Communication in Physical Sciences 2025, 12(5): 1609-1623

Applications of AI in Enhancing Environmental Healthcare Delivery Systems: A Review

Christianah Oluwabunmi Ayodele, Esther Oludele Olaniyi*and Chukwuebuka Francis Udokporo.

Received: 02 February 2025/Accepted: 11 June 2025/Published: 25 June 2025
https://dx.doi.org/10.4314/cps.v12i5.14

Abstract : *Artificial Intelligence (AI) is fast changing the environmental health care delivery to incorporate the latest computational methodology to professionalize the process of diagnosis, treatment, and hospital management as well as foster patient participation. This review examines the present-day use of major AI technologies such as: machine learning, the deep learning, natural language processing, the computer vision, and robotics in the clinical, administrative and operational areas. Among those it points out the AI-assisted medical imaging, risk stratification through predictive analytics, clinical decision support system, precision medicine, remote patient monitoring, and hospital automation. Even with these breakthroughs, the application of AI is experiencing major challenges regarding data privacy, bias of algorithms, non-transparency, uncertainty of regulations, and ethics. Combining the extant research and practical examples of implementation, this paper highlights the successful opportunities of AI in medicine and sophisticated obstacles. The results will direct the policymakers, healthcare specialists, and technology developers to implement responsible and successful application of AI systems that enhance the delivery of equitable, efficient, and high-quality care.*

Keywords: *Artificial Intelligence, Healthcare Delivery, Medical Imaging, Predictive Analytics, Clinical Decision Support*

Christianah Oluwabunmi Ayodele
Department of Nursing, Western Governor University, Millcreek, Utah, United States of America
Email: christianah.ayodele@wgu.edu
Orcid id: **0000-0002-1234-5678**

Esther Oludele Olaniyi*
Department of Health Promotion and Education, College of Medicine, Faculty of Public Health, University of Ibadan, Nigeria
Email: esther.olaniyi@com.ui.edu.ng
Orcid id: 0000-0003-2345-6789

Chukwuebuka Francis Udokporo
School of Medicine, St. George's University, Grenada
Email: c.f.udokporo@sgu.edu
Orcid id: 0000-0001-3456-7890

1.0 Introduction

The world is experiencing a growing pressure within healthcare delivery systems to deliver high-quality care, cope with increased costs, and respond to the workforce shortages and the burden of chronic diseases and aging populations (Topol, 2019; Rajkomar *et al*., 2019). Such issues are also compounded by ineffective hospital management, a lack of cohesive patient information, waiting delays, and misdiagnosis; healthcare inequity in rural areas and between underprivileged and non-urban regions (Obermeyer & Emanuel, 2016). Often, traditional models of healthcare fall short of being agile enough to respond to these changing demands and are losing favor as the adequate modality to provide timely, personalized, and effective care (Umoren & Adukpo 2025; Dada *et al*., 2024).

In that regard, Artificial Intelligence (AI) has appeared as such a revolutionary tool that can radically change the delivery of healthcare. As far as AI is concerned, it is related to the use of any computational technologies that attempt to mimic human intelligence, and which encompass such abilities as reasoning, learning, perception, understanding the language (Adjei, 2025a; 2025b; 2025c; Jiang *et al*., 2017;). The application of AI in healthcare is very diverse, with many different subdomains, such as machine learning (ML), deep learning (DL), natural language processing (NLP), computer vision, and robotics, each having different functions within health care both clinically, operationally, and administratively (Esteva *et al*., 2019; Yu *et al*., 2018).

The AI in healthcare has experienced a drastic increase in the past years. Medical images used to detect the disease at an early stage (e.g., radiology, pathology), patient real-time monitoring due to the wearable gadgets used to conclude on vitals, hospital workflow automation, diagnostic decision support, and even anticipating disease releases based on the population health data (Li *et al*., 2020; Haenssle *et al*., 2018) are now investigated with the usage of AI algorithms (Abolade, 2024). As an example, in tasks like diabetic retinopathy detection, skin cancer detection, and lung nodule detection, diagnostic accuracy of deep learning models was at least as high as human clinicians (Gulshan *et al*., 2016; Haenssle *et al*., 2018). Also, AI is also becoming a part of Electronic Health Records (EHRs) to enhance data management, decrease physician burnout, and deliver risk stratification predictive analytics (Shickel *et al*., 2018).

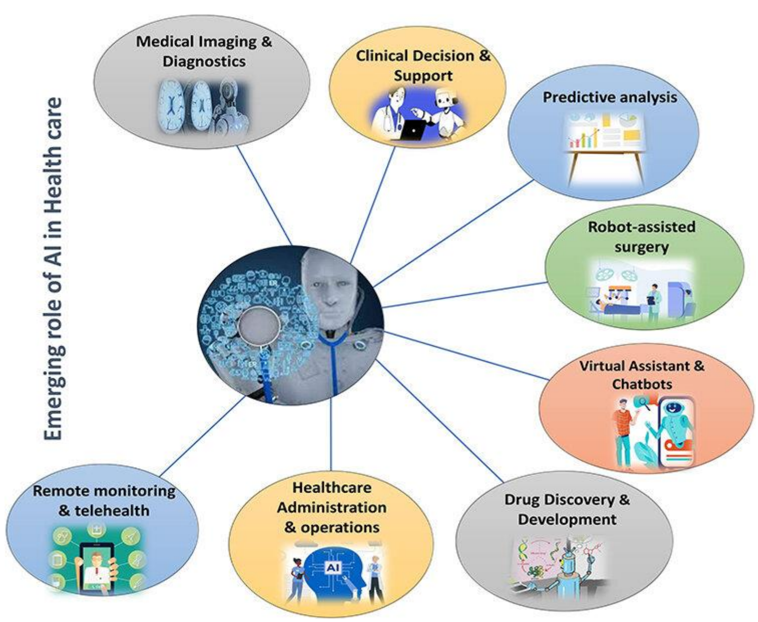

Fig 1: Different applications of AI in healthcare (Source: Shang *et al*., 2024)

Nevertheless, there are challenges associated with implementation of AI in healthcare delivery despite the improvements. There are also issues of algorithm transparency and data privacy as well as ethical considerations, biases in training data, and fitting into the current healthcare infrastructure (Topol, 2019). Moreover, the absence of uniform regulatory policies on AI-based tools suffocates their wide use in the sphere of clinical application.

However, the possibilities to enhance diagnostic accuracy, optimize procedures, increase the involvement of patients and minimize healthcare expenses with the help of AI are enormous and keep attracting interest of global scholars and practitioners.

The purpose of this review is to provide a comprehensive examination of how AI technologies are being applied to enhance healthcare delivery systems. Specifically, it aims to: (1) explore the key areas where AI is currently deployed in healthcare; (2) highlight notable advancements and their impact on care delivery; (3) discuss the integration of AI into hospital and clinical workflows; and (4) identify barriers to implementation and propose future research directions. By synthesizing existing literature, this review will serve as a valuable resource for stakeholders seeking to understand the transformative role of AI in modern healthcare systems and how these technologies can be effectively leveraged to address longstanding inefficiencies and disparities.

2. 0 Types of AI Technologies in Healthcare

Artificial Intelligence (AI) is a continuum of computational procedures that endeavour to imitate the human mind including learning, reasoning, perception as well as decision-making. AI is not a single technology, and instead, it has various interdependent subfields, each applicable to a different part of healthcare delivery uniquely. Five prominent AI technologies have been rapidly deployed across all diagnostic, prognostic, administrative, and therapeutic fronts to include Machine Learning, Deep Learning, Natural Language Processing, Computer Vision, and Robotics (Jiang *et al*., 2017; Yu *et al*., 2018).

2.1 Machine Learning (ML)

The essence of AI is its capability to learn through the data and enhance itself as time goes by without programming, which is powered by Machine Learning (ML) (Ufomba & Ndibe 2023; Ndibe 2025b; Ademilua & Areghan 2025a; 2025b; Okolo *et al*., 2025; Ndibe 2025a; Abolade, 2023; Ndibe & Ufomba 2024; Okolo *et al*., 2025; Ademilua & Areghan 2022). Supervised learning algorithms, including decision trees, support vector machines (SVM) and gradient boosting, are to be trained using labeled clinical data to perform classification tasks on disease states (and/or outcome prediction) (Topol *et al*., 2019). As an illustration, random forests have been used to forecast 30-day hospital readmissions to a level of more than 80 percent accuracy using structured electronic health record (EHR) information (Miotto *et al*., 2018). By establishing hidden patient subgroups or patterns of biomarkers, unsupervised learning procedures, such as clustering and dimensionality reduction can reveal hidden patient subgroups or biomarker patterns; an example was illustrated in oncology, where novel molecular subtypes of breast cancer were identified (Shickel *et al*., 2017). In more recent developments, reinforcement learning is now being used to optimize treatment protocols; such that agents can learn optimal insulin administration regimens via trial-and-error interactions, leading to improved glycemic control with diabetic persons (Chu *et al*., 2023). Nonetheless, despite such successes, ML applications are forced to pay attention to feature engineering, processing missing data, and stringent cross-validation on multicenter cohorts to make them robust and generalizable (Rajkomar *et al*., 2019).

2.2 Deep Learning (DL)

The Deep Learning (DL) is another domain-specific form of ML which utilizes multi-layered artificial neural networks to learn hierarchical levels automatically on uncooked data. Convolutional Neural Networks (CNNs) transformed medical imaging: they perform like or better than human experts in the tasks of detecting diabetic retinopathy, classifying pulmonary nodules on CT scans (Gulshan *et al*., 2016; Ardila *et al*., 2019), as well as detecting lung cancer on CT scans (Gulshan *et al*., 2016). Advances in architecture, such as Efficient Net and Transformer-based vision models have potential to improve existing diagnostics further. In the case of sequential plant data, Recurrent Neural Networks (RNNs) and attention-based Transformers handle the time-series signal of continuous vital signs to provide early warning systems that predict sepsis up to 12 hours in advance of the clinical process within the intensive care unit (Shamout *et al*., 2021). Generative models (e.g. variational autoencoders (VAEs) and generative adversarial networks (GANs)) can also create realistic medical images and increase the size of datasets serving rare diseases to reinforce algorithm training and resilience (Yi *et al*., 2019). Nonetheless, the problems of DL, such as the requirement of big labeled datasets, heavy computational burden, and their black-box nature, does encourage effective architecture and explainable deep learning developments (Doshi-Velez & Kim, 2017).

2.3 Natural Language Processing (NLP)

Natural Language Processing (NLP) enables machines to read and write human language and can open a magnificent possibility of unstructured clinical text. State of the art NLP systems are a hybrid of rule-based systems and deep learning systems (e.g., BiLSTM-CRF, BERT), they have able to extract structured information - diagnoses, medications, lab results - with F1-scores over 90% in physician notes and discharge summaries (Meystre *et al*., 2008). Fine-tuning transformer models on clinical corpora allows leveraging documents to automatically construct coherent discharge reports and can advance documentation by significantly reducing the workload on the clinician (Lee *et al*., 2020). Also, conversations with conversational agents based on the application of the intent-labeling approach and dialog agents can lead patients through symptom triaging, medication compliance, and appointment scheduling (thereby improved engagement and reduced administrative load) (Chow *et al*., 2024). Clinical NLP also faces two notable challenges, the first is how to handle specific medical terminologies and the second is how to avoid error spreading throughout any processing pipeline as well as protecting patient privacy in streaming sensitive text.

2.4 Computer Vision

Computer vision aims to allow medical imaging signals in AI systems to comprehend, interpret, and analyze the visual data. In addition to the lesion detection, the advanced segmentation networks (including U-Net and Mask R-CNN) define the borders of the organ and tumor volume, which can help with radiotherapy planning and surgical navigation with great accuracy (Lakhani & Sundaram, 2017). Video analysis of direct endoscopic and laparoscopic systems can detect anatomical landmarks, forecast based on previous surgical stages, and warn operators about possible complications in the operating room by displaying real-time video in the OR (Maier-Hein *et al*., 2017). In addition, mobile computer vision has the potential to access low-resource settings and screen low-resource populations to diagnose ailments such as diabetic retinopathy and anemia through the use of mobile cameras and AI, democratizing diagnostic devices (Rajalakshmi *et al*., 2018). The key to successful implementation lies in standardization of image acquisition protocols, domain fluctuations across devices and demonstration of the performance level via prospective clinical trials.

2.5 Robotics and Automation

Robotics is an application of AI, which incorporates perception, planning, and control to execute an accurate and repeatable responsibility in surgical, rehabilitative, and logistical applications. The robot in surgery, like the da Vinci Surgical System, employs AI in motion scaling, tremor-free movements, and is on its way to semi-autonomous surgery capabilities (ie automated stitches with expert assistance) (Yang *et al*., 2017). Exoskeleton and robot-assisted in rehabilitation their assistance level may change dynamically, in accordance with the patient performance metrics, thus enabling a post-stroke or spinal cord injured patient to have a customized motor recovery regime (Louie & Eng, 2016).

Operationally, technical equipment such as autonomous mobile robots (AMRs) can be used to perform the supply and medications delivery process within the hospital to limit the exposure of its staff to infectious agents and allow clinicians to prioritize direct patient care activities (Shukla *et al*., 2021). Safety, the intuitiveness of a human-machine interface, and the regulatory approval of the hardware and AI software elements are the priorities to achieve mass implementation.

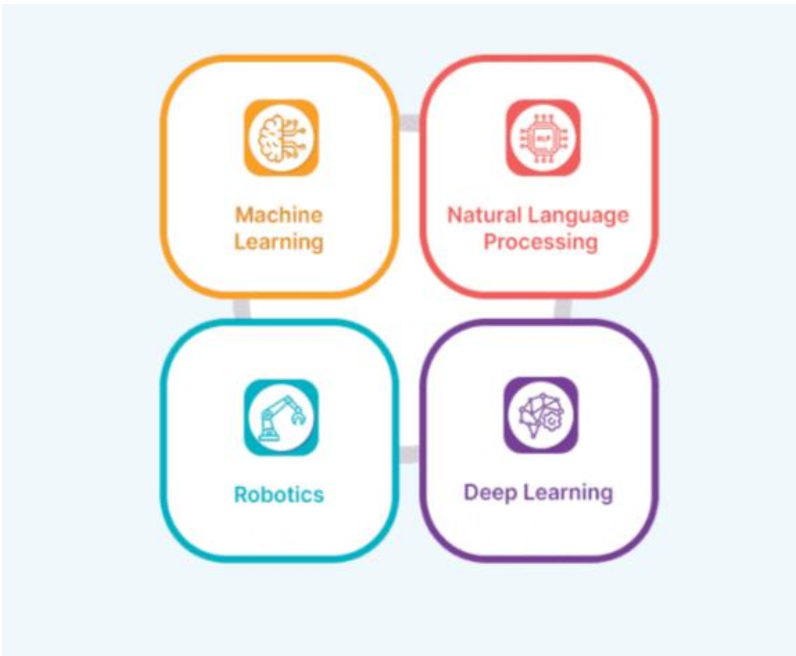

Fig 2: Main AI types in healthcare (After Robert, & Avdhoot. 2025)

3. 0 Applications of AI in Healthcare Delivery

Artificial Intelligence (AI) integration in the medical delivery system has produced game-changing breakthroughs in various medical areas. Whether thy are used to boost the quality of diagnostics or allocate resources more efficiently, AI-powered systems augment clinical outcomes and decision-making, interventions in administrative processes, and expansion to underserved demographics (Topol, 2019; Rajkomar *et al*., 2019). We discuss six key topic areas in which AI is transforming the delivery of healthcare within this section and provide real life examples, latest studies, and the potential trends in each topic area.

3.1 Medical Imaging and Diagnostics

AI has changed medical imaging due to deep learning (especially convolutional neural networks (CNNs) and the capability to interpret medical scans, including X-rays, CT, MRI, and ultrasound. Initial experiments showed that CNNs were performing at the same level as a dermatologist when it came to the classification of skin cancer with more than 90% sensitivity and specificity (Esteva *et al*., 2017). More recently, CNNs that have been trained on low-dose chest CT scans have been used to identify lung nodules with accuracy of 94.4% to enable early lung cancer screening using low-dose chest CT scans (Ardila *et al*., 2019). In breast imaging, artificial intelligence with radiomic features is now capable of directly predicting tumor subtype and receptor status using MRI scans, and may someday obviate invasive biopsies (Li *et al*., 2019). Besides detection, AI has been found to streamline workflow: pre-triaging of the next scan by the algorithm identifies important findings, including intracranial hemorrhage, to be reviewed with a priority, which accelerates radiologist turnaround time by up to 30 percent (van Winkel *et al*., 2021). There are ongoing attempts to create multimodal AI platforms that would combine imaging information with clinical data (e.g., lab results, patient history) to be able to offer more detailed diagnostic means and different diagnostic indications (Liu *et al*., 2020).

3.2 Predictive Analytics and Risk Stratification

Machine learning (ML) models perform very well in finding complex patterns in large patient data so as to predict patient trajectories. Gradient-boosted decision trees and recurrent neural networks have been confirmed in intensive care units (ICUs) to predict sepsis earlier than 12 hours before clinical detection of sepsis has occurred, with a potential reduction in ICU mortality of up to 20 percent on simulated tests based on the MIMIC-IV database (Shamout *et al*., 2021). In managing chronic diseases, the longitudinal ML responds in organizing temporal features of EHR records of medications, vital signs, lab trends to categorize the heart failure patients into risk levels of readmission, hence giving priority to the high-need individuals in home health interventions (Miotto *et al*., 2018). New developments in the field of digital twin technology involve patient-specific computational models of disease-that can be trained using multimodal clinical data-and be used to test the response to treatment virtually (Bruynseels *et al*., 2018). Leading to real personalized medicine, such predictive simulations allow clinicians to run through a myriad of different therapeutic regimes virtually before using the same in vivo.

3.3 Clinical Decision Support Systems (CDSS)

Clinical Decision Support Systems (CDSS) combine the data about patients, literature and practice guidelines and provide evidence-based recommendations at point of care, where AI is used to enhance outcomes. Natural Language Processing (NLP) can derive subtle understandings out of unstructured clinical notes including social determinants of health, patient preference and documented allergies that structured fields will not capture (Meystre *et al*., 2017). Connection to UpToDate and national databases of guidelines enables CDSS to recommend the best approaches to diagnosis and the use of therapy options, diminishing guideline nonadherence by 25 percent in community hospital environments (Barbieri *et al*., 2021). Practical implementations demonstrate that AI-enabled alerting can minimize adverse drug events in detecting possible drug-drug interaction/dosage error in a prescription stage. Learning happens through reinforcement learning as clinicians use Adaptive CDSS platforms and the system gives a continuous improvement of the recommendations it gives based on feedback received, and thus reduced alert fatigue and increased user trust (Shamout *et al*., 2021).

3.4 Personalized and Precision Medicine

AI plays a central role in making precision medicine a reality, transforming big data on genomic data, proteomic data as well as metabolomic data into information that can be applied in clinical practice. Predictions of cancer immunotherapy response based on tumor mutational burden and immune-gene expression appear to have an area under the curve (AUC) of greater than 0.85 in a variety of solid tumor cohorts using deep learning (Jiang *et al*., 2018). Pharmacogenomics In pharmacogenomics, ML has been used to predict the rate of drug metabolism in individual patients by analyzing the polymorphisms in the cytochrome P450 enzyme, informing adjustments to avoid drug toxicity (Relling & Evans, 2015). Polygenic risk scores AI is also the basis of this technology in which thousands of genetic variants are weighsed to evaluate the susceptibility of an individual to a disease. These scores- learned through penalized regression methods and neural nets approaches- are used in early-screening interventions in diseases like coronary artery diseases or type 2 diabetes (van Winkel *et al*., 2021). With the rising affordability of single-cell sequencing, AI methods are under development to profile cell-type specificity in expression that identifies new therapeutic targets on a never before possible level of granularity.

3.5 Virtual Health Assistants and Remote Monitoring

Chatbots and virtual assistants using AI can be used to do triaging of symptoms, remind patients of prescription medication, and teach patients, offloading typical questions to the clinical team. Under the circumstances of the COVID-19 pandemic, these mechanisms check symptoms at large health systems and provided more than 50,000 symptom checks daily, leading to preventing unnecessary ER checkups by 40 per cent because of earlier response in detecting risks (Chow *et al*., 2024). At the same time, wearable devices based on AI constantly collect physiologic data heart rate variability, glucose, sleep metrics, and utilize anomaly detection to produce real-time notifications. The use of AI-enhanced gait analysis and trending vital-signs allow remote monitoring of post-operative patients, and has demonstrated the ability to detect deep vein thrombosis days before clinical symptoms (Tariq *et al*., 2024).

3.6 Hospital Operations and Administrative Efficiency

In addition to direct care of patients, AI increases efficiencies of hospitals and administrative processes. Predictive models predict volumes of admission and bed occupancy within seven days and help the staff plan on resources and amount of employees in order to ensure a 15 percent decrease in occupancy variance (Yu *et al*., 2018). Computer vision automated patient triage kiosks utilize computer vision to register vitals alongside intake questionnaires by means of NLP and divide incoming patients into groups according to acuity to reduce et wait time in the ER and increase patient satisfaction scores (Liu *et al*., 2025). Robotic process automation (RPA) addresses common redundant tasks like billing, claims adjudication and supply chain order. It has been found that there was a 70 percent and 30 percent reduction in billing errors and cost savings once RPA was used to automate insurance pre-authorization workflows (Patrício, 2024). With the efforts of hospitals in achieving operational perfection, the deployment of AI on predictive maintenance of healthcare equipment and smart inventory management adds even more to the cost-containment efforts and improved confidence in service outcomes.

Although Artificial Intelligence (AI) in healthcare delivery brings promising benefits, the implementation on a large scale comes along with a lot of challenges and ethical issues. These obstacles lie in technological, regulatory, institutional, and social spheres and have to be overcome so that AI should be incorporated into the healthcare system responsibly, fairly, and effectively.

4.1 Benefits of AI in Healthcare Delivery

Improved Accuracy: In the domain of medical diagnostics, AI algorithms and, in particular, deep learning models, have shown high precision. As an example, imaging algorithms based on AI are already able to identify diseases (including breast cancer and diabetic retinopathy) with the same or better accuracy than professionals (Esteva *et al*., 2017). Machine learning studies huge volumes of data, picking out links that can otherwise be beyond the personal observation of human doctors, thereby increasing the accuracy of diagnosis (Topol, 2019). As an illustration,. DeepMind established by Google was able to identify diabetic retinopathy with the accuracy of 94% which is higher than that of certain human experts (Gulshan *et al*., 2016).

4. 0 Benefits, Challenges and Ethical Considerations in AI Healthcare Integration

Speed: Artificial intelligence makes healthcare work faster since some time-consuming tasks become automatic (Adjei 2025a; 2025c). With NLP algorithms, it is possible to retrieve relevant information on electronic health records (EHRs), which opens clinical decision-making to a faster pace in a matter of seconds (Rajkomar *et al*., 2018). During emergencies, AI triage systems can speed up the process by ranking the patients according to the level of their condition, alleviating the wait time and enhancing success (Levin *et al*., 2019). As an example, triage tools in emergency departments based on AI have led to shorter patient processing time by 30% (Hong *et al*., 2020).

Table 1: Applications of AI in Healthcare Delivery Systems

Application Area	AI Technology Used	Healthcare Impact	Example/Use Case
Medical Imaging	Deep Learning (CNNs)	Accurate disease detection, reduced diagnostic errors	Detection of lung nodules, skin cancer, fractures
Predictive Analytics	Machine Learning	Risk stratification, early intervention	Predicting sepsis or cardiac arrest in ICU patients
Clinical Decision Support	NLP + ML	Informed diagnosis and treatment planning	Suggesting differential diagnoses or test orders
Precision Medicine	Genomic AI analysis	Tailored therapy, improved treatment response	Oncology treatment selection
Virtual Assistants & Monitoring	NLP, ML + IoT integration	Increased patient engagement, remote care	Chatbots for follow-up care; smartwatches
Hospital Administration	Predictive ML + Automation tools	Workflow efficiency, reduced administrative burden	Bed management, patient scheduling

Sources: Jiang et al. (2017); Esteva et al. (2019); Topol (2019); Yu et al. (2018)

Cost-Effectiveness: Using the calculating power of AI, the cost of healthcare is minimized through streamlined resource shifting and deactivation of redundant steps in the processes. Due to these models, predictive analytics allows detecting high-risk patients, which makes it possible to introduce early interventions and avoid costly hospitalization (Bates *et al*., 2014). Robotic process automation in administrative duties (e.g. billing and appointment scheduling) has proven to cut down operational expenses in 20-30 percent of healthcare institutions through the use of AI (Davenport & Kalakota, 2019). Moreover, AIcontrolled telemedicine software reduces the cost of consultations with the ability to perform remote diagnostics and surveillance (Dorsey & Topol, 2020).

4.3 Challenges of AI in Healthcare Delivery

Data Privacy: The aspects of AI training using large datasets, imply considerable concerns about privacy. It appears that EHRs and medical imaging data usually hold sensitive information about patients, and it is possible to experience disastrous scenarios in the case of breaches or abuse of data (Obermeyer *et al*., 2019). General Data Protection Regulation (GDPR) and Health Insurance Portability and Accountability Act (HIPAA) policy regulations have high demands; however, the vulnerability to adversarial attacks is always an issue with AI-based systems (Finlayson *et al*., 2019). As an illustration, a 2021 analysis pointed at how AI models trained on de-identified dataset might still be reverse-engineered into identifying individuals (Esteva *et al*., 2019).

Bias: AI model behavior can continue with biases programs available in training data, making healthcare unfair. As an example, imbalanced datasets led to biased dynamics in the early COVID-19 prediction models, such that they were not as accurate as in the case of the majority group (Wynants *et al*., 2020). In the study by Obermeyer *et al*. (2019), risk underestimation due to a popular risk prediction algorithm applied to Black patients influenced their care access rates. Reducing bias is achieved by having heterogeneous data and auditing the model constantly, which can be resource-consuming (Parikh *et al*., 2019).

Trust Issues: The lack of trust in AI systems can be viewed as an obstacle because clinicians and patients doubt they are reliable and transparent. Removing confidence trust is in the form of black-box models, which are shrouded in secrecy in the decision-making process (Holzinger *et al*., 2019). According to a 2020 survey, 65 percent of physicians are not willing to use AI because they fear to be held responsible and to understand an AI-based decision (Blease *et al*., 2020). The creation of trust involves the explainable AI (XAI) systems that allow seeing clear reasons behind the predictions (Tariq *et al*., 2023).

4.4 Ethical Considerations

AI use in medical applications poses several ethical issues such as informed consent, responsibility, and access. The involvement of AI in patient care has to be disclosed to them, although most do not know about it (Cohen *et al*., 2020). accountability A problem with AI errors that result in harm has not yet been answered: who is at fault- the developer, the clinician or the institution? (Price & Cohen, 2019). Moreover, the introduction of AI can increase healthcare disparities because sophisticated AI models will be used in well-financed systems, and underserved populations will be left behind (Panch *et al*., 2019).

4.5 Regulatory and Legal Implications

Regulation of AI in the field of healthcare is dynamic yet fluid. As of 2023, more than 500 AI-based medical devices were approved by the U.S. Food and Drug Administration (FDA), and existing regulatory frameworks have a hard time keeping up with rapid development (Muehlematter *et al*., 2021). The main issues that remain to be overcome are the constant AI monitoring after the implementation and the liability in the event of a malpractice (Tobia *et al*., 2021). In Europe, the AI Act suggests risk-based regulations, but it is complicated to align it with medical device regulations there (Gerke *et al*., 2020). There is also a legal issue of intellectual property regarding AI algorithms, data ownership, and how they can impede innovation (Price, 2019).

5.0 Conclusion

In this context, this review highlights the revolutionizing ability of Artificial Intelligence (AI) to improve healthcare delivery systems at clinical, operational, and administrative levels.

Machine learning, which is an artificial intelligence technology, as well as deep learning, natural language processing, computer vision, and robotics, are already having profound effects via enhanced diagnostic precision and enhanced precision medicine to optimized hospital operations and increased access to care through remote monitoring and virtual health assistants.

AI has demonstrated that it is capable of minimizing diagnostic errors, optimizing efficiency, individualizing treatment regimes, and minimizing costs. Such applications as disease detection in the early stages with the help of screening and imaging, risk assessment in the intensive care settings, and robotic surgery illustrate the potential of AI as a way to assist clinicians and improve patient care. Additionally, its incorporation in the administration of hospitals is smoothing operations, reducing wastage and enhancing resource distribution. Nonetheless, the popularization of AI has its problems. The issues of ethical concern, data privacy, algorithmic biases, and lack of transparency of decision-making models are real obstacles. Additionally, its extensive use in clinical settings is complicated by the uncertainty of regulators and infrastructural shortcomings.

In order to gain the full potential of AI, research directions in the future should be aimed at explainable and equitable AI, strong regulatory supervision, patient data security, and building the trust of land professionals and patients. In general, AI has significant potential to transform healthcare delivery, however, with a proper ethical, legal, and clinical implementation.

6.0 References

Abolade, Y.A. (2023). Bridging Mathematical Foundations and intelligent system: A statistical and machine learning approach. Communications in Physical Sciences, 9, 4, pp. 773-783

Abolade, Y. A., & Zhao, Y. (2024). A Study of EM Algorithm as an Imputation Method: A Model-Based Simulation Study with Application to a Synthetic Compositional Data. Open Journal of Modelling and Simulation, 12, 02, pp. 33–42. https://doi.org/10.4236/ojmsi.2024.122002

Ademilua, D.A., & Areghan E., (2025a). Cloud computing and Machine Learning for Scalable Predictive Analytics and Automation: A Framework for Soslving Real-world Problem. Communication in Physical Sciences, 2025 12, 2, pp. 406-416 https://dx.doi.org/10.4314/cps.v12i2.16

Ademilua, D.A., & Areghan E., (2025b). Review and Experimental Analysis on the Integration of Modern Tools for the Optimization of Data Center Performance. International Journal of Advanced Trends in Computer Science and Engineering. 2025, 14, 2, pp. 2278-3091 https://doi.org/10.30534/ijatcse/2025/0614 22025

Ademilua, D. A., & Areghan, E. (2022). AI-Driven Cloud Security Frameworks: Techniques, Challenges, and Lessons from Case Studies. Communication in Physical Sciences, 8, 4, pp. 674–688.

Adjei, F.A. (2025b). Artificial Intelligence and Machine Learning in Environmental Health Science: A Review of Emerging Applications. Communication in Physical Sciences, 12, 5, pp. 1480-1492

Adjei, F.A. (2025a). A Concise Review on Identifying Obesity Early: Leveraging AI and ML Targeted Advantage. Applied Sciences, Computing and Energy, 3, 1, pp. 19-31

Adjei, F.A. (2025c). Enhancing stroke diagnosis and detection through Artificial Intelligence. World Journal of Advanced Research and Reviews WJARR. 27, 01, pp. 1039-1049. https://doi.org/10.30574/wjarr.2025.27.1.2609

Ardila, D., Kiraly, A. P., Bharadwaj, S., Choi, B., Reicher, J. J., Peng, L., ... & Shetty, S. (2019). End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography. Nature medicine, 25, 6, pp. 954-961.

Amann, J., Blasimme, A., Vayena, E., Frey, D., & Madai, V. I. (2020). Explainability for artificial intelligence in healthcare: A multidisciplinary perspective. BMC Medical Informatics and Decision Making, 20, 1, pp. 310. https://doi.org/10.1186/s12911-020-01332-6

Barbieri, D., Giuliani, E., Del Prete, A., Losi, A., Villani, M., & Barbieri, A. (2021). How artificial intelligence and new technologies can help the management of the COVID-19 pandemic. International Journal of Environmental Research and Public Health, 18, 14, pp. 7648.

Bates, D. W., Saria, S., Ohno-Machado, L., Shah, A., & Escobar, G. (2014). Big data in health care: Using analytics to identify and manage high-risk and high-cost patients. Health Affairs, 33, 7, pp. 1123–1131. https://doi.org/10.1377/hlthaff.2014.004

Bruynseels, K., Santoni de Sio, F., & van den Hoven, J. (2018). Digital twins in health care: Ethical implications of an emerging engineering paradigm. Frontiers in Genetics, 9, pp. 31. https://doi.org/10.3389/fgene.2018.00031

Chow, J. C., Wong, V., & Li, K. (2024). Generative pre-trained transformer-empowered healthcare conversations: Current trends, challenges, and future directions in large language model-enabled medical chatbots. BioMedInformatics, 4, 1, pp. 837-852.

Chu, A., Mathews, L. R., & Yu, K. H. (2023). Artificial intelligence in health care: past and present. In Artificial Intelligence, Machine Learning, and Deep Learning in Precision Medicine in Liver Diseases (pp. 3-17). Academic Press.

Cohen, I. G., Evgeniou, T., Gerke, S., & Minssen, T. (2020). The European artificial intelligence strategy: implications and challenges for digital health. The Lancet Digital Health, 2, 7, pp. e376-e379.

Dada, S.A, Azai, J.S, Umoren, J., Utomi, E., & Akonor, B.G. (2024). Strengthening U.S. healthcare Supply Chain Resilience Through Data-Driven Strategies to Ensure Consistent Access to Essential Medicines. International Journal of Research Publications, 164, 1, pp. https://doi.org/10.47119/IJRP1001641120257438

Davenport, T. H., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. Future Healthcare Journal, 6, 2, pp. 94–98. https://doi.org/10.7861/futurehosp.6-2-94

Dorsey, E. R., & Topol, E. J. (2020). Telemedicine 2020 and the next decade. The Lancet, 395, 10227, pp. 859. https://doi.org/10.1016/S0140-6736(20)30424-4

Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. arXiv preprint. https://arxiv.org/abs/1702.08608

Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., ... & Dean, J. (2019). A guide to deep learning in healthcare. Nature Medicine, 25, 1, pp. 24–29.

Finlayson, S. G., Bowers, J. D., Ito, J., Zittrain, J. L., Beam, A. L., & Kohane, I. S. (2019). Adversarial attacks on medical machine learning. Science, 363, 6433, pp. 1287-1289.

Gerke, S., Minssen, T., & Cohen, G. (2020). Ethical and legal challenges of artificial intelligence-driven healthcare. Artificial Intelligence in Healthcare, pp. 295–336.

https://doi.org/10.1016/B978-0-12-818438-7.00012-5

Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., ... & Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. jama, 316, 22, pp. 2402-2410.

Haenssle, H. A., Fink, C., Schneiderbauer, R., Toberer, F., Buhl, T., Blum, A., ... & Zalaudek, I. (2018). Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists. Annals of oncology, 29, 8, pp. 1836-1842.

Holzinger, A., Langs, G., Denk, H., Zatloukal, K., & Müller, H. (2019). Causability and explainability of artificial intelligence in medicine. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 9, 4, pp. e1312. https://doi.org/10.1002/widm.1312

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., ... & Wang, Y. (2017). Artificial intelligence in healthcare: past, present and future. Stroke and vascular neurology, 2, 4.

Jiang, P., Gu, S., Pan, D., Fu, J., Sahu, A., Hu, X., ... & Liu, X. S. (2018). Signatures of T cell dysfunction and exclusion predict cancer immunotherapy response. Nature medicine, 24, 10, pp. 1550-1558.

Lakhani, P., & Sundaram, B. (2017). Deep learning at chest radiography: automated classification of pulmonary tuberculosis by using convolutional neural networks. Radiology, 284, 2, pp. 574-582.

Lee, J., Yoon, W., Kim, S., Kim, D., Kim, S., So, C. H., & Kang, J. (2020). BioBERT: a pre-trained biomedical language representation model for biomedical text mining. Bioinformatics, 36, 4, pp. 1234-1240.

Levin, S., Toerper, M., Hamrock, E., Hinson, J. S., Barnes, S., Gardner, H., Dugas, A., Linton, B., Kirsch, T., & Kelen, G. (2018). Machine-Learning-Based Electronic Triage More Accurately Differentiates Patients with Respect to Clinical Outcomes Compared With the Emergency Severity Index. Annals of emergency medicine, 71, 5, pp. 565–574.e2. https://doi.org/10.1016/j.annemergmed.2017.08.005

Li, L., Qin, L., Xu, Z., Yin, Y., Wang, X., Kong, B., ... & Xia, J. (2020). Using artificial intelligence to detect COVID-19 and community-acquired pneumonia based on pulmonary CT: evaluation of the diagnostic accuracy. Radiology, 296, 2, pp. E65-E71.

Liu, X., Faes, L., Kale, A. U., Wagner, S. K., Fu, D. J., Bruynseels, A., & Denniston, A. K. (2019). A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis. The lancet digital health, 1, 6, pp. e271-e297.

Liu, Y., Cao, X., Chen, T., Jiang, Y., You, J., Wu, M., ... & Chen, J. (2025). A Survey of Embodied AI in Healthcare: Techniques, Applications, and Opportunities. arXiv preprint arXiv:2501.07468.

Louie, D. R., & Eng, J. J. (2016). Powered robotic exoskeletons in post-stroke rehabilitation of gait: a scoping review. Journal of neuroengineering and rehabilitation, 13, pp. 1-10.

Maier-Hein, L., Mountney, P., Bartoli, A., Elhawary, H., Elson, D., Groch, A., ... & Stoyanov, D. (2013). Optical techniques for 3D surface reconstruction in computer-assisted laparoscopic surgery. Medical image analysis, 17, 8, pp. 974-996.

Meystre, S. M., Savova, G. K., Kipper-Schuler, K. C., & Hurdle, J. F. (2008). Extracting information from textual documents in the electronic health record: a review of recent research. Yearbook of medical informatics, 17, 01, pp. 128-144.

Meystre, S. M., Lovis, C., Bürkle, T., Tognola, G., Budrionis, A., & Lehmann, C. U. (2017). Clinical data reuse or secondary use: current status and potential future progress. Yearbook of medical informatics, 26, 01, pp. 38-52.

Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2018). Deep learning for healthcare: review, opportunities and challenges. Briefings in bioinformatics, 19, 6, pp. 1236-1246.

Muehlematter, U. J., Daniore, P., & Vokinger, K. N. (2021). Approval of artificial intelligence and machine learning-based medical devices in the USA and Europe (2015–20): A comparative analysis. The Lancet Digital Health, 3, 3, pp. e195–e203. https://doi.org/10.1016/S2589-7500(20)30292-2

Ndibe, O. S. (2025a). AI-Driven Forensic Systems for Real-Time Anomaly Detection and Threat Mitigation in Cybersecurity Infrastructures. International Journal of Research Publication and Reviews, 6, 5, pp. 389–411. https://doi.org/10.55248/gengpi.6.0525.1991

Ndibe, O. S. (2025b). Integrating Machine Learning with Digital Forensics to Enhance Anomaly Detection and Mitigation Strategies. International Journal of Advance Research Publication and Reviews. ijrpr 2, 05, pp. 365-388,

Ndibe, O.S., Ufomba , P.O. (2024). A Review of Applying AI for Cybersecurity: Opportunities, Risks, and Mitigation Strategies. Applied Sciences, Computing, and Energy, 1, 1, pp. 140-156

Okolo, J. N., Agboola, S. O., Adeniji, S. A., & Fatoki, I. E. (2025). Enhancing cybersecurity in communication networks using machine learning and AI: A Case Study of 5G Infrastructure Security. World Journal of Advance Reseach and Review, 26, 01, pp. 1210–1219. https://doi.org/10.30574/wjarr.2025.26.1.1098

Obermeyer, Z., & Emanuel, E. J. (2016). Predicting the future—big data, machine learning, and clinical medicine. The New England Journal of Medicine, 375, 13, pp. 1216–1219. https://doi.org/10.1056/NEJMp1606181

Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. Science, 366, 6464, pp. 447–453. https://doi.org/10.1126/science.aax2342

Panch, T., Mattie, H., & Celi, L. A. (2019). The "inconvenient truth" about AI in healthcare. NPJ Digital Medicine, 2, 1, pp. 77. https://doi.org/10.1038/s41746-019-0155-4

Parikh, R. B., Teeple, S., & Navathe, A. S. (2019). Addressing bias in artificial intelligence in health care. JAMA, 322, 24, pp. 2377–2378. https://doi.org/10.1001/jama.2019.18058

Patrício, L. (2024). Literature review and proposal framework for assessing robotic process automation and artificial intelligence projects in healthcare services. Journal of Artificial Intelligence and Autonomous Intelligence, 1, 2, pp. 11.

Price, W. N. (2019). Medical AI and contextual bias. Harvard Journal of Law & Technology, 33, 1, pp. 65–116.

Price, W. N., & Cohen, I. G. (2019). Privacy in the age of medical big data. Nature Medicine, 25, 1, pp. 37–43. https://doi.org/10.1038/s41591-018-0272-7

Rajalakshmi, R., Subashini, R., Anjana, R. M., & Mohan, V. (2018). Automated diabetic retinopathy detection in smartphone-based fundus photography using artificial intelligence. Eye, 32, 6, pp. 1138-1144.

Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. The New England Journal of Medicine, 380, 14, pp. 1347–1358. https://doi.org/10.1056/NEJMra1814259

Relling, M. V., & Evans, W. E. (2015). Pharmacogenomics in the clinic. Nature, 526, 7573, pp. 343–350. https://doi.org/10.1038/nature15817

Robert, & Avdhoot. (2025). AI use cases in healthcare. eLuminous Technologies. https://eluminoustechnologies.com/blog/ai-use-cases-in-healthcare/

Shang, Z., Chauhan, V., Devi, K., & Patil, S. (2024). Artificial Intelligence, the Digital Surgeon: Unravelling Its Emerging Footprint in Healthcare–The Narrative Review. Journal of Multidisciplinary Healthcare, pp. 4011-4022.

Shamout, F. E., Zhu, T., Sharma, P., Watkinson, P. J., & Clifton, D. A. (2019). Deep interpretable early warning system for the detection of clinical deterioration. IEEE journal of biomedical and health informatics, 24, 2, pp. 437-446.

Shickel, B., Tighe, P. J., Bihorac, A., & Rashidi, P. (2017). Deep EHR: a survey of recent advances in deep learning techniques for electronic health record (EHR) analysis. IEEE journal of biomedical and health informatics, 22, 5, pp. 1589-1604.

Tariq, A., Gill, A. Y., & Hussain, H. K. (2023). Evaluating the potential of artificial intelligence in orthopedic surgery for value-based healthcare. International Journal of Multidisciplinary Sciences and Arts, 2, 2, pp. 27-35.

Tobia, K., Nielsen, A., & Stremitzer, A. (2021). When does physician use of AI increase liability? Journal of Nuclear Medicine, 62, 1, pp. 17–21. https://doi.org/10.2967/jnumed.120.256032

Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. Nature Medicine, 25, 1, pp. 44–56. https://doi.org/10.1038/s41591-018-0300-7

van Winkel, S. L., Rodríguez-Ruiz, A., Appelman, L., Gubern-Mérida, A., Karssemeijer, N., Teuwen, J., ... & Mann, R. M. (2021). Impact of artificial intelligence support on accuracy and reading time in breast tomosynthesis image interpretation: a multi-reader multi-case study. European radiology, 31, 11, pp. 8682-8691.

Ufomba , P.O., Ndibe, O. S. (2023). IoT and Network Security: Researching Network Intrusion and Security Challenges in Smart Devices. Communication In Physical Sciences. 9, 4.

Umoren, J., Utomi, E., & Adukpo, T. K. (2025). AI-powered Predictive Models for U.S. Healthcare Supply Chains: Creating AI Models to Forecast and Optimize Supply Chain. IJMR, 11, 6, pp. 784–795

Utomi. E., Osifowokan, A. S., Donkor. A. A, & Yowetu. I. A. (2024). Evaluating the Impact of Data Protection Compliance on AI Development and Deployment in the U.S. Health sector. World Journal of Advanced Research and Reviews, 24, 2, pp. 1100–1110. https://doi.org/10.30574/wjarr.2024.24.2.3398

Wynants, L., Van Calster, B., Collins, G. S., Riley, R. D., Heinze, G., Schuit, E., ... & Moons, K. G. (2020). Prediction models for diagnosis and prognosis of COVID-19: Systematic review and critical appraisal. BMJ, 369, pp. m1328. https://doi.org/10.1136/bmj.m1328

Yang, G. Z., Cambias, J., Cleary, K., Daimler, E., Drake, J., Dupont, P. E., ... & Taylor, R. H. (2017). Medical robotics—Regulatory, ethical, and legal considerations for increasing levels of autonomy. Science robotics, 2, 4, pp. eaam8638.

Yi, X., Walia, E., & Babyn, P. (2019). Generative adversarial network in medical imaging: A review. Medical Image Analysis, 58, pp. 101552.

Yu, K. H., Beam, A. L., & Kohane, I. S. (2018). Artificial intelligence in healthcare. Nature Biomedical Engineering, 2, 10, pp. 719–731. https://doi.org/10.1038/s41551-018-0305-z

Declaration

Consent for publication

Not applicable

Availability of data

Data shall be made available on demand.

Competing interests

The authors declared no conflict of interest

Ethical Consideration

Not applicable

Funding

There is no source of external funding.

Authors' Contribution

C.O.A. led the manuscript drafting and contributed to sections on clinical applications of AI. E.O.O. conceptualized the study, conducted the literature synthesis, and revised the paper for public health relevance. C.F.U. contributed to content on diagnostic tools and AI technologies and assisted in reference validation. All authors reviewed and approved the final manuscript.