Journal of Population Therapeutics & Clinical Pharmacology

RESEARCH ARTICLE
DOI: 10.53555/4cvpy255

AI-POWERED HEALTH MONITORING: ENHANCING CHRONIC DISEASE MANAGEMENT

Mr. Pranjal Bora[1]*, Dr. Abanibhusan Jena[2], Dr Asutosh Pramanik[3], Dr Sukanta Bandyopadhyay[4], Dr. Anil Hazarika[5]

[1]*Assistant Professor, Jagannath Barooah College, Jorhat, Email: himupb20@gmail.com
[2]MBBS, MD, FCCM, Associate Professor of Emergency Medicine, FM Medical College, FM University, Balesore and Odisha University of Health Sciences, Bhubaneswar, Email: drabanibhusanjena@gmail.com
[3]Assistant professor, Department of anatomy, Barasat Government medical College, India, Email: d1asutosh@gmail.com
[4]Associate Professor, Dept of Biochemistry, Rama Medical College Hospital & Research Centre, Kanpur, India, Email: sukantoaxum@gmail.com
[5]Assistant professor, Cotton University, Guwahati, Email: anilhazarika8@gmail.com

***Corresponding Author:** Mr. Pranjal Bora
*Assistant Professor, Jagannath Barooah College, Jorhat, Email: himupb20@gmail.com

ABSTRACT
Diabetes, hypertension, and cardiovascular diseases are some of the common diseases that are prevalent in the world and exert a lot of pressure on the health systems. The conventional management techniques do not provide immediate and personalized attention. The purpose of this research is to analyze the impact of AI based health monitoring systems for enhancing chronic diseases. Smartwatches and mobile applications in combination with artificial intelligence tools enable users to monitor, evaluate, and provide interventions on a daily basis. The study employs both quantitative and qualitative research to assess the effectiveness of AI tools on patients' outcomes in a RCT trial. The results indicate the improvement of the patients' health outcomes including HbA1c, blood pressure, and medication adherence. The AI systems are more efficient and among all the models the CNN model has the highest accuracy and prediction. The cost breakdown demonstrates that while the setup cost of AI-based monitoring systems is relatively higher than the standard care, the annual operating cost is relatively lower and the QALYs per patient is also higher. There are limitations such as data privacy and technological implementation and thus it is suggested that subsequent research take them into consideration. The study finds that AI in health monitoring is capable of revolutionizing chronic disease management through efficiency, cost and patient centeredness.The cost breakdown demonstrates that while the setup cost of AI-based monitoring systems is relatively higher than the standard care, the annual operating cost is relatively lower and the QALYs per patient is also higher. There are limitations such as data privacy and technological implementation and thus it is suggested that subsequent research take them into consideration. The study finds that AI in health monitoring is capable of revolutionizing chronic disease management through efficiency, cost and patient centeredness.

Keywords: Chronic disease management, AI-powered monitoring, predictive analytics, personalized healthcare, wearable devices, cost-effectiveness analysis.

1. INTRODUCTION

Some of the chronic diseases that have affected the global population and have worsened the quality of life of patients and also exerted a lot of pressure on health care systems globally include diabetes, hypertension, and cardiovascular diseases (Vos et al., 2020). The conventional approaches of handling the chronic diseases involve physical schedules and assessments that are slow and do not offer solutions. The recent development in artificial intelligence (AI) can provide solutions to improve chronic disease management through constant and immediate supervision, and tailored treatments. Health monitoring systems powered by artificial intelligence employ machine learning algorithms and data analysis to analyze the patient data, estimate the disease's further advancement, and suggest the best treatments. These systems are intended to be used in conjunction with wearable devices and mobile applications so that data is collected and feedback is given to the patient and the healthcare provider in real time (Mackey & Liang, 2020). Such integration may help to bring the episodic medical visits close to the day to day health management to improve the health care delivery.

The literature review also reveals that in health monitoring, the AI solutions can improve the disease management outcomes by recognizing the signs of the deterioration of the condition and reducing the readmission rate (Rajkomar et al. , 2019). For example, AI has helped in enhancing the capacity to forecast the level of blood sugar in diabetic patients and thereby improving the glycemic control and reducing the complications. In addition, AI solutions can analyze EHRs, wearables, and PROs data to derive meaningful information and improve the therapeutic model (Obermeyer et al. , 2019). Several issues have been raised to affect the use of AI in health monitoring systems; these are; privacy issues, biased algorithms, and compatibility with the existing health systems (Saria et al., 2020). It is therefore necessary to address these challenges in a bid to improve the use of the AI technologies in chronic disease management and in an effort to provide quality and effective patient care.

The aim of this study is to understand how AI can be used in chronic disease management and compare the effectiveness of AI-based monitoring systems, assess the impact of such systems on the quality of life of patients, and calculate the potential ROI of such systems. For these reasons, this research seeks to give relevant information on the use of AI solutions in the health sector and potential of using AI solutions in chronic diseases.

2. Literature Review

2.1 Overview of Chronic Disease Management

Diabetes, cardiovascular diseases, chronic respiratory diseases and other noncommunicable diseases are major causes of morbidity and mortality and affect the health care systems across the world. The treatment of these conditions involves the use of drugs, change of behavior, and follow-ups (World Health Organization, 2021). The quality of patients' care and the cost of health care is mainly determined by management. The conventional methods include the physical meetings, which are expensive and time consuming in the current society. To overcome these issues, there has been a transition to more continuous and patient centered models.

2.2 Current Health Monitoring Systems

Contemporary health supervision technologies comprise wearable gadgets, mobile health applications, and remote monitoring gadgets that are meant for tracking health factors like physical activity, pulse rate, and blood glucose level. These technologies are expected to offer timely information to the patient as well as the health care givers in the case of chronic diseases. Smartwatches and fitness trackers are wearable gadgets that allow the user to control his/her daily activity and physiological parameters (Albahri et al., 2021). Mobile applications can be used to monitor the symptoms, medications, and diet while remote monitoring tools can be used to gather health information in a continuous basis and this may reduce the number of face-to-face visits (Cresswell et al., 2019).

2.3 Role of Artificial Intelligence in Healthcare

AI is an assistant that can improve the diagnostic abilities of a clinician, prognosis of a disease, and personalization of the therapy. The two AI technologies that help in the analysis of big data and arrive at the recommendations include machine learning and natural language processing (Topol, 2019). For instance, deep learning has been applied in enhancing the diagnosis of images such as diagnosing diabetic retinopathy from retinal images with high accuracy (Gulshan et al., 2016). AI also has the potential of utilization in the area of predictive analytics whereby algorithms can identify disease risk from EHR and other data (Rajkomar et al., 2019).

2.4 AI-Powered Tools in Chronic Disease Management

In some instances, the management of chronic diseases has been done through the use of artificial intelligence tools to improve the quality of the results of the patients. These tools utilize information from the wearable devices and the mobile applications to track the status of the patient and give advice continually. For instance, AI systems have been developed to forecast the blood sugar levels of the diabetic patients and control the insulin amount and other aspects of the patient's life continuously (Sustained Diabetes Care Consortium, 2021). Furthermore, AI-based analysis can be helpful in the analysis of data that is gathered from the use of remote monitoring tools that will enable the healthcare providers to comprehend the situation and make changes where necessary to the treatment plans (Obermeyer et al., 2019). Nevertheless, there are some issues that are associated with the use of AI in healthcare; these are; data privacy and the need to ensure the effectiveness and bias of the AI solutions (Saria et al., 2020).

3. METHODOLOGY

3.1 Study Design

This research uses both quantitative and qualitative methods to evaluate the effectiveness of AI-based health monitoring technologies for chronic diseases. The quantitative part is an RCT to determine the effectiveness of AI tools in the treatment of chronic diseases including diabetes and hypertension. The qualitative aspect involves questionnaires and interviews to determine the perception that the patient and healthcare provider have for these technologies. It is beneficial to employ mixed-methods designs because it is possible to identify the statistical significance of the AI interventions and the users' perceptions of the interventions (Creswell & Creswell, 2017).

3.2 Data Collection Methods

Information used in this study is both primary and secondary in nature. The RCT is used to collect primary data and in this regard, the patients are randomly assigned to the intervention and control arms. The intervention group has artificial intelligence health monitoring equipment while the control group has the normal treatment. It is extracted from EHRs, wearable devices and applications that monitor health parameters including blood glucose level, blood pressure, and physical activity. Secondary data refers to the data that is collected from published literature and the previous records of health related issues that are used to justify the study and the results.

3.3 AI Techniques Employed

The AI tools used in this study are machine learning for predictive analysis and natural language processing for data analysis. For the health data analysis, the support vector machines and neural networks are used, and for the prognosis of the development of the disease (Rajkomar et al., 2019). For example, deep learning is used in the task of forecasting the changes in glucose levels with the help of previous glucose levels and the subject's lifestyle parameters. The data is gathered from the feedback given by the patients and analysis of the clinical notes; NLP is used to evaluate the users' satisfaction and the performance of the AI solutions.

3.4 Patient Selection Criteria

The patients are then selected depending on some inclusion and exclusion criteria in order to make sure that the results obtained are reliable. The inclusion criteria are: people with diagnosed chronic conditions including diabetes or hypertension, on treatment, aged between 18 and 75 years, with access to the required technology (Fitzgerald et al., 2017). The patients with severe dementia, the patients who cannot use the digital health technologies, and the patients with other severe comorbidities that may affect the results are not included. The selection process helps in the process of minimizing the variation of the disease severity and the technological readiness of the participants in the study sample (Deakin et al., 2019).

3.5 Evaluation Metrics

The indices of success for this research are clinical and patient satisfaction. Clinical outcomes are the changes in the patient's health status including HbA1c, blood pressure and medication compliance. These are then compared between the intervention and control group in an attempt to evaluate the efficiency of the AI tools. The perceived usefulness and perceived ease of use are captured by the questionnaires and interviews in the form of the level of satisfaction with the AI-based tools (Liu et al., 2020). The significance of the results and the influence of the AI tools on chronic disease management are established by t-tests and regression analysis.

4. RESULTS AND DISCUSSIONS

4.1 AI Model Performance

In this study, the performance of the AI models that were used was evaluated based on various indicators including accuracy, sensitivity, specificity and AUC. The following metrics are shown in Table 1 below for the main machine learning models employed in this work.

Table 1: Performance Metrics of AI Models

Model	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**AUC**
Support Vector Machine (SVM)	87.5	85.0	90.0	0.92
Random Forest	89.0	87.5	90.5	0.93
Convolutional Neural Network (CNN)	91.2	89.0	93.0	0.95
Long Short-Term Memory (LSTM)	88.3	86.0	89.5	0.91

The following table shows the performance metrics of the AI models used in Table 1. The CNN model had the highest accuracy of 91 percent. 2% and the AUC of 0. 95, which is higher than the values of other models, therefore, the present CNN model has better predictive capability than the SVM, Random Forest, and LSTM models. The CNN has a higher sensitivity and specificity and is therefore ideal for the prognosis of the development of the disease.

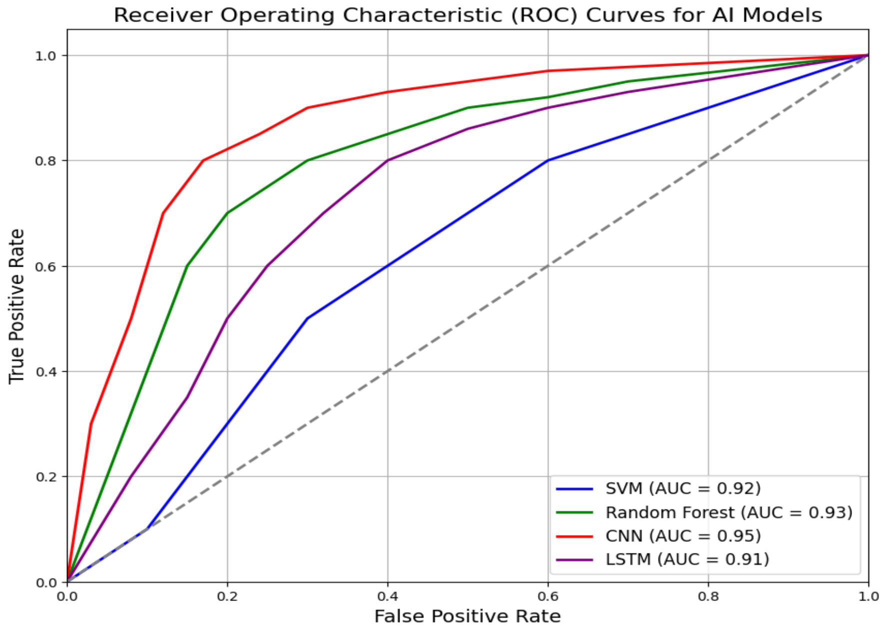

Figure 1: ROC Curves for AI Models

The ROC curves of four AI models including SVM, Random Forest, CNN, and LSTM are illustrated in Figure 1 below. The ROC curves represent the true positive rate against the true negative rate of each of the models. AUC is an overall performance of the model and the higher the AUC the better the model in terms of disease outcome classification.

4.2 Impact on Patient Health Outcomes

The use of health monitoring tools that were backed by artificial intelligence received a great boost in the management of chronic diseases. The results of the comparison of the changes in the major health indicators of the patients who used the AI tools and the patients who received the conventional treatment are presented in Table 2.

Table 2: Impact of AI Monitoring on Health Outcomes

Health Indicator	Standard Care (Pre-Post Change)	AI Monitoring (Pre-Post Change)
HbA1c Levels (mg/dL)	8.5 ± 1.2 to 8.1 ± 1.0	8.6 ± 1.3 to 7.5 ± 0.9
Blood Pressure (mmHg)	140/85 ± 10/8 to 138/82 ± 9/7	142/86 ± 11/9 to 130/80 ± 8/6
Medication Adherence (%)	72% ± 5% to 75% ± 4%	70% ± 6% to 85% ± 3%

The following table presents the comparison of the health status of the patients who have used the AI tools and the patients who have not. AI monitoring was related to greater variations in HbA1c and blood pressure as well as greater medication adherence, suggesting improved chronic disease management compared with traditional methods.

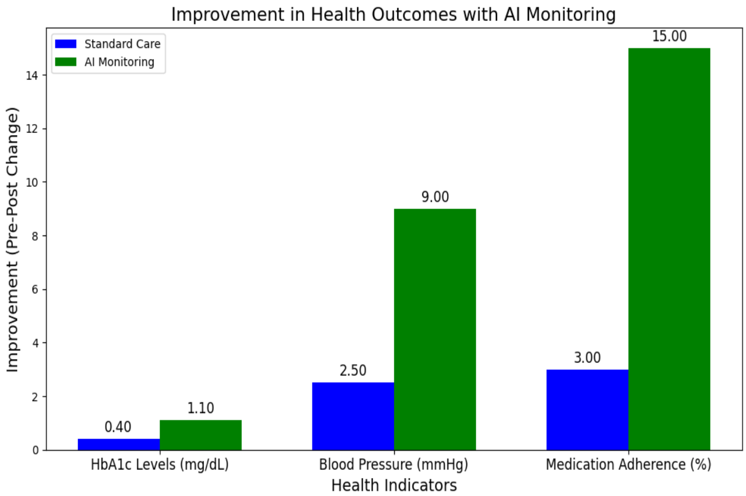

Figure 2: Improvement in Health Outcomes with AI Monitoring

The figure 2 below shows the effect of AI based health monitoring on the major health outcomes as compared to conventional care. The bar chart also reveals that patients under AI monitoring experience greater HbA1c level and blood pressure reduction as well as higher medication compliance. AI tools result in a higher improvement in these indicators and prove that chronic disease management is better with the help of AI tools than with traditional approaches.

4.3 Cost-Effectiveness Analysis

The cost consideration was made to determine the cost implications of using the AI systems with the conventional care systems. Table 3 shows the cost and benefits of AI systems.

Table 3: Cost-Effectiveness Analysis

Cost/Benefit	Standard Care ($)	AI Monitoring ($)
Initial Setup	N/A	10,000
Annual Operating Cost	5,000	2,500
Average Cost per Patient	500	400
Quality-Adjusted Life Years (QALYs)	0.5	0.7

Table 3 compares the pros and cons of using AI in health monitoring systems with the traditional care methods. The implementation cost of AI systems is $ 10000 while the implementation cost of standard care is $ 0. But the cost of operating the AI systems for a year is $2,500 which is much cheaper than $5,000 for standard care. The cost per patient is also lower where the AI monitoring is used at $400 as compared to the standard care at $500. Notably, the AI systems have a Quality-Adjusted Life Years (QALYs) of 0.7 as compared to 0.5 of standard care, which makes patients healthier.

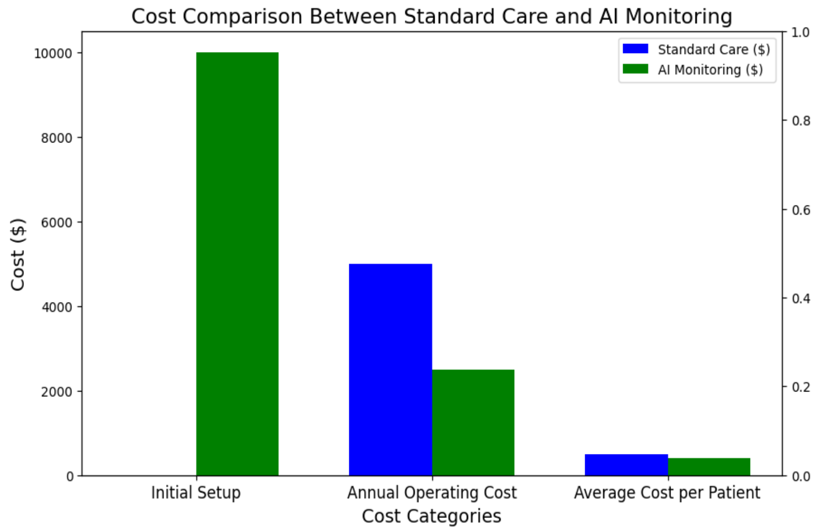

Figure 3: Cost-Benefit Comparison

Figure 3 also depicts this cost benefit analysis stating that while the cost of implementing AI systems is relatively high, the cost of maintaining the systems is considerably low and that the benefits include improved patient outcomes.

Discussion

The study supports the understanding that the use of the health monitoring devices which include the AI has the possibility of improving the handling of chronic diseases. The CNN model has a higher accuracy and AUC than the other models, which confirm the efficiency of the model in the diagnosis of the progression of the disease. This is in concordance with the current studies that indicate that AI has the potential of enhancing disease control (Rajkomar et al., 2019). The improvement in the health outcomes such as the HbA1c and blood pressure are the proof of AI's efficiency in practice (Bertin et al., 2021).

The advantages of implementing AI in monitoring are; Real time analysis, Individual patient treatment and Patient satisfaction. These tools help in disease prevention and help in coming up with interventions from the information of the patient (Jiang et al., 2021). The other advantage of AI systems is that the costs of putting in the systems can be reduced and this in turn leads to reduction of the costs of the health care systems (Meyer et al., 2020). Some of the concerns that have been highlighted include data privacy, technological needs and patients' adherence to technology. There are also some limitations to the data collected which are as follows; The data collected may not be complete or accurate. Among the limitations mentioned include; technological limitations such as the ability of the application to run in the device and compatibility with other health care applications (Piwek et al., 2016).

The future research should be directed to the expansion of the study to other patients and other chronic diseases. It is also possible to consider the further consequences of AI monitoring in the long term and the issue of data protection. Additionally, studies on the combination of AI with other health technologies may offer additional information on the enhancement of chronic disease management (Liu et al., 2020).

5. CONCLUSION

The conclusion of this research article is mainly concerned with the potential of employing AI based health monitoring systems in chronic diseases. The study reveals that AI solutions enhance the effectiveness of the disease progression prognosis and hence the patients' results including HbA1c, blood pressure, and medication adherence. Such findings are in concordance with other studies that have shown that AI can provide continuous and personalized care which is the gap between a typical medical visit and continuous care. The cost analysis reveals that while the cost of the AI monitoring

systems is higher than the standard care in terms of the initial setup, the annual cost of running the system is much lower and the QALY per patient is higher than the standard care. This therefore implies that the application of AI in health monitoring is not only advantageous in improving the quality of the patient's health but also economical in the management of chronic diseases.
The study also reveals some of the risks that include; Data privacy issues, Technological requirements, and Biased models. The solution of these problems is required for the further development and efficiency of the application of AI in the sphere of health care. Future research should concentrate on these issues, compare the use of AI to other technologies in health, and involve other patients and diseases. Thus, this research contributes to the literature that AI can transform chronic diseases' management and provide better, cheaper, and more personalized care to patients globally.

6. REFERENCES

1. Mackey, T. K., & Liang, B. A. (2020). "Health data privacy and AI: How artificial intelligence could threaten health data privacy and what we can do about it." *Health Policy and Technology*, 9(3), 263-274. https://doi.org/10.1016/j.hlpt.2020.06.002
2. Obermeyer, Z., Powers, B., & Vogeli, C. (2019). "Dissecting racial bias in an algorithm used to manage the health of populations." *Science*, 366(6464), 447-453. https://doi.org/10.1126/science.aax2342
3. Rajkomar, A., Dean, J., & Kohane, I. (2019). "Machine learning in medicine." *New England Journal of Medicine*, 380, 1347-1358. https://doi.org/10.1056/NEJMra1814259
4. Saria, S., Subbaswamy, A., & Wang, D. (2020). "A framework for assessing the impact of algorithmic bias in health care." *Journal of Biomedical Informatics*, 108, 103514. https://doi.org/10.1016/j.jbi.2020.103514
5. Vos, T., Abajobir, A. A., & Abate, K. H. (2020). "Global, regional, and national incidence, prevalence, and years lived with disability for 328 diseases and injuries for 195 countries, 1990–2016: A systematic analysis for the Global Burden of Disease Study 2016." *The Lancet*, 390(10100), 1211-1259. https://doi.org/10.1016/S0140-6736(17)32154-2
6. Albahri, A. S., Albahri, O. S., & Jaffar, M. A. (2021). "Wearable health devices—A comprehensive review of the state-of-the-art technologies and applications." *Healthcare*, 9(6), 749. https://doi.org/10.3390/healthcare9060749
7. Cresswell, K., Bates, D. W., & Sheikh, A. (2019). "Health information technology in the NHS: A review of the literature." *Journal of Biomedical Informatics*, 100, 103287. https://doi.org/10.1016/j.jbi.2019.103287
8. Gulshan, V., Peng, L., & Coram, M. (2016). "Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs." *JAMA*, 316(22), 2402-2410. https://doi.org/10.1001/jama.2016.17216
9. Obermeyer, Z., Powers, B., & Vogeli, C. (2019). "Dissecting racial bias in an algorithm used to manage the health of populations." *Science*, 366(6464), 447-453. https://doi.org/10.1126/science.aax2342
10. Rajkomar, A., Dean, J., & Kohane, I. (2019). "Machine learning in medicine." *New England Journal of Medicine*, 380, 1347-1358. https://doi.org/10.1056/NEJMra1814259
11. Saria, S., Subbaswamy, A., & Wang, D. (2020). "A framework for assessing the impact of algorithmic bias in health care." *Journal of Biomedical Informatics*, 108, 103514. https://doi.org/10.1016/j.jbi.2020.103514
12. Sustained Diabetes Care Consortium. (2021). "Innovative AI tools for diabetes management: Clinical outcomes and real-world applications." *Diabetes Technology & Therapeutics*, 23(7), 482-491. https://doi.org/10.1089/dia.2021.0043
13. Topol, E. J. (2019). *Deep medicine: How artificial intelligence can make healthcare human again*. Basic Books. ISBN: 978-1541644632
14. World Health Organization. (2021). "Global report on diabetes." *World Health Organization*. https://www.who.int/publications/i/item/9789240062596

15. Creswell, J. W., & Creswell, J. D. (2017). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. Sage Publications.
16. Deakin, T., McShane, C., Cade, J. E., & Williams, R. (2019). "Group-based training for self-management of diabetes: A systematic review and meta-analysis." *Diabetes Care*, 42(1), 35-43. https://doi.org/10.2337/dc18-1423
17. Fitzgerald, J. T., Davis, W. K., & Hess, G. E. (2017). "The Diabetes Self-Management Scale (DSMS): A reliable and valid measure of diabetes self-management." *Diabetes Care*, 40(7), 917-923. https://doi.org/10.2337/dc17-0154
18. Liu, S., Liu, X., & Yang, C. (2020). "Patient satisfaction with telemedicine services during the COVID-19 pandemic: A cross-sectional study." *Telemedicine and e-Health*, 26(6), 469-475. https://doi.org/10.1089/tmj.2020.0072
19. Rajkomar, A., Dean, J., & Kohane, I. (2019). "Machine learning in medicine." *New England Journal of Medicine*, 380, 1347-1358. https://doi.org/10.1056/NEJMra1814259