



Healing with Intelligence: A Review of AI-Enabled Healthcare Solutions

Shah Zeb^{1*}

¹Washington University of Science and Technology, 2900 Eisenhower Ave, Alexandria, VA

¹szeb.student@wust.edu



Corresponding Author

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ABSTRACT

Artificial intelligence (AI) is taking the healthcare field by storm as healthcare providers adopt its use to inform data-based decisions, improve clinical decision-making, and make their operations more efficient. This review discusses the fundamentals of AI, including machine learning, deep learning, and natural language processing technologies and how they can be applied to diagnostics, individualized treatment, remote patient monitoring, hospital operations, and population health monitoring. The strengths of AI are the ability to identify early disease, custom care plans, and precognitive analysis to direct resources. Nevertheless, integration in healthcare systems is stalled by risk of having biased algorithms, data privacy, interoperability, and changing demands of regulatory guidelines. A solution to such barriers is interdisciplinary: combining multiple views to develop and validate the models legitimately, with transparency and trustworthiness. Future trends, such as explainable AI, federated learning and integration of the robots aim at a more flexible and patient-centered future. After all, the best role that AI can play is to augment human expertise by providing more precise, proactive and fair care but without losing that critical human touch in healthcare.

INTRODUCTION

The healthcare sector across the globe has witnessed a deep change in the context of healthcare in the recent decade, but the changes owes greatly to the sharp rise in the evolution and development of digital technology. Artificial intelligence (AI) has been considered one of the most promising and disruptive innovations, among others [1]. The ability of AI to consume miles of big and complex data, identify patterns not visible to the human eye, and provide actionable insights in real-time makes it an ideal partner in alleviating some of the most stubborn problems healthcare continues to face [2]. The world healthcare conditions are under a scorching pressure. Drivers like an ageing population, increased burden of chronic diseases, increased medical expenses and dearth of skilled health professionals have put pressure on the current systems. Meanwhile, interests and activities such as the proliferation of health-related data, in the form of electronic health records (EHRs) and medical imaging, genomics, and wearable devices, have presented themselves as an opportunity and a challenge [3]. Although these data are a great source of enhancing patient outcomes, their abundance and complexity far exceed the capability of conventional methods of analysis. Such an overload of data is an opportunity that AI with its complex algorithms and ability to learn can turn into clinically significant decisions [4].

Healthcare and AI are attractive in various ways. In terms of the clinical side, AI has proven to be exceptionally promising in diagnostic imaging, early discovery of diseases, treatment planning, and precision medicine. Diverse large databases can usually train algorithms with sensitivity and specificity similar to or even better than experienced clinicians. The potential to enhance diagnostic accuracy is not the only benefit of this; it can also increase access to high-quality care to underserved regions [5].

In addition to direct patient care, the domain of AI in healthcare has been playing a growing number of roles in supporting operations and systems management. Application of predictive analytics in hospitals will in turn save them money by enabling efficient streamlining of resources, workflow optimization and enabling hospitals to predict number of patients they will be able to accommodate based on available resources [6]. Better detection of outbreaks can be implemented using AI in the field of public health since AI is able to analyze trends in clinical, environmental, social data, helping to detect outbreaks earlier than possible with human resources.

Nevertheless, the process of introducing AI in medicine cannot be described as challenge-free. Algorithmic bias, data privacy, interoperability, regulatory oversight, and clinician trust are just some of the issues that should not be overlooked as a barrier to broad adoption. Ethical issues need to be addressed primarily concerning the way decisions are taken (transparency); concerning the responsibility of those decisions (accountability), in order to secure that the benefit of using AI is reflected in a just and responsible way [7].

This review shall set out to give a detailed scan of the category of AI-empowered medical solutions, including addressing the technologies behind them, their various applications, their exciting operations, current drawbacks, and scopes of interest. The rationale behind it, by harmonizing the existing evidence and opinions of experts, is to provide medical workers, governmental representatives, and scientists with a non-bias picture of what AI is today and where it



is probably going to go in the nearest future [8]. Finally, there is a major point to emphasize following the discussion: AI is not ultimately about obsoleting the human expertise; it is about augmenting it, about healing intelligently.

THE CORE TECHNOLOGIES OF AI IN MEDICINE KEYED IN MEDICINE

Artificial intelligence in healthcare is not one technology, but is instead an assortment of computation techniques and systems which are created to demonstrate or replicate some parts of the human mental ability. In order to best comprehend the transformative value of AI in medicine it is necessary to become familiar with specific technologies that make its capability possible. These are machine learning (ML), deep learning (DL), natural language processing (NLP) among others [9]. All of these technologies bring to the AI system its distinct capabilities to manipulate the complex and heterogeneous quantities of data observed in healthcare.

A computer learning is also known as machine learning that is the learning of patterns within a data set without being programmed to handle all situations. ML models are usable in healthcare to diagnose disease risk factors, help predict patient outcomes, and aid in clinical decision-making. Logistic regression models may be used to estimate likelihood of occurrence of sepsis in a given patient, and ensemble methods (e.g. random forests) can be used to aggregate a larger number of variables in order to make more confident predictions. ML has power in resilience the models can be retrained again when new data is available hence accurate and up to date in terms of predictions [10].

Deep learning is a specialization of ML that deploys artificial neural networks that have many layers (hence “deep”). Deep learning can be used to process large and high-dimensional data. DL has had a significant effect especially in the use of medical imaging where features that cannot be identified by the naked eye can be identified by CNNs on medical X-rays, MRIs and CT scans. Transformers and recurrent neural networks (RNNs) are used to predict the disease dynamics of sequential health data, including patients records [11]. The ease of feature hierarchy extraction through deep learning, combined with the potential for deep unsupervised learning, makes the technique of particular interest to unstructured data such as images, waveforms and genomic sequences [12].

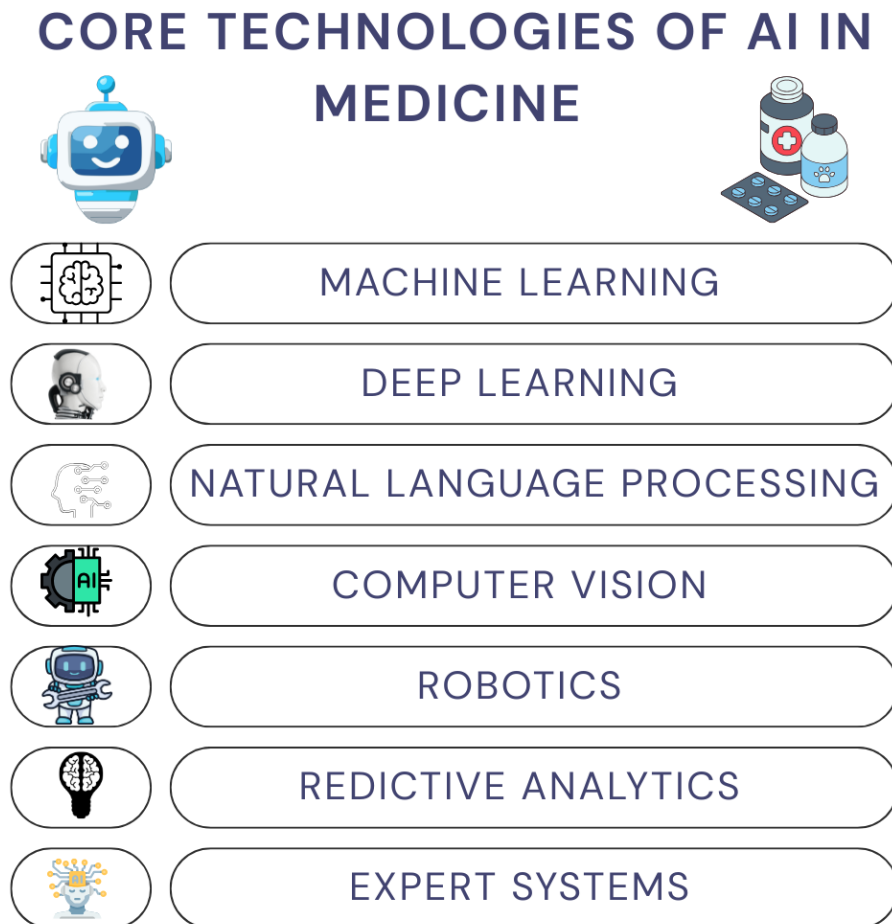


Figure: 1 showing core technologies of Ai in medicine

Some of the most useful data in healthcare has met its storage in unstructured texts--physician notes, discharge summaries, pathology reports. NLP allows computer systems to interpret, extract and interpret such information. Clinical NLP use cases run the gamut of automatically coding diagnosis in support of billing to more exotic applications of seizing potential adverse drug reactions out of EHR data [13]. Even more sophisticated NLP systems, such as

transformer-based ones like BERT or GPT, can summarize patient’s charts or respond to questions posed by clinicians in unnatural language, which improves efficiency and access to it [14].

Intelligence of AI in healthcare largely relies on the surrounding system. Big data platforms facilitate storage of huge and heterogeneous information and processing. Training of complex models provides scalable platforms of computation through cloud computing. Data interoperability standards, like HL7 FHIR, are dedicated to allowing the exchange of patient data across systems efficiently. Moreover, the processing of data on the edge (portable ultrasound scanners, wearable monitors, etc.) narrows the latency gap and increases privacy [15].

These fundamental technologies of AI do not often work independently. A diagnostic tool may consist of a combination of deep learning to analyze the images, NLP to read clinical notes, and ML to connect to the past history of the patients to give a final recommendation. It is important to know about these building blocks not only to create AI tools but also in assessing their weaknesses, possible bias, and usefulness in certain medical scenarios [16].

DATA TO DECISIONS: LEARNING IN A HEALTHCARE ENVIRONMENT WITH AI

Healthcare artificial intelligence systems are as effective as the data they have been trained on. The pathway of transforming raw medical information into the actionable and valuable knowledge takes several steps and includes gathering various data sets, organizing, and combining, training algorithms, and proving them in the real-life situations [17]. The knowledge of this process forms the basis of understanding the potential as well as the scope of limitations of AI-enabled healthcare solutions.

Raw health data tend to be fragmented and incomplete, non-standardized and in different systems. These data have to be cleaned, standardized and integrated before they can be used to teach AI models what to learn. This can include: The do no harm principle AI regulations or policy governance: The aim of AI is to help make a decision at the point of care. To use an example, an AI algorithm may identify an abnormal appearing lesion on an X-ray of the chest, causing a radiologist to focus their attention, or may suggest patients who are likely to be readmitted, allowing in advance interventions [18]. Notably, the AI tools must have the capacity to fit within the current workflows of clinicians and deliver interpretable results that can be relied on by clinicians.

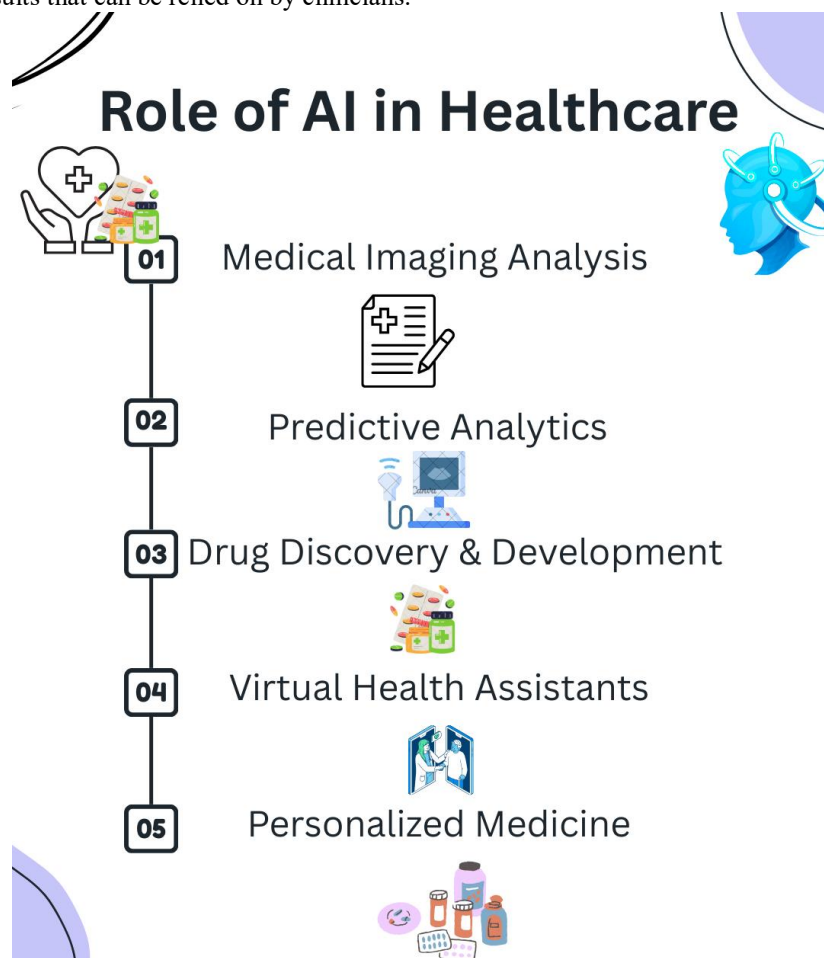


Figure: 2 showing the role of Ai in healthcare

The field of healthcare is dynamic because the pattern of diseases changes, and the treatment method gets altered, and the population of patients also changes. Such successful examples of AI systems are based on continuous learning



where models regularly update. It makes this adaptable, which is relevant but forms a need of strong governance to avoid performance drift or the injection of fresh biases [19]. Knowing the data-to-decision pipeline, the stakeholders can appropriately assess the AI systems, as their efficiency depends not only on advanced algorithms but also on the data that they are fed with the accuracy of medical information provided [20].

AIAS DIAGNOSTIC ALLY: DIAGNOSE FASTER AND ACCURATE DIAGNOSIS OF DISEASES

Diagnosis is the key to effective healthcare and it must be early and precise. However, diagnostic error is a major problem globally and has led to loss of time, escalated expenses, and even avoidable patient morbidities. Artificial intelligence has also become a potent diagnostic companion providing tools capable of scanning through medical data and providing a swift diagnosis at a rate that even the most embedded clinical experts can hardly notice [21].

Medical imaging analysis is one of the best applications of AI in diagnostics. Deep learning in the form of convolutional neural networks (CNNs) have shown performance on par with or beating that of human experts in the detection of lung nodules in computed tomography (CT) images, the detection of breast cancer in mammography images, and the recognition of skin lesions using dermatologic images [22]. By detecting the subtle features, such algorithms have the ability to increase the detection sensitivity and lower the probability of missing in the volume settings.

As an example, AI systems are implemented to aid radiologists by prioritizing images most likely to have an abnormality so that urgent cases can be reviewed. In ophthalmology, AI models are able to screen retinal images diagnosed with diabetic retinopathy which prevents the loss of vision in at-risk patients at an earlier stage. Movements of AI in pathology and laboratory medicine have taken place, too. AI-driven digital pathology platforms are able to analyze whole slide images to distinguish cancer cells, tumor grading, and demonstrate prognostic indicators [23]. In microbiology, image recognition systems can be used to automatically recognise the shapes of bacterial colonies and blood cells, and thus automate this process to accelerate diagnosis. In hematology and clinical chemistry, any unusual pattern in a complex laboratory panel can be interpreted using AI models, which will flag an abnormal trend that might be a rare or emerging disease [24].

In addition to unimodal data, AI is becoming an increasing part of multimodal data integration where imaging, clinical notes, genetic profile, and laboratory results are analyzed together to offer a more in-depth view on a diagnostic assessment. The holistic approach is capable of correcting errors because it takes into consideration a wider clinical picture, and not individual test results. As an example, AI tools in oncology have been able to integrate histopathology images into genomic data to predict tumor behavior and probable response to treatment as a means of precision medicine [25].

The advantages of AI in diagnostics cannot be overstated: increased speed of processing, minimization of human error, and the possibility to provide the high quality of diagnostic services in undermined areas via telemedicine services. Still, there are constraints. Actually, the models trained using the data on a specific population cannot generalize to another population, and thus the problem of the bias arises. In addition, AI results should be explicable to instill trust in clinicians and speak to regulatory needs [26].

CUSTOMIZING TREATMENTS: AI APPLICATIONS IN CLINICAL DECISION-MAKING AND INDIVIDUALIZED CARE

The modern medicine is leaving the one-size-fits-all situation and shifting to individual patient-specific personalized, data-based and adaptive approaches to treatments. The leading change is the implementation of artificial intelligence, which can help healthcare providers step beyond conformity to standardized protocols and custom-design interventions to correspond to a specific patient's clinical, genetically, and lifestyle profile. The use of AI in treatment planning and decision-making is complex and covers predictive analytics processes, therapy optimization, and real-time tweaking of care [27]. Predicting disease developments and how patients will be treated with AI is one of the most influential contributions that AI brings. AI may detect risk factors and predict how a certain condition may progress based on big data analyzing clinical records, imaging studies, lab values, and genomic sequences [28].



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AI Applications in Clinical



Decision





Figure: 3 showing AI applications in clinical decision

It is possible to use AI to help clinicians design the best treatment regimens because a clinician can simulate different therapeutic scenarios. Machine learning algorithms can take various considerations into consideration- efficacy of drugs, their side effects, presence of comorbidities and even pharmacogenomic data- to propose the most appropriate treatment to an individual patient. Drug dosing Artificial intelligence AI-driven drug dosing algorithms are being used to calculate the exact dosage of medication based on patient-specific input, e.g., kidney function or body weight, to increase safety and minimize adverse drug effects in pharmacology [29].

Improvements in genomics have precipitated the development of precision medicine, and AI is vital in deciphering the large volumes of data produced by the sequencing technologies. Classification of genetic mutations into groups associated with treatment response can be identified through Deep learning algorithms leading to targeted interventions in cancer, rare genetic disorders, and infectious diseases [30]. As an example, AI systems may help contrast the tumor mutation profile of a patient and the list of drugs that would most probably work, or suggest the patient enroll into clinical trials based on his/her molecular specifics.

MONITORING THE PATIENTS FROM ANYWHERE: AI IN REMOTE SURVEILLANCE AND TELEHEALTH

Digital health technologies have exploded in the last few years, which has made remote tracking and telehealth part and parcel of the modern healthcare designed system. Global events like the COVID-19 pandemic are just further fuelling these innovations since they highlighted the necessity of safe, accessible, and efficient care beyond the walls of a traditional hospital. Artificial intelligence can be a central component of such an environment allowing constant health monitoring, any deviation in clinical outcomes or preemptive intervention plans to be identified, especially in the case of a patient residing outside the facility [31].

On the consumer side, wearable devices such as fitness trackers produce huge amounts of physiological data, along with sensor-based medical products. This information is fed to AI algorithms where they are assessed in real-time to highlight trends and deviations that can indicate emerging health problems. As an example, atrial fibrillation can be detected by AI-enabled heart monitors prior to the appearance of any symptoms, which leads to timely clinical assessment [32]. The coupling of continuous glucose monitors and machine learning models can be used to predict potentially dangerous highs or lows so that diabetic patients can preemptively act to remedy the situation. The more sophisticated devices where AI is used are smart inhalers that monitor the consumption of medication as well as environmental factors to enhance asthma control [33].

The world of telehealth is becoming more involved with the usage of AI technologies to improve virtual interactions.





Since NLP is able to transcribe and summarize patient clinician interactions, essential points can also be captured in the medical record. Extraneous time because of taking patient history, triaging symptoms and even offering basic health education can be reduced through chatbots and virtual assistants prior to the teleconsult itself making appointments more efficient [34].

Visual assessments during telehealth visits are also enhanced by the help of AI. Facial pallor, respiratory rate, or neurological indicators can be analyzed by computer vision algorithms in video feeds to give additional pointers to clinicians as to the diagnosis. The significant power of AI in remote monitoring is forecasting. Through the constant evaluation of patient data, AI systems are able to predict the risk of returning to the hospital, worsening of chronic illness, or any such negative outcome [35]. As another example, AI models could be used to pick up minor weight fluctuations and fluid retention patterns in heart failure patients that leads to acute events, resulting in early intervention, and thus, possibly hospitalization.

AI-Powered telehealth is beneficial in the management of chronic illnesses such as hypertension, COPD, and kidney illness. The systems have the potential to make monitoring frequency personal as well as adjust treatment recommendations and notify care teams in cases where thresholds have been exceeded. Not only does this increase outcomes, but it also actively gives the patient control in helping to manage their health. Nevertheless, AI-driven remote monitoring has drawbacks. Poor connectivity, availability of devices and digital literacy may restrict it, especially in the rural or underserved communities [36]. With sensitive health information being sent or transmitted on the networks, data security and privacy issues are still a thorny issue. In addition, false positive or over-alerting may cause anxiety among the patients and burnout among clinicians when not handled above board [37].

Incorporating continuous data measurement and smart analysis, AI takes remote monitoring beyond being a passive system of monitoring to become an active, predictive healthcare assistant. This change will make it possible to intervene earlier and it will minimize in-person visits and promote a more patient-centered mode of care. As AI algorithms evolve, and more devices can coordinate handoffs, remote care could become not only an option to in-person care, but core elements of proactive, personalized medicine in the years to accompany [38].

BEHIND THE SCENES: HOSPITAL OPERATIONS AND PUBLIC HEALTH AI

Artificial intelligence in healthcare gets a lot of publicity when the topic comes up; however, some of the most powerful applications are in the background making hospitals more effective and caring providers more effective. Although these less-explicit functions do not deal directly with patients, they are pivotal in promoting effective, sustainable and responsive delivery of care to the new health challenges. Healthcare organisations are dynamic ecologies where any lack of efficiency may cause delays, allocating more resources unnecessarily, and expenditures [39]. The systems with AI will be able to optimize workflows with historical and real-time data on operations. As an illustration, the predictive models could be used to predict seasonal levels of admission of the patients due to seasonal events or disease outbreaks. Such predictions enable the administrators to flex the levels of staffing, bed availability, and inventories of supplies accordingly [40].

At the emergency department, AI would allow prioritizing the patient triage by his/her severity score that will be calculated out of their clinical data so that the most serious cases will be taken as soon as possible. Just as well, AI-powered scheduling systems feature better utilization of operating rooms in ways that minimize idle time and optimize surgical throughput. The supply chain is complex and functions through hospitals as they receive care in terms of medications and blood products to surgical equipment and personal protective equipment [41]. This supply chain can be optimized with the aid of AI, as it can help in predicting the changes in demand, find the bottlenecks in the process and recommend procurements plans. Such predictive measures were used during the COVID-19 pandemic to allow healthcare facilities to foresee shortages and appropriately redistribute resources [42].

Through its successful implementation, AI can become an effective undertaking in the functioning of a hospital and in the realm of public health by causing superior usage of resources, the decreased expenditures, and an enhanced preparedness to satisfy the regular healthcare requirements and avert the public health crisis. As it works in the background without making much noise, AI makes the healthcare system operate more efficiently, thus establishing a context in which clinicians can do what they are supposed to do: take care of patients [43].



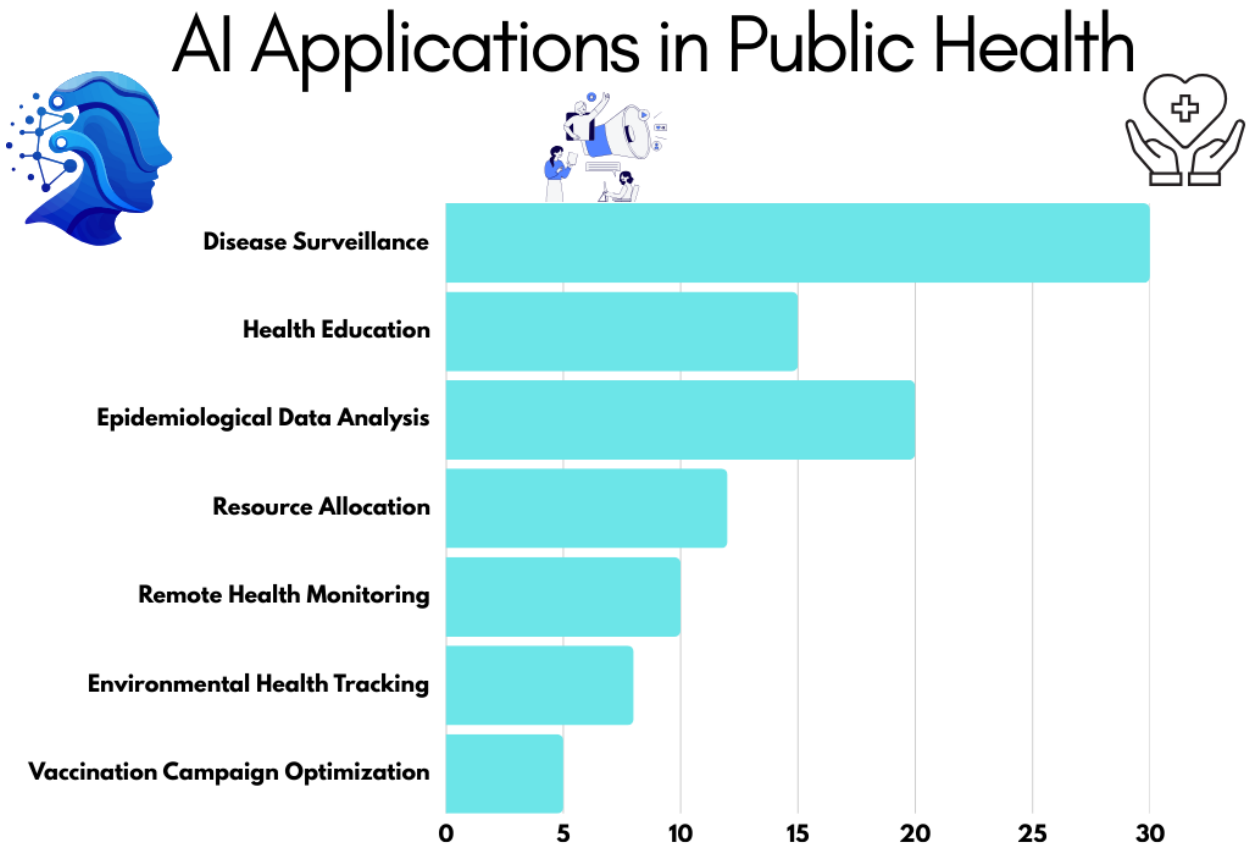


Figure: 4 showing AI applications in public health

THE ROADBLOCKS: TECHNICAL, REGULATORY, AND ETHICAL OBSTACLES

Although the prospects of artificial intelligence in healthcare are very bright, there are multiple obstacles to be overcome when integrating this technology into the medical sphere. Technological difficulties are not the only issues: ethical challenges, regulatory issues, complexities and organizational hurdles all have to be resolved prior to successfully and ethically implementing AI to a large supply. Algorithmic bias is one of the most urgent concerns, as biased results may take place when the deployed AI is trained on non-representative data [44]. The system that has been trained to perform better in some descriptive categories or demographics might be less accurate in new areas, especially the underrepresented ones, which will increase the gaps in healthcare disparities. To overcome this, there must be a planned diversification of the dataset and continuous performance monitoring in various categories of patients [45].

Autonomy and accountability are other ethical responsibilities as well. Who is the final responsible party in a situation where an AI makes a recommendation involving a diagnosis, or treatment and by doing so, causes a certain degree of harm to the patient? Clearing up responsibility is the most necessary to retain trust of the patients and be negligent of the law. AI healthcare systems rely on enormous sets of sensitive personal information. This questions the confidentiality state and the adherence to laws like the Health Insurance Portability and Accountability Act of 1996 in the United States or the General Data Protection Regulation in the European Union in general [46]. Adoption is also complicated by cybersecurity related threats such as data breaches and malicious attacks on AI system. Non-negotiable safeguards include commendable encryption, storage security of data, and the element of transparency in the consent processes [47].

Technically, most artificial intelligence systems have inefficiencies in the data interoperability aspect which is the capability of exchanging information and communicating with one another in different healthcare systems. IT systems in legacy hospitals do not usually integrate well with the contemporary AI tools and hence present difficulties in the modernization process. What is more, the AI models tested in a set clinical environment cannot always be reliable in other settings since they may differ in terms of practice, equipment, and population groups [48]. The law enforcers have a very challenging role of promoting innovation and maintaining patient safety. Contrary to standard medical technology, AI systems can never be constant since they can progress constantly as they learn new information and therefore regulatory structures that anticipate that a product will always remain the same will not work under AI systems. The FDA and elsewhere are looking into adaptive approval processes, though international standards are



immature [49].

The only way to meet these challenges is to pursue a multidisciplinary approach- including clinicians, data scientists, ethicists, policy-makers, and patients. Clear models, strict validation, ethical supervision and strict, robust regulatory pathways will be essential. The only way forward to make AI reach its potential may be as a trusted and transformative partner in delivering healthcare is by a genuine confrontation with these impediments [50].

CONCLUSION

Artificial intelligence is no longer a future dream in healthcare; it is an immediate and developing agent that has generated a significant impact on all the phases in the care continuum. Whether it is diagnostics and personalized treatment to remote monitoring, hospital operations, and surveillance of the health of the wider population, AI has proven to have the ability to improve the clinical and operational accuracy, efficiency, and patient engagement. The evidence looked at brings out the fact that when used intelligently, AI is not out to displace human expertise but it enhances it and ensures that healthcare professionals can work smarter, faster and in a more precise manner.

Deep learning, Natural language processing, and machine learning are the key technologies that make the source of power to convert different medical data into decisions. However, the pathway to take data to decisions is complicated, and it entails demanding and working with high-quality interoperable datasets, solid model training, and proper integration within clinical workflows. The most obvious successes of AI, especially in the field of diagnostics, illustrate the possibility that it can observe the disease earlier and more precisely than before, and the increasing sophistication of treatments in the field of personalized medicine is evidence that it is able to provide interventions that specifically target an individual patient.

On the backstage of medical practice, AI reinforces the healthcare provision system. Predictive analytics support staffing and allocation of resources, whereas models of public health enable the discovery and management of upcoming health risk. In remote care, telehealth machines and platforms can help connect the geographical distance and allow continuous and immediate monitoring of the patients around the globe. Nevertheless, the review also notes that the advancement is associated with tremendous difficulties. The safe, equitable and transparent adoption of AI needs to overcome ethical concerns, algorithm bias, privacy risks, interoperability issues and evolving regulatory requirements. The answers will need to involve cross-sectoral cooperation, innovations in regulation, and an urge to ensure responsible AI manufacture.

Moving on, the next frontiers (explainable AI, the idea of federated learning, integrating robotics, and global health applications) will ultimately increase the capabilities of AI. It should be aimed at the development of patient-centered systems that are reliable, flexible and adaptable. The main approach will be continuous reviewing, repetitive advanced development, and key stakeholder input in fully ensuring that AI is utilized as an empowerment tool and not isolating. In the end, AI should not be the one to lead healthcare, but should walk with clinicians, patients and health systems- healing with intelligence. As a result of combining the accuracy of computations with the empathy of humans, AI will enable the future of healthcare that will be more proactive, personalized, and fair, as it produces superior outcomes on the levels of both individuals and groups.

REFERENCES

1. Abbasian M, Khatibi E, Azimi I, et al. Foundation metrics for evaluating effectiveness of healthcare conversations powered by generative AI. *NPJ Digit Med* 2024; 7:82.
2. Moreira MWL, Rodrigues JJPC, Korotaev V, AlMuhtadi J, Kumar N. A comprehensive review on smart decision support systems for health care. *IEEE Syst J* 2019; 13:3536-3545.
3. Reddy S, Rogers W, Makinen VP, et al. Evaluation framework to guide implementation of AI systems into healthcare settings. *BMJ Health Care Inform* 2021; 28: e100444.
4. Sokolova M, Japkowicz N, Szpakowicz S. Beyond accuracy, F-score and ROC: A family of discriminant measures for performance evaluation. *Lecture Notes in Computer Science*. New York: Springer, 2006; 1015-1021. 530 S. S. SINGH RANA ET AL.
5. Zhang D, Wang J, Zhao X. Estimating the uncertainty of average F1 scores. In: *Proceedings of the 2015 International Conference on the Theory of Information Retrieval*. New York: Association for Computing Machinery, 2015; 317-320.
6. Shankar, K., Perumal, E., Díaz, V. G., Tiwari, P., Gupta, D., Saudagar, A. K. J., & Muhammad, K. (2021). An optimal cascaded recurrent neural network for intelligent COVID-19 detection using Chest X-ray images. *Applied Soft Computing*, 113, and 107878.
7. Sharma, G. D., Yadav, A., & Chopra, R. (2020). Artificial intelligence and effective governance: A review, critique and research agenda. *Sustainable Futures*, 2, 100004.
8. Shi, F., Wang, J., Shi, J., Wu, Z., Wang, Q., Tang, Z., Shen, D. (2020). Review of artificial intelligence techniques in imaging data acquisition, segmentation and diagnosis for covid-19. *IEEE Reviews in Biomedical Engineering*.





9. Sim, S., & Cho, M. (2021). Convergence model of AI and IoT for virus disease control system. *Personal and Ubiquitous Computing*, 1-11.
10. J. Bajwa, U. Munir, A. Nori, B. Williams, Artificial intelligence in healthcare: transforming the practice of medicine, *Future Health J.* 8 (2) (2021) e188–e194, <https://doi.org/10.7861/fhj.2021-0095>.
11. Kerketta A., Balasundaram S. “Leveraging AI Tools to Bridge the Healthcare Gap in Rural Areas in India.” Published online August 1, 2024. doi:10.1101/2024.07.30.24311228.
12. V.S. Baljepally, W. Metheny, Rural-urban disparities in baseline health factors and procedure outcomes, *J. Natl. Med. Assoc.* 114 (2) (2022) 227–231, <https://doi.org/10.1016/j.jnma.2022.01.001>.
13. E.C. Loccoh, K.E. Joynt Maddox, Y. Wang, D.S. Kazi, R.W. Yeh, R.K. Wadhwa, Rural-urban disparities in outcomes of myocardial infarction, heart failure, and stroke in the United States, *J. Am. Coll. Cardiol.* 79 (3) (2022) 267–279, <https://doi.org/10.1016/j.jacc.2021.10.045>.
14. S. Bhatia, W. Landier, E.D. Paskett, et al., Rural–urban disparities in cancer outcomes: opportunities for future research, *JNCI J. Natl. Cancer Inst.* 114 (7) (2022) 940–952, <https://doi.org/10.1093/jnci/djac030>.
15. Javeedullah M. Big Data and Health Informatics: Managing Privacy, Accuracy, and Scalability. *Global Trends in Science and Technology.* 2025 Jul 3;1(3):29-47.
16. S. Yaemsiri, J.M. Alfier, E. Moy, et al., Healthy people 2020: rural areas lag in achieving targets for major causes of death, *Health Aff.* 38 (12) (2019) 2027–2031, <https://doi.org/10.1377/hlthaff.2019.00915>.
17. Weeks W.B., Chang J.E., Pagan J.A., et al. Rural-urban disparities in health outcomes, clinical care, health behaviors, and social determinants of health and an action-oriented, dynamic tool for visualizing them, Wang Z, ed., *PLOS Glob Public Health.* 2023; 3(10):e0002420. doi:10.1371/journal.pgph.0002420.
18. J. Loftus, E.M. Allen, K.T. Call, S.A. Everson-Rose, Rural-urban differences in access to preventive health care among publicly insured Minnesotans, *J. Rural Health* 34 (S1) (2018), <https://doi.org/10.1111/jrh.12235>.
19. Rn Bell, Msn, D. Mha S, Lawrence, C. MSc, S. Dobrin, et al., Near-term digital health predictions: a glimpse into tomorrow’s ai-driven healthcare, *Telehealth Med. Today* 8 (5) (2023), <https://doi.org/10.30953/thmt.v8.452>.
20. S. Khavandi, F. Zaghoul, A. Higham, E. Lim, N. De Pennington, L.A. Celi, Investigating the impact of automation on the health care workforce through autonomous telemedicine in the cataract pathway: protocol for a multicenter study, *JMIR Res. Protoc.* 12 (2023) e49374, <https://doi.org/10.2196/49374>.
21. Javeedullah M. Integrating Health Informatics Into Modern Healthcare Systems: A Comprehensive Review. *Global Journal of Universal Studies.*;2(1):1-21.
22. J. Guo, B. Li, The application of medical artificial intelligence technology in rural areas of developing countries, *Health Equity* 2 (1) (2018) 174–181, <https://doi.org/10.1089/heq.2018.0037>.
23. F. Jiang, Y. Jiang, H. Zhi, et al., Artificial intelligence in healthcare: past, present and future, *Stroke Vasc. Neurol.* 2 (4) (2017) 230–243, <https://doi.org/10.1136/svn-2017-000101>.
24. J. Khubchandani, S. Banerjee, R.A. Yockey, K. Batra, Artificial intelligence for medicine, surgery, and public health, *J. Med. Surg. Public Health* 3 (2024) 100141, <https://doi.org/10.1016/j.glmedi.2024.100141>.
25. Paine SJ, Benator SG. JCAHO initiative seeks to improve patient safety. *Medscape.* 2003; 15(1):23–24
26. Winters BD, Cvach MM, Bonafide CP, Hu X, Konkani A, O'Connor MF, Rothschild JM, Selby NM, Pelter MM, McLean B, Kane-Gill SL, Society for Critical Care Medicine AlarmAlert Fatigue Task Force Technological Distractions (Part 2): A Summary of Approaches to Manage Clinical Alarms With Intent to Reduce Alarm Fatigue. *Crit Care Med.* 2018 Jan;46(1):130–137.
27. Hu X. An algorithm strategy for precise patient monitoring in a connected healthcare enterprise. *NPJ Digit Med.* 2019;2:30.
28. Javeedullah M. Future of Health Informatics: Bridging Technology and Healthcare. *Global Trends in Science and Technology.* 2025 Apr 4;1(1):143-59.
29. Woodward S. Moving towards a safety II approach. *J Patient Safe Risk Manage.* 2019 Jun 08;24(3):96–99.
30. J., Yang, H., Jin, R., Tang, X., Han, Q., Feng, H., Jiang, S., Zhong, B., Yin, & X., Hu, “Harnessing the power of llms in practice: A survey on chatgpt and beyond”, *ACM Transactions on Knowledge Discovery from Data*, 18(6), pp. 1-32, 2024, DOI: <https://doi.org/10.1145/3649506>
31. J. L., Ba, J. R., Kiros, & G. E., Hinton, (2016). Layer normalization. arXiv: 1607.06450. Retrieved December 12, 2024, from <https://arxiv.org/abs/1607.06450>
32. A., Ziaee, & E., Çano, “Batch Layer Normalization A new normalization layer for CNNs and RNNs”, In *Proceedings of the 6th International Conference on Advances in Artificial Intelligence* (pp. 40-49), 2022, October, DOI: <https://doi.org/10.1145/3571560.3571566>
33. Javeedullah M. Security and Privacy in Health Informatics: Safeguarding Patient Data in A Digital World. *AlgoVista: Journal of AI and Computer Science.*;2(3):52-68.
34. S., Naseem, “Advancing Health Literacy Through Generative AI: The Utilization of Open-Source Large Language Models (LLMs) for Text Simplification and Readability”, Master thesis, Michigan Technological University, 2024, DOI: <https://doi.org/10.37099/mtu.dc.etr/1762>





35. A., Vaswani, N., Shazeer, N., Parmar, J., Uszkoreit, L., Jones, A. N., Gomez, L., Kaiser, & I., Polosukhin, (2017). Attention is all you need. *Advances in Neural Information Processing Systems*, arXiv (Cornell University), 30, pp. 5998–6008. Retrieved December 12, 2024, from <https://arxiv.org/pdf/1706.03762v5>
36. B., Lutkevich, & E., Burns, (2021). Natural language processing (NLP). TechTarget: Newton, MA, USA. Retrieved December 12, 2024, from <https://www.techtarget.com/searchenterpriseai/definition/natural-language-processing-NLP>
37. Smith-Bindman, R., Kwan, M. L., Marlow, E. C., Theis, M. K., Bolch, W., Cheng, S. Y., Bowles, E. J., Duncan, J. R., Greenlee, R. T., & Kushi, L. H. (2019). Trends in Use of Medical Imaging in US Health Care systems and in Ontario, Canada, 2000–2016. *Journal of the American Medical Association*, 322, 843–856
38. Panayides AS, Amini A, Filipovic ND, Sharma A, Tsafaris SA, Young A, Foran D, Do N, Golemati S, Kurc T, Huang K, Nikita KS, Veasey BP, Zervakis M, Saltz JH, Pattichis CS. AI in Medical Imaging Informatics: Current Challenges and Future Directions. *IEEE J Biomed Health Inform.* 2020 Jul; 24(7):1837-1857
39. Kulikowski CA, —Medical imaging informatics: Challenges of definition and integration, *J. Amer. Med. Inform. Assoc.*, vol. 4, pp. 252–3, 1997.
40. Hsu W, Markey MK, and Wang MD, —Biomedical imaging informatics in the era of precision medicine: Progress, challenges, and opportunities, *J. Amer. Med. Inform. Assoc.*, vol. 20, pp. 1010–1013, 2013
41. Evens R, Kaitin K. The evolution of biotechnology and its impact on health care. *Health Aff (Millwood)*. 2015; 34(2):210–9. <https://doi.org/10.1377/hlthaff.2014.1023>.
42. Au L, da Silva RGL. Globalizing the Scientific Bandwagon: Trajectories of Precision Medicine in China and Brazil. *Science, Technology, and Human Values*. 2021. 46 (1):192–225.
43. Raimbault B, Cointet J-P, Joly P-B. Mapping the emergence of Synthetic Biology. *PLoS ONE*. 2016; 11(9):e0161522. <https://doi.org/10.1371/journal.pone.0161522>.
44. Lock K, Nguyen V-K. *An Anthropology of Biomedicine*. Malden, MA: WileyBlackwell; 2010. xii+506 pp. 20.
45. Aspuru-Guzik A. A decade of Artificial Intelligence in Chemistry and materials. *Digit Discovery*. 2022; 2:10.
45. Papanastassiou M, Pearce R, Zanfei A. Changing perspectives on the internationalization of R&D and innovation by multinational enterprises: a review of the literature. *J Int Bus Stud*. 2020; 51:623–64.
46. Pascasio L, Rihm S, Naseri A, Mosbach S, Akroyd J, Kraft M. Chemical species Ontology for Data Integration and Knowledge Discovery. *J Chem Inf Model*. 2023 Oct; 26. <https://doi.org/10.1021/acs.jcim.3c00820>.
47. Soldatova LN, Clare A, Sparkes A, King RD. An ontology for a Robot scientist. *Bioinformatics*. 2006; 22(14):e464–71. <https://doi.org/10.1093/bioinformatics/btl207>.
48. King RD, Rowland J, Oliver SG, Young M, Aubrey W, Byrne E, Liakata M, Markham M, Pir P, Soldatova LN, Sparkes A, Whelan KE, Clare A. *Autom Sci Sci*. 2009;324(5923):85–9.
49. Sparkes A, Aubrey W, Byrne E, et al. Towards Robot scientists for autonomous scientific discovery. *Autom Exp*. 2010; 2(1). <https://doi.org/10.1186/1759-4499-2-1>.
50. Choi N, Kim H. Technological Convergence of Blockchain and Artificial Intelligence: A Review and Challenges. *Electronics*. 2025 Jan; 14(1):84.

