American Journal of Innovation in Science and Engineering (AJISE)

ISSN: 2158-7205 (ONLINE)

VOLUME 4 ISSUE 2 (2025)

PUBLISHED BY
E-PALLI PUBLISHERS, DELAWARE, USA

American Journal of Innovation in Science and Engineering (AJISE)

Volume 4 Issue 2, Year 2025
ISSN: 2158-7205 (Online)
DOI: https://doi.org/10.54536/ajise.v4i2.4432
https://journals.e-palli.com/home/index.php/ajise

The Current Landscape of AI Application in Healthcare: A Review

Gbenga Alex Ajimatanrareje[1], Chikodi Ekeh[1], Samuel Igwilo[1*], Chisom Osunkwo[1]

Article Information

Received: January 31, 2025

Accepted: March 03, 2025

Published: April 18, 2025

Keywords

Artificial Intelligence, Disease Diagnosis, Drug Discovery, Healthcare, Precision Medicine

ABSTRACT

The evolution of Artificial Intelligence (AI) in healthcare presents a unique blend of opportunities and challenges, particularly in enhancing healthcare delivery across important healthcare domains. These developments makes this review an interesting one as it explores AI's capacity to improve healthcare by making processes like drug discovery faster and more cost-effective, enabling early disease detection, tailoring healthcare to individual patient needs and continuous health monitoring. The paper examines the diverse applications of AI tools in healthcare across five (5) key domains (disease diagnosis and prognosis, drug discovery, precision medicine, clinical decision support, and smart wearables), highlighting their role in improving diagnostic accuracy, personalising treatment plans, aiding in medical decision-making, forecasting patient health trends and facilitating continuous patient monitoring. The insights from this review lead to a balanced perspective on AI's role in healthcare, emphasising the importance of adopting AI in a patient centric and ethically responsible manner while navigating the challenges that comes with it.

INTRODUCTION

Artificial Intelligence (AI) is transforming healthcare by enhancing diagnostic accuracy, accelerating drug discovery, enabling personalized treatment, and improving clinical decision-making (Bohr & Memarzadeh, 2020; Noorbakhsh-Sabet *et al.*, 2019). As healthcare systems increasingly adopt AI-driven solutions, these technologies are revolutionizing traditional medical practices, making healthcare more efficient, accessible, and data-driven.

Traditionally, medical diagnosis, prognosis, and drug discovery have relied on labor-intensive and time-consuming processes, often subject to human error and variability (Scannell *et al.*, 2012; Chang, 2016; Zhou & Zhong, 2017). AI, through machine learning and deep learning, is addressing these limitations by automating complex analyses, identifying patterns in vast datasets, and assisting healthcare professionals in making faster and more precise decisions (Lavecchia, 2014; Plenge, 2016). From AI-powered imaging in disease detection to predictive analytics in personalized medicine, AI is proving to be a disruptive force in healthcare innovation (Mumtaz *et al.*, 2023).

Despite its potential, the integration of AI in healthcare presents significant challenges, including ethical concerns, data privacy risks, regulatory complexities, and biases in AI models (Kamala *et al.*, 2022; Katoh & Katoh, 2019; Rawat *et al.*, 2023a; Delpierre & Lefèvre, 2023). Ensuring AI adoption remains patient-centric and ethically sound is critical to maximizing its benefits while minimizing unintended consequences.

This review provides a comprehensive analysis of AI applications in healthcare, examining its role in five key domains: disease diagnosis and prognosis, drug discovery, precision medicine, clinical decision support, and smart wearables. Additionally, it explores the challenges hindering AI's widespread adoption and discusses the future implications of AI-driven healthcare.

LITERATURE REVIEW

Overview of AI Tools in Healthcare

This section delves into the diverse array of AI tools that are being used in healthcare, focusing on the key technologies that drive these tools. Artificial Intelligence is the science of machines that can perform intelligent tasks that are comparable to human intelligence (Bini, 2018; Toh *et al.*, 2019). In general, AI is an umbrella term that covers Machine learning and other subfields of AI (Toh *et al.*, 2019). Machine learning also has various subfields and deep learning is one of them (Rahman & Afroz, 2013). Figure 1. shows the relationship between AI, machine learning and deep learning.

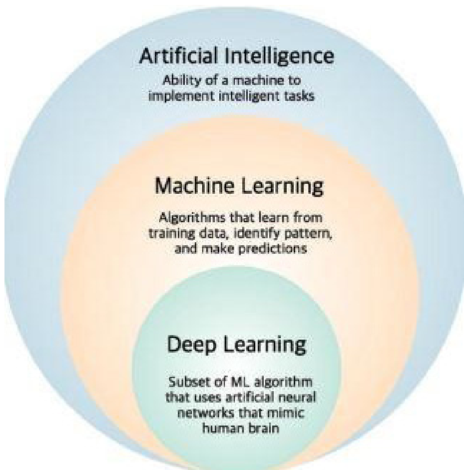

Figure 1: Hierarchy of artificial intelligence, machine learning and deep learning (Rahman & Afroz, 2013).

[1] Department of Data Science and AI, Bournemouth University, United Kingdom
[*] Corresponding author's e-mail: s5552175@bournemouth.ac.uk

Classification of Machine Learning

Machine Learning (ML) algorithms are changing the way we understand and predict health outcomes. These algorithms are good at learning from data, identifying complex patterns, and also making predictions about new and unseen data, all without explicit programming (Schuhmacher *et al.*, 2021b). There are three primary types of ML algorithms: supervised, unsupervised, and reinforcement learning. The type of machine learning algorithm chosen depends on several factors, which includes the type of data set and also the type of problem (Schuhmacher *et al.*, 2021b). Figure 2 shows the classification of different machine learning methods.

Supervised learning methods are machine learning methods that use labelled data to train models and once these models have been trained, the models can then be used to predict outcomes on unseen data (Vamathevan *et al.*, 2019). Supervised learning methods can be divided into regression based and classification modelling approaches (Vamathevan *et al.*, 2019). Furthermore, classification methods can be categorised into multiclass, binary and multi-label depending on the specific classification tasks. These methods excel in healthcare applications by mapping complex data, such as molecular structures, and have shown to outperform other methods in certain instances (Rahman & Afroz, 2013).

Unlike supervised learning, unsupervised algorithms work with unlabeled data, which is often used in exploratory data analysis. Some unsupervised algorithms like k-means clustering are prevalent in healthcare, particularly in drug design, as they are used to contribute to developing Quantitative Structure-Activity Relationship (QSAR) models (Vamathevan *et al.*, 2019).

Reinforcement learning (RL) systems are systems that continuously interact with the environment using a feedback mechanism from its previous experiences and actions to achieve their new objectives and goals. Unlike supervised and unsupervised learning, RL trains algorithms to learn from their environments and each time an RL agent acts, its objective function is designed such that it gets rewarded if the output it produces is acceptable and penalised if it produces an incorrect or unacceptable output (Rahman & Afroz, 2013). RL algorithms such as Generative Tensorial Reinforcement Learning (GENTRL), and Reinforcement Learning for Structural Evolution (ReLeaSE), have been used in designing molecules with desired properties, significantly impacting drug development and generative modelling (Zhavoronkov *et al.*, 2019).

Deep learning (DL), which is a subset of machine learning and part of the artificial neural network (ANN) family, mirrors the human brain's structure with multiple layers of processing elements (or neurons). DL methods, particularly Convolutional Neural Networks (CNNs) (Schuhmacher *et al.*, 2021b), have been particularly instrumental in drug discovery. Deep learning networks model complex interactions, such as a small molecule binding to a protein (Gomes *et al.*, 2017), and therefore improves property prediction (Soares *et al.*, 2022). The strength of a deep learning model lies in its ability to process vast amounts of data and extract meaningful patterns, and therefore this makes it an important tool in modern healthcare technology.

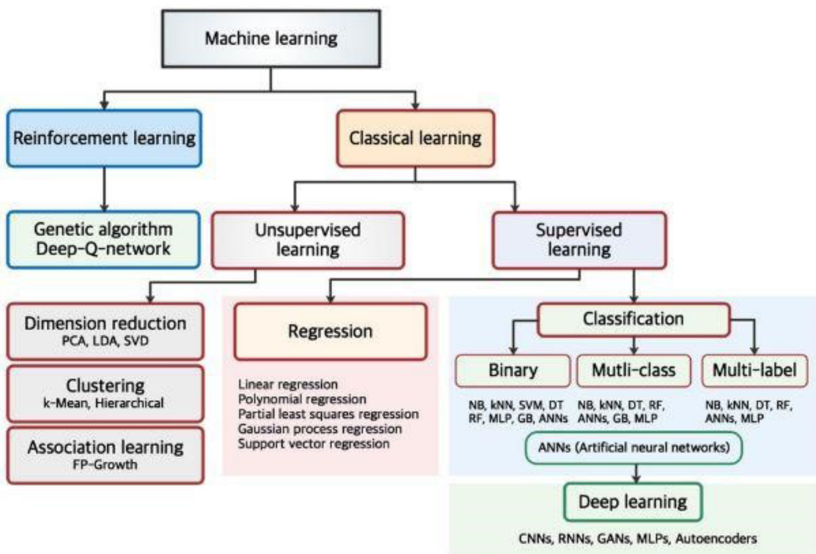

Figure 2: Classification of machine learning methods (Rahman & Afroz, 2013).

AI application in disease diagnosis and prognosis

Radiological imaging is one of the cornerstones of modern diagnostics that has been transformed by AI using convolutional neural networks (CNNs) (Yamashita *et al.*, 2018). One such advancement is the work done by Wang *et al.* (2019) that applied Convolution Neural Networks to interpret chest X-rays which identified lung nodules critical for early lung cancer detection (Wang

& Xia, 2018). These deep learning models are good at discerning minute details in imaging data which surpasses human accuracy in some instances. The impact of this Artificial Intelligence technology is profound because it offers not just enhanced diagnostic accuracy but also a significant reduction in image analysis time (Wang & Xia, 2018). Radiologists that are equipped with these AI tools can now diagnose more efficiently which leads to faster patient care and potentially better outcomes. The application of Artificial Intelligence in radiology is not just limited to lung cancer but it extends to other varieties of conditions which makes it a versatile tool in diagnostic medicine (Soares *et al.*, 2022).

AI has made progress in the realm of dermatology, especially in skin cancer detection. Esteva *et al.* (2017) harnessed deep learning to distinguish between benign and malignant skin lesions, training their model on an extensive dataset of skin images. The deep learning model they developed achieved diagnostic precision that is on par with experienced dermatologists which marks a substantial advancement in the early detection of skin cancers, including melanoma. This AI technology's potential goes beyond clinical settings to applications in routine screenings and remote consultations which makes it a valuable tool in telemedicine (Dildar *et al.*, 2021). Given that this technology is non-invasive, its rapid, and highly accurate make it not only useful in early detection but also reduces the need for unnecessary biopsies which streamlines patient care and reduces healthcare costs (Esteva & Topol, 2019). This development in Artificial intelligence-facilitated dermatology is a testament to how artificial intelligence techniques such as convolutional neural networks can help enhance patient outcomes and improve traditional diagnostic practices (Dildar *et al.*, 2021).

Similarly, AI integration into pathology in cancer diagnosis marks a notable evolution in this critical medical field. Bera *et al.* showcased the potential of Artificial Intelligence, specifically a machine learning model in analysing histopathology slides, and this is usually a task that is traditionally reliant on the expertise of pathologists (Bera *et al.*, 2019). The artificial intelligence system they developed efficiently identifies and classifies various cancer cells which provide essential insights for accurate diagnosis and treatment planning. This advancement that artificial intelligence offers brings a significant enhancement over conventional microscopy by bringing consistency, speed, and precision to cancer diagnosis (Wang *et al.*, 2019). The application of AI in pathology is not only limited to cancer but also extends to various diseases, which aids pathologists in diagnosing a wide range of conditions more accurately and efficiently (Bera *et al.*, 2019). Automating part of the diagnostic process allows pathologists to focus on more complex aspects of case analysis and patient care and thus augmenting the overall diagnostic workflow (Lu *et al.*, 2021).

Also, the application of AI in cardiac care through predictive analytics has improved patient outcomes (Rumsfeld *et al.*, 2016). Churpek *et al.* (2011) used a machine learning model that analyses electronic health records (EHRs) to identify patients at heightened risk of heart failure. This model is skilled at sifting through vast amounts of patient data including medical histories, laboratory results, and vital signs, to predict heart failure even before it becomes clinically apparent. Having this kind of early detection is important for initiating preventive measures because it potentially averts severe cardiac events. Additionally, the ability of AI to process and analyse data beyond human capacity enables a more nuanced approach to cardiac care which tailors interventions to individual risk profiles (Wessler *et al.*, 2015). The predictive capability of artificial intelligence models is particularly valuable when managing chronic cardiac conditions because it offers a proactive approach to healthcare that can reduce hospital admissions and improve the quality of life for patients with heart conditions (Churpek *et al.*, 2011).

Additionally, AI has also brought about advancements in the field of neurology particularly in the early detection of neurodegenerative diseases. EL-Geneedy *et al.* (2022) utilised a deep learning model to analyse brain imaging for early signs of neurological disorders, such as Alzheimer's disease. This approach helps to identify subtle neurodegenerative changes that are often missed in standard diagnostic procedures, and early diagnosis is critical in neurodegenerative diseases because it allows for earlier intervention, which can slow disease progression and improve patient outcomes. The application of AI in neurological disorders exemplifies how this technology can enhance the capabilities of neurologists and radiologists, it also provides them with powerful tools to detect and monitor neurological disorders more effectively (Raghavendra *et al.*, 2019). This use case shows the potential of Artificial intelligence to transform the landscape of neurological disorder care which offers hope for earlier and more accurate diagnoses for patients with these challenging conditions.

Furthermore, the COVID-19 pandemic accelerated the integration of AI in public health, notably in the area of diagnostics. A significant contribution was made by Le *et al.* (2021) where they developed a system combining Internet of Things (IoT) technology with Artificial Intelligence for COVID-19 diagnosis. The system they developed employed IoT sensors to collect essential health data from patients; this data was then processed through 5G networks to cloud storage. Here, AI algorithms, particularly Support Vector Machines (SVM) and Convolutional Neural Networks (CNNs) were used to analyse the data for diagnostic purposes. Their approach exemplified how AI, when integrated with other technologies like IoT, can play a crucial role in rapid, accurate disease diagnosis, which is crucial for effective pandemic management. Such applications underscore AI's potential not only in routine healthcare but also in responding to global health emergencies, marking a significant step in digital healthcare evolution (Malik *et al.*, 2020).

These use cases which are summarised in Table I below is a summary of the transformative impact of AI in various aspects of disease diagnosis and prognosis, the methods employed and the papers where these use cases are discussed. So, by harnessing the capabilities of machine learning and deep learning, these AI applications are redefining disease diagnosis and prognosis processes, enabling earlier disease detection and improving prognostic accuracy, which ultimately leads to better patient outcomes and more efficient healthcare delivery.

Table 1: Summary of impacts of AI in various aspects of disease diagnosis and prognosis

Applications	**AI methods employed**	**Authors**
Radiological Imaging	Convolutional Neural Networks	Wang and Xia (2018)
Skin Cancer Detection	Deep Learning Models	Esteva and Topol (2019)
Pathology for Cancer Diagnosis	Machine Learning Algorithms	Bera *et al.* (2019)
Predictive Analytics in Cardiac Care	Machine Learning Algorithm	Churpek *et al.* (2011)
Neurological Disorder Diagnosis	Deep Learning Algorithm	EL-Geneedy *et al.* (2022)
COVID-19 Diagnosis and Pandemic Response	Convolutional Neural Networks and Support Vector Machines	Le *et al.* (2021)

AI application in drug discovery

In the domain of drug discovery, machine learning has been used to identify intensely bitter molecules early in the drug development process, this is a crucial factor considering the taste can influence a medication's acceptability. Margulis *et al.* (2021) successfully used machine learning as an alternative to animal testing to predict the bitterness of drug molecules with 80% match to traditional taste aversion experiments. This study has helped in revealing machine learning's potential in identifying bitter molecules in the drug development process and also helped to reveal that bitterness and toxicity do not always go hand in hand, thereby challenging previous assumptions.

Further study that showcases the potential of machine learning in identifying molecules features was conducted by Raschka and Kaufman (2020) by using machine learning to recognize molecules that interact with G-protein coupled receptors (GPCRs), this is a cornerstone in developing new drugs. Their machine learning algorithm's predictions were as reliable as established experimental methods, thereby suggesting a future where such AI technology can be used to streamline the drug discovery process (Raschka & Kaufman, 2020).

Also, Cui and Zhu (2021) used a deep learning algorithm - ResNet to predict the physicochemical properties of drugs. These physicochemical properties are partition coefficient, solubility and dissociation constant. This application of AI in drug discovery proved to be more precise in forecasting drug solubility than traditional methods, and thereby indicating a significant leap towards enhancing drug development procedures. Similarly, Lusci *et al.* (2013) employed a recursive neural network (RNN) to predict the solubility of molecules in water, and this resulted with their AI model outperforming conventional techniques. These studies collectively underscore AI's transformative role in drug discovery as not just as a tool for prediction but also as a means to accelerate and refine the pharmaceutical development pipeline.

Daynac *et al.* (2015) leveraged the power of an artificial neural network (ANN) to predict which molecules possess antimicrobial properties, this breakthrough promises to make the drug discovery process to be not only faster but also more cost effective. Their study showed that the artificial neural network predicted antimicrobial activity with more than 70% accuracy, this keeps the error margin low. Additionally, the ANN capability to simultaneously predict the behaviour of multiple molecules marks an advancement in comparison to existing methods therefore showcasing the efficiency of AI in enhancing the rapid identification of new antimicrobials.

Stokes *et al.* (2020) deployed a deep learning network to search the ZINC database thereby successfully identifying Halicin and eight other potential antibiotics. The AI model used was trained to spot various compounds that are effective against formidable antibiotic resistant bacteria, this is a feat that marks a significant stride in the fight against global antibiotic resistance.

In order to compare the performance of different machine learning subcategories, Turki and Taguchi (2019) demonstrated the speed of reinforcement learning in identifying promising drugs, and this resulted in cutting down the discovery process to 46 days, this is a significant reduction from traditional timelines. On the other hand, Rantanen and Khinast (2015) employed transfer learning to accurately predict drug responses in multiple myeloma patients, and therefore achieving greater predictive accuracy than prior methods used.

Polykovskiy *et al.* (2018) showcased how AI could finetune the drug discovery process. Their study focused on using an adversarial autoencoder which is a type of AI model to predict the activity of newly synthesised molecules. This method along with a recurrent neural network has proved to be complementary in generating both random and targeted drug-like compounds. The results they obtained showed an increased efficiency in identifying viable molecules and it shed light on target interactions, and thus affirming that AI can enhance the precision of drug screening while also unlocking new insights into molecule behaviour.

Kadurin *et al.* (2017) and Al-Safarini and El-Sayed (2021) examined two AI methodologies to streamline drug discovery. Kadurin *et al.* (2017) applied adversarial autoencoders to speed up the search for anticancer agents, and this successfully sifted through millions of candidates with a good efficiency. However, Maram and Hamdy took a different approach, they used AI to predict how various molecules would react with different cell types, this technique demonstrated a higher accuracy and a lower error margin than traditional methods, and therefore underscoring AI's potential to transform pharmaceutical development.

Pu *et al.* (2019) used AI with the goal of redefining toxicity testing. Their program, which was named 'eToxPred' was designed to swiftly and accurately assess the safety of different compounds, and the result showed the AI model predicted toxicity in over 72% of cases with few errors. These findings suggest that AI could one day reduce or even replace the need for some clinical trials, thereby speeding up the time it would take for new drugs to reach those in urgent need of them.

Table 2 below shows an overview of exemplary studies for drug discovery, the methods of AI adopted in the case studies and the authors of these papers.

Table 2: Summary of applications of AI in drug discovery

Applications	**AI methods employed**	**Authors**
Test to predict the bitterness of molecules used in the design of drugs.	Machine Learning Algorithms	Margulis *et al.* (2021)
Integration of G-protein coupled receptor (GPCR) ligand recognition.	Machine Learning Algorithms	Raschka and Kaufman (2020)
Prediction of the physicochemical properties of various drugs.	Deep Learning Algorithm	Raschka (2019)
Predicting antimicrobial properties of different molecules.	Artificial Neural Networks	Daynac *et al.* (2015)
Prediction of the levels of toxicity of different biological and synthetic compounds.	Artificial Neural Networks	Pu *et al.* (2019)
COVID-19 Diagnosis and Pandemic Response	Convolutional Neural Networks and Support Vector Machines	Le *et al.* (2021)

AI application in precision medicine and treatment

AI has played a significant role in enhancing cardiovascular conditions' precision care using machine learning-based ensemble algorithms (Gruson *et al.*, 2020; Cikes *et al.*, 2018). AI in cardiovascular disease is applied in the forecasting of mortality using a Cox model on over 82,000 patients Electronic Health Data described by Steele *et al.* (2018). Top performing Machine learning algorithms - Elastic net Cox regression yielded 0.801 C- indexes, demonstrating the feasibility of prognosis prediction using ML in comparison to conventional Cox models with 0.793 C- indexes, relying on existing electrocardiogram (ECGs) technology for personalised heart disease detection.

Similarly, Baydoun *et al.* (2019) investigated the viability of transforming printed or scanned ECG to a digital ECG signal using a ML algorithm built-in MATLAB-based tool. The validated result from the study showed an extremely high correlation between ECG parameters from various records, with more than 95% of the scanned ECGs converted into digital ECG signals. This facilitates personalised diagnosis and prognostic evaluation of patients with cardiovascular illness by allowing the integration of historical ECG signals in machine learning algorithms to identify trends in heart disease.

Optical care has also benefited from AI technology and precision medicine. To develop a prediction model that could analyse information for glaucoma diagnosis, Kim *et al.* (2017) examined four machine-learning algorithms in their work. Random forest (RF), support vector machine (SVM), and k-nearest neighbour (KNN) were examined. Random forest had the highest performance score proposing a discovery on how to diagnose and treat visual conditions with AI and Precision Medicine.

Dekhil *et al.* (2018) developed an automated diagnostic system for autism, which influenced customised autism medication that operates a stack encoder fed Power Spectral Densities (PSDs). The National Database of Autism Research supplied the data used in constructing a classifier with probabilistic support vector machines which gained accuracy, specificity and sensitivity of 90%.

Treatment optimization of individual genetic makeup and characteristics is the primary focus of precision medicine. AI algorithms have been used in various research, including clinical trials to evaluate personalised patient outcomes and predict treatment responses (Bartlett *et al.*, 2018; Webb *et al.*, 2018; Van Bronswijk *et al.*, 2019). In a trial study, Webb *et al.*, 2018 examined the efficacy of a placebo and eight weeks of sertraline for persons with depression. Using endophenotype profiles combined with clinical and demographic data, machine learning and a Personalized Advantage Index (PAI) were used to create individualised treatment plans for patients experiencing major depressive episodes. It was found that older patients and those with less severe cognitive control impairments responded better to Selective Serotonin Reuptake Inhibitors (SSRIs).

Similar investigation on depression treatment, employed machine learning models, specifically Classification-Regression Trees (CRT) and Support Vector Machines (SVM), along with Genome-Wide Association Study

(GWAS) data to assess the effects of duloxetine (SSRI) and patient outcomes in individuals with Major Depressive disorder (MDD). The models demonstrated favourable sensitivity, although specificity was only moderately satisfactory (Maciukiewicz *et al.*, 2018).

In cancer therapy, a machine learning methodology - Support Vector Machine (SVM) may be utilised in conjunction with the more conventional recursive feature elimination (RFE) method. Patient-specific predictive models were developed using data on gene expression and treatment response from the National Cancer Institute panel. The models correctly predicted the pharmacological responses of a variety of cancer cell lines (Huang *et al.*, 2017).

According to the research by Albizu *et al.* (2020), machine learning algorithms in the form of cutting-edge techniques like Finite Element Models (FEM) and SVM algorithms were able to classify responders and non-responders to transcranial direct current stimulation (tDCS) treatment with 86% accuracy. The work offered the first proof that individual prognosis categorization of tDCS treatment response can be significantly accurate when obtained from MRI-derived tDCS current models through pattern recognition analyses.

Christie *et al.* (2019) described an AI potential use case in a traumatic condition. Using 1,494 severely injured patients, an ensemble ML algorithm named Super Learner was utilized to assess precision medicine in trauma to identify modifiable conditions patients may suffer following severe trauma. The researchers concluded that ML algorithms can help transform trauma patient data into real-time, dynamic decision-making support based on the algorithm's outputs.

Sharma *et al.* (2021) designed a working prototype of an intelligent chatbot that can predict stress levels and its management. A decision tree algorithm was used to train the data and predict the most accurate stress level based on the patient-associated factors.

AI has been used to prioritise treatment for COVID-19 patients, perform triage, and more effectively assign the few resources available (Santus *et al.*, 2021). Using a Logistic regression-trained model, a team of China researchers developed an online triage tool to treat adult patients presented with fever and who may likely have COVID-19 (Feng *et al.*, 2021). Their research utilised data sets from clinical symptoms, standard laboratory testing, and admission. The ML algorithm achieved 0.841 as the area under the receiver operating characteristic curve (AUROC) (100 percent sensitivity and 72.7 percent specificity) (Feng *et al.*, 2021).

A breakthrough in cancer treatment using AI is the IBM Watson for Oncology (WFO) (Rawat *et al.*, 2023). Watson for Oncology (WFO) is a trained cognitive computing system that provides confidence-ranked, evidence-based cancer treatment recommendations. WFO utilises natural language processing and machine learning to analyse both organised and unstructured data from laboratory reports, medical records, medical literature, and treatment guidelines (Rawat *et al.*, 2023). Recent studies Zhou *et al.* (2018), Park *et al.* (2023), and Zou *et al.* (2020) demonstrated substantial coherence between IBM Watson for Oncology (WFO) and real-world decisions made by clinicians for specific cancer malignancies.

Bentley *et al.* (2014) applied machine learning to forecast and evaluate the effectiveness of stroke therapy. Owing to how intravenous thrombolysis (tPA) can determine patient survival rate, Support Vector Machines were used to show if tPA-treated patients would experience symptomatic cerebral haemorrhage using CT scan. Results revealed that SVM fed with whole-brain image data outperformed traditional radiology-based techniques.

Chatbots and virtual assistants driven by AI offer personalised healthcare services and assistance with self-management. Natural language processing (NLP) and machine learning (ML) algorithms facilitate effective communication between patients and chatbots as well as gradual improvement of responses (Rawat *et al.*, 2023). A review study conducted by Vaidyam *et al.* (2019) revealed the potential of AI conversational agents to increase psychoeducation and self-adherence thereby being recommended as a helpful tool for the treatment of psychiatric conditions.

Table 3 below shows a summary of the studies for application of AI in Precision medicine and Treatment optimization, the AI methods and the authors.

Table 3: Summary of applications of AI in Precision medicine and Treatment optimization

Applications	**AI methods employed**	**Authors**
Personalized/Precision Cardiovascular disease detection.	Elastic net Cox regression	Steele *et al.* (2018) and Baydoun *et al.* (2019)
Personalised diagnosis and treatment of visual conditions like glaucoma	Random forest (RF), support vector machine (SVM), and K-Nearest Neighbour (KNN)	Kim *et al.* (2017)
Customised Autism diagnosis	Support Vector Machines	Dekhil *et al.* (2018)
Personalised therapy for Major Depressive Disorder	Decision Tree	Webb *et al.* (2018) and Maciukiewicz *et al.* (2018)
Treatment Response for Cancer	Support Vector Machine (SVM)	Feng *et al.* (2021)
Personalised prediction of stress level	Decision Tree	Huang *et al.* (2017)

Personalised treatment of COVID-19	Logistic regression	Huang *et al.* (2017)
Personalised cancer treatment by IBM Watson for Oncology (WFO)	Natural Language Processing and Machine Learning	Somashekhar *et al.* (2017)
Treatment adherence using Chatbots	Natural Language Processing and Machine Learning	Vaidyam *et al.* (2019)

AI application in clinical decision support

This section elaborates on various studies that indicate the actual application of artificial intelligence tools to aid in clinical decision support in healthcare. According to a case study, Rajkomar *et al.* (2018) used deep learning models to predict patient outcomes by analysing electronic health records (EHRs). Their study concentrated on how well recurrent neural networks (RNNs) could identify temporal correlations in patient data. The study found that RNNs showed the potential to enhance forecast accuracy by identifying subtle patterns and fluctuations because of their capacity to manage the time-dependent nature of EHRs. This study highlights the significance of taking temporal dynamics into account when analysing patient data, which adds to the expanding field of machine learning applications in healthcare (Rajkomar *et al.*, 2018).

Another research study conducted by Esteva *et al.* (2017) showed how well a deep learning algorithm can classify skin lesions with accuracy in line with dermatologists. Their study demonstrated the algorithm's ability to analyse photos for early skin cancer identification, highlighting its value as a diagnostic tool for dermatology. According to Esteva *et al.* (2017), the study demonstrated how AI might help medical practitioners increase the effectiveness of skin cancer screenings and enable early intervention for better patient outcomes.

Another notable study by Hannun *et al.* (2019) showed how artificial intelligence (AI) may be used to diagnose heart diseases. To demonstrate the accuracy of AI in diagnosing a range of heart problems, the research focused on applying machine learning algorithms to analyse electrocardiogram (ECG) data. The results demonstrated how well AI can identify tiny irregularities in ECGs, highlighting its potential as a useful tool for healthcare providers to diagnose heart diseases accurately and early.

A significant study investigating the use of artificial intelligence in mammography-based breast cancer screening was carried out by McKinney *et al.* (2020). The study showed that artificial intelligence (AI) algorithms could improve breast cancer detection accuracy, especially in the early stages. The study demonstrated how AI might be used as an additional diagnostic tool for radiologists, enhancing accuracy by looking for minute abnormalities in mammography pictures. According to the research, including AI in breast cancer screening could help with early diagnosis and better patient outcomes.

A study conducted by Shameer *et al.* (2017), examined the clinical notes of individuals with heart failure in electronic medical records using Natural Language Processing (NLP). Predicting readmissions for heart failure and enhancing patient outcomes were the goals. Important data, such as symptoms, comorbidities, and treatment plans, were extracted from unstructured data using natural language processing (NLP) approaches. The study showed that integrating NLP-derived insights considerably improved the accuracy of prediction models as compared to using simply structured data by merging this knowledge with structured data. This case study serves as an excellent illustration of how to effectively use natural language processing (NLP) to leverage clinical notes for enhanced clinical decision-making and predictive modelling.

Nemati *et al.* (2018) aimed to develop a machine learning algorithm that can identify early sepsis in ICU patients using Artificial Intelligence. The model attempted to quickly detect sepsis trends by using continuous physiological data from remote monitoring equipment, such as vital signs and test results. The excellent accuracy of an AI-powered method in predicting sepsis demonstrated its potential for proactive clinical decision-making. The research highlights the importance of artificial intelligence (AI) in remote patient monitoring, presenting a useful tool to augment healthcare practitioners' capacity to immediately intervene and enhance patient outcomes.

The applicability of AI-enhanced remote patient monitoring was examined by Pecchia *et al.* (2011), with a particular emphasis on heart failure patients. The study investigated the use of wearable technology to track physiological markers including heart rate and activity level continuously. The gathered data was analysed using AI algorithms with the goal of finding any deviations from the norm. Enabling early detection of possible health deteriorations was the aim to facilitate prompt actions. The case study highlights the value of proactive and individualised clinical decision-making in the management of chronic diseases by demonstrating how AI-driven remote monitoring can assist doctors in making knowledgeable decisions based on real-time patient data.

CheXNet, a CNN-based system that outperforms board-certified radiologists in pneumonia detection from chest X-rays, is the subject of this discovery. Rajpurkar *et al.* (2017) describe how CheXNet can match or exceed radiologist-level accuracy in correctly identifying pneumonia. CheXNet is trained on a wide range of data sets, and its ability to generalise across instances marks a significant advancement in the use of AI in radiology. This finding emphasises how deep learning models can improve diagnostic precision, especially when interpreting complicated medical images.

According to Bejnordi *et al.* (2017), Google researchers created a deep learning algorithm for identifying lymph node metastases as part of their effort to improve breast cancer pathology diagnoses. The Camelyon16 Challenge saw the system outperform board-certified pathologists, having been trained on a dataset of hematoxylin and eosin-stained pathology slides. This achievement demonstrates the algorithm's capacity to identify minute signs of metastasis and highlights the revolutionary effects of artificial intelligence (AI) in pathology. These results are consistent with further uses of deep learning, especially in medical image processing using Convolutional Neural Network (CNN) methods. The study provides an in-depth analysis of the methods and practical applications of these innovative investigations which highlights the critical role that artificial intelligence plays in improving diagnostic precision in pathology and dermatology.

The final study in this literature review that demonstrates the use of artificial intelligence in clinical decision support was carried out by Liu *et al.* (2018), which used artificial intelligence (AI) and neuroimaging data analysis to predict the course of Alzheimer's disease. The study showed how their AI model could analyse intricate structural and functional data from neuroimaging modalities to find patterns suggestive of the onset of Alzheimer's disease. The model's capacity to identify minor patterns linked to cognitive decline is what makes the study significant; it holds promise for early Alzheimer's disease diagnosis and intervention (Liu *et al.*, 2018).

AI application in smart wearable

There is an increasing interest in wearable devices that constantly monitor our health and well-being. Some examples of this technology include using smart wearable devices for circadian rhythms and sleep monitoring (Bianchi, 2018), fatigue detection (Moshawrab *et al.*, 2022), fall detection for elderly people (Pierleoni *et al.*, 2015), and human emotion and stress recognition (Zamkah *et al.*, 2020). This section of the review will focus on highlighting a few exemplary studies where AI has made a real impact in healthcare using smart wearables.

One study that revealed the application of machine learning in smart wearables was done by Desai *et al.* (2020). They created a special belt called 'Hip-grip' that can tell if someone is about to fall. This belt has sensors that can tell the difference between walking, jogging, running, and even bending or squatting. If it senses a fall, it knows if it's forward, sideways, or backward. The results from this study showed that the belt based wearable device was able to detect a fall within a quarter seconds with good accuracy.

Similarly, a study performed by Zurbuchen *et al.* (2020) is another exemplary application of a system that can detect falls using a smart wearable waist device that utilises machine learning algorithms. This device uses a combination of motion sensors to track movements. They used a public database called SisFall, which has lots of information on everyday activities and fall incidents. By analysing this data with different machine learning algorithms, they found that some methods, like random forest and gradient boosting, were almost 99% accurate in sensing a fall (Zhao *et al.*, 2020).

Zhao *et al.* (2020) conducted a study using artificial neural networks, a type of AI, to analyse bowel sounds. They developed a wearable system that can tell the difference between important bowel sounds from just background noise. The system they developed uses convolutional neural networks (CNN) to analyse the sound data, and It works by converting the sounds into a visual format like a spectrogram, and then the AI can figure out which sounds are relevant. In tests, their system classified bowel sounds with an accuracy 99.92% as at the time of the study.

Ali *et al.* (2021) designed a system that monitors healthcare, utilising smart wearable and AI technologies to improve data handling efficiently and also classifying the healthcare data for monitoring patients' health. Their system uses a type of AI called bidirectional long short-term memory (Bi-LSTM) to sort through health data, and this data could come from different places like phones, wearables, or medical records. The system they developed stores all this data in the cloud and then analyses it to spot any health issues, such as adverse drug reactions or changes in a patient's condition. This technology is helpful for people with conditions like diabetes or high blood pressure because it keeps them and their healthcare providers updated on their health status (Ali *et al.*, 2021).

Jacobson *et al.* (2021), Bauer *et al.* (2020) and Janarthanan *et al.* (2020) explored the use of AI in wearable devices for different purposes. Jacobson *et al.* (2021) used deep learning, which is an advanced AI technique with wearables to track and predict changes in panic disorder and anxiety symptoms throughout the day and night. Bauer *et al.* (2020) on the other hand focused on helping people with vision impairments make sense of their environment. They used a smartwatch with deep learning to create a 3D view of the wearer's surroundings by identifying obstacles and making navigation easier. Another study by Janarthanan *et al.* Janarthanan *et al.* (2020) used deep learning to improve how wearable sensors recognize different human activities, such as walking or climbing stairs. Their approach was unique in reducing errors and increasing accuracy in activity recognition.

Young *et al.* (2020) proposed an approach which utilised a deep learning-based wearable device to help people who have a hearing disability to communicate with others. Using the Internet of Things system, the approach contains a server application that converts the output of Google's online speech recognition system into text. The content of the text information is displayed using the deployment of a micro-display device for people with a hearing disability. This approach helps in assisting deaf people to communicate with others with a non-hearing disability (Young *et al.*, 2020).

Rad *et al.* (2017) proposed a wearable device that detects motion in patients with autism spectrum disorder using a convolutional neural network. To learn the characteristics from raw data that were obtained from different wearable sensors, three convolution neural network layers known as SMM, LSTM, and CNN were employed. The authors also introduced a concept which combines this neural network for the improvement of stereotypical motor movement.

Table 4 below shows a summary of the exemplary studies for healthcare in smart wearables, the AI methods employed and the authors.

Table 4: Summary of applications of AI in smart wearables

Applications	AI methods employed	Authors
A wearable belt device that can detect falls	Machine Learning Algorithms	Desai *et al.* (2020)
An edge bowel sound (BS) wearable system that select idle BS events	Convolutional Neural Networks	Zhao *et al.* (2020)
Smart wearable for monitoring the health of patients	Machine Learning Algorithms	Ali *et al.* (2021)
Monitor and forecast the decline in anxiety and panic disorder symptoms	Deep Learning Algorithm	Bauer *et al.* (2020)
A smart device that assist patients with hearing disability to communicate with others	Deep Learning Algorithm	Janarthanan *et al.* (2020)
A wearable device that detects motion in patients with autism spectrum disorder	Convolutional Neural Networks	Young *et al.* (2020)

RESULTS AND DISCUSSION

Challenges of AI Application in Healthcare

Data Limitations and Technical Barriers

AI models, particularly deep learning, require vast amounts of high-quality, well-annotated data for effective training (Dash *et al.*, 2019; Willemink *et al.*, 2020). However, challenges such as data scarcity, privacy concerns, and inconsistencies in healthcare data collection hinder AI performance. Incomplete or biased datasets can lead to inaccurate predictions, posing risks to patient care (Ching *et al.*, 2018).

Ethical and Privacy Concerns

AI's reliance on patient health data raises significant privacy and ethical challenges, making data protection and secure authentication critical concerns. Adhering to strict data protection regulations while ensuring patient confidentiality remains a delicate balance (Morley *et al.*, 2020; Radanliev & De Roure, 2022). Additionally, the rise of AI-driven healthcare applications increases the risk of data breaches, threatening public trust and the responsible deployment of AI technologies (Morley *et al.*, 2020).

Ensuring the security and privacy of AI-driven healthcare systems requires robust authentication and verification mechanisms. Similar to the Biometrics-Enhanced Blockchain for Privacy and Verifiability (BEBPV) system, which employs facial biometric authentication and blockchain to ensure privacy and verifiability in e-voting (Ajimatanrareje, 2024), AI-integrated healthcare platforms can leverage biometric authentication and decentralized verification to enhance patient data security, mitigate unauthorized access, and improve trust in AI-powered medical systems.

Bias and Fairness Issues

AI models can perpetuate biases if trained on non-representative or skewed datasets, potentially worsening healthcare disparities (Parikh *et al.*, 2019; Mehrabi *et al.*, 2021). This is particularly concerning in precision medicine, where biased algorithms may lead to inequitable treatment recommendations. Ensuring fairness requires diverse training datasets, algorithm transparency, and continuous bias monitoring (Esteva & Topol, 2019; Schmidt *et al.*, 2020; Magrabi *et al.*, 2019).

Explainability and Trust in AI

The "black-box" nature of AI models limits transparency, making it difficult for clinicians to trust AI-driven decisions (Ferrario & Loi, 2022; Hoffman *et al.*, 2018). Enhancing AI interpretability through explainability features, feature importance scoring, and regular validation is critical to fostering adoption (Štiglic *et al.*, 2020; Lundberg *et al.*, 2020). Additionally, educating healthcare professionals on AI's capabilities and limitations can strengthen trust (Gille *et al.*, 2020; Richardson *et al.*, 2021).

Integration and Workflow Challenges

AI implementation often disrupts existing healthcare workflows, requiring additional training for clinicians and seamless integration with legacy systems (Shamszare & Choudhury, 2023; Bayramzadeh & Aghaei, 2021). If poorly designed, AI tools can increase rather than reduce the workload, limiting adoption (Shamszare & Choudhury, 2023).

Regulatory and Standardization Issues

The rapid advancement of AI often outpaces regulatory updates, creating uncertainty in compliance and oversight (He *et al.*, 2019; Gerke *et al.*, 2020; Meskó & Topol, 2023). Standardizing AI applications to ensure safety, efficacy, and fairness is essential for widespread acceptance (Reddy *et al.*, 2019).

Discussions

AI is revolutionizing healthcare by enhancing early disease detection, accelerating drug discovery, personalizing treatment, and improving clinical decision-making (Noorbakhsh-Sabet *et al.*, 2019). These technologies are no longer futuristic concepts but are actively reshaping medical practices, leading to improved patient outcomes and greater efficiency (Bohr & Memarzadeh, 2020).

This review aligns with existing research, confirming AI's role in expediting drug development, streamlining healthcare delivery, and advancing diagnostics (Margulis *et al.*, 2021; Raschka & Kaufman, 2020; Raschka, 2019). AI-driven diagnostics, for instance, enable earlier interventions that are less invasive and more effective (Esteva *et al.*, 2017; Esteva & Topol, 2019), while in drug discovery, AI reduces development timelines, ensuring faster access to new treatments (Cui & Zhu, 2021). However, its integration must be carefully managed to minimize disruptions in healthcare workflows and professional roles (Bayramzadeh & Aghaei, 2021).

Despite its transformative potential, barriers remain, particularly in data privacy, system interoperability, and ethical AI adoption (Morley *et al.*, 2020; Gerke *et al.*, 2020). Integrating AI into existing healthcare infrastructure requires significant adaptation, posing challenges for hospitals and clinicians (Bayramzadeh & Aghaei, 2021). Addressing these challenges will require collaborative efforts across disciplines to develop AI models that are both highly accurate and interpretable, fostering trust among healthcare professionals.

Looking ahead, future research should prioritize data security, AI explainability, and regulatory frameworks to enhance adoption. As AI continues to evolve, it is poised to redefine patient care, making healthcare more efficient, precise, and patient-centered (Jiang *et al.*, 2017).

CONCLUSIONS

As we conclude this comprehensive review on the applications of AI Technologies in Healthcare, it is clear that artificial intelligence is playing a major role in transforming various aspects of the healthcare industry. From enhancing disease diagnosis and prognosis to expediting the time for drug discovery. Personalised treatment and precision medicine have also benefited from artificial intelligence by tailoring healthcare to the individual needs of patients and ensuring more effective and targeted therapeutic strategies.

Also, in the domain of clinical decision support, artificial intelligence has played a major role in aiding healthcare professionals to make more informed and accurate decisions, and thereby improving patient outcomes and care efficiency. Additionally, the predictive analysis capabilities of artificial intelligence have been helpful in anticipating disease trends and patient responses, and thus adding a proactive layer to healthcare management. Therefore, this not only ensures timely interventions but also paves the way for a more efficient healthcare system. In the same vein, smart wearables that are augmented with artificial intelligence have emerged as a major advancement in continuous patient's health monitoring and management. These smart wearable devices provide real time insights into patients health, thus significantly contributing to proactive healthcare and patient management. Additionally, the integration of artificial intelligence in smart wearables have opened up new possibilities for remote monitoring and patient care, which is particularly beneficial in managing chronic conditions and improving the overall quality of life.

However, this journey of integrating AI in healthcare is not devoid of challenges that needs to be overcomed. Challenges such as data privacy, ethics consideration, algorithmic bias, and the need for transparent and interpretable AI models remain at the forefront of concerns that need to be addressed for artificial intelligence to be fully integrated into healthcare. Moreover, the successful adoption of artificial intelligence in healthcare requires a collaborative effort among technologists, healthcare professionals, and policymakers to navigate these challenges effectively.

As we move forward, it is essential to continue this momentum of innovation while also being mindful of the ethical and practical challenges that AI brings. Embracing AI in healthcare promises a future where healthcare is more patient personalised, predictive, and patient centred, which ultimately leads to better health outcomes and improved quality of life for patients worldwide.

REFERENCES

Ajimatanrareje, G. A. (2024). Advancing E-Voting Security: Biometrics-Enhanced Blockchain for Privacy and VerifiAbility (BEBPV). *American Journal of Innovation in Science and Engineering, 3*(3), 88–93. https://doi.org/10.54536/ajise.v3i3.3876

Al-Safarini, M. Y., & El-Sayed, H. H. (2021). The role of artificial intelligence in revealing the results of the interaction of biological materials with each other or with chemicals. *Materials Today: Proceedings, 45,* 4954–4959. https://doi.org/10.1016/j.matpr.2021.01.387

Albizu, A., Fang, R., Indahlastari, A., O'Shea, A., Stolte, S. E., See, K. B., Boutzoukas, E. M., Kraft, J. N., Nissim, N. R., & Woods, A. J. (2020). Machine learning and individual variability in electric field characteristics predict tDCS treatment response. *Brain Stimulation, 13*(6), 1753–1764. https://doi.org/10.1016/j.brs.2020.10.001

Ali, F., El-Sappagh, S., Islam, S. M. R., Ali, A., Attique, M., Imran, M., & Kwak, K.-S. (2021). An intelligent healthcare monitoring framework using wearable sensors and social networking data. *Future Generation Computer Systems, 114,* 23–43. https://doi.org/10.1016/j.future.2020.07.047

Aljaaf, A. J., Al-Jumeily, D., Hussain, A. J., Fergus, P., Al-Jumaily, M., & Abdel-Aziz, K. (2015). Toward an optimal use of artificial intelligence techniques within a clinical decision support system. *IEEE Xplore,* 548–554. https://doi.org/10.1109/sai.2015.7237196

Bartlett, E. A., DeLorenzo, C., Sharma, P., Yang, J., Zhang, M., Petkova, E., Weissman, M., McGrath, P. J., Fava, M., Ogden, R. T., Kurian, B. T., Malchow, A., Cooper, C. M., Trombello, J. M., McInnis, M., Adams, P., Oquendo, M. A., Pizzagalli, D. A., Trivedi, M., & Parsey, R. V. (2018). Pretreatment and early-treatment cortical thickness is associated with SSRI treatment response in major depressive disorder. *Neuropsychopharmacology, 43*(11), 2221–2230. https://doi.org/10.1038/s41386-018-0122-9

Bauer, Z., Dominguez, A., Cruz, E., Gomez-Donoso, F., Orts-Escolano, S., & Cazorla, M. (2020). Enhancing perception for the visually impaired with deep learning techniques and low-cost wearable sensors. *Pattern Recognition Letters, 137*, 27–36. https://doi.org/10.1016/j.patrec.2019.03.008

Baydoun, M., Safatly, L., Hassan, Ghaziri, H., Hajj, A. E., & Isma'eel, H. (2019). High Precision Digitization of Paper-Based ECG Records: A Step Toward Machine Learning. *IEEE Journal of Translational Engineering in Health and Medicine, 7,* 1–8. https://doi.org/10.1109/jtehm.2019.2949784

Bayramzadeh, S., & Aghaei, P. (2021). Technology integration in complex healthcare environments: A systematic literature review. *Applied Ergonomics, 92,* 103351–103351. https://doi.org/10.1016/j.apergo.2020.103351

Bejnordi, B. E., Veta, M., Johannes, P., Ginneken, B. van, Karssemeijer, N., Litjens, G., Hermsen, M., Manson, Q. F., Balkenhol, M., Geessink, O., Stathonikos, N., Dijk, van, Bult, P., Beca, F., Beck, A. H., Wang, D., Khosla, A., Gargeya, R., Irshad, H., & Zhong, A. (2017). Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer. *JAMA, 318*(22), 2199–2199. https://doi.org/10.1001/jama.2017.14585

Bentley, P., Ganesalingam, J., Jones, C., Mahady, K., Epton, S., Rinne, P., Sharma, P., Halse, O., Mehta, A., & Rueckert, D. (2014). Prediction of stroke thrombolysis outcome using CT brain machine learning. *NeuroImage Clinical, 4*, 635–640. https://doi.org/10.1016/j.nicl.2014.02.003

Bera, K., Schalper, K. A., Rimm, D. L., Velcheti, V., & Madabhushi, A. (2019). Artificial intelligence in digital pathology — new tools for diagnosis and precision oncology. *Nature Reviews Clinical Oncology, 16*(11), 703–715. https://doi.org/10.1038/s41571-019-0252-y

Bianchi, M. T. (2018). Sleep devices: wearables and nearables, informational and interventional, consumer and clinical. *Metabolism, 84*, 99–108. https://doi.org/10.1016/j.metabol.2017.10.008

Bini, S. A. (2018). Artificial Intelligence, Machine Learning, Deep Learning, and Cognitive Computing: What Do These Terms Mean and How Will They Impact Health Care? *The Journal of Arthroplasty, 33*(8), 2358–2361. https://doi.org/10.1016/j.arth.2018.02.067

Bohr, A., & Memarzadeh, K. (2020). The rise of artificial intelligence in healthcare applications. *Elsevier EBooks,* 25–60. https://doi.org/10.1016/b978-0-12-818438-7.00002-2

Chang, A. C. (2016). Big data in medicine: The upcoming artificial intelligence. *Progress in Pediatric Cardiology, 43,* 91–94. https://doi.org/10.1016/j.ppedcard.2016.08.021

Ching, T., Himmelstein, D. S., Beaulieu-Jones, B. K., Kalinin, A. A., Do, B. T., Way, G. P., Ferrero, E., Agapow, P.-M., Zietz, M., Hoffman, M. M., Xie, W., Rosen, G. L., Lengerich, B. J., Israeli, J., Lanchantin, J., Woloszynek, S., Carpenter, A. E., Shrikumar, A., Xu, J., & Cofer, E. M. (2018). Opportunities and obstacles for deep learning in biology and medicine. *Journal of the Royal Society Interface, 15*(141), 20170387–20170387. https://doi.org/10.1098/rsif.2017.0387

Christie, S. A., Conroy, A. S., Callcut, R. A., Hubbard, A. E., & Cohen, M. J. (2019). Dynamic multi-outcome prediction after injury: Applying adaptive machine learning for precision medicine in trauma. *PLoS ONE, 14*(4), e0213836–e0213836. https://doi.org/10.1371/journal.pone.0213836

Churpek, M. M., Yuen, T. C., Huber, M. T., Park, S. Y., Hall, J. B., & Edelson, D. P. (2011). Predicting Cardiac Arrest on the Wards. *CHEST Journal, 141*(5), 1170–1176. https://doi.org/10.1378/chest.11-1301

Cikes, M., Sanchez-Martinez, S., Claggett, B., Duchateau, N., Piella, G., Butakoff, C., Pouleur, A. C., Knappe, D., Biering-Sørensen, T., Kutyifa, V., Moss, A., Stein, K., Solomon, S. D., & Bijnens, B. (2018). Machine learning-based phenogrouping in heart failure to identify responders to cardiac resynchronization therapy. *European Journal of Heart Failure, 21*(1), 74–85. https://doi.org/10.1002/ejhf.1333

Cui, R., & Zhu, F. (2021). Ultrasound modified polysaccharides: A review of structure, physicochemical properties, biological activities and food applications. *Trends in Food Science & Technology, 107*, 491–508. https://doi.org/10.1016/j.tifs.2020.11.018

Dash, S., Shakyawar, S. K., Sharma, M., & Kaushik, S. (2019). Big data in healthcare: management, analysis and future prospects. *Journal of Big Data, 6*(1). https://doi.org/10.1186/s40537-019-0217-0

Daynac, M., Cortes-Cabrera, A., & Prieto, J. M. (2015). Application of Artificial Intelligence to the Prediction of the Antimicrobial Activity of Essential Oils. *Evidence-Based Complementary and Alternative Medicine, 2015,* 1–9. https://doi.org/10.1155/2015/561024

Dekhil, O., Hajjdiab, H., Shalaby, A., Ali, M. T., Ayinde, B., Switala, A., Elshamekh, A., Ghazal, M., Keynton, R., Barnes, G., & El-Baz, A. (2018). Using resting state functional MRI to build a personalized autism diagnosis system. *PLoS ONE, 13*(10), e0206351–e0206351. https://doi.org/10.1371/journal.pone.0206351

Delpierre, C., & Lefèvre, T. (2023). Precision and personalized medicine: What their current definition says and silences about the model of health they promote. *Implication for the development of personalized health. Frontiers in Sociology, 8*. https://doi.org/10.3389/fsoc.2023.1112159

Desai, K., Mane, P., Dsilva, M., Zare, A., Shingala, P., & Ambawade, D. (2020). A Novel Machine Learning Based Wearable Belt For Fall Detection. 2020 IEEE International Conference on Computing, Power and Communication Technologies (GUCON). https://doi.org/10.1109/gucon48875.2020.9231114

Dildar, M., Akram, S., Irfan, M., Khan, H. U., Ramzan, M., Mahmood, A. R., Ayed Alsaiari, S., Hakeem, A., Alraddadi, M. O., & Ayed Alsaiari, S. (2021). Skin Cancer Detection: A Review Using Deep Learning Techniques. *International Journal of Environmental Research and Public Health, 18*(10), 5479–5479. https://doi.org/10.3390/ijerph18105479

EL-Geneedy, M., Moustafa, H. E.-D., Khalifa, F., Khater, H., & AbdElhalim, E. (2022). An MRI-based deep learning approach for accurate detection of Alzheimer's disease. *Alexandria Engineering Journal, 63,* 211–221. https://doi.org/10.1016/j.aej.2022.07.062

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017a). Dermatologist-level classification of skin cancer with deep neural networks. *Nature, 542*(7639), 115–118. https://doi.org/10.1038/nature21056

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017b). Dermatologist-level classification of skin cancer with deep neural networks. *Nature, 542*(7639), 115–118. https://doi.org/10.1038/nature21056

Esteva, A., & Topol, E. (2019). Can skin cancer diagnosis be transformed by AI? *The Lancet, 394*(10211), 1795. https://doi.org/10.1016/s0140-6736(19)32726-6

Feng, C., Wang, L., Chen, X., Zhai, Y., Zhu, F., Chen, H., Wang, Y., Su, X., Huang, S., Tian, L., Zhu, W., Sun, W., Zhang, L., Han, Q., Zhang, J., Pan, F., Chen, L., Zhu, Z., Xiao, H., & Liu, Y. (2021). A novel artificial intelligence-assisted triage tool to aid in the diagnosis of suspected COVID-19 pneumonia cases in fever clinics. *Annals of Translational Medicine, 9*(3), 201–201. https://doi.org/10.21037/atm-20-3073

Ferrario, A., & Loi, M. (2022). How Explainability Contributes to Trust in AI. 2022 ACM Conference on Fairness, *Accountability, and Transparency,* 1457–1466. https://doi.org/10.1145/3531146.3533202

Gerke, S., Minssen, T., & Cohen, G. (2020). Ethical and legal challenges of artificial intelligence-driven healthcare. *Elsevier EBooks,* 295–336. https://doi.org/10.1016/b978-0-12-818438-7.00012-5

Gille, F., Jobin, A., & Ienca, M. (2020). What we talk about when we talk about trust: Theory of trust for AI in healthcare. *Intelligence-Based Medicine,* 1-2, 100001–100001. https://doi.org/10.1016/j.ibmed.2020.100001

Gomes, J., Ramsundar, B., Feinberg, E. N., & Pande, V. S. (2017). Atomic Convolutional Networks for Predicting Protein-Ligand Binding Affinity. ArXiv.org. https://doi.org/10.48550/arXiv.1703.10603

Gruson, D., Bernardini, S., Kumar Dabla, P., Gouget, B., & Stankovic, S. (2020). Collaborative AI and Laboratory Medicine integration in precision cardiovascular medicine. *Clinica Chimica Acta, 509*, 67–71. https://doi.org/10.1016/j.cca.2020.06.001

Hamid Shamszare, & Choudhury, A. (2023). Clinicians' Perceptions of Artificial Intelligence: Focus on Workload, Risk, Trust, Clinical Decision Making, and Clinical Integration. *Healthcare, 11*(16), 2308–2308. https://doi.org/10.3390/healthcare11162308

Hannun, A. Y., Rajpurkar, P., Haghpanahi, M., Tison, G. H., Bourn, C., Turakhia, M. P., & Ng, A. Y. (2019). Publisher Correction: Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. *Nature Medicine, 25*(3), 530–530. https://doi.org/10.1038/s41591-019-0359-9

He, J., Baxter, S. L., Xu, J., Xu, J., Zhou, X., & Zhang, K. (2018). The practical implementation of artificial intelligence technologies in medicine. *Nature Medicine, 25*(1), 30–36. https://doi.org/10.1038/s41591-018-0307-0

Hoffman, R. R., Mueller, S. T., Klein, G., & Litman, J. (2018). Metrics for Explainable AI: Challenges and Prospects. ArXiv.org. https://arxiv.org/abs/1812.04608

Hong, L., Luo, M., Wang, R., Lu, P., Lu, W., & Lu, L. (2018). Big Data in Health Care: Applications and Challenges. *Data and Information Management, 2*(3), 175–197. https://doi.org/10.2478/dim-2018-0014

Huang, C., Mezencev, R., McDonald, J. F., & Vannberg, F. (2017). Open source machine-learning algorithms for the prediction of optimal cancer drug therapies. *PLoS ONE, 12*(10), e0186906–e0186906. https://doi.org/10.1371/journal.pone.0186906

Jacobson, N. C., Lekkas, D., Huang, R., & Thomas, N. (2020). Deep learning paired with wearable passive sensing data predicts deterioration in anxiety disorder symptoms across 17–18 years. *Journal of Affective Disorders, 282*, 104–111. https://doi.org/10.1016/j.jad.2020.12.086

Janarthanan, R., Doss, S., & Baskar, S. (2020). Optimized unsupervised deep learning assisted reconstructed coder in the on-nodule wearable sensor for human activity recognition. *Measurement, 164,* 108050. https://doi.org/10.1016/j.measurement.2020.108050

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y. (2017). Artificial intelligence in healthcare: past, present and future. *Stroke and Vascular Neurology, 2*(4), 230–243. https://doi.org/10.1136/svn-2017-000101

Kadurin, I., Rothwell, S., Ferron, L., Meyer, O., & Dolphin, A. (2017). Investigation of the Proteolytic Cleavage of α 2 δ Subunits: A Mechanistic Switch from Nhibition to Activation of Voltage-Gated Calcium Channels? *Biophysical Journal, 112*(3), 244a244a. https://doi.org/10.1016/j.bpj.2016.11.1335

Kamala, Y. Lakshmi., Rao, K. V. S. N. R., & Josephine, B. Manjula. (2022). Comparison and Evaluation of Studies on Precision Medicine using AI. IEEE

Xplore, 330–335. https://doi.org/10.1109/icscds53736.2022.9760969

Katoh, M., & Katoh, M. (2019). Precision medicine for human cancers with Notch signaling dysregulation (Review). *International Journal of Molecular Medicine*. https://doi.org/10.3892/ijmm.2019.4418

Khan, H. M., & Zaidi, S. M. H. (2024). Detecting Security System Misconfiguration Threats in Cloud Computing Environments Using AI. *American Journal of Innovation in Science and Engineering, 3*(3), 31–40. https://doi.org/10.54536/ajise.v3i3.3272

Khan, H. M., & Zaidi, S. M. H. (2024). Detecting Security System Misconfiguration Threats in Cloud Computing Environments Using AI. *American Journal of Innovation in Science and Engineering, 3*(3), 31–40. https://doi.org/10.54536/ajise.v3i3.3272

khan, Z. F., & Alotaibi, S. R. (2020). Applications of Artificial Intelligence and Big Data Analytics in m-Health: A Healthcare System Perspective. *Journal of Healthcare Engineering, 2020,* 1–15. https://doi.org/10.1155/2020/8894694

Kim, S. J., Cho, K. J., & Oh, S. (2017). Development of machine learning models for diagnosis of glaucoma. *PLoS ONE, 12*(5), e0177726–e0177726. https://doi.org/10.1371/journal.pone.0177726

Lavecchia, A. (2014). Machine-learning approaches in drug discovery: methods and applications. *Drug Discovery Today, 20*(3), 318–331. https://doi.org/10.1016/j.drudis.2014.10.012

Le, D.-N., Subbiah Parvathy, V., Gupta, D., Khanna, A., J.P.C, J., & Shankar, K. (2021). IoT enabled depthwise separable convolution neural network with deep support vector machine for COVID-19 diagnosis and classification. *International Journal of Machine Learning and Cybernetics, 12*(11), 3235–3248. https://doi.org/10.1007/s13042-020-01248-7

Liu, M., Zhang, J., Adeli, E., & Shen, D. (2017). Landmark-based deep multi-instance learning for brain disease diagnosis. *Medical Image Analysis, 43,* 157–168. https://doi.org/10.1016/j.media.2017.10.005

Lu, M. Y., Chen, T. Y., Drew, Zhao, M., Shady, M., Lipkova, J., & Mahmood, F. (2021). AI-based pathology predicts origins for cancers of unknown primary. *Nature, 594*(7861), 106–110. https://doi.org/10.1038/s41586-021-03512-4

Lundberg, S. M., Erion, G., Chen, H., DeGrave, A., Prutkin, J. M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., & Lee, S.-I. (2020). From local explanations to global understanding with explainable AI for trees. *Nature Machine Intelligence, 2*(1), 56–67. https://doi.org/10.1038/s42256-019-0138-9

Lusci, A., Pollastri, G., & Baldi, P. (2013). Deep Architectures and Deep Learning in Chemoinformatics: The Prediction of Aqueous Solubility for Drug-Like Molecules. Journal of *Chemical Information and Modeling, 53*(7), 1563–1575. https://doi.org/10.1021/ci400187y

Machine Learning An Artificial Intelligence Approach. (2013). In J. G. Carbonell, R. S. Michalski, & T. M. Mitchell (Eds.), Google.co.uk (p. 572). Springer Berlin Heidelberg. https://www.google.co.uk/books/edition/Machine_Learning/-eqpCAAAQBAJ?hl=en

Maciukiewicz, M., Marshe, V. S., Hauschild, A.-C., Foster, J. A., Rotzinger, S., Kennedy, J. L., Kennedy, S. H., Müller, D. J., & Geraci, J. (2018). GWAS-based machine learning approach to predict duloxetine response in major depressive disorder. *Journal of Psychiatric Research, 99,* 62–68. https://doi.org/10.1016/j.jpsychires.2017.12.009

Magrabi, F., Elske Ammenwerth, McNair, J. B., Nicolet, Hannele Hyppönen, Pirkko Nykänen, Rigby, M., Scott, P. J., Tuulikki Vehko, Wong, Z. S.-Y., & Georgiou, A. (2019). Artificial Intelligence in Clinical Decision Support: Challenges for Evaluating AI and Practical Implications. *Yearbook of Medical Informatics, 28*(01), 128–134. https://doi.org/10.1055/s-0039-1677903

Malik, Y. S., Sircar, S., Bhat, S., Ansari, M. I., Pande, T., Kumar, P., Mathapati, B., Balasubramanian, G., Kaushik, R., Natesan, S., Ezzikouri, S., El Zowalaty, M. E., & Dhama, K. (2020). How artificial intelligence may help the Covid-19 pandemic: Pitfalls and lessons for the future. *Reviews in Medical Virology, 31*(5), 1–11. https://doi.org/10.1002/rmv.2205

Margulis, E., Dagan-Wiener, A., Ives, R. S., Jaffari, S., Siems, K., & Niv, M. Y. (2021). Intense bitterness of molecules: Machine learning for expediting drug discovery. *Computational and Structural Biotechnology Journal, 19,* 568–576. https://doi.org/10.1016/j.csbj.2020.12.030

McKinney, S. M., Sieniek, M., Godbole, V., Godwin, J., Antropova, N., Ashrafian, H., Back, T., Chesus, M., Corrado, G. S., Darzi, A., Etemadi, M., Garcia-Vicente, F., Gilbert, F. J., Halling-Brown, M., Hassabis, D., Jansen, S., Karthikesalingam, A., Kelly, C. J., King, D., & Ledsam, J. R. (2020). *International evaluation of an AI system for breast cancer screening. Nature, 577*(7788), 89–94. https://doi.org/10.1038/s41586-019-1799-6

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A Survey on Bias and Fairness in Machine Learning. *ACM Computing Surveys, 54*(6), 1–35. https://doi.org/10.1145/3457607

Meskó, B., & Topol, E. J. (2023). The imperative for regulatory oversight of large language models (or generative AI) in healthcare. *Npj Digital Medicine, 6*(1). https://doi.org/10.1038/s41746-023-00873-0

Morley, J., Machado, C. C. V., Burr, C., Cowls, J., Joshi, I., Taddeo, M., & Floridi, L. (2020). The ethics of AI in health care: A mapping review. *Social Science & Medicine, 260,* 113172. https://doi.org/10.1016/j.socscimed.2020.113172

Moshawrab, M., Adda, M., Bouzouane, A., Ibrahim, H., & Raad, A. (2022). Smart Wearables for the Detection of Occupational Physical Fatigue: A *Literature Review. Sensors, 22*(19), 7472. https://doi.org/10.3390/s22197472

Mumtaz, H., Saqib, M., Jabeen, S., Muneeb, M., Mughal, W., Sohail, H., Safdar, M., Mehmood, Q., Khan, M. A., & Ismail, S. M. (2023). Exploring alternative approaches to precision medicine through genomics and artificial intelligence – a systematic review. *Frontiers in Medicine, 10*. https://doi.org/10.3389/fmed.2023.1227168

Navarrete-Welton, A. J., & Hashimoto, D. A. (2020). Current applications of artificial intelligence for intraoperative decision support in surgery. *Frontiers of Medicine, 14*(4), 369–381. https://doi.org/10.1007/s11684-020-0784-7

Nemati, S., Holder, A., Razmi, F., Stanley, M. D., Clifford, G. D., & Buchman, T. G. (2017). An Interpretable Machine Learning Model for Accurate Prediction of Sepsis in the ICU. *Critical Care Medicine, 46*(4), 547–553. https://doi.org/10.1097/ccm.0000000000002936

Noorbakhsh-Sabet, N., Zand, R., Zhang, Y., & Abedi, V. (2019). Artificial Intelligence Transforms the Future of Health Care. *The American Journal of Medicine, 132*(7), 795–801. https://doi.org/10.1016/j.amjmed.2019.01.017

Parikh, R. B., Teeple, S., & Navathe, A. S. (2019). Addressing Bias in Artificial Intelligence in Health Care. *JAMA, 322*(24), 2377–2377. https://doi.org/10.1001/jama.2019.18058

Park, T., Gu, P., Kim, C.-H., Kim, K. T., Chung, K. J., Kim, T. B., Jung, H., Yoon, S. J., & Oh, J. K. (2023). Artificial intelligence in urologic oncology: the actual clinical practice results of IBM Watson for Oncology in South Korea. *Prostate International, 11*(4), 218–221. https://doi.org/10.1016/j.prnil.2023.09.001

Pecchia, L., Melillo, P., & Bracale, M. (2011). Remote Health Monitoring of Heart Failure With Data Mining via CART Method on HRV Features. *IEEE Transactions on Biomedical Engineering, 58*(3), 800–804. https://doi.org/10.1109/tbme.2010.2092776

Pesapane, F., Codari, M., & Sardanelli, F. (2018). Artificial intelligence in medical imaging: threat or opportunity? Radiologists again at the forefront of innovation in medicine. *European Radiology Experimental, 2*(1). https://doi.org/10.1186/s41747-018-0061-6

Pierleoni, P., Belli, A., Palma, L., Pellegrini, M., Luca Pernini, & Valenti, S. (2015). A High Reliability Wearable Device for Elderly Fall Detection. *IEEE Sensors Journal, 15*(8), 4544–4553. https://doi.org/10.1109/jsen.2015.2423562

Plenge, R. M. (2016). Disciplined approach to drug discovery and early development. *Science Translational Medicine, 8*(349). https://doi.org/10.1126/scitranslmed.aaf2608

Polykovskiy, D., Zhebrak, A., Vetrov, D., Ivanenkov, Y., Aladinskiy, V., Mamoshina, P., Bozdaganyan, M., Aliper, A., Zhavoronkov, A., & Kadurin, A. (2018). Entangled Conditional Adversarial Autoencoder for de Novo Drug Discovery. *Molecular Pharmaceutics, 15*(10), 4398–4405. https://doi.org/10.1021/acs.molpharmaceut.8b00839

Popova, M., Isayev, O., & Tropsha, A. (2018). Deep reinforcement learning for de novo drug design. *Science Advances, 4*(7). https://doi.org/10.1126/sciadv.aap7885

Pu, L., Naderi, M., Liu, T., Wu, H.-C., Mukhopadhyay, S., & Brylinski, M. (2019). eToxPred: a machine learning-based approach to estimate the toxicity of drug candidates. *BMC Pharmacology and Toxicology, 20*(1). https://doi.org/10.1186/s40360-018-0282-6

Rad, N. M., Kia, S. M., Zarbo, C., Laarhoven, van, Jurman, G., Venuti, P., Marchiori, E., & Furlanello, C. (2017). Deep Learning for Automatic Stereotypical Motor Movement Detection using Wearable Sensors in Autism Spectrum Disorders. ArXiv.org. https://arxiv.org/abs/1709.05956

Radanliev, P., & De Roure, D. (2022). Advancing the cybersecurity of the healthcare system with self-optimising and self-adaptative artificial intelligence (part 2). *Health and Technology, 12*(5), 923–929. https://doi.org/10.1007/s12553-022-00691-6

Raghavendra, U., Acharya, U. Rajendra, & Adeli, H. (2019). Artificial Intelligence Techniques for Automated Diagnosis of Neurological Disorders. *European Neurology, 82*(1-3), 41–64. https://doi.org/10.1159/000504292

Rahman, R. M., & Afroz, F. (2013). Comparison of Various Classification Techniques Using Different Data Mining Tools for Diabetes Diagnosis. *Journal of Software Engineering and Applications, 06*(03), 85–97. https://doi.org/10.4236/jsea.2013.63013

Rajkomar, A., Oren, E., Chen, K., Dai, A. M., Hajaj, N., Hardt, M., Liu, P. J., Liu, X., Marcus, J., Sun, M., Sundberg, P., Yee, H., Zhang, K., Zhang, Y., Flores, G., Duggan, G. E., Irvine, J., Le, Q., Litsch, K., & Mossin, A. (2018). Scalable and accurate deep learning with electronic health records. *Npj Digital Medicine, 1*(1). https://doi.org/10.1038/s41746-018-0029-1

Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz, C., Shpanskaya, K., Lungren, M. P., & Ng, A. Y. (2017). CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning. ArXiv.org. https://arxiv.org/abs/1711.05225

Rantanen, J., & Khinast, J. (2015). The Future of Pharmaceutical Manufacturing Sciences. *Journal of Pharmaceutical Sciences, 104*(11), 3612–3638. https://doi.org/10.1002/jps.24594

Raschka, S. (2019). Automated discovery of GPCR bioactive ligands. *Current Opinion in Structural Biology, 55*, 17–24. https://doi.org/10.1016/j.sbi.2019.02.011

Raschka, S., & Kaufman, B. (2020). Machine learning and AI-based approaches for bioactive ligand discovery and GPCR-ligand recognition. *Methods, 180,* 89–110. https://doi.org/10.1016/j.ymeth.2020.06.016

Rawat, B., Joshi, Y., & Kumar, A. (2023a). AI in Healthcare: Opportunities and Challenges for Personalized Medicine and Disease Diagnosis. *IEEE Xplore,* 374–379. https://doi.org/10.1109/icirca57980.2023.10220746

Rawat, B., Joshi, Y., & Kumar, A. (2023b). AI in Healthcare: Opportunities and Challenges for Personalized Medicine and Disease Diagnosis. *2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA),* 374–379. https://doi.org/10.1109/icirca57980.2023.10220746

Reddy, S., Allan, S., Coghlan, S., & Cooper, P. (2019). A governance model for the application of AI in health care. *Journal of the American Medical Informatics Association, 27*(3), 491–497. https://doi.org/10.1093/jamia/ocz192

Richardson, J. P., Smith, C., Curtis, S., Watson, S., Zhu, X., Barry, B., & Sharp, R. R. (2021a). Patient apprehensions about the use of artificial intelligence in healthcare. *Npj Digital Medicine, 4*(1). https://doi.org/10.1038/s41746-021-00509-1

Richardson, J. P., Smith, C., Curtis, S., Watson, S., Zhu, X., Barry, B., & Sharp, R. R. (2021b). Patient apprehensions about the use of artificial intelligence in healthcare. *Npj Digital Medicine, 4*(1). https://doi.org/10.1038/s41746-021-00509-1

Rumsfeld, J. S., Joynt, K. E., & Maddox, T. M. (2016). Big data analytics to improve cardiovascular care: promise and challenges. *Nature Reviews Cardiology, 13*(6), 350–359. https://doi.org/10.1038/nrcardio.2016.42

Santus, E., Marino, N., Cirillo, D., Chersoni, E., Montagud, A., Chadha, A. S., Valencia, A., Hughes, K., & Lindvall, C. (2021). Artificial Intelligence–Aided Precision Medicine for COVID-19: Strategic Areas of Research and Development. *Journal of Medical Internet Research, 23*(3), e22453–e22453. https://doi.org/10.2196/22453

Scannell, J. W., Blanckley, A., Boldon, H., & Warrington, B. (2012). Diagnosing the decline in pharmaceutical R&D efficiency. *Nature Reviews Drug Discovery, 11*(3), 191–200. https://doi.org/10.1038/nrd3681

Schmidt, P., Biessmann, F., & Teubner, T. (2020). Transparency and trust in artificial intelligence systems. *Journal of Decision Systems, 29*(4), 260–278. https://doi.org/10.1080/12460125.2020.1819094

Schuhmacher, A., Gatto, A., Kuss, M., Gassmann, O., & Hinder, M. (2021a). Big Techs and startups in pharmaceutical R&D – A 2020 perspective on artificial intelligence. *Drug Discovery Today, 26*(10), 2226–2231. https://doi.org/10.1016/j.drudis.2021.04.028

Schuhmacher, A., Gatto, A., Kuss, M., Gassmann, O., & Hinder, M. (2021b). Big Techs and startups in pharmaceutical R&D – A 2020 perspective on artificial intelligence. *Drug Discovery Today, 26*(10), 2226–2231. https://doi.org/10.1016/j.drudis.2021.04.028

Shameer, K., Johnson, K. W., Yahi, A., Miotto, R., Li, L., Ricks, D., Jebakaran, J., Kovatch, P., Sengupta, P. P., Gelijns, S., Moskovitz, A., Darrow, B., David, D. L., Kasarskis, A., Tatonetti, N. P., Pinney, S., & Dudley, J. T. (2016). Predictive Modeling Of Hospital Readmission Rates Using Electronic Medical Record-Wide Machine Learning: A Case-Study Using Mount Sinai Heart Failure Cohort. Biocomputing. Https://Doi.org/10.1142/9789813207813_0027

Sharma, T., Parihar, J., & Singh, S. (2021). Intelligent Chatbot for Prediction and Management of Stress. *IEEE Xplore,* 937–941. https://doi.org/10.1109/confluence51648.2021.9377091

Soares, T. A., Nunes-Alves, A., Mazzolari, A., Ruggiu, F., Wei, G.-W., & Merz, K. (2022). The (Re)-Evolution of Quantitative Structure–Activity Relationship (QSAR) Studies Propelled by the Surge of Machine Learning Methods. *Journal of Chemical Information and Modeling, 62*(22), 5317–5320. https://doi.org/10.1021/acs.jcim.2c01422

Somashekhar, S. P., Sepúlveda, Martín-J., Norden, A. D., Rauthan, A., Arun, K., Patil, P., Ethadka, R. Y., & Kumar, R. C. (2017). Early experience with IBM Watson for Oncology (WFO) cognitive computing system for lung and colorectal cancer treatment. *Journal of Clinical Oncology, 35(15_suppl),* 8527–8527. https://doi.org/10.1200/jco.2017.35.15_suppl.8527

Steele, A. J., Denaxas, S. C., Shah, A. D., Hemingway, H., & Luscombe, N. M. (2018). Machine learning models in electronic health records can outperform conventional survival models for predicting patient mortality in coronary artery disease. *PLoS ONE, 13*(8), e0202344–e0202344. https://doi.org/10.1371/journal.pone.0202344

Stiglic, G., Kocbek, P., Fijacko, N., Zitnik, M., Verbert, K., & Cilar, L. (2020). Interpretability of machine learning-based prediction models in healthcare. *WIREs Data Mining and Knowledge Discovery, 10*(5). https://doi.org/10.1002/widm.1379

Stokes, J. M., Yang, K., Swanson, K., Jin, W., Cubillos-Ruiz, A., Donghia, N. M., MacNair, C. R., French, S., Carfrae, L. A., Bloom-Ackermann, Z., Tran, V. M., Chiappino-Pepe, A., Badran, A. H., Andrews, I. W., Chory, E. J., Church, G. M., Brown, E. D., Jaakkola, T. S., Barzilay, R., & Collins, J. J. (2020). A Deep Learning Approach to Antibiotic Discovery. *Cell, 180*(4), 688-702.e13. https://doi.org/10.1016/j.cell.2020.01.021

Toh, T. S., Dondelinger, F., & Wang, D. (2019). Looking beyond the hype: Applied AI and machine learning in translational medicine. *EBioMedicine, 47,* 607–615. https://doi.org/10.1016/j.ebiom.2019.08.027

Turki, T., & Taguchi, Y-h. (2019). Machine learning algorithms for predicting drugs–tissues relationships. *Expert Systems with Applications, 127,* 167–186. https://doi.org/10.1016/j.eswa.2019.02.013

Vaidyam, A. N., Wisniewski, H., Halamka, J. D., Kashavan, M. S., & Torous, J. B. (2019). Chatbots and Conversational Agents in Mental Health: A Review of the Psychiatric Landscape. *The Canadian Journal of Psychiatry, 64*(7), 456–464. https://doi.org/10.1177/0706743719828977

Vamathevan, J., Clark, D., Czodrowski, P., Dunham, I., Ferran, E., Lee, G., Li, B., Madabhushi, A., Shah, P., Spitzer, M., & Zhao, S. (2019). Applications of machine learning in drug discovery and development. *Nature Reviews Drug Discovery, 18*(6), 463–477. https://

doi.org/10.1038/s41573-019-0024-5

van Bronswijk, S. C., DeRubeis, R. J., Lemmens, L. H. J. M., Peeters, F. P. M. L., Keefe, J. R., Cohen, Z. D., & Huibers, M. J. H. (2019). Precision medicine for long-term depression outcomes using the Personalized Advantage Index approach: cognitive therapy or interpersonal psychotherapy? *Psychological Medicine, 51*(2), 279–289. https://doi.org/10.1017/s0033291719003192

Wang, H., & Xia, Y. (2018). ChestNet: A Deep Neural Network for Classification of Thoracic Diseases on Chest Radiography. ArXiv.org. https://doi.org/10.48550/arXiv.1807.03058

Wang, S., Yang, D. M., Rong, R., Zhan, X., Fujimoto, J., Liu, H., Minna, J., Wistuba, I. I., Xie, Y., & Xiao, G. (2019). *Artificial Intelligence in Lung Cancer Pathology Image Analysis. Cancers, 11*(11), 1673. https://doi.org/10.3390/cancers11111673

Webb, C. A., Trivedi, M. H., Cohen, Z. D., Dillon, D. G., Fournier, J. C., Goer, F., Fava, M., McGrath, P. J., Weissman, M., Parsey, R., Adams, P., Trombello, J. M., Cooper, C., Deldin, P., Oquendo, M. A., McInnis, M. G., Huys, Q., Bruder, G., Kurian, B. T., & Jha, M. (2018). Personalized prediction of antidepressant v. placebo response: evidence from the EMBARC study. *Psychological Medicine, 49*(07), 1118–1127. https://doi.org/10.1017/s0033291718001708

Wessler, B. S., YH, L. L., Kramer, W., Cangelosi, M., Raman, G., Lutz, J. S., & Kent, D. M. (2015). Clinical Prediction Models for Cardiovascular Disease. *Circulation Cardiovascular Quality and Outcomes, 8*(4), 368–375. https://doi.org/10.1161/circoutcomes.115.001693

Willemink, M. J., Koszek, W. A., Hardell, C., Wu, J., Fleischmann, D., Harvey, H., Folio, L. R., Summers, R. M., Rubin, D. L., & Lungren, M. P. (2020). Preparing Medical Imaging Data for Machine Learning. *Radiology, 295*(1), 4–15. https://doi.org/10.1148/radiol.2020192224

Yamashita, R., Nishio, M., Do, R. K. G., & Togashi, K. (2018). Convolutional neural networks: an overview and application in radiology. *Insights into Imaging, 9*(4), 611–629. https://doi.org/10.1007/s13244-018-0639-9

Young, F., Zhang, L., Jiang, R., Liu, H., & Wall, C. (2020). A Deep Learning based Wearable Healthcare IoT Device for AI-enabled Hearing Assistance Automation. ArXiv.org. https://arxiv.org/abs/2005.08076

Zamkah, A., Hui, T., Andrews, S., Dey, N., Shi, F., & Sherratt, R. S. (2020). Identification of Suitable Biomarkers for Stress and Emotion Detection for Future Personal Affective Wearable Sensors. *Biosensors, 10*(4), 40–40. https://doi.org/10.3390/bios10040040

Zhao, K., Jiang, H., Yuan, T., Zhang, C., Jia, W., & Wang, Z. (2020). A CNN Based Human Bowel Sound Segment Recognition Algorithm with Reduced Computation Complexity for Wearable Healthcare System. *2020 IEEE International Symposium on Circuits and Systems (ISCAS),* 1–5. https://doi.org/10.1109/iscas45731.2020.9180432

Zhavoronkov, A., Ivanenkov, Y. A., Aliper, A., Veselov, M. S., Aladinskiy, V. A., Aladinskaya, A. V., Terentiev, V. A., Polykovskiy, D. A., Kuznetsov, M. D., Asadulaev, A., Volkov, Y., Zholus, A., Shayakhmetov, R. R., Zhebrak, A., Minaeva, L. I., Zagribelnyy, B. A., Lee, L. H., Soll, R., Madge, D., & Xing, L. (2019). Deep learning enables rapid identification of potent DDR1 kinase inhibitors. *Nature Biotechnology, 37*(9), 1038–1040. https://doi.org/10.1038/s41587-019-0224-x

Zhou, N., Zhang, C.-T., Lv, H.-Y., Hao, C.-X., Li, T.-J., Zhu, J.-J., Zhu, H., Jiang, M., Liu, K.-W., Hou, H.-L., Liu, D., Li, A.-Q., Zhang, G.-Q., Tian, Z.-B., & Zhang, X.-C. (2018). Concordance Study Between IBM Watson for Oncology and Clinical Practice for Patients with Cancer in China. *The Oncologist, 24*(6), 812–819. https://doi.org/10.1634/theoncologist.2018-0255

Zhou, S.-F., & Zhong, W.-Z. (2017). Drug Design and Discovery: *Principles and Applications. Molecules, 22*(2), 279–279. https://doi.org/10.3390/molecules22020279

Zou, F., Tang, Y., Liu, C., Ma, J., & Hu, C. (2020). Concordance Study Between IBM Watson for Oncology and Real Clinical Practice for Cervical Cancer Patients in China: *A Retrospective Analysis. Frontiers in Genetics, 11*. https://doi.org/10.3389/fgene.2020.00200

Zurbuchen, N., Bruegger, P., & Wilde, A. (2020). *A Comparison of Machine Learning Algorithms for Fall Detection using Wearable Sensors.* 427–431. https://doi.org/10.1109/icaiic48513.2020.9065205