DOI: https://doi.org/10.17816/medjrf635256

Artificial intelligence systems for predicting chronic ischemic heart disease outcomes in cardiac surgery patients based on presence of anemia: a literature review

Tatyana Yu. Kalyuta, Irina P. Emelyanova, Valeriy V. Suvorov, Alexander S. Fedonnikov

Saratov State Medical University named after V.I. Razumovsky, Saratov, Russia

ABSTRACT

BACKGROUND: In Russia, the number of people undergoing heart surgery exceeds 600 thousand annually. These include anemia in 30–70% of patients with a 4-fold increased risk of one-year death, a 5-fold increased risk of stent thrombosis, a 1.3-fold increased risk of recurrent acute coronary events, and a 2-fold increased risk of bleeding. However, among the prognostic systems developed using artificial intelligence (AI) technologies, few take the presence of anemia into account. Existing digital platforms are not designed to support clinical decision making.

AIM: The review aimed to evaluate existing AI platforms for predicting the course of ischemic heart disease (IHD) and systems that take into account the presence of anemia.

MATERIALS AND METHOD: The PubMed and Russian Science Citation Index databases from 2000 to January 2024 were analyzed. Using Keywords of “artificial intelligence”, “anemia”, “coronary heart disease”, “hemoglobin”, and “cardiac surgery”, 906 articles were found, of which 38 met the inclusion criteria for analysis.

RESULTS: In some countries, AI platforms have been created to predict the course of IHD. This review analyzes published data on the development and use of AI-based digital products for the management of patients with IHD, including those that take into account key hemodynamic parameters.

CONCLUSION: Analysis of existing developments revealed a focus on solving prognostic problems. However, in our opinion, the range of parameters analyzed is not wide enough. For example, anemia, which plays a key role in modifying the risk of adverse outcomes in IHD, has not been considered as a factor.

Keywords: artificial intelligence; anemia; ischemic heart disease; review.

To cite this article:
Kalyuta TYu, Emelyanova IP, Suvorov VV, Fedonnikov AS. Artificial intelligence systems for predicting chronic ischemic heart disease outcomes in cardiac surgery patients based on presence of anemia: a literature review. *Russian Medicine.* 2024;30(5):486–493. DOI: https://doi.org/10.17816/medjrf635256

Received: 19.08.2024 **Accepted:** 20.09.2024 **Published online:** 24.10.2024

DOI: https://doi.org/10.17816/medjrf635256

Системы искусственного интеллекта для прогнозирования исходов при хронической ишемической болезни сердца у пациентов, перенёсших кардиохирургическое вмешательство, в зависимости от наличия анемического синдрома: обзор литературы

Т.Ю. Калюта, И.П. Емельянова, В.В. Суворов, А.С. Федонников

Саратовский государственный медицинский университет имени В.И. Разумовского, Саратов, Россия

АННОТАЦИЯ

Обоснование. Ежегодно в России число лиц, перенёсших кардиохирургические вмешательства, превышает 600 тыс. Среди них анемия встречается у 30–70% человек, что в 4 раза повышает риск летального исхода в течение года, в 5 раз — риск тромбоза стента, в 1,3 раза — риск рецидивов острых коронарных событий и в 2 раза — риск кровотечений. Однако среди разработанных систем прогнозирования с применением технологий искусственного интеллекта (ИИ) лишь немногие учитывают наличие анемического синдрома. Имеющиеся цифровые платформы не сфокусированы на поддержке принятия врачебных решений.

Цель обзора — анализ существующих платформ ИИ для прогнозирования течения ишемической болезни сердца (ИБС) и систем, учитывающих наличие анемического синдрома.

Материалы и методы. Проанализированы базы данных PubMed и «Российский индекс научного цитирования» с 2000 по январь 2024 года. По ключевым словам «искусственный интеллект», «анемия», «ИБС», «гемоглобин», «кардиохирургические вмешательства» найдено 906 статей, из них критериям включения в анализ соответствовало 38.

Результаты. В ряде стран мира в настоящее время созданы платформы ИИ для прогнозирования течения ИБС. В настоящем обзоре представлен анализ опубликованных данных о разработанных и используемых цифровых продуктах на основе ИИ для ведения пациентов с ИБС, в том числе учитывающих основные гематологические показатели.

Заключение. Анализ существующих разработок показал нацеленность на решение прогностических вопросов. При этом, на наш взгляд, недостаточно широк спектр анализируемых параметров. В частности, не развит учёт наличия или отсутствия анемии, играющей ключевую роль в модификации риска неблагоприятных исходов при ИБС.

Ключевые слова: искусственный интеллект; анемия; ишемическая болезнь сердца; обзор.

Как цитировать:

Калюта Т.Ю., Емельянова И.П., Суворов В.В., Федонников А.С. Системы искусственного интеллекта для прогнозирования исходов при хронической ишемической болезни сердца у пациентов, перенёсших кардиохирургическое вмешательство, в зависимости от наличия анемического синдрома: обзор литературы // Российский медицинский журнал. 2024. Т. 30, № 5. С. 486–493. DOI: https://doi.org/10.17816/medjrf635256

Рукопись получена: 19.08.2024 **Рукопись одобрена:** 20.09.2024 **Опубликована online:** 24.10.2024

BACKGROUND

Cardiovascular disease represents a significant and growing burden on healthcare systems [1]. In Russia, the number of people undergoing heart surgery exceeds 600 thousand annually [2, 3]. Of them, 30 to 70% of patients have anemia which is associated with a 4-fold increased risk of one-year mortality, a 5-fold increased risk of stent thrombosis, a 1.3-fold increased risk of recurrent acute coronary syndrome, and a 2-fold increased risk of bleeding [1–3]. More than 10 modifiable and many non-modifiable risk factors have been identified for unfavorable prognosis of ischemic heart disease (IHD), with anemia being a significant one. Artificial intelligence (AI) is increasingly being used to determine poor prognostic factors for IHD [4–41]. Therefore, the aim of this review was to analyze existing AI platforms designed to predict IHD progression and consider anemia.

MATERIALS AND METHODS

This review presents Russian and foreign studies on the use of AI platforms to predict IHD progression considering presence or absence of anemia. The PubMed and Russian Science Citation Index databases were searched from 2000 to early 2024. Using "artificial intelligence", "anemia", "ischemic heart disease", "hemoglobin", "cardiac surgery" as keywords, 906 papers were found and analyzed according to the criteria presented. As the search for papers using all keywords did not yield any results, the above keywords were used in pairs, and papers were found presenting data on the use of digital platforms with AI elements to predict IHD outcomes. As a result, 38 papers were selected and analyzed using parameters included in the interpreted input data in AI systems. The list of outcomes (endpoints) predicted by researchers was also assessed.

RESULTS

Appendix 1 lists the key clinical parameters interpreted using AI platforms described in papers and the outcomes they predict. This review evaluated 38 proprietary AI platforms, interpreted data, and predicted outcome parameters. We classified the interpreted parameters as clinical, instrumental, and laboratory ones. This analysis showed that most platforms included parameters that are rarely determined in routine practice, and only 8 of 38 systems included complete blood count (CBC) as one of prognostic parameters.

We identified two types of outcomes predicted by developers of AI platforms: 1) probability of a clinically defined adverse outcome (acute coronary syndrome, death, etc.); 2) probability of a morphologically defined adverse outcome (e.g., plaque rupture). We believe that such a classification helps understand the practical value of using AI platforms developed by different researchers. On the one hand, the accuracy of system is improved due to increasing the amount of output data and the proportion of objective and quantifiable prognostic features. On the other hand, the need to collect and enter large amounts of information into the system is limited in practice by technical capabilities of a healthcare organization, data collection time, etc. In addition, estimated probability of a morphologically defined adverse outcome (e.g., risk of plaque rupture) is difficult to use in routine practice as a guide for clinicians because the traditional risk-oriented approach is based on assessing probability of clinically adverse conditions, not morphological ones.

Appendix 1 shows different AI platform development strategies used in the studies reviewed. Machine learning models were the most commonly used, and only four cases did not specify any algorithm.

The majority of researchers include data pertaining to the presence or absence of commonly recognized risk factors for IHD progression in the list of data to be interpreted by the AI platform. Most of these risk factors are non-modifiable, with anemia being a modifiable one. However, only 10% of researchers included this parameter in their analysis of IHD risk. D'Ascenzo et al. [25] developed the only algorithm to determine the risk of IHD in the presence of anemia. Only Ohara et al. [24] evaluated red blood cell counts as a predictor of anemia. At the same time, anemia is a significant IHD risk factor and correlates with worse outcomes [3].

According to Appendix 2, all AI systems developed for recording laboratory parameters of anemia can be classified into two groups which consider (54 papers) and disregard (6 papers) CBC parameters.

Based on this fact, anemia seems to be underestimated as a prognostically adverse factor that significantly increases the risk of adverse IHD outcomes [1–3]. Bleeding during IHD surgery is also not fully considered, although it is an independent adverse predictor: only one of the developed AI systems included this factor (D'Ascenzo et al.) [25].

Table 1 shows the frequency of using endpoints for assessment of outcomes predicted by the platform developers.

An evaluation of outcome prediction parameters suggests that the focus is predominantly on clinical endpoints such as death, arrhythmia, bleeding, while morphological adverse endpoints such as myocardial hypertrophy and stent thrombosis are evaluated in only 7.8% of cases. We believe that the focus on clinical endpoints is justified because it is consistent with the principles of recommendations to be followed in routine clinical practice.

DISCUSSION

Artificial intelligence can improve the quality of risk prediction for adverse outcomes in IHD patients. However, our study shows no current consensus on the minimum

Table 1. Frequency of using endpoints to evaluate outcomes predicted by authors of papers

Predicted outcome	Number of papers using the outcome	Percentage of papers using the outcome out of the total number (*n*=38) of papers meeting inclusion criteria and having no exclusion criteria
Anemia	1	2.60
Non-ST-elevation acute coronary syndrome	3	7.80
Unstable angina	9	23.60
Acute myocardial infarction recurrence	7	18.40
Pericarditis	3	7.84
Atrial fibrillation	4	10.50
Cardiomyopathy	4	10.50
Angioedema	1	2.60
Chronic heart failure	2	5.20
Acute heart failure	2	5.20
Myocardial hypertrophy	1	2.60
Hypertrophic cardiomyopathy	2	5.20
Cardiac death	3	7.84
Stent thrombosis	2	5.20
Brugada syndrome	2	5.20
White coat hypertension	1	2.60
Pulmonary hypertension	1	2.60
Metabolic syndrome	2	5.20
Arrhythmia	4	10.50
Bleeding	6	15.47
Death (all causes)	8	21.0

sufficient set of parameters to be analyzed using AI for prediction of cardiac surgery outcomes. In the list of data to be interpreted, most researchers include mainly medical history of commonly accepted risk factors, most of which are non-modifiable. It should be noted that anemia is a modifiable risk factor. However, only 10% of the developers included this parameter in their analysis of IHD risk. The Ohara and D'Ascenzo algorithms are the first published IHD prediction platforms that consider anemia, and both algorithms were developed for patients with bleeding and/or baseline anemia [24, 25]. In patients without anemia or no history of bleeding, none of the developers included anemia as a potential outcome to be predicted.

We believe that anemia is not considered to predict IHD progression due to the relatively short history of AI use in healthcare. Researchers seem to improve their algorithms using a relatively narrow set of the same interpretable data and outcomes (see Appendix 2), and in the next phase a wider range of parameters is expected to be included.

It should be noted that there are no AI platforms that support clinical decision making to recommend a personalized treatment or diagnostic strategy. The only exception is the system developed by Noh et al. [6] to assess the "need for revascularization."

The relatively small number of developments is remarkable. At the same time, AI platforms are being developed in Russia to improve the quality of life of IHD patients and optimize use of healthcare resources. There is a high demand for such services among healthcare professionals and patients, but no available services have been offered.

CONCLUSION

In some countries, AI platforms have been created to predict IHD progression. They address prognostic issues and do not focus enough on treatment strategies. At present, the methods for AI platform development for IHD patients are still in their infancy and are based on a limited set of input data. Anemia is not considered by most teams developing AI models for patients after cardiac surgery. Therefore, it is important to develop AI platforms for predicting IHD progression, considering anemia as a risk factor. This will increase their medical, social, and economic effectiveness.

ADDITIONAL INFORMATION

Appendix 1. Analysis of interpreted and predicted parameters in publications on developed artificial intelligence systems. doi: 10.17816/rmj635256-4221253

Appendix 2. The frequency of use of indicators included in the data interpreted by the authors of the articles. doi: 10.17816/rmj635256-4221255

Funding source. The work was performed as part of a scientific study of the Saratov State Medical University named after V.I. Razumovsky of the Ministry of Health of the Russian Federation on the subject of the state assignment of the Ministry of Health of the Russian Federation "Development of an expert artificial intelligence system for personalized diagnosis, correction of cognitive impairment and prediction of outcomes in chronic coronary heart disease depending on the presence of anemic syndrome" (EGISU R&D No. 124020600005-4, PTNI 1023022700025-8 dated 06.02.2024)

Competing interests. The authors claim that there is no conflict of interest in the article.

Authors' contribution. All authors confirm compliance of their authorship with the international ICMJE criteria. The largest contribution is distributed as follows: T.Yu. Kalyuta — research concept and design, writing the text, editing; I.P. Emelyanova — collection and processing of material, writing the text; V.V. Suvorov — writing the text, compilation of the list of literature; A.S. Fedonnikov — writing the text, editing.

REFERENCES

1. Kontsevaya AN, Drapkina OM, Balanova YuA, et al. Economic burden of cardiovascular diseases in the russian federation in 2016. *Rational Pharmacotherapy in Cardiology.* 2018;14(2):156–166. EDN: XNSQUP doi: 10.20996/1819-6446-201814-2-156-166

2. Lanser L, Fuchs D, Scharnagl H, et al. Anemia of chronic disease in patients with cardiovascular disease. *Front Cardiovasc Med.* 2021;8:666638. doi: 10.3389/fcvm.2021.666638

3. Kalyuta TYu, Glushakova VD, Glushakov IA, et al. Anemia and acute coronary syndromes: epidemiology, etiology, prognostic value and bleeding risks. *Challenges in Modern Medicine.* 2022;45(4):325–342. EDN: UNCZUF doi: 10.52575/2687-0940-2022-45-4-325-342

4. Wang H, Zu Q, Chen J, et al. Application of artificial intelligence in acute coronary syndrome: a brief literature review. *Adv Ther.* 2021;38(10):5078–5086. doi: 10.1007/s12325-021-01908-2

5. Kulkarni H, Amin AP. Artificial intelligence in percutaneous coronary intervention: improved prediction of PCI-related complications using an artificial neural network. *medRxiv.* 2020. doi: 10.1101/2020.08.17.20177055

6. Noh YK, Park JY, Choi BG, et al. A machine learning-based approach for the prediction of acute coronary syndrome requiring revascularization. *J Med Syst.* 2019;43(8):253. doi: 10.1007/s10916-019-1359-5

7. Zack CJ, Senecal C, Kinar Y, et al. Leveraging machine learning techniques to forecast patient prognosis after percutaneous coronary intervention. *JACC Cardiovasc Interv.* 2019;12(14):1304–1311. doi: 10.1016/j.jcin.2019.02.035

8. Pinaire J, Chabert E, Azé J, et al. Sequential pattern mining to predict medical in-hospital mortality from administrative data: application to acute coronary syndrome. *J Healthc Eng.* 2021;2021:5531807. doi: 10.1155/2021/5531807

9. Berikol GB, Yildiz O, Özcan IT. Diagnosis of acute coronary syndrome with a support vector machine. *J Med Syst.* 2016;40(4):84. doi: 10.1007/s10916-016-0432-6

10. Than MP, Pickering JW, Sandoval Y, et al. Machine learning to predict the likelihood of acute myocardial infarction. *Circulation.* 2019;140(11):899–909. doi: 10.1161/CIRCULATIONAHA.119.041980

11. Wu CC, Hsu WD, Islam MM, et al. An artificial intelligence approach to early predict non-ST-elevation myocardial infarction patients with chest pain. *Comput Methods Programs Biomed.* 2019;173:109–117. doi: 10.1016/j.cmpb.2019.01.013

12. Baxt WG, Shofer FS, Sites FD, et al. A neural network aid for the early diagnosis of cardiac ischemia in patients presenting to the emergency department with chest pain. *Ann Emerg Med.* 2002;40(6):575–583. doi: 10.1067/mem.2002.129171

13. Hadanny A, Shouval R, Wu J, et al. Predicting 30-day mortality after ST elevation myocardial infarction: Machine learning- based random forest and its external validation using two independent nationwide datasets. *J Cardiol.* 2021;78(5):439–446. doi: 10.1016/j.jjcc.2021.06.002

14. Sherazi SWA, Bae JW, Lee JY. A soft voting ensemble classifier for early prediction and diagnosis of occurrences of major adverse cardiovascular events for STEMI and NSTEMI during 2-year follow-up in patients with acute coronary syndrome. *PLoS One.* 2021;16(6):e0249338. doi: 10.1371/journal.pone.0249338

15. Zeron RMC, Serrano Junior CV. Artificial intelligence in the diagnosis of cardiovascular disease. *Rev Assoc Med Bras (1992).* 2019;65(12):1438–1441. doi: 10.1590/1806-9282.65.12.1438

16. Gruson D, Bernardini S, Dabla PK, et al. Collaborative AI and laboratory medicine integration in precision cardiovascular medicine. *Clin Chim Acta.* 2020;509:67–71. doi: 10.1016/j.cca.2020.06.001

17. Fominykh AM. A complex for automatic diagnostics of cardiovascular activity based on an artificial intelligence system. *Fundamental'nye i prikladnye issledovaniya: problemy i rezul'taty.* 2013;(3):54–58. (In Russ.) EDN: RDMQSX

18. Geltser BI, Rublev VYu, Tsivanyuk MM, Shakhgeldyan KI. Machine learning in predicting immediate and long-term outcomes of myocardial revascularization: a systematic review. *Russian Journal of Cardiology.* 2021;26(8):115–124. EDN: PVUHFE doi: 10.15829/1560-4071-2021-4505

19. Johnson KW, Torres Soto J, Glicksberg BS, et al. Artificial intelligence in cardiology. *J Am Coll Cardiol.* 2018;71(23):2668–2679. doi: 10.1016/j.jacc.2018.03.521

20. Johnson AE, Brewer LC, Echols MR, et al. Utilizing artificial intelligence to enhance health equity among patients with heart failure. *Heart Fail Clin.* 2022;18(2):259–273. doi: 10.1016/j.hfc.2021.11.001

21. Pieszko K, Hiczkiewicz J, Budzianowski P, et al. Machine-learned models using hematological inflammation markers in the prediction of short-term acute coronary syndrome outcomes. *J Transl Med.* 2018;16(1):334. doi: 10.1186/s12967-018-1702-5

22. Duan H, Sun Z, Dong W, Huang Z. Utilizing dynamic treatment information for MACE prediction of acute coronary syndrome. *BMC Med Inform Decis Mak.* 2019;19(1):5. doi: 10.1186/s12911-018-0730-7

23. Ma M, Hao X, Zhao J, et al. Predicting heart failure in-hospital mortality by integrating longitudinal and category data in electronic health records. *Med Biol Eng Comput.* 2023;61(7):1857–1873. doi: 10.1007/s11517-023-02816-z

24. Ohara T, Ikeda H, Sugitani Y, et al. Artificial intelligence supported anemia control system (AISACS) to prevent anemia in maintenance hemodialysis patients. *Int J Med Sci.* 2021;18(8):1831–1839. doi: 10.7150/ijms.53298

25. D'Ascenzo F, De Filippo O, Gallone G, et al. Machine learning-based prediction of adverse events following an acute coronary syndrome (PRAISE): a modelling study of pooled datasets. *Lancet.* 2021;397(10270):199–207. doi: 10.1016/S0140-6736(20)32519-8

26. Laumer F, Di Vece D, Cammann VL, et al. Assessment of artificial intelligence in echocardiography diagnostics in differentiating takotsubo syndrome from myocardial infarction. *JAMA Cardiol.* 2022;7(5):494–503. doi: 10.1001/jamacardio.2022.0183
27. Chan PZ, Ramli MAIB, Chew HSJ. Diagnostic test accuracy of artificial intelligence-assisted detection of acute coronary syndrome: a systematic review and meta-analysis. *Comput Biol Med.* 2023;167:107636. doi: 10.1016/j.compbiomed.2023.107636
28. Kumar S, Chu M, Tu S, et al. Physiologic and compositional coronary artery disease extension in patients with takotsubo syndrome assessed using artificial intelligence: an optical coherence tomography study. *Coron Artery Dis.* 2022;33(5):349–353. doi: 10.1097/MCA.0000000000001130
29. Hong H, Zeng M, et al. Risk stratification in acute coronary syndrome by comprehensive morphofunctional assessment with optical coherence tomography. *JACC Asia.* 2022;2(4):460–472. doi: 10.1016/j.jacasi.2022.03.004
30. Thießen N, Schnabel R. Diagnosis of acute coronary syndrome. *Dtsch Med Wochenschr.* 2024;149(9):488–495. (In Germany). doi: 10.1055/a-2163-2586
31. Emakhu J, Monplaisir L, Aguwa C, et al. Acute coronary syndrome prediction in emergency care: A machine learning approach. *Comput Methods Programs Biomed.* 2022;225:107080. doi: 10.1016/j.cmpb.2022.107080
32. Glessgen CG, Boulougouri M, Vallée JP, et al. Artificial intelligence-based opportunistic detection of coronary artery stenosis on aortic computed tomography angiography in emergency department patients with acute chest pain. *Eur Heart J Open.* 2023;3(5):oead088. doi: 10.1093/ehjopen/oead088
33. Chopannejad S, Sadoughi F, Bagherzadeh R, Shekarchi S. Predicting major adverse cardiovascular events in acute coronary syndrome: a scoping review of machine learning approaches. *Appl Clin Inform.* 2022;13(3):720–740. doi: 10.1055/a-1863-1589
34. Kayvanpour E, Gi WT, Sedaghat-Hamedani F, et al. microRNA neural networks improve diagnosis of acute coronary syndrome (ACS). *J Mol Cell Cardiol.* 2021;151:155–162. doi: 10.1016/j.yjmcc.2020.04.014
35. Park J, Yoon Y, Cho Y, Kim J. Feasibility of artificial intelligence-based electrocardiography analysis for the prediction of obstructive coronary artery disease in patients with stable angina: validation study. *JMIR Cardio.* 2023;7:e44791. doi: 10.2196/44791
36. Kumar S, Chu M, Sans-Roselló J, et al. In-hospital heart failure in patients with takotsubo cardiomyopathy due to coronary artery disease: an artificial intelligence and optical coherence tomography study. *Cardiovasc Revasc Med.* 2023;47:40–45. doi: 10.1016/j.carrev.2022.09.010
37. Wang Y, Chen H, Sun T, et al. Risk predicting for acute coronary syndrome based on machine learning model with kinetic plaque features from serial coronary computed tomography angiography. *Eur Heart J Cardiovasc Imaging.* 2022;23(6):800–810. doi: 10.1093/ehjci/jeab101
38. Li R, Shen L, Ma W, et al. Use of machine learning models to predict in-hospital mortality in patients with acute coronary syndrome. *Clin Cardiol.* 2023;46(2):184–194. doi: 10.1002/clc.23957
39. Boeddinghaus J, Doudesis D, Lopez-Ayala P, et al. Machine learning for myocardial infarction compared with guideline-recommended diagnostic pathways. *Circulation.* 2024;149(14):1090–1101. doi: 10.1161/CIRCULATIONAHA.123.066917
40. Jing M, Xi H, Sun J, et al. Differentiation of acute coronary syndrome with radiomics of pericoronary adipose tissue. *Br J Radiol.* 2024;97(1156):850–858. doi: 10.1093/bjr/tqae032
41. Herman R, Meyers HP, Smith SW, et al. International evaluation of an artificial intelligence-powered electrocardiogram model detecting acute coronary occlusion myocardial infarction. *Eur Heart J Digit Health.* 2023;5(2):123–133. doi: 10.1093/ehjdh/ztad074

СПИСОК ЛИТЕРАТУРЫ

1. Концевая А.В., Драпкина О.М., Баланова Ю.А., и др. Экономический ущерб сердечно-сосудистых заболеваний в Российской Федерации в 2016 году // Рациональная фармакотерапия в кардиологии. 2018. Т. 14, № 2. P. 156–166. EDN: XNSQUP doi: 10.20996/1819-6446-201814-2-156-166
2. Lanser L., Fuchs D., Scharnagl H., et al. Anemia of chronic disease in patients with cardiovascular disease // Front Cardiovasc Med. 2021. Vol. 8. P. 666638. doi: 10.3389/fcvm.2021.666638
3. Калюта Т.Ю., Глушакова В.Д., Глушаков И.А., и др. Анемия и острые коронарные синдромы: эпидемиология, этиология, прогностическое значение и риски кровотечений // Актуальные проблемы медицины. 2022. Т. 45, № 4. С. 325–342. EDN: UNCZUF doi: 10.52575/2687-0940-2022-45-4-325-342
4. Wang H., Zu Q., Chen J., et al. Application of artificial intelligence in acute coronary syndrome: a brief literature review // Adv Ther. 2021. Vol. 38, N 10. P. 5078–5086. doi: 10.1007/s12325-021-01908-2
5. Kulkarni H., Amin A.P. Artificial intelligence in percutaneous coronary intervention: improved prediction of PCI-related complications using an artificial neural network // medRxiv. 2020. doi: 10.1101/2020.08.17.20177055
6. Noh Y.K., Park J.Y., Choi B.G., et al. A machine learning-based approach for the prediction of acute coronary syndrome requiring revascularization // J Med Syst. 2019. Vol. 43, N 8. P. 253. doi: 10.1007/s10916-019-1359-5
7. Zack C.J., Senecal S., Kinar Y., et al. Leveraging machine learning techniques to forecast patient prognosis after percutaneous coronary intervention // JACC Cardiovasc Interv. 2019. Vol. 12, N 14. P. 1304–1311. doi: 10.1016/j.jcin.2019.02.035
8. Pinaire J., Chabert E., Azé J., et al. Sequential pattern mining to predict medical in-hospital mortality from administrative data: application to acute coronary syndrome // J Healthc Eng. 2021. Vol. 2021. P. 5531807. doi: 10.1155/2021/5531807
9. Berikol G.B., Yildiz O., Özcan İ.T. Diagnosis of acute coronary syndrome with a support vector machine // J Med Syst. 2016. Vol. 40, N 4. P. 84. doi: 10.1007/s10916-016-0432-6
10. Than M.P., Pickering J.W., Sandoval Y., et al. Machine learning to predict the likelihood of acute myocardial infarction // Circulation. 2019. Vol. 140, N 11. P. 899–909. doi: 10.1161/CIRCULATIONAHA.119.041980
11. Wu C.C., Hsu W.D., Islam M.M., et al. An artificial intelligence approach to early predict non-ST-elevation myocardial infarction patients with chest pain // Comput Methods Programs Biomed. 2019. Vol. 173. P. 109–117. doi: 10.1016/j.cmpb.2019.01.013
12. Baxt W.G., Shofer F.S., Sites F.D., Hollander J.E. A neural network aid for the early diagnosis of cardiac ischemia in patients presenting to the emergency department with chest pain // Ann Emerg Med. 2002. Vol. 40, N 6. P. 575–583. doi: 10.1067/mem.2002.129171
13. Hadanny A., Shouval R., Wu J., et al. Predicting 30-day mortality after ST elevation myocardial infarction: Machine learning-based

random forest and its external validation using two independent nationwide datasets // J Cardiol. 2021. Vol. 78, N 5. P. 439–446. doi: 10.1016/j.jjcc.2021.06.002

14. Sherazi S.W.A., Bae J.W., Lee J.Y. A soft voting ensemble classifier for early prediction and diagnosis of occurrences of major adverse cardiovascular events for STEMI and NSTEMI during 2-year follow-up in patients with acute coronary syndrome // PLoS One. 2021. Vol. 16, N 6. P. e0249338. doi: 10.1371/journal.pone.0249338

15. Zeron R.M.C., Serrano Junior C.V. Artificial intelligence in the diagnosis of cardiovascular disease // Rev Assoc Med Bras (1992). 2019. Vol. 65, N 12. P. 1438–1441. doi: 10.1590/1806-9282.65.12.1438

16. Gruson D., Bernardini S., Dabla P.K., et al. Collaborative AI and laboratory medicine integration in precision cardiovascular medicine // Clin Chim Acta. 2020. Vol. 509. P. 67–71. doi: 10.1016/j.cca.2020.06.001

17. Фоминых А.М. Комплекс автоматической диагностики сердечно-сосудистой деятельности на базе системы искусственного интеллекта // Фундаментальные и прикладные исследования: проблемы и результаты. 2013. № 3. С. 54–58. EDN: RDMQSX

18. Гельцер Б.И., Рублев В.Ю., Циванюк М.М., Шахгельдян К.И. Машинное обучение в прогнозировании ближайших и отдаленных результатов реваскуляризации миокарда: систематический обзор // Российский кардиологический журнал. 2021. Т. 26, № 8. С. 115–124. EDN: PVUHFE doi: 10.15829/1560-4071-2021-4505

19. Johnson K.W., Torres S.J., Glicksberg B.S., et al. Artificial intelligence in cardiology // J Am Coll Cardiol. 2018. Vol. 71, N 23. P. 2668–2679. doi: 10.1016/j.jacc.2018.03.521

20. Johnson A.E., Brewer L.C., Echols M.R., Mazimba S., et al. Utilizing artificial intelligence to enhance health equity among patients with heart failure // Heart Fail Clin. 2022. Vol. 18, N 2. P. 259–273. doi: 10.1016/j.hfc.2021.11.001

21. Pieszko K., Hiczkiewicz J., Budzianowski P., et al. Machine-learned models using hematological inflammation markers in the prediction of short-term acute coronary syndrome outcomes // J Transl Med. 2018. Vol. 16, N 1. P. 334. doi: 10.1186/s12967-018-1702-5

22. Duan H., Sun Z., Dong W., Huang Z. Utilizing dynamic treatment information for MACE prediction of acute coronary syndrome // BMC Med Inform Decis Mak. 2019. Vol. 19, N 1. P. 5. doi: 10.1186/s12911-018-0730-7

23. Ma M., Hao X., Zhao J., et al. Predicting heart failure in-hospital mortality by integrating longitudinal and category data in electronic health records // Med Biol Eng Comput. 2023. Vol. 61, N 7. P. 1857–1873. doi: 10.1007/s11517-023-02816-z

24. Ohara T., Ikeda H., Sugitani Y., et al. Artificial intelligence supported anemia control system (AISACS) to prevent anemia in maintenance hemodialysis patients // Int J Med Sci. 2021. Vol. 18, N 8. P. 1831–1839. doi: 10.7150/ijms.53298

25. D'Ascenzo F., De Filippo O., Gallone G., et al. Machine learning-based prediction of adverse events following an acute coronary syndrome (PRAISE): a modelling study of pooled datasets // Lancet. 2021. Vol. 397, N 10270. P. 199–207. doi: 10.1016/S0140-6736(20)32519-8

26. Laumer F., Di Vece D., Cammann V.L., et al. Assessment of artificial intelligence in echocardiography diagnostics in differentiating takotsubo syndrome from myocardial infarction // JAMA Cardiol. 2022. Vol. 7, N 5. P. 494–503. doi: 10.1001/jamacardio.2022.0183

27. Chan P.Z., Ramli M.A.I.B., Chew H.S.J. Diagnostic test accuracy of artificial intelligence-assisted detection of acute coronary syndrome: a systematic review and meta-analysis // Comput Biol Med. 2023. Vol. 167. P. 107636. doi: 10.1016/j.compbiomed.2023.107636

28. Kumar S., Chu M., Tu S., et al. Physiologic and compositional coronary artery disease extension in patients with takotsubo syndrome assessed using artificial intelligence: an optical coherence tomography study // Coron Artery Dis. 2022. Vol. 33, N 5. P. 349–353. doi: 10.1097/MCA.0000000000001130

29. Hong H., Jia H., Zeng M., et al. Risk stratification in acute coronary syndrome by comprehensive morphofunctional assessment with optical coherence tomography // JACC Asia. 2022. Vol. 2, N 4. P. 460–472. doi: 10.1016/j.jacasi.2022.03.004

30. Thießen N., Schnabel R. Diagnose des akuten Koronarsyndroms // Dtsch Med Wochenschr. 2024. Vol. 149, N 9. P. 488–495. doi: 10.1055/a-2163-2586

31. Emakhu J., Monplaisir L., Aguwa C., et al. Acute coronary syndrome prediction in emergency care: A machine learning approach // Comput Methods Programs Biomed. 2022. Vol. 225. P. 107080. doi: 10.1016/j.cmpb.2022.107080

32. Glessgen C.G., Boulougouri M., Vallée J.P., et al. Artificial intelligence-based opportunistic detection of coronary artery stenosis on aortic computed tomography angiography in emergency department patients with acute chest pain // Eur Heart J Open. 2023. Vol. 3, N 5. P. oead088. doi: 10.1093/ehjopen/oead088

33. Chopannejad S., Sadoughi F., Bagherzadeh R., Shekarchi S. Predicting major adverse cardiovascular events in acute coronary syndrome: a scoping review of machine learning approaches // Appl Clin Inform. 2022. Vol. 13, N 3. P. 720–740. doi: 10.1055/a-1863-1589

34. Kayvanpour E., Gi W.T., Sedaghat-Hamedani F., et al. microRNA neural networks improve diagnosis of acute coronary syndrome (ACS) // J Mol Cell Cardiol. 2021. Vol. 151. P. 155–162. doi: 10.1016/j.yjmcc.2020.04.014

35. Park J., Yoon Y., Cho Y., Kim J. Feasibility of artificial intelligence-based electrocardiography analysis for the prediction of obstructive coronary artery disease in patients with stable angina: validation study // JMIR Cardio. 2023. Vol. 7. P. e44791. doi: 10.2196/44791

36. Kumar S., Chu M., Sans-Roselló J., et al. In-hospital heart failure in patients with takotsubo cardiomyopathy due to coronary artery disease: an artificial intelligence and optical coherence tomography study // Cardiovasc Revasc Med. 2023. Vol. 47. P. 40–45. doi: 10.1016/j.carrev.2022.09.010

37. Wang Y., Chen H., Sun T., et al. Risk predicting for acute coronary syndrome based on machine learning model with kinetic plaque features from serial coronary computed tomography angiography // Eur Heart J Cardiovasc Imaging. 2022. Vol. 23, N 6. P. 800–810. doi: 10.1093/ehjci/jeab101

38. Li R., Shen L., Ma W., et al. Use of machine learning models to predict in-hospital mortality in patients with acute coronary syndrome // Clin Cardiol. 2023. Vol. 46, N 2. P. 184–194. doi: 10.1002/clc.23957

39. Boeddinghaus J., Doudesis D., Lopez-Ayala P., et al. Machine learning for myocardial infarction compared with guideline-recommended diagnostic pathways // Circulation. 2024. Vol. 149, N 14. P. 1090–1101. doi: 10.1161/CIRCULATIONAHA.123.066917

40. Jing M., Xi H., Sun J., et al. Differentiation of acute coronary syndrome with radiomics of pericoronary adipose tissue // Br J Radiol. 2024. Vol. 97, N 1156. P. 850–858. doi: 10.1093/bjr/tqae032

41. Herman R., Meyers H.P., Smith S.W., et al. International evaluation of an artificial intelligence-powered electrocardiogram model detecting acute coronary occlusion myocardial infarction // Eur Heart J Digit Health. 2023. Vol. 5, N 2. P. 123–133. doi: 10.1093/ehjdh/ztad074

AUTHORS' INFO

*** Tatyana Yu. Kalyuta,** MD, Cand. Sci. (Medicine);
address: 112 Bolshaya Kazachya street, 410012 Saratov, Russia;
ORCID: 0000-0003-3172-0804;
eLibrary SPIN: 4982-7861;
e-mail: tatianakaluta@yandex.ru

Irina P. Emelyanova;
ORCID: 0000-0002-4178-9437;
eLibrary SPIN: 1766-8528;
e-mail: irisha-9966@mail.ru

Valeriy V. Suvorov, Cand. Sci. (History);
ORCID: 0000-0002-4181-9034;
eLibrary SPIN: 4757-5250;
e-mail: valeriy_s@inbox.ru

Alexander S. Fedonnikov, MD, Dr. Sci. (Medicine);
ORCID: 0000-0003-0344-4419;
eLibrary SPIN: 2248-5246;
e-mail: fedonnikov@mail.ru

ОБ АВТОРАХ

*** Калюта Татьяна Юрьевна,** канд. мед. наук;
адрес: Россия, 410012, Саратов, ул. Большая Казачья, д. 112;
ORCID: 0000-0003-3172-0804;
eLibrary SPIN: 4982-7861;
e-mail: tatianakaluta@yandex.ru

Емельянова Ирина Павловна;
ORCID: 0000-0002-4178-9437;
eLibrary SPIN: 1766-8528;
e-mail: irisha-9966@mail.ru

Суворов Валерий Владимирович, канд. ист. наук;
ORCID: 0000-0002-4181-9034;
eLibrary SPIN: 4757-5250;
e-mail: valeriy_s@inbox.ru

Федонников Александр Сергеевич, д-р мед. наук;
ORCID: 0000-0003-0344-4419;
eLibrary SPIN: 2248-5246;
e-mail: fedonnikov@mail.ru

* Corresponding author / Автор, ответственный за переписку