, which simplifies the processing of evolving data [46].

At the same time, the relational model has well-known advantages, among which are consistency and integrity of data. A significant argument in favor of the relational data storage model in CDSS is the fact that the basic information standards for medical organizations [2], [3] are based on the relational data models. Nevertheless, it is noteworthy that, according to analytical reviews, most of the implemented medical data warehouses use these three types of models, and not relational ones.

Concerning the architecture of inference engines, as literature analysis has shown, most of them are built as rule-based directly [16, 31–33, 48, 49] or with some modifications [47, 50, 51]. For example, in [47] a three-layer (disease-symptom-property) knowledge base model is proposed, which allows the user to clarify the rules. In [50] reasoning is done by writing queries directly to an openEHR based data repository in a specialized Archetype Query Language (AQL) built into the openEHR standard. Other specialized languages for querying medical databases are described in [16]. In [52] the Markov logic inference engine for a rule based CDSS is proposed. As authors claim, this approach allows to deal with uncertainty of data by integrating first-order-logic with probabilistic graphical models.

It is easy to see that such systems implement low-level approaches to supporting clinical processes, i.e. basically solve the problem of making a diagnosis by using a set or combination of individual clinical symptoms. In [51] a “heavy” multilevel solution is proposed, including various knowledge acquisition algorithms for information of various modalities (dialog, structured, unstructured, descriptive, image-based). However, after processing, sets of rules are extracted from each information type, on which the corresponding inference engines operate.

When building inference engines for CDSS, machine learning algorithms are widely used [53–56]. In general, machine learning algorithms as part of the CDSS are used to predict and refine the values of individual indicators of the

clinical process [54], as well as to highlight and evaluate individual clinical symptoms [55], [56]. In particular, in [53] the inference engine is built on a decision tree in combination with the voted ensemble multi-classification algorithm in order to analyze all of the historically hospitalized patient care data including those received from experts. Besides, in order to integrate heterogeneous clinical information clinical tabular document syntax (DocLang) is used.

The architectural solutions discussed above have a significant drawback in terms of implementing CDSS, as it is stated in [1]: they do not allow the clinical protocol to be described as a sequence of activities. Certain advantages in this regard are provided by the use of an automata model [4], [57] within the framework of CDSS. The analysis of the terminology given in Section 2A suggests that the state in the automata model and the state of the patient in the clinical process are close not only terminologically, but also conceptually. Note also that the use of the state machine (close to automata model) is supported in the medical standard [openEHR].

The concept of automata is widely used in healthcare – for example, to assess the spread of bacteria in a disease [58], to plan remote care for patients [59], and to analyze the effectiveness of interaction between individual organs [60]. However, in modeling the actual clinical processes, the automata approach is used mainly as a rigidly determined construction [21], [61], [62], while modern means of supporting automata programming provide ample opportunities for modeling decision-making processes [63].

There are certain examples of using the concept of states and transitions between them when constructing CDSS. Authors [64] define states, actions, observations and rewards based on clinical practice, expert knowledge and data representations in an EHR dataset of 1492 patients and infer the probability distribution of the current state of patients with sepsis, thus forming a probabilistic framework for clinical decision support in sepsis-related cases. In [65], the state machine formalism was proposed to be used to record individual scenarios of allergic rhinitis management, however, the general inference engine is built as a decision tree. A similar solution was proposed by [66] in CDSS for apnoea of prematurity management.

It is worth noting the interesting approach proposed in [67]. Authors consider the whole process of decision making in CDSS as a “finite state machine”. The system regards decision making as a workflow, treats the solutions as steps of the workflow, and treats the possible result as a status transition set of the workflow or the decision link for references in the knowledge base. However, the approach of the authors in the article is set out only at the concept level, without a model representation, and moreover, without practical implementation.

Thus, the review confirmed that the requirements for the CDSS formulated in Introduction remain largely unfulfilled in existing systems. At the same time, an adequate terminological structure was determined and promising approaches were highlighted for building the architecture of such a CDSS.

Accordingly, the authors of this article set themselves the following tasks:

1. to consider the possibility of constructing an intellectual support system for clinical processes based on finite automata, using the example of treating patients with stable coronary artery disease and high-grade ventricular arrhythmias;

2. to develop a data structure within the above described system, allowing to isolate, store and process the conflicting clinical information;

3. to consider the effectiveness of the proposed approach in comparison with existing approaches.

III. PROPOSED SOLUTION

A. The automaton model

The solution is based on an automata model, which represents the clinical process as a set of automata states and possible transitions between them.

The initial information for constructing an automata model can be a diagram of the clinical process presented by clinicians in a form convenient for them. However, a direct transition from this scheme to an automata model is difficult, since, as experience in relationships with doctors shows, in clinical practice the entities stated in the standard (see paragraph 2A) are not used explicitly.

In this regard, we have developed a technique for this transition, based on the processing of textual descriptions of components of the initial scheme using natural language processing:

1. Among the components of the initial scheme, we distinguish entities named by verbs, gerunds or verbal nouns (for example, Registration, Search, Testing...). They form a set of clinical activities (healthcare activities, HA).

2. In the initial scheme, we highlight the outputs of entities marked in point 1. They form a set of predicates concerned as the results of activities. If several outputs are the result of activity, then they are collapsed into one predicate using logical functions (for example, HC5.1 = 5b AND 5b.1). Each predicate corresponds to a specific clinical symptom (health condition, HC). The components of the set of HC form the alphabet of the finite state machine.

3. States (HSt) are formed as associations that combine certain HA and HC in accordance with the logic of the clinical process. For example, HA3 activity (ECG exercise stress testing) and possible transitions from it — HC 3.1 and HC 3.2.1, which correspond to nodes 3A and 3B in the initial circuit (Fig. 1), are included in the HS3 state. The 3C node in this case merges into the HC 3.1 transition, and the solution based on Ischemic / Nonischemic VA is transferred to HS4. The else transition is intended for all results that did not fall into HC 3.1 and HC 3.2.1, and includes a 3D node and a transition from 3 to 2B in the original diagram. The selected states should correspond to the main decision points in the clinical process, and its adequacy is evaluated by experts - clinicians. If the adequacy at the first iteration is not achieved, points 1-3 are repeated.

The components of the automata model for the clinical process of managing patients with stable coronary artery disease and high-grade ventricular arrhythmias, selected in accordance with the scheme of Fig. 1, are presented in Table I.

TABLE I. COMPONENTS OF AUTOMATON MODEL

Process component	Description in the initial scheme
Actions	
HA 1	ECG, ECG Monitoring
HA 2	Search for Trigger VA
HA 3	ECG exercise stress testing: TT, Bicycle testing
HA 3.1	Exercise stress test with Ng. exercise stress ECG test
HA 4	Coronary angiography
HA 5	Определение показаний к MR
HA 6.1	MR done
HA 6.2	Recover after MR (6-9 months)
HA 7	MR efficiency evaluation
HA 8.1	Exercise stress ECG test, PET/SPECT, NIFCGM
HA 8.2	MR Repeat decision
HA 9	Psychodiagnostics requirement evaluation
HA 10	Psychodiagnostics
HA 11	Psychotherapy, psychotropic drugs
HA 12	Clarification
Transitions	
HC 1	VA registered
HC 2	CAD (+) && VA && (LVEF >= 40%)
HC 3.1	Test (+)
HC 3.2.1	Test uncertain
HC 3.2.2	Test (+)
HC 4.1	Coronary Angiography (+)
HC 4.2	Coronary Angiography (-) && Nonischemic VA
HC 4.3	Coronary Angiography (-) && Ischemic VA
HC 4.4	Clarification required
HC 5.1	MR (+)
HC 5.2	MR (-) && Nonischemic VA
HC 5.3	MR (-) && Ischemic VA
HC 7.1	AAE (+)
HC 7.2	AAE (-) && Ischemic VA
HC 7.3	AAE (-) && Nonischemic VA
HC 8.1	MR Repeat
HC 8.2	MR Repeat doesn't indicate
HC 9.1	Psychodiagnostics not indicated
HC 9.2	Psychodiagnostics indicated
HC 9.3	Clarification required
HC 9.4	New statement
HC 10.1	AD (-)
HC 10.2	AD (+)
HC 11.1	AAE (-)
HC 11.2	AAE (+)
States	
HSt 1	VA Not registered
HSt 2	Algorithm for the management of patients with VA
HSt 3	Medical therapy
HSt 4	Optimal Medical Therapy CAD, AAT, CA, ICD
HSt 5	Beta-blockers
HSt 6	Ambulatory treatment
HSt 7	Switch to another state machine

TABLE II. COMPONENTS OF CLINICAL IN TERMS OF AN AUTOMATA MODEL

Automata model components	Clinical process components
V	HC 1, HC 2, HC 3.1, HC 3.2.1, HC 3.2.2, HC 4.1, HC 4.2, HC 4.3, HC 4.4, HC 5.1, HC 5.2, HC 5.3, HC 7.1, HC 7.2, HC 7.3, HC 8.1, HC 8.2, HC 9.1, HC 9.2, HC 9.3, HC 9.4, HC 10.1, HC 10.2, HC 11.1, HC 11.2,
Q	HS 1 – HS 12
q0	HS 1
F	HSt 0 – HSt 7
δ	Transition function (see Table 3)

Table II presents the components of the state diagram in

terms of a typical automata model [4]

$$A = (V, Q, q_0, F, \delta), \tag{1}$$

where V is the input alphabet, Q is the finite set of states of the automata, q_0 is the initial state, F is the set of final states, δ are the transition function, represented by Table III.

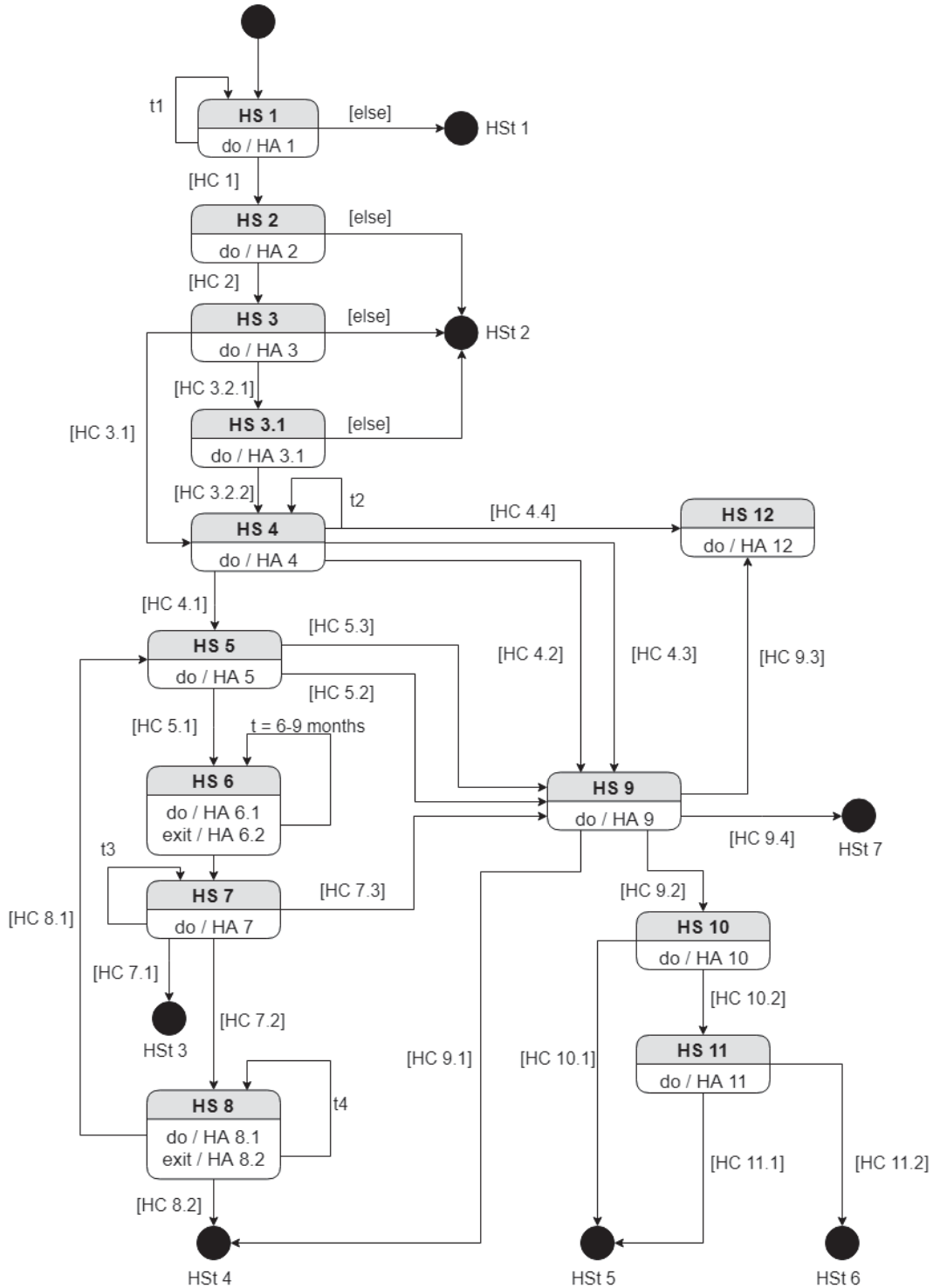


Fig. 1. Automata state diagram

Let's single out the specifics of the proposed automata model in correlation with its use in the clinical process. The user of the system chooses the next state from the proposed list

of available transitions. The process of changing the states lasts until one of the terminal states is reached. Each such condition (state) corresponds to a specific event, for example,

recovery, hospitalization, change in the diagnosis made earlier and, accordingly, treatment.

All transition functions here are not absolute, but informative - at a certain point they initiate a notification to the doctor about the need for a transition. The moment of making a medical decision about the transition can be set by a timer or a return counter, which is correlated with the corresponding clinical symptom. An example of such a timer is presented on the automata state diagram (Fig. 1) in HS6 state, where after MR the patient needs 6–9 months to recover.

The use of an automata model gives the following advantages [4]:

- formal verification and recording of the actions of all participants in the clinical process is possible;
- the observability of the clinical process is improved by using one internal variable;

- within each state, it is easy to organize new and interchangeable studies, which allows you to flexibly adapt the clinical process to changing external conditions.

For example, Fig. 1 shows the transition from the state of HS 9 (Psychodiagnostics requirement evaluation) to another machine. To do this, we have introduced the transition HC 9.4 (New statement - a new state that appeared as a result of the expansion of the algorithm) and HSt 7 - a state that is terminal for the current automata and indicates a transition to another specific automata.

Thus, the use of an automata model as an inference engine in the intelligent support system for clinical processes guarantees the effective fulfillment of the requirements for such a system (see Introduction), namely: the first two items correspond to requirement R4, and the last point to requirement R3.

TABLE III. TRANSITION FUNCTION OF AN AUTOMATA MODEL

	HS 1	HS 2	HS 3	HS 3.1	HS 4	HS 5	HS 6	HS 7	HS 8	HS 9	HS 10	HS 11
HC 1	HS 2											
HC 2		HS 3										
HC 3.1			HS 4									
HC 3.2.1			HS3.1									
HC 3.2.2				HS 4								
HC 4.1					HS 5							
HC 4.2					HS 9							
HC 4.3					HS 9							
HC 4.4					HS 12							
HC 5.1						HS 6						
HC 5.2						HS 9						
HC 5.3						HS 9						
HC 7.1								HSt 1				
HC 7.2								HS 8				
HC 7.3								HS 9				
HC 8.1									HS 5			
HC 8.2									HSt 4			
HC 9.1										HSt 9.1		
HC 9.2										HS 10		
HC 9.3										HS 12		
HC 9.4										HSt 7		
HC 10.1											HSt 5	
HC 10.2											HS 11	
HC 11.1												HSt 5
HC 11.2												Hst 6

B. Data storage and processing structure as a means of managing conflicting clinical information

During the maintenance of the clinical process, various medical entities interact in it, many of which may conflict with each other. For example, if a cardiologist patient suffers from asthma, then the simultaneous use of prednisone and cardiac glycosides due to the resulting hypokaliemia increases the risk of cardiac arrhythmias (https://www.rlsnet.ru/mnn_index_id_433.htm#vzaimodejstvie).

Today, information about the interaction between different medical entities is contained in various information sources. It

can be “heavy” solutions in the form of integrated databases, combining all available information about contraindications [25–27], or “light” solutions, primarily ontologies [29], to identify inconsistencies for a particular patient or disease. Contraindications can also be formed on-line on the basis of data stored in various sources, including not only external databases and ontologies, but system cache and electronic health record (EHR). Various scenarios for the occurrence of contradictions in the processing of medical information in clinical processes and work with them are considered in previous works of the authors of this article [68], [69].

To work with the contradictions that arise during the clinical process, the specialized design patterns are used in the structure of the developed CDSS. The Design pattern architecture diagram is presented in Fig. 2.

For flexible assignment of various strategies for working with contradictions, the Strategy and Facade patterns were used. The IMedicalStrategy interface is implemented by specific strategies containing behavior for each of the scenarios of working with inconsistencies. DiseaseStrategy contains behavior for HA-HP contradiction, DrugStrategy contains behavior for HA-HA contradiction and AnamnesisStrategy contains behavior for HA-HSt contradiction. The advantage of the Strategy pattern is that it allows you to create an unlimited number of behaviors for different scenarios of working with contradictions. This allows us to easily add new behaviors and scenarios for working with new types of contradictions.

The logic of working with the automata (Fig. 1) is hidden in the StateMachine class, which interacts with the methods that it provides as an interface - setState(), getState() and getAllStates(). To make clinical decisions, the attending physician must be provided with a quick and easy way to work with a different number of sources of medical information. For this purpose, the Adapter pattern is used, which allows bringing various data sources to a single interaction interface and using them together. The whole complexity of working with an automata machine and a mechanism for resolving contradictions is hidden behind the AutomataFacade facade, which represents one point of work with the presented solution.

The use of the selected patterns has allowed us to develop a system that can be easily understood by doctors and, at the same time, that is fairly generalized and easily extensible - by

allowing the connection of external sources and expanding scenarios of working with inconsistencies without changing the structure of the code.

Besides, the adopted approach to data processing in the designed CDSS made it possible to use a fairly simple relational database schema as the storage structure, which is shown in Fig. 3.

The chosen data scheme provides independent storage of various data, such as information about the doctor and patient, ontological information, information about drugs and contraindications. The scheme also allows you to add and modify data without restriction.

Note that the database presented in Fig. 3 DB contains the minimum necessary amount of information to support the process. New data is easily added to the database through integration with any external source of medical data.

In other words, the chosen data scheme meets the requirements for storing medical information (SR1)–(SR4) justified in Section 2.

For example, information about medicines is organized as follows: the table Medicine stores general information about the medicine, the Active_Substance_In_Medicine table, which has a foreign key to the Medicine table, stores information about the active substance in the medicine, the Medicine_For_Disease table provides a link between the medicine and the disease. Connection with contraindications is provided through a foreign key to the Contradiction table. Information about the patient is stored in the Patient table, where, in addition to personal data, the patient's illness, his status and information about the attending physician are indicated.

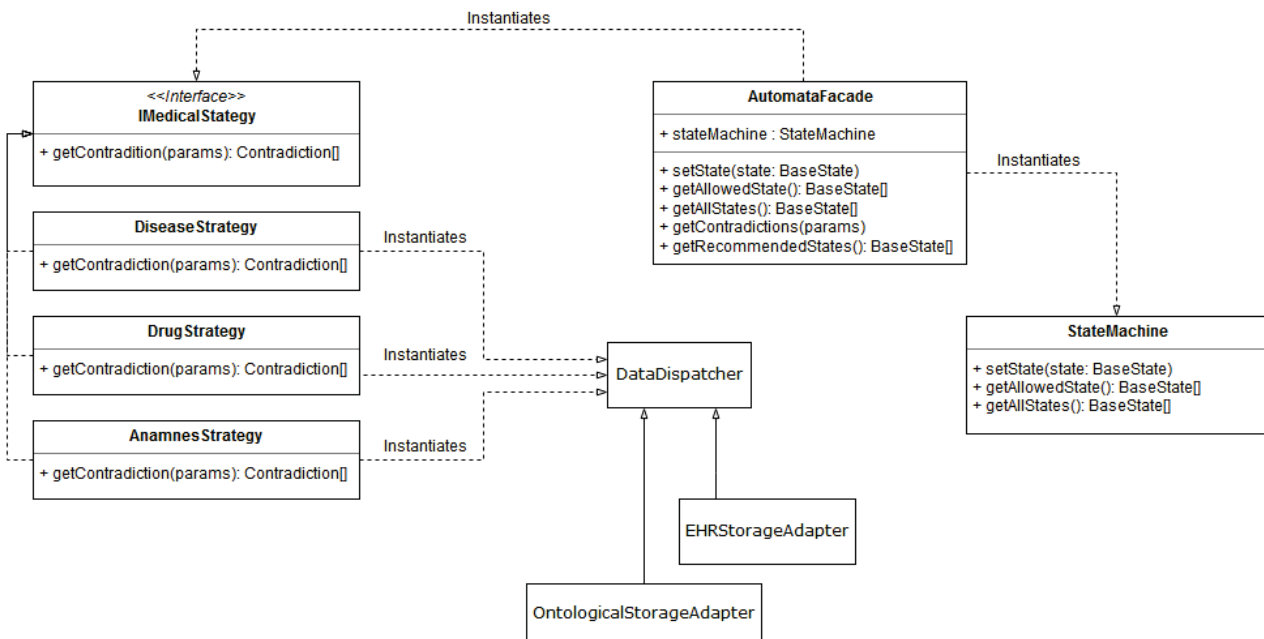


Fig. 2 Design pattern architecture diagram

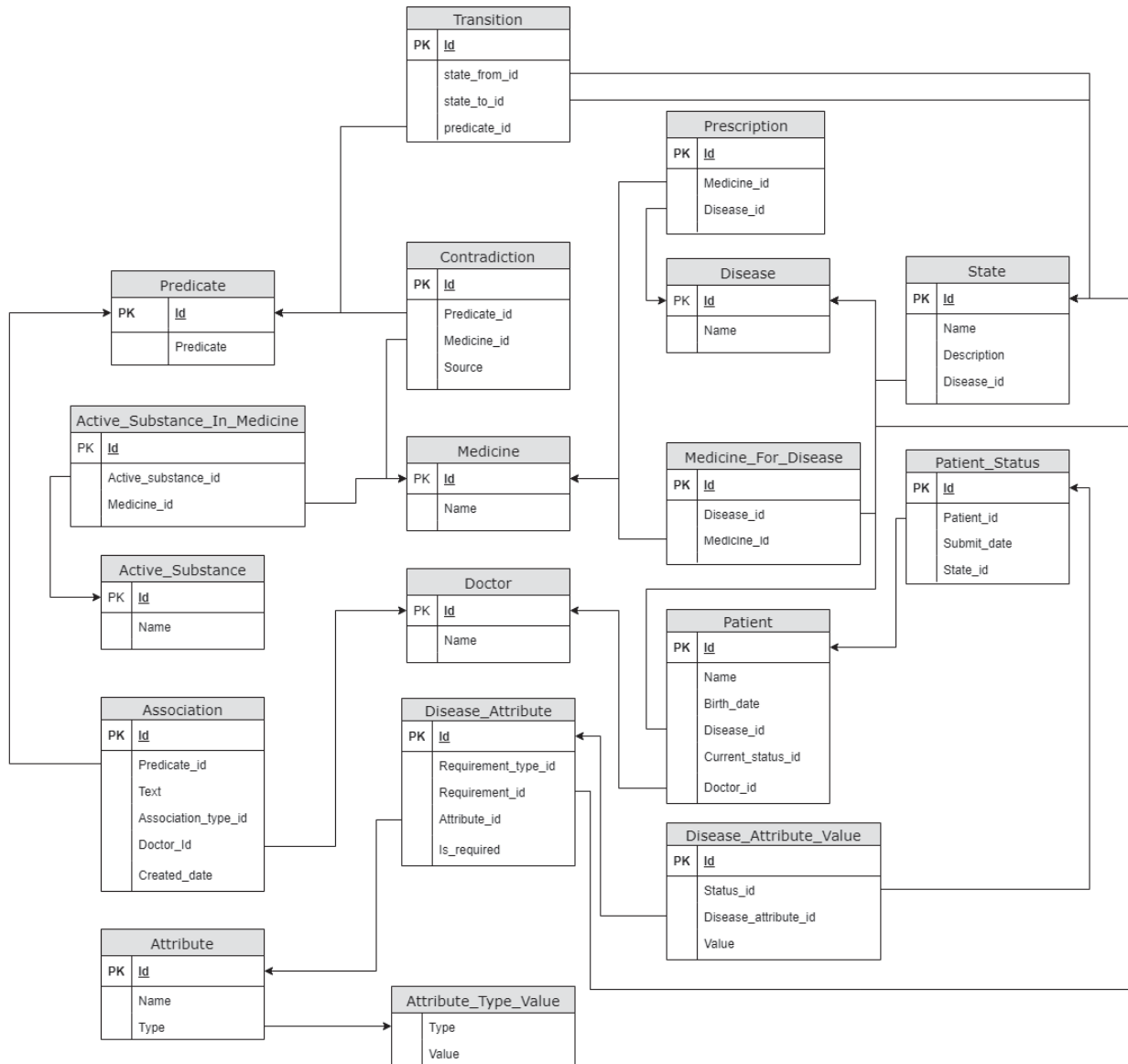


Fig. 3. Data base schema

Thus, the architecture of the developed intelligent support system for clinical processes combines a database as a static repository and a set of design patterns for dynamic data processing. This ensures that the requirements R3 and R4 for such a system (see Introduction) are successfully met.

C. The interface of interaction with the doctor

The main idea of the developed system functioning is as follows. Firstly, it aggregates the information about the patient: medical history, medical contraindications, results of medical studies, tests and measurements. Then, based on these data, taking into account contraindications, history and current state of the automata model, lists of available transitions of the automaton model, recommended transitions and possible contraindications are formed.

As it is emphasized above, the developed system is not intended to replace the doctor, but it is aimed to support the adoption of personalized clinical decisions.

The following general use case stages of the system can be distinguished:

1. Initializing the new clinical process;
2. Creating a new patient essence;
3. Entering the current state, notification about it (in accordance with the HSt status number)
4. Filling out the patient's history;
5. Fixing the medical contraindications for the patient;
6. Getting the results of analyzes and measurements; obtaining the necessary external information
7. Checking conditions for exiting the current state, available (in accordance with the `getAvailableStates()` method) and recommended transitions (in accordance with the `getRecommendedStates()` method).
8. Incoming formation of an alert about the need for transition;
9. Incoming assessment of recommended conditions on the basis of information about contraindications

10. Providing information on available conditions, recommended condition and contraindications (or other contradictions in the transition chosen by the doctor (in accordance with the `getContradictions()` method)

11. Transitioning to a new state of the automata model;

12. Reaching one of the terminal states.

IV. CASE STUDY

The effectiveness of the proposed solution with respect to the requirements (R1) - (R4) stated in the Introduction is shown in Section III at the logical (substantive) level. For a quantitative assessment of effectiveness, we consider typical task that can be solved with the help of CDSS, namely the identification of contraindications to the prescription of a specific medicine for a particular patient.

To do this, we use the case mentioned above, typical for cardiac patients: if a cardiological patient suffers from asthma, then the simultaneous use of prednisone and cardiac glycosides due to the resulting hypokaliemia increases the risk of cardiac arrhythmias.

While using the developed system, based on automata model, the presence of contraindications to the prescription of a medicine is determined using the information stored in the database. In this case, the system will detect this contraindication in a state where it may be possible to prescribe prednisone and cardiac glycosides, and notify the attending physician. To obtain such information, the doctor needs only to enter information about the patient into the system and go through the automata model of clinical process to the desired state, simultaneously entering the results of the clinical actions into the system.

If alternative solutions are used (see examples in Section II), the doctor is forced to additionally compile at least one request for each medicine and each disease into the corresponding ontologies, and then manually compare the data to draw conclusions about the existing contraindications. In the considered case, the doctor must perform at least 4 requests - 2 for medicines and 2 for diseases.

Thus, the developed system, firstly, ensures the identification of potential contraindications at the right point in the clinical process and informs the doctor about it, and secondly, the doctor does not need to make additional steps to find information about possible contraindications.

Both of these features are a significant advantage of the approach to the development of intelligent support system for clinical processes based on automata model proposed by the authors.

System development is developed as an open source project. Project materials are available at the following links:

<https://github.com/itmo-mpa/mpa-backend>

<https://github.com/itmo-mpa/mpa-frontend>

V. CONCLUSION

The article proposes a solution for creating an intelligent support for clinical processes, built on automata approach. Based on the statements of the National Healthcare project of Russia, the system requirements have been formulated. The specifics of the solution is demonstrated on the real clinical

process of management of patients with stable coronary artery disease and high-grade ventricular arrhythmia.

All the tasks set in the article have been completed, namely:

- We have shown the prospects of constructing a system of intellectual support for clinical processes based on finite automata.
- We have developed a database structure within the above mentioned system, allowing to isolate, store and process the conflicting clinical information.
- We have shown the effectiveness of the proposed system in comparison with existing approaches.

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