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New Approaches to the JSM Method in Obstetrics and Gynecology Research

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Abstract—An intellectual system has been created that implements the JSM method of automated research support for the task of predicting the risk of pelvic organ prolapse in women with a history of birth through the birth canal. Methods for expanding fact bases are applied. For the first time, a lattice of strategies formed by predicates of simple similarity, difference, and similarity-difference (a, ad_0, ad_2) has been implemented and an algorithm for optimizing the replenishment of the fact base that uses the value of explainability has been proposed. Three experiments that were carried out according to the same scheme are described; in the second experiment, noise was removed when analyzing a subset of the initial data. New tasks have been formulated that allow further improvement of research results.

Keywords: JSM method, artificial intelligence, prognosis, empirical patterns, pelvic organ prolapse, labor

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INTRODUCTION

In recent years, areas related to information technology in medicine have been intensively developing. The introduction of artificial intelligence systems in the diagnosis, prevention, and treatment of diseases is of paramount importance. To assess the condition of patients, modern researchers use various options for intelligent decisions using methods of reasoning by precedents, intelligent analysis, the study of linear discriminant functions, and neural networks. These technologies are reflected in the MODIS (diagnostics of forms of arterial hypertension), DIAGEN (differential diagnostics of hereditary diseases), MYCIN (choice of antibiotic therapy), ABEL (diagnostics and choice of treatment for imbalances of acids and bases), MGUA (method of group consideration of arguments), and JSM method (automated research support) [1–9] automated programs.

To implement some intelligent system (a method for predicting a disease or any other condition), it is necessary, first of all, to structure the available clinical data (anamnesis) and train the system for making a diagnosis to predict the development of diseases. This technology is carried out using machine learning, where, in addition to the classical methods, the following methods are used: creation of a decision tree, a random forest, a naive Bayesian classifier, support vector machines, k-nearest neighbors, etc. [10–16]. It should be noted that each of these technologies has its own advantages and disadvantages [17–20].

According to Russian and foreign scientists, one of the most promising research methods is machine learning on the basis of modern technology of multilayer artificial neural networks [4].

The goal of this article was to assess the possibility of early diagnosis of pelvic organ prolapse by creating a neural network, the information content of which is compared with the JSM method for automated research support. Neural networks require a certain minimum (threshold) dataset, on the basis of which they become able to learn. To study the risk of pelvic organ prolapse, a set of such data must consist of several hundred records (facts), which is due to a sufficiently large number of risk factors that can cause the formation of prolapse with varying degrees of their effect on the body, in particular, on the functions of the pelvic organs.

In case of using the JSM method, this threshold is absent, and, as noted by many researchers, its applicability is provided by the following criteria [20]:

(1) The ability to structure data and formalize the similarity of facts from the existing fact base (BF);

(2) The presence of both positive and negative examples (($\pm$)-examples) in the BF;

(3) The presence of cause-and-effect relationships in the BF, which are given in one way or another (denoted as the ($\pm$)-reasons of the studied effects);

(4) The presence of definite (explicit or implicit) patterns that are preserved under the expansion of the BF. This criterion was proposed by O.L. Shesternikova in 2019. It allows us to determine whether it is permissible for the researcher to use many factors identified by other researchers when assessing the pelvic organ prolapse in a particular woman. Shesternikova used the term "empirical pattern", which is believed by us to be synonymous with the term "regularity" [18, 19].

A feature of the JSM method is the principle of extraction of knowledge of the cause–effect type, which is based on the rule: "the similarity of facts gives rise to the similarity of effects and their recurrence" [16–20]. It should be considered that this principle differs from the probabilistic approach, which is that the similarity of facts is determined by the frequency of effects. In contrast to statistical methods, the JSM method is applicable even on relatively small amounts of data and has the ability to take into account individual differences in the objects of study (in our case, the differences in women who underwent birth through the natural birth canal (PVN: per vias naturalis)). However, at the same time, the JSM method supports the expansion of the data volume (BF), which is comparable to the methodology of neural networks.

PROBLEM STATEMENT, MATERIALS, AND METHODS

This article describes the use of the JSM method to predict the risk of pelvic organ prolapse in women with a history of birth through the natural birth canal. The objective of the study is to predict the possibility of pelvic organ prolapse. According to most experts, the main risk factor here is a history of birth through the natural birth canal; however, it should be noted that this disease can also be observed in nulliparous women. The source material of the database includs information about patients who underwent inpatient treatment at the gynecological departments of two clinical centers: Kuvatov Republican Clinical Hospital (Republic of Bashkortostan) and clinics of the Chita State Medical Academy. The initial database was formed by including information about patients of two study groups: patients with pelvic organ prolapse and patients without this disease. The main criterion for inclusion in the study groups was the presence of birth through the natural birth canal in the anamnesis.

We have created an intelligent system based on the JSM method of automatic hypothesis generation, which includes the following components.

1. solver;

2. information environment of the BF, consisting of ($\pm$)-facts (positive and negative), as well as τ-facts (undefined);

3. information environment of the knowledge base;

4. user interface, which includes components: dialogue, presentation of results.

It is obvious that $BF = BF^+ \cup BF^- \cup BF^\tau$ and also that $BF^+ \cap BF^- = \varnothing$, $BF^+ \cap BF^\tau = \varnothing$, $BF^- \cap BF^\tau = \varnothing$.

As we can see, the sets of positive, negative, and uncertain facts do not overlap.

The solver is based on the JSM method of automatic hypothesis generation using automatic plausible reasoning based on available facts. The developed plausible reasoning forms a formalized heuristic for extracting dependences of a causal type from bases of structured facts.

Hypotheses about the ($\pm$)-causes extracted from the BF are formed based on the induction algorithm we implemented. It uses object similarity as an input parameter (source), which is otherwise referred to as the cause of the presence (or absence) of an effect (i.e., the presence or absence of pelvic organ prolapse in women). The prediction of this effect is performed on the basis of an algorithmic analogy using the hypothesis of ($\pm$)-causes that are available in the knowledge base and generated as a result of induction.

As a result, JSM reasoning ends with an abductive procedure for the purpose of determining abductive convergence. This involves the explanation of the initial state of the BF, which is either a sufficient basis for accepting hypotheses, or a variant of expanding the BF for subsequent repetition (one more iteration) of the JSM reasoning, if there are unexplained facts from the BF.

After applying the JSM reasoning, the solver carries out a JSM study that implements the identification of those regularities that are preserved when expanding the BF. Such identification occurs on the basis of the analysis of the truth values ν of the generated hypotheses, which can be within the interval from -1 to $+1$:

$$\nu \in [-1;+1].$$

The truth value of the regularity is $+1$ if the fact is positive and -1 if the fact is negative. In all other cases, the value ν is within the segment indicated above.

As the BF expands, the sets $BF_{0,1}$, $BF_{0,2}$, ..., or $BF_{0,i}$, $i = 1,\ldots, n$ are formed from the initial set $BF_{0,0}$. The relationship is obvious: $BF_{0,0} \subset BF_{0,1} \subset \ldots \subset BF_{0,n}$, since each newly expanded set of facts (in which the regularities have been preserved, see above criterion

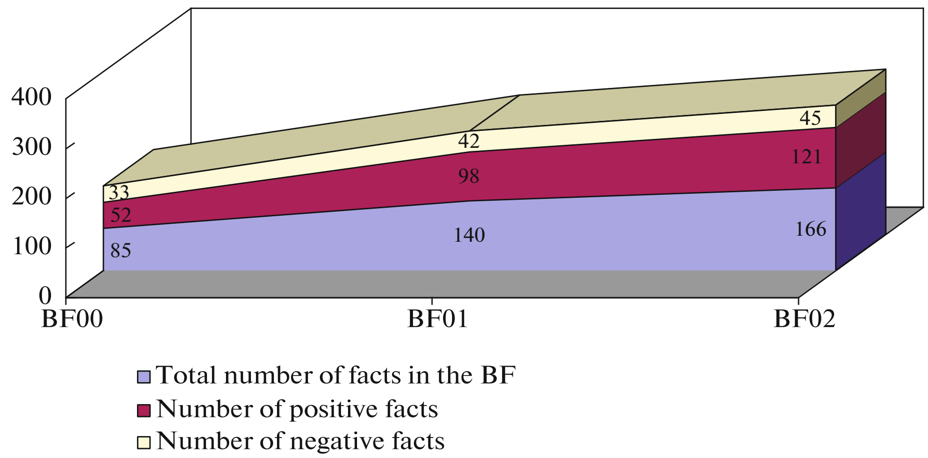

Fig. 1. The dynamics of the factor base by types of facts in the case of expansion of the set of the fact base.

No. 4 of applicability of the JSM method) contains the earlier obtained previous sets. In other words, all the previous sets are subsets of the very last set $BF_{0,n}$.

As the set of the BF expands, the number of both positive and negative facts increases. Figure 1 shows the dynamics of its size.

In this case, it is assumed that the initial set $BF_{0,0}$ included no facts. This can only be observed once, at the very beginning of the study. Then, one or another already existing (at the time of the continuation of the study) set $BF_{0,1}$ will act as $BF_{0,0}$. In addition, it is advisable to accept existing sets of facts as $BF_{0,0}$, for example, those obtained by other researchers, if: (1) their reliability is beyond doubt; (2) when they are expanded, the regularities are preserved.

1. FACT BASE

Positive (+)-examples in the research were women with pelvic organ prolapse who had a history of birth through the natural birth canal (natural delivery), which defines a property in the terminology of the JSM method.

A negative (-)-example was women with pelvic organ prolapse who had no history of natural birth.

In the course of working with case histories, the information was structured and collected into an array in a specially developed language for data presentation. An example of one record in the fact base that represents part of the obstetric-gynecological history data (taken from the patient's medical history) is given in Appendix. The list of factors that make up each fact was determined and optimized by us during the gynecological study [9].

Each fact consists of a reasonable list of factors of pelvic organ prolapse (anamnesis data of a particular patient):

$$\Phi_j^{(i)} = \{F_1 \cup F_2 \cup \ldots \cup F_{42}\} \subset BF_{0,i},$$

where $j = 1,..., J_i$, J_i is the number of facts in the $BF_{0,i}$ (fact base of the ith study), i is the ordinal number of the study (stage), and 42 is the number of risk factors for the formation of pelvic organ prolapse.

The totality of all the facts obviously represents the entire fact base:

$$\{\Phi_1{}^{(i)} \cup \Phi_2{}^{(i)} \cup \ldots \cup \Phi_{Ji}^{(i)}\} = BF_{0,i}.$$

In the course of the study, the array of case histories was constantly replenished, which made it possible to organize the data into an expanding array of nested BFs and apply JSM research procedures to analyze the regularities (empirical patterns) in these arrays. Two extensions have been added for the initial BF dataset. Three studies were carried out based on the obtained datasets.

Zero study (initial data). The training sample obtained in the first study consisted of 85 patients, 52 of whom had pelvic organ prolapse and 33 did not. Thus, $BF_{0,0}$ contains the data of obstetric and gynecological examination of 85 patients (see Fig. 1).

First study. The first study examined the risk factors for pelvic organ prolapse in 140 patients, 98 of whom had prolapse and 42 did not. As a result, the base of factors $BF_{0,01}$ was formed.

For the purposes of predicting the risk of prolapse, ten patients from different age groups who had undergone natural childbirth were included in the BF.

Second study. The second study examined the risk factors for prolapse in 166 patients, 121 of whom had prolapse and 45 did not. As a result, $BF_{0,01}$ was expanded to $BF_{0,02}$ (obviously, $BF_{0,1} \subset BF_{0,2}$).

For the purposes of predicting the risk of pelvic organ prolapse, the same ten patients from different age groups were presented.

Third study. The designated ten patients were examined by expert doctors for the possibility of prolapse.

2. RESEARCH PROCESS

We have chosen strategies of the form $\mathrm{Str}_{x,y}$, where $x, y \in \{a^\sigma, d_0^\sigma, d_2^\sigma\}$, a^σ, d_0^σ, and d_2^σ are representations (names) of M^σ-predicates of similarity, difference, and similarity-difference, respectively;

$$\sigma \in \{+1, -1, 0, \tau\}.$$

M^σ-predicates are used to define rules for inductive inference.

We note that researchers usually also propose to use a predicate for the prohibition of counterexamples (b) [17–19]; however, its application seems to be inappropriate in our study, since the analysis of the available fact bases $\mathrm{BF_i}$ revealed that a counterexample was one of the indicators of expediency of their expansion. In addition, in our opinion, the fewer is the number of predicates used, the simpler is the study from a conceptual point of view. Therefore, we did not use predicate b.

Taking the listed predicates into account, the following strategies were used in the research process: (1) $\mathrm{Str}_{a,a}$, (2) $\mathrm{Str}_{a,d0}$, (3) $\mathrm{Str}_{\mathrm{a,\ d2}}$, (4) $\mathrm{Str}_{d0,a}$, (5) $\mathrm{Str}_{d2,a}$, (6) $\mathrm{Str}_{d0,d0}$, (7) $\mathrm{Str}_{d2,d2}$, (8) $\mathrm{Str}_{d0,d2}$, and (9) $\mathrm{Str}_{d2,d0}$.

2.1. JSM Reasoning

The study carried out a JSM reasoning, including a search of the strategy from the set $\mathrm{Str}_{x,y}$ for the sets of facts $\mathrm{BF}_{0,1}$ and $\mathrm{BF}_{0,2}$, respectively.

2.2. JSM Research

2.2.1. For each reasoning, we determine the value $\rho_{0,i}^\sigma$ (explainability (be due to: bdt)) of the *i*th array of the fact base. We determine whether such reasoning is appropriate:

(1) If $\rho_{0,i+1}^\sigma > \rho_{0,i}^\sigma$, then the explainability has improved, i.e., the regularity has been preserved. Therefore, it is advisable to add this fact to the $\mathrm{BF}_{0,i+1}$, thereby expanding it. Hence, the reasoning is appropriate.

(2) If $\rho_{0,i+1}^\sigma < \rho_{0,i}^\sigma$ and, at the same time, $\sigma \neq \tau$, then this means that the explainability has worsened, i.e., regularity has not been preserved (worsened). Consequently, it is necessary to change the system (structure) of facts, removing interfering factors from it, or, on the contrary, adding missing facts to it. Thus, the reasoning is not suitable for a specific fact base, and it is necessary to change (optimize) the approach to the formation of the BF. This case indicates the need for in-depth analysis and optimization of the BF. If the BF optimization is not performed in this case, then the quality of prediction using the JSM method will decrease.

(3) If $\rho_{0,i+1}^\sigma = \rho_{0,i}^\sigma$,, then the explainability has remained unchanged. The regularity has not changed either. Consequently, such a fact, on the one hand, does not contradict $\mathrm{BF}_{0,i+1}$, but, on the other hand, adding it to the fact base will not have any positive effect, will not contribute to the growth of explainability. Therefore, it is not expedient to add it to the fact base, since this will only lead to cluttering (duplication) of facts. This reasoning is appropriate, but duplicates at least one reasoning from the BF.

Figure 2 presents the information that made it possible to develop an algorithm, and Fig. 3 shows a diagram of the information system we used for research, reasoning, and making hypothesis.

We note that it is actually significant for reasoning 3 (coincidence of explainability within the margin of error) that a new fact is a confirmation of already existing facts, and this creates statistics. The more such confirmations are given, the more reliable the result of reasoning will be. Therefore, the reason formulated as a result of such reasoning will be more likely.

As mentioned, we did not save the facts that are confirming for the already existing facts in the BF so as not to duplicate the entries in the BF. However, information on the existence of supporting facts was retained by adding the identifier of the respective patient to the identifier array (see Appendix, indicator No. 42).

Explainability can be both a positive and a negative fact; therefore, in the general case, the increase in entries in the BF will occur approximately as shown in Table 1.

The BF included the data from the history of patients with conditional numbers 1, 2, and 5 (see Table 1), while the history of patients with conditional numbers 3 and 4 was not included in the BF for the reason that the error for them was within $\rho_{0,1}^\sigma = \rho_{0,2}^\sigma$. Since the explainability did not change in the second study in comparison with the first one, the regularity of the BF was preserved, and, therefore, there was no need to adjust the structure of the facts.

The fact that is due to the history of the first patient (see Table 1) caused a decrease in explainability (parameter $\delta_1 < 0$). This fact corresponds to one hypothesis. For the rest of the patients, the parameters δ_1 are positive. For the second and fifth patient, four and two hypotheses were found, respectively.

2.2.2. After the studies, based on the information from Table 1 built as a result of the first and second stages, it is necessary to determine the causes of pelvic organ prolapse. Hypotheses with the same truth values fulfill a predicate, which is formally denoted by an expression of the form

$$\Psi^s(\delta,\ Q)\ (\sigma \in \{+1; -1\}),$$

where Q is a constant denoting the occurrence of pelvic organ prolapse for positive examples and the absence of prolapse for negative examples; $\delta_\mathrm{i} = \mathrm{sign}\,(\rho_{0,i+1}^\sigma - \rho_{0,i}^\sigma)$ is

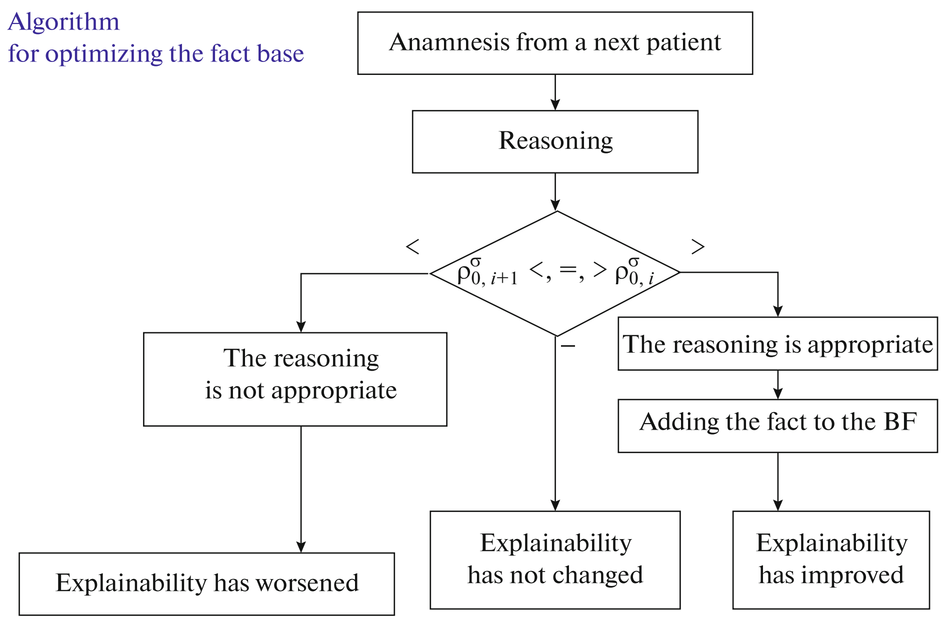

Fig. 2. The author's algorithm for optimizing the fact base of the JSM system.

the regularity preservation function; sign is the mathematical function that is equal to –1 at negative values of the argument, +1 at positive values, and 0 at zero values; Ψ^{σ} is the predicate that is applied to prediction hypotheses and uses the regularity preservation function whose value must be 1.

This means that the hypotheses on all expansions of the BF array received the same truth values.

Thus, we select reasonings for which the value chains are the same. Among them, we identify the reasonings that make up a quasi-composition of the form (in terms of the JSM-L language) [19]:

$$\exists Z \Psi^{s}_{1,2}(V,Z,Q) \vee \exists Z\,(\Psi^{s}_{1}(Z,Q) \\ \&(\Psi^{s}_{2}(V,Q)\ \&\ (V \subset Z)),$$

where $\sigma \in \{+1; -1\}$.

Hence, we obtain many reasons:

$$V = \{V | \exists Z \Psi^{s}_{1}(Z,W)\ \&\ \Psi^{s}_{2}(V,W)\ \&\ (V \subset Z)\}.$$

2.2.3. In this case, for each of their strategies $\mathrm{Str}_{x,y}$, we can specify the corresponding set of reasons V' such that $V' \subseteq V$. Such reasons are generated by using this strategy. Otherwise, the set of strategies $\mathrm{Str} \rightarrow 2^{\mathrm{V}}$ is repesented (Tables 2–6).

As we can see, the explainability does not decrease with the expansion of the BF, i.e., with $\mathrm{BF}_{0,0} \rightarrow \mathrm{BF}_{0,1} \rightarrow \mathrm{BF}_{0,2}$. This means that the BF does not need optimization (see Fig. 2). Therefore, it is not required to remove the factors Φ_j ($j = 1, \ldots, J_i$) from it or add new ones.

2.2.4. We assess the previously identified reasons for the mechanisms of regularities. To this end, the predictions of the risk of pelvic organ prolapse made for ten patients were compared with the actual truth values. The history of these ten patients provided additional facts that expanded the fact base to $\mathrm{BF}_{0,3}$.

In doing this, we calculated the following for each strategy:

(1) Correct predictions (l_0).

Table 1. An example of analyzing entries in the fact base of an information intelligent JSM system*

Patient identifier	Number of hypotheses	$\mathrm{BF}_{0,1}$	$\mathrm{BF}_{0,2}$	$\rho_{0,1}{}^{\sigma}$	$\rho_{0,2}{}^{\sigma}$	δ_1
1	1	+	+	0.71	0.62	–
2	4	+	+	0.94	1.00	+
5	2	-	–	0.67	1.00	+
…						

*The parameter $\delta_1 = \mathrm{sign}\,(\rho^{\sigma}_{0,2} - \rho^{\sigma}_{0,1})$ is the regularity preservation function, sign is a mathematical function that is equal to –1 for negative argument values, +1 for positive values, and 0 for zero values.

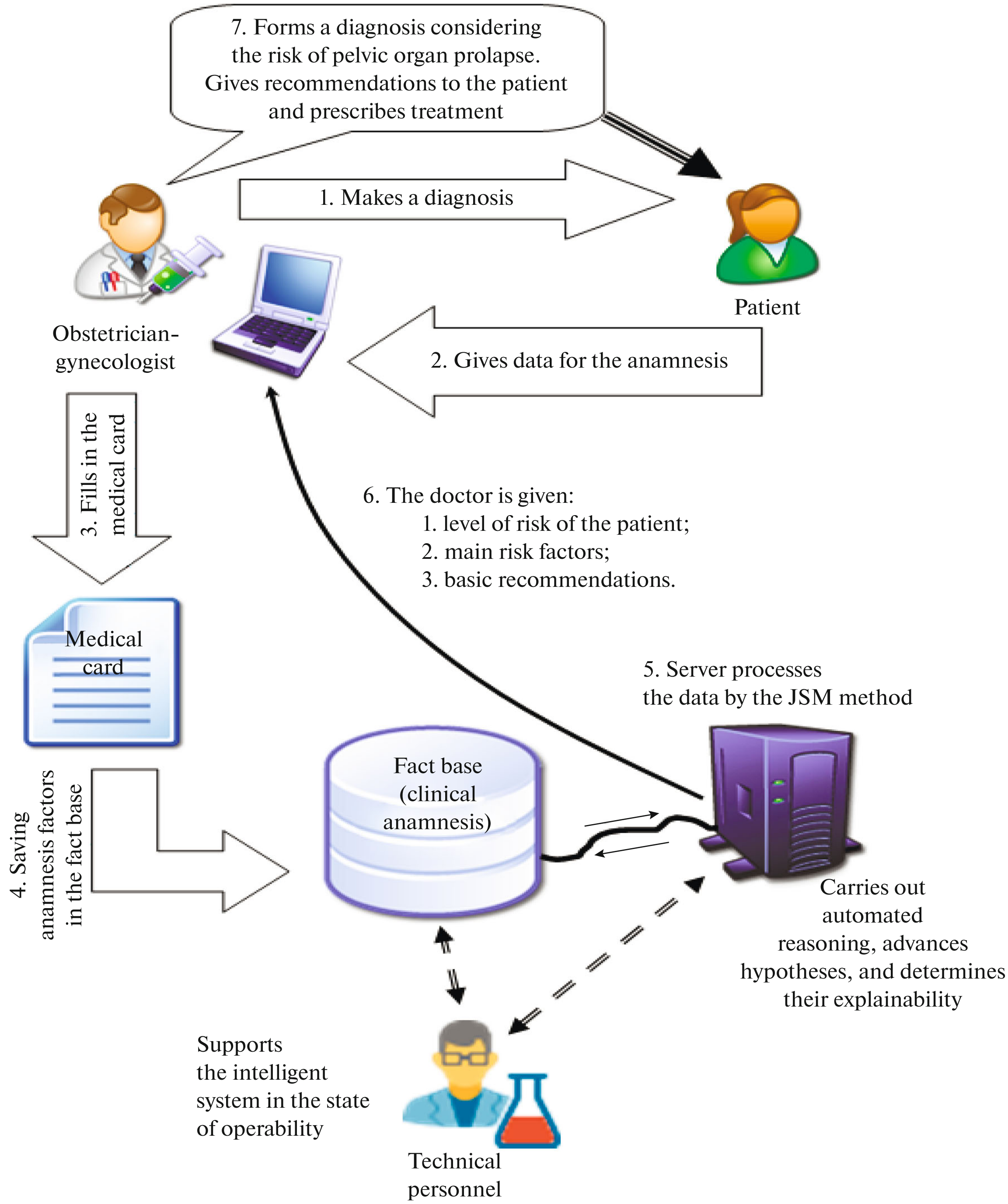

Fig. 3. The scheme of the intelligent system for determining the risk of origin and development of pelvic organ prolapse in nulliparous patients, which has been tested by the authors of this study.

(2) Significant errors (when the result that is opposite to the actual one was predicted: instead of a positive result, a negative one was predicted, or, conversely, instead of a negative result, a positive one was predicted) (a).

(3) Insignificant errors (when, instead of a positive or negative result, its absence is predicted, while the value is 0) (b).

(4) Failures of prediction (truth values are equal to τ). This situation is called uncertain (c).

Table 7 shows the results of counting the indications for each strategy.

Based on the results of these calculations, the strategies used in the study were sorted and the optimal ones were selected among them, considering the number of correct and incorrect predictions. In our opin-

Table 2. Explainability values for $\mathrm{Str}_{x,y}$ and $\mathrm{BF}_{0,1}$, $\mathrm{BF}_{0,2}$ (using the example of nine strategies)

$\mathrm{Str}_{x,y}$	$\mathrm{BF}_{0,0}$		$\mathrm{BF}_{0,1}$		$\mathrm{BF}_{0,2}$	
	$\mathrm{BF}^{+}_{0,0}$	$\mathrm{BF}^{-}_{0,0}$	$\mathrm{BF}^{+}_{0,1}$	$\mathrm{BF}^{-}_{0,1}$	$\mathrm{BF}^{+}_{0,2}$	$\mathrm{BF}^{-}_{0,2}$
1	0.71	0.82	0.71	0.82	0.82	1.00
2	1.00	1.00	1.00	1.00	1.00	1.00
3	1.00	0.77	1.00	0.80	1.00	0.92
4	0.74	0.95	0.88	1.00	1.00	1.00
5	1.00	0.74	1.00	0.89	1.00	1.00
6	0.75	0.90	0.94	1.00	0.90	1.00
7	1.00	0.54	1.00	0.79	1.00	0.80
8	0.74	1.00	0.82	1.00	0.93	1.00
9	1.00	0.68	1.00	0.72	1.00	0.87

Table 3. The correspondence of positive regularities of $\mathrm{BF}_{0,1}$ to strategies ($\mathrm{Str}_{x,y} \to 2^{\mathrm{V}}$)*

Regularity identifiers	$\mathrm{Str}_{x,y}$								
	1	2	3	4	5	6	7	8	9
1345	1			1	1			1	
36, 172, 3059		1		1		1		1	1
378, 1920, **4550**, 5239			1	1			1		

*In lines 2–4 of Tables 3–6, 1 means "truth", its absence means "false"; the numbers of the hypotheses that are of the greatest interest within the framework of our study are in bold.

Table 4. The correspondence of negative regularities of $\mathrm{BF}_{0,1}$ to strategies ($\mathrm{Str}_{x,y} \to 2^{\mathrm{V}}$)

Regularity identifiers	$\mathrm{Str}_{x,y}$								
	1	2	3	4	5	6	7	8	9
16	1	1				1		1	1
25, 135, 309, 440		1	1			1	1	1	
120, **553**, 1394	1			1	1				1

Table 5. The correspondence of positive regularities of $\mathrm{BF}_{0,2}$ to strategies ($\mathrm{Str}_{x,y} \to 2^{\mathrm{V}}$)

Regularity identifiers	$\mathrm{Str}_{x,y}$								
	1	2	3	4	5	6	7	8	9
1345	1		1	1	1			1	
36, 172, 3059		1				1	1		1
378, 1920, **4550**, 5239				1	1		1		

Table 6. The correspondence of negative regularities of $\mathrm{BF}_{0,2}$ to strategies ($\mathrm{Str}_{x,y} \to 2^{\mathrm{V}}$)

Regularity identifiers	$\mathrm{Str}_{x,y}$								
	1	2	3	4	5	6	7	8	9
16	1	1		1		1		1	1
25, 135, 309, 440		1	1					1	1
120, **553**, 1394	1			1	1	1			1

ion, the following selection criteria are obvious (in decreasing order of importance):

$K1$ is the maximum total number of correct predictions (both positive and negative) minus the number of significant errors and failures.

$K2$ is the minimum of the total number of insignificant errors at the maximum of the $K1$ criterion.

The $K2$ criterion is applied if there are two or more strategies for which the $K1$ criteria are the same.

Based on the definitions of the $K1$ and $K2$ criteria we have:

$$K1 = l_0 - a - c,$$
$$K2 = K1 - b.$$

Based on the $K1$ and $K2$ criteria, the strategies were ranked according to the degree of optimality and, accordingly, their usefulness for practical predictions of the risk of pelvic organ prolapse (Table 8).

Judging from Table 8, it seems that the highest relevance is characteristic of strategies No. 6 and No. 8 (highlighted in the table in bold), which, according to the results of the second study, have a value $\rho^{\sigma}_{0,2}$ that is equal to 1.00 for both positive and negative regularities, i.e., their explainability is the maximum possible. The rest of the strategies can be applied in practice only if it is impossible to implement either strategy No. 6 or strategy No. 8 for some reason.

Strategies 4 and 9 were found to have the same values for the $K1$ and $K2$ criteria; thus their ranks are denoted with a fractional number, as is usually accepted, for example, in a number of statistical ranking criteria.

2.2.5. Analysis of the most relevant hypotheses about the cause of pelvic organ prolapse in women with a history of natural childbirth (see Tables 3–6).

Positive hypotheses:

No. 1345: Performed obstetric operations can cause a high risk of pelvic organ prolapse.

No. 4550: Injuries to the pelvic organs and alcohol consumption are associated with the risk of prolapse.

Negative hypotheses:

No. 16: A patient's height in isolation from other factors does not affect the risk of prolapse.

Table 9 summarizes the results on these hypotheses for clarity.

We note that the hypotheses given in Table 9 coincide with the results of the corresponding strategies indicated in Table 8. It can be seen that, according to the results of the first study, the explainability of these (and many other) hypotheses was lower than 1.00, although it was high. However, the second study made it possible to slightly increase the explainability.

The results of the first study confirmed the hypotheses linking the risk of pelvic organ prolapse in parous women with the following factors:

• high body mass-to-height ratio;

Table 7. The distribution of the strategies by the quality of predicting the risk of pelvic organ prolapse

$Str_{x,y}$	Correct predictions		Significant errors (a)		Insignificant errors (b)		Failures (c)		The total number of patients diagnosed
	+1	−1	+1	−1	+1	−1	+1	−1	
1	3	2			4		1		10
2		3	1	2		3		1	10
3	2	2	3			3			10
4		4		1	2	3			10
5	3	1	1	1	2		2		10
6	2	5			2	1			10
7	4				2	2		2	10
8	3	3			2	2			10
9	1	3	1		3	2			10

Table 8. Ranking the strategies by degree of optimality and usefulness for practical predictions of the risk of pelvic organ prolapse

$Str_{x,y}$	$K1$	$K2$	Strategy rank	$\rho_{0,2}^{\sigma+}$	$\rho_{0,2}^{\sigma-}$
1	**4**	**0**	**3**	**0.82**	**1.00**
2	−1	−4	9	1.00	1.00
3	1	−2	7	1.00	0.92
4	3	−2	5.5	1.00	1.00
5	0	−2	8	1.00	1.00
6	**7**	**4**	**1**	**0.90**	**1.00**
7	2	−2	4	1.00	0.80
8	**6**	**2**	**2**	**0.93**	**1.00**
9	3	−2	5.5	1.00	0.87

Table 9. Analytical indicators of some of the most relevant hypotheses about the cause of pelvic organ prolapse

Hypothesis, No.	Nature of the hypothesis	What strategy it results from	$\rho_{0,2}^{\sigma+}$	$\rho_{0,2}^{\sigma-}$
1345	+	6	0.90	1.00
16	–	8	0.93	1.00
4550	+	1	0.82	1.00

• hard physical labor, age of over 60 years;

• the presence of diseases of the cardiovascular system and respiratory system;

• dysfunction of the pelvic organs (hemorrhoids, urinary incontinence, constipation);

• dissatisfaction with sex life.

The average explainability of these hypotheses turned out to be 0.86, which is very close to 1.00. The second study confirmed these hypotheses; the explainability increased and amounted to 0.97. Consequently, the expansion of $BF_{0,2}$ compared with $BF_{0,1}$ increased the ability of the BF to explain the hypotheses about the factors contributing to a high risk of pelvic organ prolapse in nulliparous women. In addition, this means that the BF used by us has regularities (empirical patterns), some of which were discovered in the course of reasoning and advancing hypotheses.

2.2.6. Expert research on the hypotheses. Based on strategies No. 6, No. 8, and No. 10, a list of possible causes (in the form of a set of hypotheses) was formulated and presented to obstetricians-gynecologists of clinical centers that conducted the research; these were five people who acted as experts. Each hypothesis was assessed by them on a five-point system,

Table 10. The results of expert assessments of the most relevant hypotheses of the risk of pelvic organ prolapse in women who have undergone natural childbirth

Hypothesis	Content of the hypothesis	Consistency assessment
1345	Performed obstetric operations can cause a high risk of pelvic organ prolapse	4
4550	Injuries to the pelvic organs and alcohol consumption are associated with the risk of pelvic organ prolapse	5
16	The patient's height in isolation from other factors does not affect the risk of pelvic organ prolapse	5

where a point equal to 1 denoted the least consistency (insignificance) of the hypothesis, and a point equal to 5 denoted the greatest consistency. Scores in the range from 2 to 4 meant that the hypothesis could be considered as consistent; however, at the same time, the corresponding (to the hypothesis) factors F_j from the BF ambiguously indicate a significant risk of pelvic organ prolapse in women who have undergone natural childbirth.

An expert study of the hypotheses was necessary to make an independent comparison and to determine to what extent the results of predicting the risk of prolapse in women with a history of natural childbirth can be assessed by professional doctors (in addition to the authors of this work). Table 10 shows the results of expert assessments.

3. COMPARISON OF THE RESEARCH RESULTS

1. The empirical patterns of the fact base and its regularities are synonymous.

2. Comparing the results of the first and second studies, we can conclude that the expansion of the fact base increases its explainability for all strategies or makes it necessary to perform its structural optimization.

3. The results of the first and second studies have shown that the available fact base can be used as a basis to carry out reasoning that makes it possible to formulate hypotheses with a very high level of explainability.

3. Expandability of the number of anamnesis (fact) data contributes to an increase in the number of hypotheses.

4. The JSM method made it possible to identify a number of relevant hypotheses (for example, this work provides strategies No. 16, No. 1345, and No. 4550). These hypotheses were highly rated by experts, which confirms their high explainability.

5. Based on the results of the first and second studies, it has been revealed that the main risk factors for pelvic organ prolapse are as follows: too high body mass-to-height ratio (i.e., overweight), constant hard physical labor, and an age of more than 60 years. An important role is played by the presence of diseases of the cardiovascular system, respiratory system, as well as dysfunctions of the pelvic organs (for example, constipation, hemorrhoids). In addition, it has turned out that dissatisfaction with sex life is also associated with a high risk of pelvic organ prolapse in women who have undergone natural childbirth.

CONCLUSIONS

Decisions made by obstetricians-gynecologists must be based on some reliable argumentation and rely upon the available clinical data. These decisions can be both unambiguous and hypothetical.

Until recently, a doctor made a decision based on professional experience, considering the level of his qualifications. The more experience and knowledge there was, the more developed were the professional competencies that allowed the doctor to successfully understand clinical situations and provide adequate treatment. Now, when conducting medical diagnostics, it is possible to make decisions based on the results of the work of automated artificial intelligence systems, which permit reliable and consistent data to be analyzed.

Currently, high computer technologies are available, in particular, the methodology of artificial intelligence. In this regard, the JSM method is relevant for the purpose of predicting the risk of pelvic organ prolapse in patients. The JSM method in relation to medical diagnostics shows amazing properties:

• Diagnostic predictions have become possible even under the conditions of incomplete, distorted, incorrect, and sometimes contradictory information, which is important due to the fact that the anamnesis collected from patients can often be subjective, since it depends not only on the psychological state of the doctor but also on the patient.

• The JSM-L language used in the JSM method is capable of describing the solution of problems of varying degrees of formalization, which seems to be very important for the purposes of medical diagnostics.

• The JSM method formulates hypotheses based on both explicit and implicit empirical patterns (regularities of the fact base). This is one of its main advantages. If there is a sufficiently large fact base, it is quite problematic for researchers to identify empirical patterns, especially if they are not very familiar with the mathematical apparatus, while the JSM method permits this to be done automatically.

It is important to note that the calculation based on the JSM method is implemented due to its intrinsic properties, as well as the presence of an array of facts (BF), which has a certain structure and regularity. This allows one to do without the use of mathematical modeling and programming, i.e., making allowance for new facts consists in retraining and/or optimizing the BF considering new conditions (facts) and, perhaps, clarifying the facts by adding or removing new factors, rather than in remaking or rewriting the program and/or mathematical model. It should be noted that the JSM methodology resembles neural networks in this sense; however, at the same time, it is capable of processing even small amounts of data.

Previously, there was no computer technology capable of automating the process of reasoning, developing hypotheses, and testing them. Therefore, the quality of the medical decisions made depended solely on the knowledge and information contained in the mind (memory) of the obstetrician-gynecologist. Today, the situation has changed, in particular, thanks to the JSM method: now, the doctor does not need to store all the necessary data in her memory. Modern computer artificial intelligence technologies make it possible to propose hypotheses automatically in real time based on the corresponding fact base. Moreover, it is important that its size is unlimited, because the computer has enormous capabilities for automated data processing and the identification of empirical patterns (regularities) contained in it.

There are a number of indicators by which the JSM method carries out reasoning on the basis of the fact base by identifying similarities; these indicators are positive or negative arguments in favor of the hypothesis generated by the intelligent system about a particular level of risk of the onset and development of pelvic organ prolapse in parous women.

Thus, our study has proven the ability to identify not only those patterns that are obvious to the doctor, but also hidden, implicit empirical patterns contained in the fact base. Implicit patterns can be identified only with the help of one or another mathematical method; however, the classical model of statistics is often not able to help under the conditions of incomplete and contradictory data. The JSM method, in turn, makes it possible to identify empirical patterns in this case. At the same time, the expansion of the fact base either contributes to an increase in the explainability of hypotheses or indicates the need to optimize the structure of the fact base. In our case, the use of the JSM method allowed us to form a number of hypotheses about the main causes of pelvic organ prolapse in parous women. At the same time, the hypotheses we obtained had a high degree of explainability, and some of them were tested on the basis of expert assessments that confirmed their validity.

APPENDIX

An example of an obstetric-gynecological fact (one entry in the BF)

I. Uncontrollable risk factors	
Factor	Value
1. Age (years)	47
2. Age of onset of menstruation (years)	17
3. Age at the end of menstruation (years)	46
4. Family history of maternal prolapse	Prolapse in the mother
5. Features:	
5.1	Joint hypermobility, tendency to dislocation, sprains of the ligamentous apparatus of the joints
5.2	Propensity to allergic reactions and colds
5.3	Biliary dyskinesia
II. Controllable risk factors	
6. Number of births	2
7. Age of first birth (years)	20
8. Body weight (kg)	58
9. Height (cm)	162
10. Alcohol consumption	Consumes

Table. (Contd.)

11. Tobacco smoking	No smoking
12. Lifestyle	Sedentary
III. Conditionally controllable risk factors	
During pregnancy, childbirth and in the post-natal period	
13. Fetus weight (g)	2450
14. Perineal trauma	
15. Obstetric operations	
16. Disorders of the pelvic organs function	Yes
17. Extragenital diseases during pregnancy	
18. Premature birth	
Diseases you have suffered	
19. Inflammatory diseases of the genital organs	Yes
20. Benign genital diseases	
21. Surgical interventions for gynecological diseases	
22. Injuries to the pelvic organs	
23. Operations on the external genital and pelvic organs	
Somatic diseases	
24. Diseases of the endocrine system	
25. Diseases of the respiratory system	Yes
26. Diseases of the urinary system	
27. Diseases of the cardiovascular system	
28. Diseases of the gastrointestinal tract	Yes
29. Diseases of the organs of vision	
30. Diseases of the nervous system	
31. Diseases of the blood system	
32. Musculoskeletal diseases	
33. Pathology of the dentoalveolar system	Yes
34. Postponed abdominal operations	
35. Other non-abdominal operations	
Disorders of the pelvic organs	
36. Disorders of urination	
37. Defecation disorders	
38. Sexual dysfunction	
39. Duration of pelvic organ dysfunction (years)	6
40. Nosological form according to ICD-X	N81.2
41. Concomitant diseases	Cyst-rectocele, GB2
42. Patient identifiers	No. 1239, No. 1349

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