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IMPLEMENTING AN ARTIFICIAL INTELLIGENCE SYSTEM IN THE WORK OF GENERAL PRACTITIONER IN THE YAMALO-NENETS AUTONOMOUS OKRUG: PILOT CROSS-SECTIONAL SCREENING OBSERVATIONAL STUDY

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ABSTRACT

Background. Early identification of risk factors (RF) associated with cardiovascular diseases (CVD) is essential for the prevention of CVDs and their complications. CVD risk factors can be identified using Artificial Intelligence (AI) systems, which are capable of learning, analyzing and drawing conclusions. The advantage of AI systems consists in their capacity to process large amounts of data over a short period of time and produce ready-made information.

Objectives. Evaluation of the efficiency of implementing an AI software application by a general practitioner for identifying CVD risk factors.

Methods. The study included data from 1778 electronic medical histories of patients aged over 18, assigned to an outpatient and polyclinic department of Muravlenkovskaya Gorodskaya Bolnitsa (Muravlenko municipal hospital), Yamalo-Nenets Autonomous Okrug (Russia). The study was conducted in four stages. The first stage involved a preliminary training of the Artificial Intelligence (AI) system under study using numerous CVD risk assessment scales. The Webiomed predictive analytics and risk management software by K-SkAI, Russia, was selected as a platform for this purpose. The second stage included an analysis of medical data to identify CVD risk factors according to the relative risk scale for patients under 40 and the SCORE scale for patients over 40. At the third stage, a specialist analyzed the previous and new information received about each patient. According to the results of the third stage, four risk groups for CVD (low, medium, high and very high) were formed. At the fourth stage, newly diagnosed patients with a high risk of CVD, who had not been previously subject to regular medical check-up, were directed for additional clinical, laboratory and instrumental follow-up examination and consultations of relevant specialists. Statistical data in absolute terms and as a percentage were obtained. Statistical processing of the results was carried out by a computer program aimed at medical decision support. Content visualization was performed in spreadsheets and charts.

Results. Based on the data obtained, the AI system under study divided all patients into CVD risk groups and identified uncounted factors. The AI system confirmed a high and very high risk of CVD according to SCORE (Systematic COronary Risk Evaluation) in 623 people, who were already receiving appropriate cardiological assistance. The RFs that had not previously been taken into account in the diagnosis were recorded in 41 (11.5%) patients from the very high-risk group and in 37 (12.7%) high-risk patients. The AI system identified a high risk of CVD in 29 people who had not been previously under care of a general practitioner or other specialists due to their infrequent visits to health care facilities. These patients were detected by the AI system following periodic and preliminary medical check-ups (35%), full in-patient treatment for other diseases (31%), when seeking help of other specialists (17%), as well as when obtaining a medical certificate for a driving license (12%), admission to a swimming pool (3%) or possessing a weapon (2%). In a group with the newly diagnosed patients at a high risk of CVD, men dominated (24 persons, 82%) and women comprised only 8% (5 persons). All these people were of working age between 40 and 50. In order to confirm the information received, the supervising physician subsequently referred patients for a follow-up examination, as a result of which only 1 person (3%) was not diagnosed with a somatic pathology.

Conclusion. The efficiency of the AI system under study comprised 97%. Permanent monitoring of all parameters of electronic medical histories and outpatient records is an efficient method for timely identification of RF at any visit of a person to a health care facility (preventive and periodic medical examinations, regular check-ups, specialist consultations, etc.) and their assignment to respective CVD risk groups. Such monitoring ensures an effective medical supervision of able-bodied populations.

Keywords: risk factors, risk groups, cardiovascular diseases, artificial intelligence in medicine, prevention of cardiovascular diseasese,hfnm

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ОПЫТ ВНЕДРЕНИЯ ПИЛОТНОГО ПРОЕКТА «ИСКУССТВЕННЫЙ ИНТЕЛЛЕКТ» В РАБОТЕ УЧАСТКОВОГО ТЕРАПЕВТА НА ТЕРРИТОРИИ ЯМАЛО-НЕНЕЦКОГО АВТОНОМНОГО ОКРУГА: ПИЛОТНОЕ ОДНОМОМЕНТНОЕ СКРИНИНГОВОЕ ОБСЕРВАЦИОННОЕ ИССЛЕДОВАНИЕ

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АННОТАЦИЯ

Введение. Раннее выявление факторов риска (ФР) сердечно-сосудистых заболеваний (ССЗ) имеет важнейшее значение для профилактики возникновения ССЗ и развития их осложнений. Для выявления факторов риска ССЗ можно использовать системы искусственного интеллекта (ИИ), способные к обучению, обобщению и выводу. ИИ за короткий срок обрабатывает огромные массивы данных и выдает готовую информацию.

Цель исследования — оценить эффективность использования программы ИИ для выявления факторов риска ССЗ у пациентов в практике участкового врача-терапевта.

Методы. В исследование включены данные 1778 электронных амбулаторных карт пациентов старше 18 лет, прикрепленных к одному участку амбулаторного-поликлинического отделения государственного бюджетного учреждения здравоохранения Ямало-Ненецкого автономного округа «Муравленковская городская больница». Исследование проведено в четыре этапа. Первым этапом выполнено предварительное «обучение» программы «Искусственный интеллект» многочисленными шкалами оценки риска ССЗ. Платформой для ее работы явилась программа прогнозной аналитики и управления рисками Webiomed (компания «К-Скай», Россия). Второй этап: анализ медицинской информации для выявления факторов риска ССЗ по шкале относительного риска для пациентов младше 40 лет и шкалы SCORE для пациентов старше 40 лет. Третий этап: специалист проанализировал имеющуюся ранее и полученную новую информацию о каждом пациенте. По результатам третьего этапа исследования были сформированы 4 группы риска ССЗ (низкий, средний, высокий и очень высокий). Четвертым этапом впервые выявленные пациенты с высоким риском ССЗ, ранее не состоявшие на диспансерном учете, направлены на дополнительное клинико-лабораторное и инструментальное дообследование, консультации специалистов. Получены статистические данные в абсолютном и процентном отношениях. Статистическая обработка результатов осуществлена компьютерной программой системы поддержки принятия врачебных решений. Визуализация контента осуществлялась в электронных таблицах и диаграммах.

Результаты. На основании выявленных данных ИИ разделил всех пациентов на группы риска по ССЗ, а также указал на неучтенные факторы. ИИ подтвердил очень высокий и высокий риск ССЗ по SCORE (Systematic Coronary Risk Evaluation) у 623 человек, которые уже состояли на диспансерном учете у терапевта, кардиолога и получали соответствующую терапию. ФР, которые ранее не были учтены при постановке диагноза, были зафиксированы у 41 (11,5%) пациента из группы очень высокого риска и 37 (12,7%) пациентов с высоким риском. Система ИИ впервые выявила высокий риск ССЗ у 29 человек, который ранее не наблюдался участковым терапевтом и другими узкими специалистами по причине редкого обращения в медицинские учреждения. Эти пациенты были обнаружены системой ИИ по результатам периодических и предварительных медицинских осмотров (35%), после курса терапии других заболеваний в условиях круглосуточного стационара (31%), при обращении к узким специалистам (17%), при оформлении медицинского заключения на вождение транспортного средства (12%), при получении справки в бассейн (3%) или на оружие (2%). Среди впервые выявленных пациентов с высоким риском ССЗ основную группу составили мужчины — 24 человека (82%) и только 5 женщин (8%). Все эти лица были трудоспособного возраста от 40 до 50 лет. С целью подтверждения полученной информации врачом-куратором впоследствии назначено дообследование пациентов, в результате которого только у 1 человека (3%) была исключена соматическая патология.

Заключение. Эффективность использования программы ИИ составила 97%. Постоянный мониторинг всех параметров электронных историй болезни и амбулаторных карт в короткое время позволяет выявить наличие ФР при любом обращении человека в медицинское учреждение (профилактические и периодические медицинские осмотры, плановая диспансеризация, обращение к узким специалистам и т.д.) и формировать группы риска по ССЗ. Данный мониторинг дает возможность эффективного медицинского контроля за трудоспособным контингентом.

Ключевые слова: факторы риска, группы риска, сердечно-сосудистые заболевания, искусственный интеллект в медицине, профилактика сердечно-сосудистых заболеваний

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INTRODUCTION

The development and implementation of Artificial Intelligence (AI) technologies is a priority for many countries [1, 2]. The growing interest in AI is being driven by the following trends: the emergence of powerful graphics processing units, the increasing capacity of modern computers, the development of cloud computing and the expansion of big data. These technologies support automated machine learning and produce highly accurate models, thus providing opportunity for successful automation and digitalization of various processes, including those in healthcare systems.

In the Russian Healthcare National Project, digital transformation of healthcare is defined as one of its core tasks, approved by the Presidential Decree No. 490 enshrined 10.10.2019. The National Strategy for the Development of Artificial Intelligence (AI) throughout the Russian Federation for the period up to 2030 is aimed at establishing the Russian Federation as one of the leading countries in the field of AI. In comparison with simple computer-based algorithms, AI systems are capable of learning, analyzing large amounts of information and drawing conclusions over a fairly short period of time. AI systems have been successfully applied for cancer diagnosis [3–5]. AI carries out preliminary processing of images, performs their segmentation to highlight the studied objects of diagnosis and classifies these objects for differentiation of malignant or benign neoplasms. The prognosis assessment and treatment adjustments can be carried out via monitoring of various vital parameters of patients in intensive care units [6, 7].

Currently, Russia is in urgent need for implementation of innovative technologies in cardiology, since the prevalence of cardiovascular morbidity (CVM) as the main cause of mortality in the Russian Federation grows every year, as well as throughout the world [8, 9]. According to statistical data, about 40% of people in Russia die in their prime working years (25–64 years)[1] [10, 11]. Available methods for treating cardiovascular diseases (medical, endovascular and surgical) fail to ensure a full recovery of such patients. The mortality rate of able-to-work men caused by coronary heart disease (CHD) in Russia is more than 10 times higher [11] than, e.g., in France [4, 6]. The low detection of diseases at early stages and the reluctance of patients to follow the medical recommendations for the prevention of CVD are the reasons behind the high mortality rate. Many globally recognized guidelines clearly describe the sequence of the doctor's actions: assessing objective data, identifying risk factors (RF) in a particular patient and only then solving the issue of reducing the risk of CVD [12, 13].

There are serious obstacles to implementing these recommendations in Russia. Firstly, the presence of over 40 different scales for CVD risk assessment impedes their application by a general practitioner during a regular consultation. Moreover, every modern doctor is overloaded with work: 70% of doctors experience an increase in the volume of work, and the amount of medical staff remains the same. 50% of the interviewed doctors complain about the amount of work not related to treatment of patients [14, 15]. A doctor is not capable to fully assess the risk of CVD during a routine, 15-minute or shorter, visit of a patient seeking medical care. A doctor spends a tremendous amount of time on paperwork, which takes up to 80% of the entire time of a patient visit [16, 17].

AI can be used to prevent the development of cardiovascular morbidity (CVM) and its negative consequences, as well as to improve the overall health prognosis by early detection and correction of CVD risk factors [18–20]. An Artificial Intelligence (AI)[2] system was developed within the framework of the national projects "Development of a network of national medical research centers and the implementation of innovative medical technologies" and "Creation of a single digital contour in health care on the basis of a common state information system of health care (EGISZ)" to improve the effectiveness of pre-nosological diagnostics, primary and secondary prevention of CVDs.

The developer of the first AI pilot project in Russia is the Webiomed predictive analytics and risk management platform by K-SkAI Company (Webiomed Clinical Decision Support System, CDSS), Skolkovo

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[2] Machine-assisted predictive analytics and healthcare risk management platform. Available at: https://files.sk.ru/navigator/company_files/1122678/1595485799_Webiomed.pdf
[3] Webiomed machine-assisted predictive analytics and healthcare risk management platform. Available at: https://leader.orgzdrav.com/storage/app/uploads/public/626/534/bb9/626534bb93cd8859825910.pdf

Innovation Center, Skolkovo Institute of Science and Technology, 2019. The project was registered by Roszdravnadzor as a software medical application[3]. AI CDSS Webiomed is a cloud-based system capable of integrating all medical information systems in a city, including electronic outpatient records, medical histories of all inpatient departments, as well as all data of clinical and diagnostic departments of a city hospital. Next, anonymized medical information obtained at any visit of a patient to a health care facility is processed. The system derives information from electronic medical histories in automatic mode, including unstructured data, analyzes the information using AI methods (electronic analytical systems and machine learning). The program independently analyzes patient health data using various analytical methods, including risk scales and artificial intelligence methods. The two approaches employed for data processing — algorithms and neural networks — allow large amounts of information to be timely processed [23, 24]. The AI system forwards the collected information to a project supervisor. The specialist compares the previously available data and the new information received for each patient and inputs feedback to the AI. The system analyzes the patient's electronic medical history automatically and sends a package of anonymized data to Webiomed via open APIs (Application Programming Interface). Based on the processed information, the system identifies CVD risk factors, automatically dividing patients into groups, makes an assumption about certain diseases and an overall risk assessment for each patient according to enlarged nosological groups [21–23].

In this study, we evaluate the efficiency of implementing the AI system under study for identifying CVD risk factors in patients by a general practitioner.

METHODS

Research design

A pilot cross-sectional screening observational study of 1778 people from one district covered by a physician of one municipal health care facility was conducted.

Research conditions

An analysis of the obtained data was carried out on the basis of an outpatient and polyclinic department of Muravlenkovskaya Gorodskaya Bolnitsa (Muravlenko municipal hospital). This study covered the period from February to May, 2019.

Compliance criteria

Eligibility criteria

According to the main eligibility criterion, in order to be included in the study, adults had to be from one district covered by a therapist of one municipal health care facility. Other criteria were electronic medical history; age over 18; signing of a voluntary informed consent.

Exclusion criteria

Exclusion criteria: age under 18.

Description of compliance criteria (diagnostic criteria)

The AI system analyzed data from electronic medical histories and outpatient records made at any request of a patient for medical care at the health care facility during the previous two years. The AI derived information from the computer network about the potential CVD risk factors: medical history data (hypodynamia, smoking, alcohol abuse, hereditary tainted CVD and DM history); clinically proven CVDs (previous myocardial infarction (MI) or acute coronary syndrome (ACS), coronary and other artery revascularization surgery, brain stroke or transient ischemic attack, aortic aneurysm, peripheral arterial diseases, chronic heart failure; data of physical examination with measurement of anthropometric and clinical parameters; data from standard general clinical blood and urine tests, biochemical profile (glucose level and lipid profile indicators (total cholesterol, HDL, LDL, triglycerides).

Selection of participants

The sample was formed by a continuous method based on the analysis of outpatient medical records in accordance with the specified criteria.

Study Targets

Main study target

The final study target was to determine, by means of the AI system under study, statistically significant results of calculating the risk of cardiovascular events over the subsequent 10 years using the SCORE (Systematic COronary Risk Evaluation) scale in patients over 40. A relative risk scale was used for people under 40. According to the risk factors obtained by the AI, the supervisor matched this information with the previously available medical information for each of their patients.

Additional study targets

In cases where a risk factor for CVD was first detected, the patient was additionally subjected to an instrumental study (echocardiogram, ultrasound of lower extremities) followed by a consultation of relevant specialists.

Methods for measuring target indicators

The first stage involved a preliminary training of the Artificial Intelligence (AI) system using numerous scales of CVD risk assessment. To this end, the Webiomed predictive analytics and risk management program, K-SkAI (Webiomed Clinical Decision Support System, CDSS), Skolkovo Innovation Center, Skolkovo Institute of Science and Technology, 2019, was used.

At the second stage, the AI analyzed all medical information about the patient, recorded at any visit to the health care facility over the previous two years. Deriving data on suspected CVD factors from the computer network, integration, processing of anonymized medical information and sending the package of anonymized data to Webiomed via open API (application programming interface) systems to the pilot project supervisor were performed automatically using two approaches: algorithms and neural networks, which allowed large amounts of information to be timely processed.

For each patient, cardiovascular risk criteria were verified using the SCORE (Systematic COronary Risk Evaluation) and relative risk scales. The examination was conducted in accordance with the 2017 Russian Guidelines for Cardiovascular Prevention [17]. The criteria were: age (men over 45 years old, women over 55 years old), hereditary predisposition, smoking, alcohol abuse, arterial hypertension, excess body weight (body mass index over 30 kg/m^2, waist circumference over 102 cm in men, over 88 cm in women); changes in biochemical blood test: total cholesterol level over 5.2 mmol/l, low-density lipoproteins over 4.1 mmol/l, glucose over 5.5 mmol/l.

At the third stage, a specialist analyzed the previous and new information received about each patient. Feedback was forwarded to the AI in the form of confirmation or denial of the revealed CVD risk factors. According to the results of the third stage of the study, four risk groups for CVD (low, medium, high and very high) were formed.

At the fourth stage, newly diagnosed patients with a high risk of CVD were directed for additional clinical, laboratory and instrumental follow-up examination and consultations of specialists.

Variables (predictors, confounders, effect modifiers)

In order to adjust the results of the study by stratification prior to the study, all the indicators of the general computer database of the health care facility for patients from the same district were used. The parameters of patients at risk of CVD who sought medical help at the outpatient and hospital stages were analyzed.

Statistical procedures

Principles of sample size calculation

The study was carried out by a continuous method based on the study of the general population by deriving information about cardiovascular risk factors in patients assigned to a health care district from common EMH database by CDSS Webiomed AI.

Statistical methods

Statistical processing of the obtained results was carried out by the CDSS Webiomed AI computer program. The analysis was performed using a software package for working with Microsoft Excel tables (Microsoft Office, USA). The AI software used anonymized general data from the electronic medical histories of patients according to risk group, gender, age, uncounted factors, etc. The system derived all the medical information obtained at any visit of a patient to a health care facility from the entire available computer database. The revealed CVD risk factors were calculated and risk groups were formed according to SCORE and relative risk scales. The result was obtained in absolute terms and as a percentage. Based on the statistical data, we calculated the extensive indices (EI) of probable morbidity and possible complications, visibility (VI) and correlation (CI) indices, and assessed the reliability of differences in statistical values. Primary information was accumulated, processed, and the content was visualized on the basis of the results in spreadsheets, followed by drawing charts.

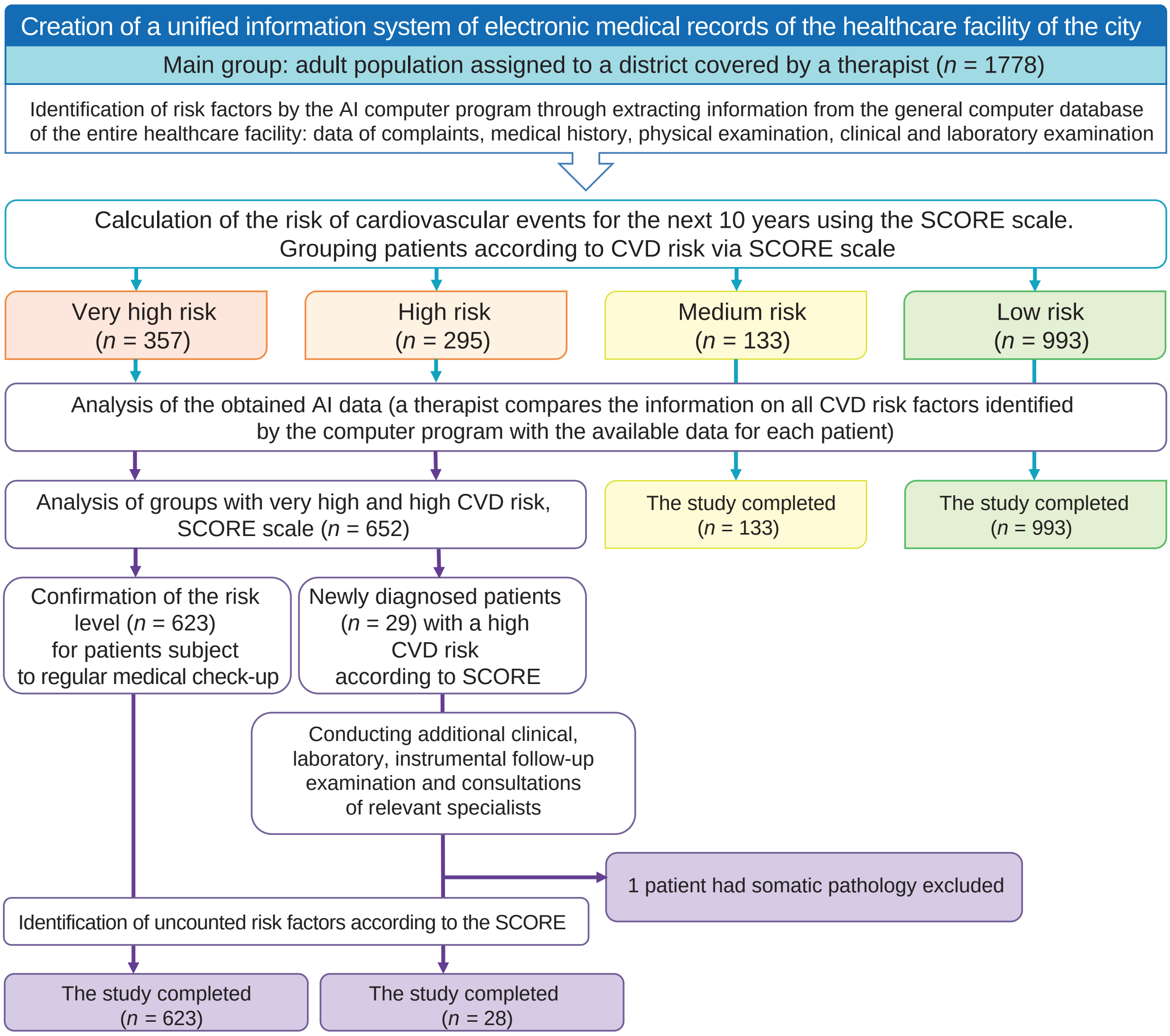

Fig. 1. Schematic diagram of the research design.
Note: CVD — cardiovascular diseases. SCORE — Systematic COronary Risk Evaluation scale.
Рис. 1. Блок-схема дизайна проведенного исследования.
Примечание: ССЗ — сердечно- сосудистые заболевания; SCORE — шкала SCORE (Systematic COronary Risk Evaluation).

RESULTS

Formation of the study sample

Figure 1 presents the principles of sampling and research design.

Characteristics of the study sample (groups)

The patients were divided into four groups depending on cardiovascular risk factors:

Very High CVD Risk Group included 357 patients with confirmed cardiovascular morbidity (CVM): MI, ACS, percutaneous coronary intervention, coronary artery bypass grafting, acute cerebrovascular disorder, transient ischaemic attack, aortic aneurysm, peripheral atherosclerosis, confirmed atheroma according to coronary angiography or Doppler Ultrasound Carotid Examination; diabetes mellitus with target organ disease; chronic kidney diseases (CKD) with glomerular filtration rate (GFR) <30 ml/min/1.73 m^2; SCORE risk ≥10%.

High CVD risk group included 295 patients with significant hypercholesterolemia (total cholesterol> 8 mmol/l), familial hypercholesterolemia, blood pressure ≥180/ 110 mm Hg; Diabetes without target organ disease (excluding young people with type 1 diabetes); CKD with GFR 30–59 ml/min/1,73 m^2; SCORE risk ≥5 and <10%.

Medium CVD risk group included 133 patients with a slight increase in total cholesterol (>5, but

<8 mmol/l), blood pressure <180/110 mm Hg; no history of diabetes and CKD; SCORE risk ≥1 and <5%.

Low CVD risk group included 993 young people without CVD RF; SCORE risk <1.

The main clinical data and laboratory findings are shown in Table 1.

Particular attention is paid to groups of very high and high CVD risk.

Main research results

According to the data obtained, the gender and age composition of the groups was comparable. The CVD risk levels among patients according to the AI analysis are shown in Table 2.

A very high risk of CVM was found in 357 people (20%): 254 men (71%) and 103 women (29%) (Fig. 2).

One half (185 people) of these patients were aged 61–70 years (Fig. 3).

All patients included in this group had previously been clinically diagnosed with CVD and were all under the supervision of a therapist. However, in 41 patients (11.5%) from this group, the AI system identified RFs that had not previously been considered when making a diagnosis (due to a lack of information): in 21 patients (51%) with diabetes in combination with hypertension and hypercholesterolemia, the software application discovered a hereditary predisposition to CVS lesions. In 11 patients (26%) with DM, AH and CHD, the AI additionally revealed signs of nephropathy, while 9 (22%) patients with DM and AH combined with hypercholesterolemia reported smoking (Fig. 4).

A high risk of CVM was revealed in 295 people (Fig. 2). This risk was confirmed in 266 patients who had already been under care of a therapist or cardiologist. At the same time, the AI system additionally detected RFs, which were not taken into account when making a diagnosis in 37 patients (12.7%) previously observed by specialists: in 12 of them (32%) with previously diagnosed hypertension, metabolic syndrome (MS) was noted for the first time; in 10 patients (27%), against the background of hypercholesterolemia and obesity, hyperglycemia was first detected. The combination of hypercholesterolemia and hyperglycemia was first recorded in 6 people (16%). In the presence of AH and MS, smoking was first registered in 6 people (16%). Against the background of AH and diabetes, a combination of smoking and alcohol abuse was recorded in 3 people (8%) for the first time (Fig. 5).

The Webiomed system identified a high risk of CVM in 29 people who had not previously been under care of a general practitioner or other specialists due to their infrequent visits to health care facilities. These patients were detected by the AI system following periodic and preliminary medical check-ups (35%), full in-patient treatment for other non-cardiac diseases (31%), when seeking help of other specialists (17%), when obtaining a medical certificate for a driving license (12%), when obtaining admission to a swimming pool (3%) or possessing a weapon (2%).

There were more men (24 or 82%) than women (5 or 18%) among newly diagnosed patients at high risk of CVD. Most of them were of working age between 40 and 50 (Fig. 6).

Additional research results

The SCORE scale was not used, and the risk was considered high or very high in the presence of CVDs based on vascular sclerosis, type I and II diabetes, very high levels of blood pressure and/or total cholesterol, CKD.

All patients with a high risk of SSP first identified by the AI system underwent clinical follow-up examinations: determination of glycosylated haemoglobin (HbA1), glucose tolerance test, assessment of lipid profile, as well as instrumental examinations: ECG, echocardiogram, daily monitoring of ECG, 24-hour blood pressure monitoring, USDG of brachiocephalic vessels, USDG of the lower extremities and consultations of specialists (endocrinologist, cardiologist, angiosurgeon). As a result, combinations of risk factors were confirmed in 28 patients: AH + smoking in 8 people (27%); MPS + smoking in 7 people (24%); AH + obesity in 4 people (13%); hyperglycemia + smoking in 3 people (10%); AH + diabetes in 2 people (7%); MBS was diagnosed in 4 patients (13%) for the first time. All patients received recommendations concerning the correction of risk factors with follow-up examinations, and 14 patients (48%) were enrolled in care of a general practitioner. Only in 1 person (3%), a man aged 29 years, any somatic pathology was excluded (Fig. 7). His inclusion in the CVD risk group may have been caused by a failure in the computer system.

Table 1. Main clinical and laboratory findings of patients included in the analysis (n = 1778)
Таблица 1. Основные клинические данные и результаты лабораторных исследований пациентов, включенных в анализ (n = 1778)

Indicators	CVD risks			Very high risk	*p*-value
	low risk	medium risk	high risk		
age, years	34.25 ± 7.70	49.25 ± 10.00	65.73 ± 11.70	69.25 ± 7.40	0.3
BMI (kg/m^2)	27.60 ± 4.15	29.61 ± 6.22	32.77 ± 13.82	31.82 ± 4.24	0.34
Waist (cm)	99.57 ± 7.72	102.41 ± 12.56	107.92 ± 14.30	100.47 ± 7.42	0.80
CBP (mm Hg)	123.83 ± 11.66	132.63 ± 18.88	148.28 ± 17.35	120.75 ± 13.56	0.04
DBP (mm Hg)	73.75 ± 7.44	89.33 ± 11.55	93.43 ± 10.97	72.75 ± 7.44	0.01
Total cholesterol (mmol/L)	4.91 ± 1.50	5.77 ± 1.25	6.76 ± 1.39	6.25 ± 1.69	0.36
Triglycerides (mmol/L)	1.10 ± 0.21	1.68 ± 1.42	1.89 ± 0.72	1.90 ± 0.23	0.35
LDL (mmol/L)	3.65 ± 0.69	4.75 ± 1.21	5.95 ± 1.07	5.94 ± 0.69	0.462

Note: BMI — Body Mass Index, SBP — Systolic Blood Pressure, DBP — Diastolic Blood Pressure, LDL — Low Density Lipoproteins.
Примечание: ИМТ — индекс массы тела, САД — систолическое артериальное давление, ДАД — диастолическое артериальное давление, ЛПНП — липопротеиды низкой плотности.

Table 2. CVD risk levels among the patients according to the AI analysis
Таблица 2. Степени риска ССЗ среди прикрепленного к участку населения по результатам анализа ИИ

CVD risk levels (SCORE scale)	Total, *n* (% of total number of patients)	Men *n*	Women *n*	Distribution by age *n* (%)
Very high risk (≥10%)	357 (20%)	254	103	20-30 years: 0 31-40 years: 17 (4.7%) 41-50 years: 69 (19.3%) 51-60 years: 67 (18.8%) **61-70 years: 185 (51.8%)** 71+: 19 (5.3%)
High risk (≥5 and <10%)	295 (266+ 29) (17%)	168	127	20-30 years: 1 (0.4 %) 31-40 years: 34 (11.5%) 41-50 years: 68 (23%) **51-60 years: 97 (32%)** 61-70 years: 87 (29%) 71+: 8 (3%)
Medium risk (≥1 and <5%)	133 (7%)	59	74	20-30 years: 14 (11%) 31-40 years: 31 (23%) **41-50 years: 72 (54%)** 51-60 years: 11 (8%) 61-70 years: 5 (4%) 71+: 0
Low risk (<1%)	993 (56%)	491	502	**20-30 years: 679 (68%)** 31-40 years: 206 (21%) 41-50 years: 104 (10%) 51-60 years: 4 (0.4%) 61-70 years: 0 71+: 0

Note: CVD — cardiovascular diseases. SCORE — Systematic COronary Risk Evaluation scale used for estimating a person's risk of death from a cardiovascular disease (CVD) within the subsequent 10 years.
Примечание: ССЗ — сердечно- сосудистые заболевания. SCORE — шкала SCORE (Systematic COronary Risk Evaluation), позволяющая оценить риск смерти человека от сердечно-сосудистого заболевания в течение ближайших 10 лет.

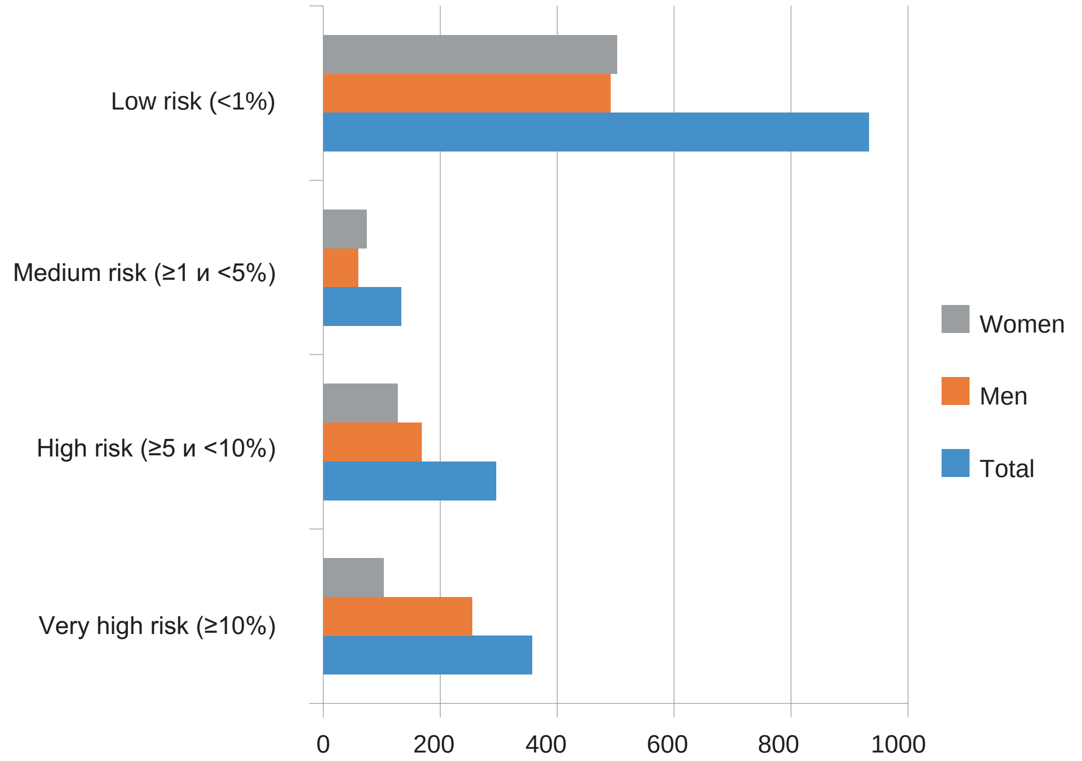

Fig. 2. CVD risk levels in the patients included in the study.
Рис. 2. Степени риска ССЗ среди прикрепленного к участку населения.

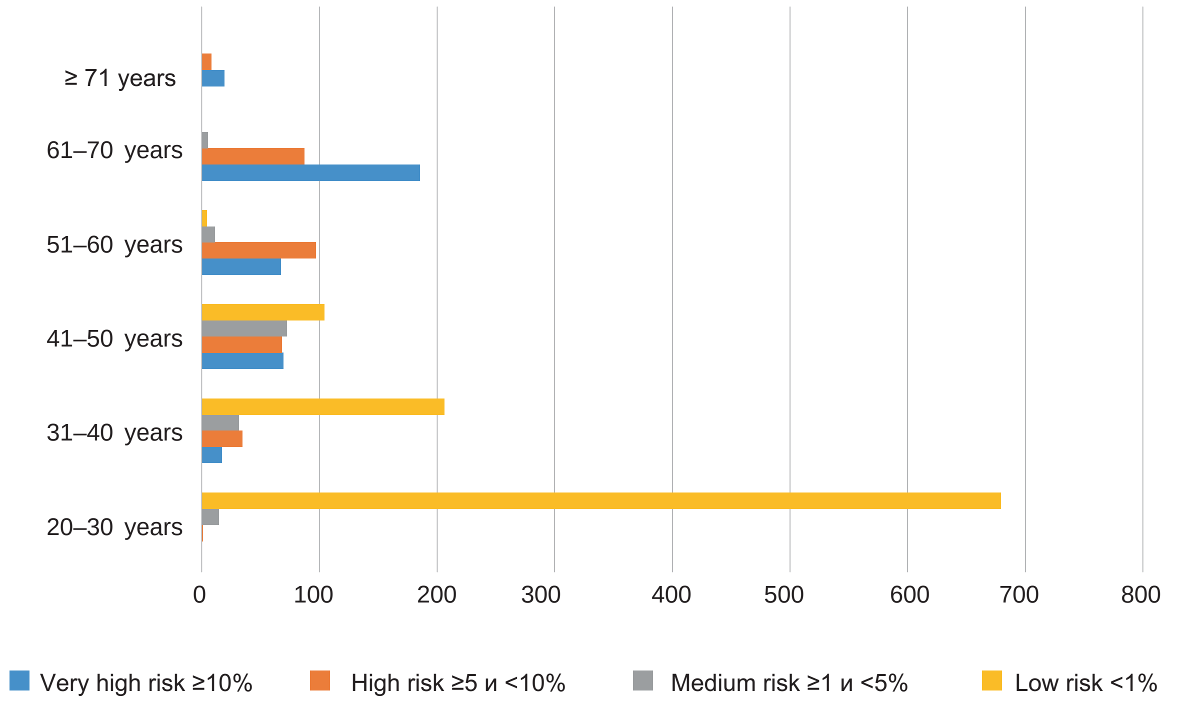

Fig. 3. Age distribution of CVD risk levels in the patients included in the study.
Рис. 3. Возрастное распределение степеней риска ССЗ среди прикрепленного населения.

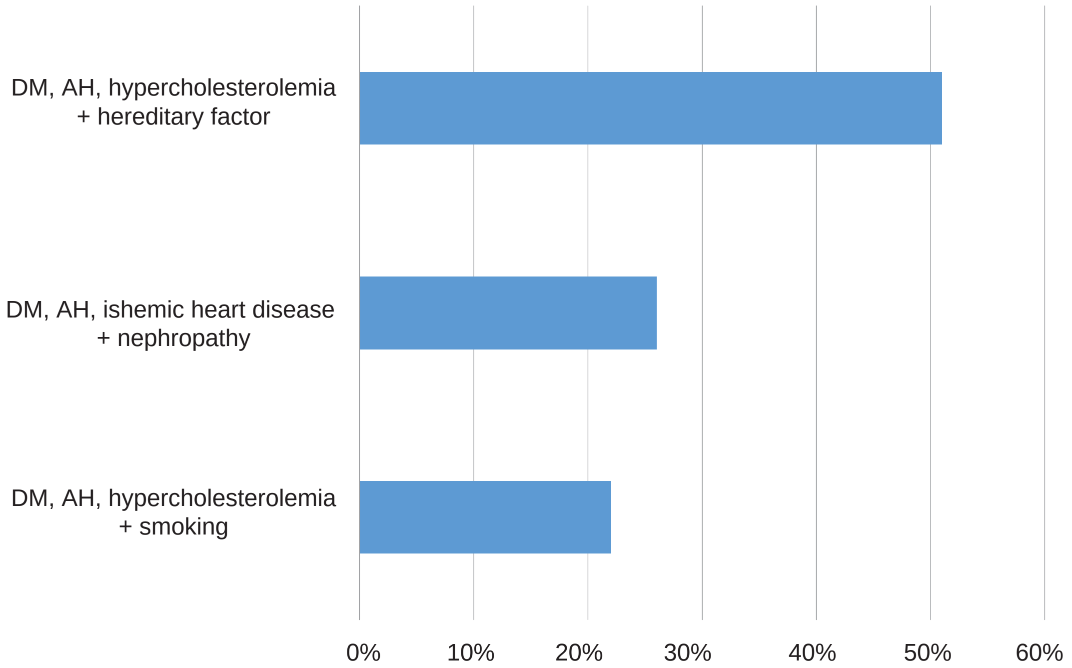

Fig. 4. Combinations of risk factors not previously considered in the diagnosis of very high risk of CVD.
Note: DM — diabetes mellitus, AH — arterial hypertension.
Рис. 4. Сочетания факторов риска, ранее не учитываемые при постановке диагноза в группе очень высокого риска ССЗ.
Примечание: СД — сахарный диабет, АГ — артериальная гипертония.

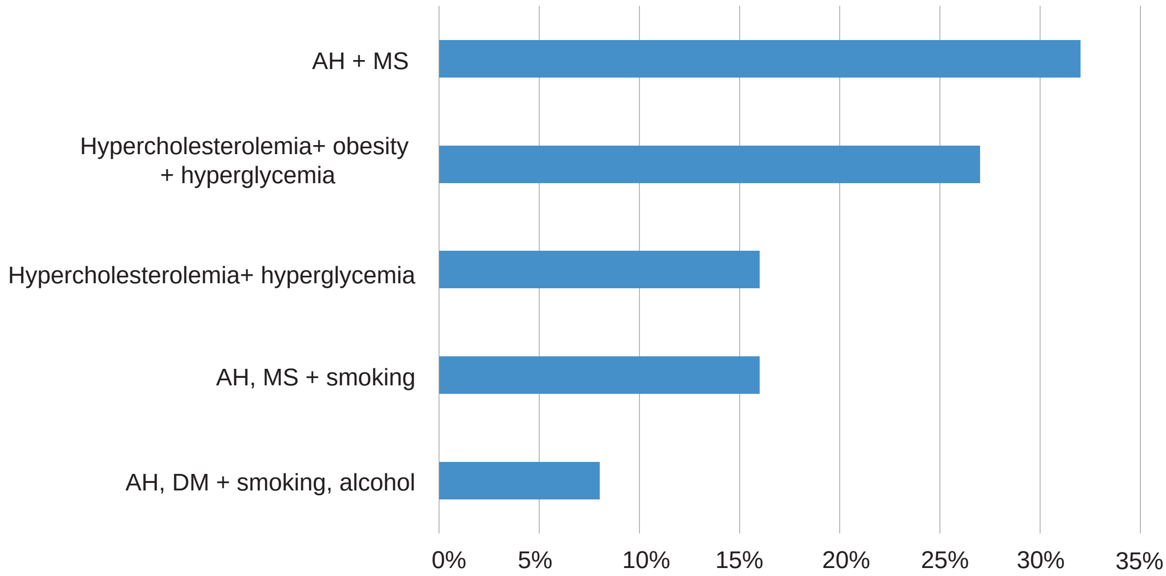

Fig. 5. Combination of risk factors not previously considered in the diagnosis of high risk of CVD.
Note: DM — diabetes mellitus, AH — arterial hypertension, MS — metabolic syndrome.
Рис. 5. Сочетания факторов риска, ранее не учитываемые при постановке диагноза, в группе высокого риска ССЗ. Примечание: СД — сахарный диабет, АГ — артериальная гипертония, МС — метаболический синдром.

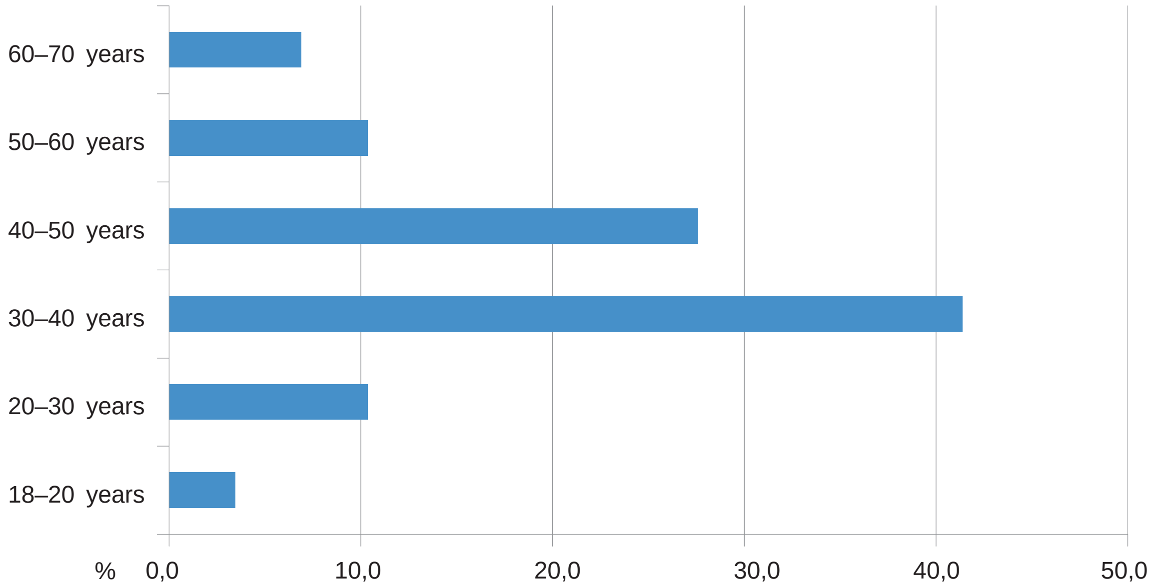

Fig. 6. Age composition of newly diagnosed patients at high risk of CVM.
Рис. 6. Возрастной состав впервые выявленных пациентов с высоким риском ССП.

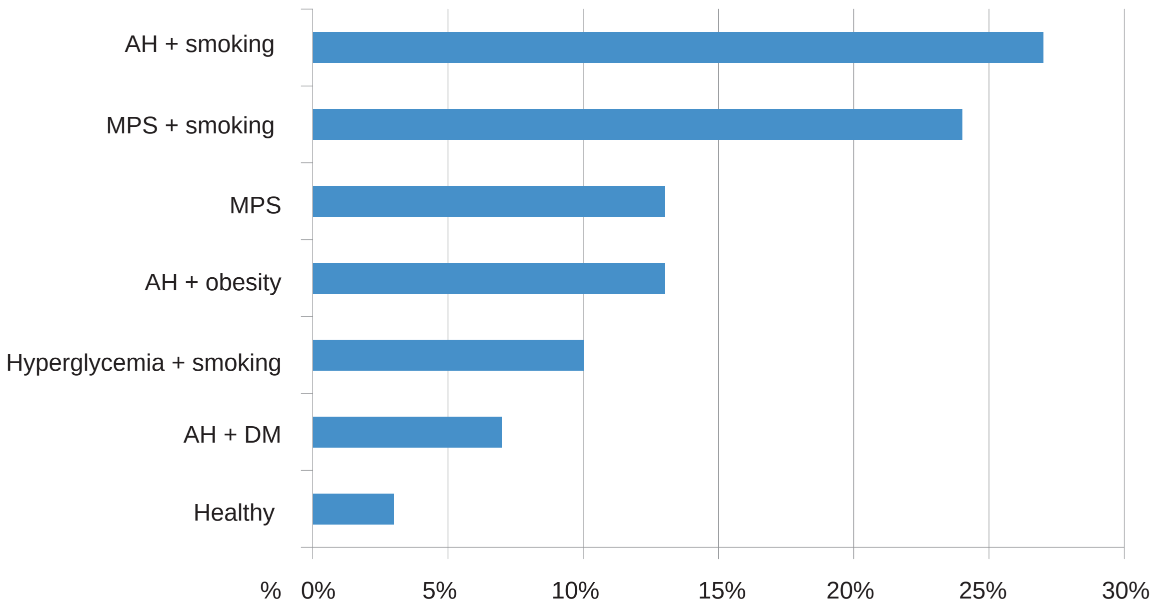

Fig. 7. Results of clinical examination of newly diagnosed patients at high risk of CVD.
Note: DM — diabetes mellitus, AH — arterial hypertension, MS — metabolic syndrome.
Рис. 7. Результаты клинического обследования впервые выявленных пациентов высокого риска ССЗ.
Примечание: СД — сахарный диабет, АГ — артериальная гипертония, МС — метаболический синдром.

DISCUSSION

Summary of the main research results

The use of the AI system under study for a rapid monitoring of electronic medical histories and outpatient records allowed a therapist to timely notice the presence of RFs, which were recorded at any visit of a patient to a health care facility (preventive and periodic medical examinations, routine check-ups, specialists' consultations, etc.), and to form, on this basis, CVD risk groups. Such a monitoring approach can be used to implement regular medical control over able-bodied populations [24, 25]. Timely detection and correction of RFs at the pre-nosological stage can minimize the risk of cardiovascular diseases and, if present, reduce the complication rate.

Study limitations

The AI system was trained on the basis of existing medical records of patients, which might have been incomplete, inaccurate or incorrect. Naturally, the use of information containing inaccuracies or even errors for AI training will reduce the quality of monitoring. AI systems operate on a black-box basis; thus, it is almost impossible to identify a reason for incorrect solutions. The development and implementation of AI systems requires significant expenses associated with the need to train the system and to adjust its work to the data accumulated in a particular medical institution. In addition, such systems require special maintenance and, therefore, a qualified and motivated team. Forming a unified digital database for all medical institutions in a city increases the informative value of AI systems.

Interpretation of study results

The AI system under study was used to analyze the data of electronic medical histories and outpatient records of 1778 people assigned to one district of a health care facility.

Among all those examined, men predominated with a slight difference (n = 972; 55%). The study focused on detecting patients of health groups II and III. These are the patients who require continuous monitoring of the RFs of CVM to prevent the onset of the disease or the development of its complications [8, 10].

A comparative analysis of CVD risk groups showed significantly higher values in the group of patients with very high CVD risk (≥10%) (n = 357). Statistically significant differences were found in gender composition in this group, with men (n = 254; 71%) aged 61–70 being prevalent (n = 185; 51.8%). The statistical values in the high CVD risk group (≥5 and <10%) (n = 295) differ from the first CVD risk group: 56% (n = 168) of men in the high-risk group were aged 51–60 (n = 97; 32%). Medium CVD risk (≥1 and <5%) was found in 7% (n = 133), mainly in women (n = 74; 56%) aged 41–50 (n = 72; 54%). The statistically most significant CVD risk group is the low CVD risk group (<1%) (n = 993; 56%), with approximately equal gender ratio. The main age group was 20–30 years old (n = 679; 68%).

The AI system fully confirmed the presence of risk factors in patients in all age groups. In addition, new, previously uncounted risk factors were detected at short intervals (n = 37; 12.7%).

Patient information may be stored in many different clinics and medical records, which complicates history taking and diagnosing [20]. At the same time, AI systems are capable of analyzing unstructured data from different sources and, on this basis, form groups of patients with different levels of CVM risk [14, 15]. AI rapidly extracts relevant factors from the vast amount of information, thereby facilitating the work of a specialist. When a physician and AI work together, the probability of errors is reduced to almost the level of statistical error.

Risk assessment of a particular patient is necessary for the subsequent organization of therapeutic and preventive measures [25] in a health care facility: clinical examination according to the standards of specialized medical care; enrolment in care and case follow-up; referral for consultation with specialists; modification of the existing CVD risk factors at an early stage of their formation; prescription of the necessary drug therapy [16]. An individualized approach to preventing and early diagnosis of CVD will increase the life expectancy of patients at high risk of CVD [25].

The use of AI systems for monitoring electronic medical histories and outpatient records allows therapists to timely detect RFs, which are recorded at any visit of a patient to a health care facility (preventive and periodic medical examinations, routine check-ups, specialists' consultations, etc.), and to form CVD risk groups. Such systems ensure effective medical control over the health of able-bodied populations [24].

An assessment of the patient's total cardiovascular risk is instrumental in the development of tactics to improve health prognosis by modifying all the available RFs, as well as in health promotion to maintain a low risk of CVD in patients with a low probability of developing the disease.

CONCLUSION

The use of the AI system under study allowed a high and very high risk of CVD to be confirmed in 652 people. In addition, the system was instrumental in detecting the uncounted RFs in patients.

The AI system under study is particularly useful for identifying RFs in patients who have not been previously subject to any medical check-up. A high risk of CVD was detected in 29 patients for the first time and was clinically confirmed in 28 cases. The conclusion of AI was refuted in a clinical laboratory study only in one case, which indicates the need to verify data by healthcare professionals. Despite this failure, the AI showed a high level of efficiency in the pre-nosological diagnosis of CVD.

COMPLIANCE WITH ETHICAL STANDARDS

The study complies with the Declaration of Helsinki. The study protocol was approved by the independent Ethics Committee of the Federal State Budgetary Educational Institution of Higher Education "Tyumen State Medical University", Ministry of Health, Russia (Odesskaya Street, 54, Tyumen, Russia), Minutes No. 101 dated 13.09.2021.

СООТВЕТСТВИЕ ПРИНЦИПАМ ЭТИКИ

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Conceptualisation — concept statement; statement and development of key goals and objectives.

Conducting research — data analysis and interpretation. Evaluation of the relevance of the study.

Text preparation and editing — critical review of a manuscript with the introduction of valuable intellectual content and remarks. Preparation and creation of a published work. Contribution to the scientific layout.

The approval of the final version of the paper — the acceptance of responsibility for all aspects of the work, the integrity of all parts of the paper and its final version.

Performing statistical analysis — the application of statistical methods for the analysis and synthesis of data. Acceptance of responsibility for all types of the work, integrity of all parts of the paper and its final version.

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