ARCHIVES OF BIOINFORMATICS AND COMPUTATIONAL BIOLOGY
Jan- Jun 2025, VOL. 1, ISSUE 1, pp. 20-35
https://doi.org/10.61577/abcb.2025.100005

RESEAPRO JOURNALS

ORIGINAL ARTICLE

OPEN ACCESS

Towards autonomous healthcare: integrating Artificial Intelligence (AI) for personalized medicine and disease prediction

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ABSTRACT

The integration of Artificial Intelligence (AI) into healthcare has revolutionized medical practices, offering vast potential for the future. This paper delves into AI's transformative impact on autonomous healthcare, with a specific focus on personalized medicine and disease prognosis. Harnessing AI's capabilities aims to enhance diagnostic precision, treatment efficacy, and overall healthcare outcomes. In personalized medicine, AI scrutinizes extensive datasets including genomics, proteomics, and patient records. Computational genomics utilizes AI algorithms to decode intricate genetic information, facilitating tailored treatment approaches based on individual genetic compositions. AI-driven proteomic analysis aids in understanding protein interactions and discovering biomarkers, paving the way for customized therapies. Integration of AI in medical imaging is crucial for personalized medicine. Machine learning interprets radiological images, enabling early disease detection and characterization. Subfields like radiomics and pathology informatics extract quantitative data from medical images, offering a holistic view of disease patterns and progression. Disease prediction is another focus, where AI analyzes diverse healthcare data to identify early disease indications. Predictive modeling, powered by machine learning, enables proactive health management, potentially preventing disease onset through timely interventions.

Predictive analytics and clinical decision support systems aid healthcare professionals in making informed decisions. This paper also addresses ethical considerations and challenges in AI integration, emphasizing responsible and transparent use. As AI advances, the convergence of technology and healthcare promises more accurate, efficient, and tailored medical practices meeting the unique needs of each patient.

KEY WORDS

Artificial intelligence; Personalized medicine; Disease prediction; Autonomous healthcare; Human; Precision medicine

ARTICLE HISTORY

Received 12 June 2025; Revised 23 June 2025; Accepted 30 June 2025

Introduction

Autonomous healthcare defines the amalgamation of artificial intelligence (AI), machine learning (ML), and automation technologies within healthcare frameworks, facilitating the delivery of more efficient, tailored, and proactive medical care. This approach leverages algorithms and data analytics to automate a range of functions including diagnostics, treatment planning, patient monitoring, and administrative tasks. The overarching objective of autonomous healthcare is to elevate patient outcomes, optimize operational processes, mitigate healthcare expenses, and bolster accessibility to healthcare services.

AI stands out as a revolutionary catalyst, reshaping the conventional frameworks of medical diagnosis, treatment, and patient care [1-4]. This study immerses itself in the domain of autonomous healthcare, unraveling the manifold applications of AI in tailoring medical approaches and predicting diseases. In response to the escalating global disease burden, innovative healthcare strategies are urgently required to address individual idiosyncrasies and forecast ailments at their nascent stages. The expansive realm of autonomous healthcare encompasses various subfields, each contributing to the realization of a healthcare system centered on patients and driven by data. At the forefront of this transformation is personalized medicine, a groundbreaking approach that customizes medical interventions based on individual patient characteristics [5-7].

AI assumes a pivotal role in advancing personalized medicine, utilizing sophisticated data analytics, machine learning algorithms, and predictive models to distill meaningful insights from extensive datasets, encompassing genetic, clinical, and lifestyle information [8-13]. Genomic medicine, a crucial subfield under the umbrella of personalized medicine, aims to unravel the intricate interplay between an individual's genetic composition and their susceptibility to diseases. AI algorithms showcase exceptional capabilities in scrutinizing genomic data, identifying genetic markers linked to diseases, and facilitating the development of targeted therapies [14-20]. The integration of AI into genomics expedites the identification of therapeutic targets and deepens our understanding of the complex genetic variations contributing to disease pathogenesis.

In the domain of clinical diagnostics, diagnostic imaging and pathology have undergone a paradigm shift with the introduction of AI. Radiology benefits from AI algorithms that analyze medical images with unparalleled accuracy, aiding in the early detection of abnormalities and assisting clinicians in making timely decisions [21-27]. Similarly, AI-powered pathology platforms heighten the precision of disease diagnosis by analyzing microscopic images, thereby reducing diagnostic errors and improving patient outcomes [28-32]. Moreover, the incorporation of AI in disease prediction holds profound implications for preventive healthcare. Predictive analytics, propelled by AI algorithms, dissect diverse datasets, including patient health records, environmental factors, and genetic information, to identify patterns indicative of potential health risks. Leveraging machine learning models, healthcare providers can proactively intervene, offering

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personalized preventive measures to individuals at risk and mitigating the onset of diseases before clinical manifestation [33-38].

Remote patient monitoring constitutes another crucial facet of autonomous healthcare, facilitated by wearable devices and sensors that continuously collect patient data. AI algorithms analyze this real-time data, offering valuable insights into patient health trends, medication adherence, and early signs of deterioration [39-43]. The integration of AI in remote monitoring not only enables timely interventions but also empowers patients to actively participate in their healthcare, shifting the focus from reactive to proactive healthcare management. The ethical considerations and data privacy are paramount in deploying AI in healthcare [44-50]. The responsible use of patient data, adherence to privacy regulations, and transparency in AI algorithms are imperative to foster trust among patients and healthcare providers.

Striking a delicate balance between innovation and ethical considerations is crucial to ensure the widespread acceptance and adoption of AI technologies in healthcare [45-47]. The amalgamation of AI in healthcare marks the advent of a new era characterized by autonomous and personalized medicine. The subfields of personalized medicine, genomics, diagnostic imaging, pathology, disease prediction, and remote patient monitoring collectively contribute to the metamorphosis of healthcare delivery. As we navigate the intricacies of implementing AI in healthcare, embracing an interdisciplinary approach is essential, fostering collaboration between clinicians, data scientists, ethicists, and policymakers. This study aims to delve into the current landscape, challenges, and future prospects of autonomous healthcare, paving the way for a more resilient and patient-centric healthcare ecosystem. The primary objective of this study is to investigate the application landscape of AI in healthcare, with a specific emphasis on personalized medicine and disease prediction.

Contribution of the Study

This study makes a significant contribution by thoroughly exploring and analyzing how AI is used in healthcare, specifically focusing on personalized medicine and disease prediction. Using a rigorous methodology involving a systematic review of existing literature and bibliometric analysis, the study offers several important findings:

Consolidating existing knowledge

By reviewing existing literature, the study brings together information on AI applications in healthcare, especially in personalized medicine and disease prediction. It presents a comprehensive overview of current research, highlighting trends, gaps, and advancements.

Identifying key themes and trends

Through systematic exploration of academic databases and keyword analysis, the study identifies important themes and trends in AI's role in healthcare. This sheds light on the evolving landscape of personalized medicine and disease prediction.

Quantitative assessment through bibliometric analysis

Incorporating bibliometric analysis adds a quantitative aspect to the study, allowing for the evaluation of scholarly output, collaboration patterns, and thematic shifts in the field. Analyzing publication trends, authorship patterns, citation networks, and keyword co-occurrence provides empirical support for the study's findings.

Providing guidance for future research and practice

By synthesizing existing knowledge and pinpointing research gaps, the study offers valuable direction for future research in AI and healthcare. It highlights areas needing further exploration and suggests potential paths for innovation in personalized medicine and disease prediction.

Informing policy and decision-making

The study's insights can guide policy-making and decision-making processes concerning the integration of AI in healthcare. By offering a comprehensive understanding of the current landscape and emerging trends, it equips stakeholders with valuable information for strategic planning and resource allocation.

Methods

Study design

Objective

This study aims to explore the utilization of AI in healthcare, particularly in personalized medicine and disease prediction.

Methodology

The study employs a two-step approach comprising a comprehensive review of relevant literature followed by a bibliometric analysis.

Inclusion and exclusion criteria

Inclusion criteria

Articles centered on AI applications in healthcare, personalized medicine, and disease prediction published between 2010 and 2023.

Exclusion criteria

Articles deemed irrelevant, lacking rigorous scientific methodologies, or published beyond the specified timeframe are excluded.

Literature review

Search strategy

Academic databases such as PubMed, IEEE Xplore, Scopus, and Web of Science are systematically searched using keywords related to AI, healthcare, personalized medicine, and disease prediction.

Timeframe

The review encompasses articles published from 2010 to 2023.

Keywords

Artificial Intelligence; healthcare; Personalised medicine; Disease prediction

Article selection

Titles, abstracts, and full-texts are screened to select relevant articles based on their recent publication dates, relevance, and scientific rigor.

Data extraction

Pertinent information is extracted from selected articles for synthesis and analysis.

Assessment of quality and bias

Quality assessment

Selected articles are evaluated to ensure adherence to rigorous scientific methodologies.

https://doi.org/10.61577/abcb.2025.100005

Bias assessment

Any biases present in the selected literature are identified and addressed.

Bibliometric analysis

Objective

The aim is to quantitatively evaluate scholarly output, collaboration patterns, and thematic evolution within the AI in healthcare domain.

Data collection

Relevant bibliometric data is retrieved from various databases.

Selected indicators

Key indicators include publication trends, authorship patterns, citation networks, and keyword co-occurrence.

Analysis

1`222222222Quantitative analysis of the collected data is conducted to discern trends and patterns in scholarly output and collaboration within the AI in healthcare field. Figure 1. Shows the methodology of the study.

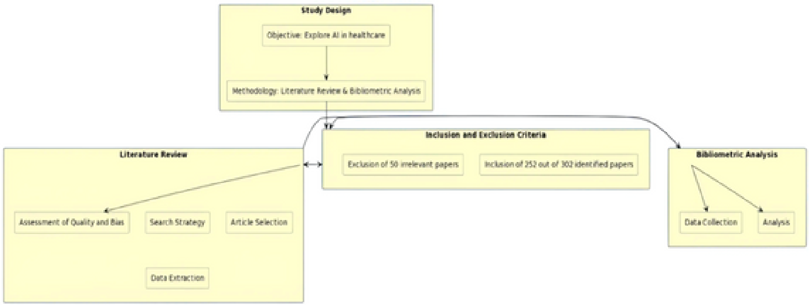

Figure 1. Methodology of the study.

Research questions

1. What are the primary applications of AI in healthcare, specifically in personalized medicine and disease prognosis?
2. How has the utilization of AI in healthcare evolved over time?
3. What prevalent themes and trends emerge from the literature on AI in healthcare, with a focus on personalized medicine and disease prognosis?
4. What are the collaboration patterns among researchers and institutions in the domain of AI in healthcare?
5. What are the most frequently appearing keywords and their patterns of occurrence in the literature concerning AI in healthcare, personalized medicine, and disease prognosis?

Hypothesis

H_0: There is no significant variance in the implementation of AI in personalized medicine compared to other healthcare domains.

H_1: AI exhibits broader application in personalized medicine compared to other areas within healthcare.

H_0: The landscape of AI applications in healthcare has remained static over time.

H_1: The landscape of AI applications in healthcare has dynamically evolved, with an increasing emphasis on personalized medicine and disease prognosis.

H_0: Thematic consistency is observed throughout the literature on AI in healthcare.

H_1: Evolving thematic patterns are discernible in the literature, reflecting shifts in research focus towards personalized medicine and disease prognosis.

H_0: Collaboration patterns among researchers and institutions in AI healthcare research are random.

H_1: Discernible collaboration patterns exist among researchers and institutions in AI healthcare research, reflecting strategic alliances and knowledge exchange.

H_0: Keyword co-occurrence patterns in the literature regarding AI in healthcare, personalized medicine, and disease prognosis are random.

H_1: Significant keyword co-occurrence patterns are present, indicating thematic clusters and research trends in the literature.

Results

AI models for personalized medicine

Personalized medicine, also referred to as precision medicine, represents a groundbreaking approach to medical treatment that considers individual variations in patients' genes, environments, and lifestyles. The integration of AI is pivotal in propelling personalized medicine forward by scrutinizing extensive data sets to discern patterns, foresee outcomes, and refine treatment strategies tailored to individual patients [51-57]. Figure 2 shows the co-occurrence analysis of the keywords in literature in which personalization and human are the most significant keywords in autonomous healthcare. Figure 3 shows the co-authorship analysis in the literature.

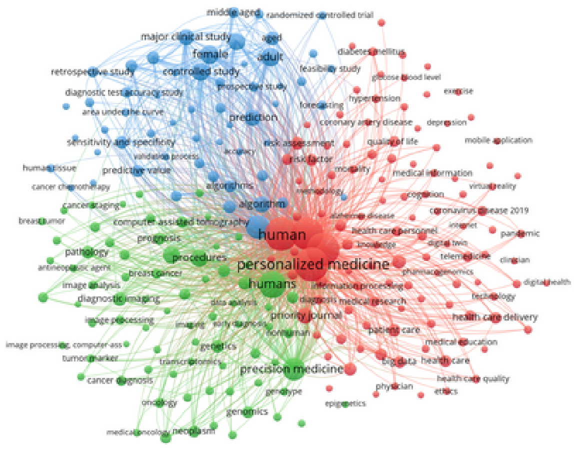

Figure 2. Co-occurrence analysis of the keywords in literature.

https://doi.org/10.61577/abcb.2025.100005

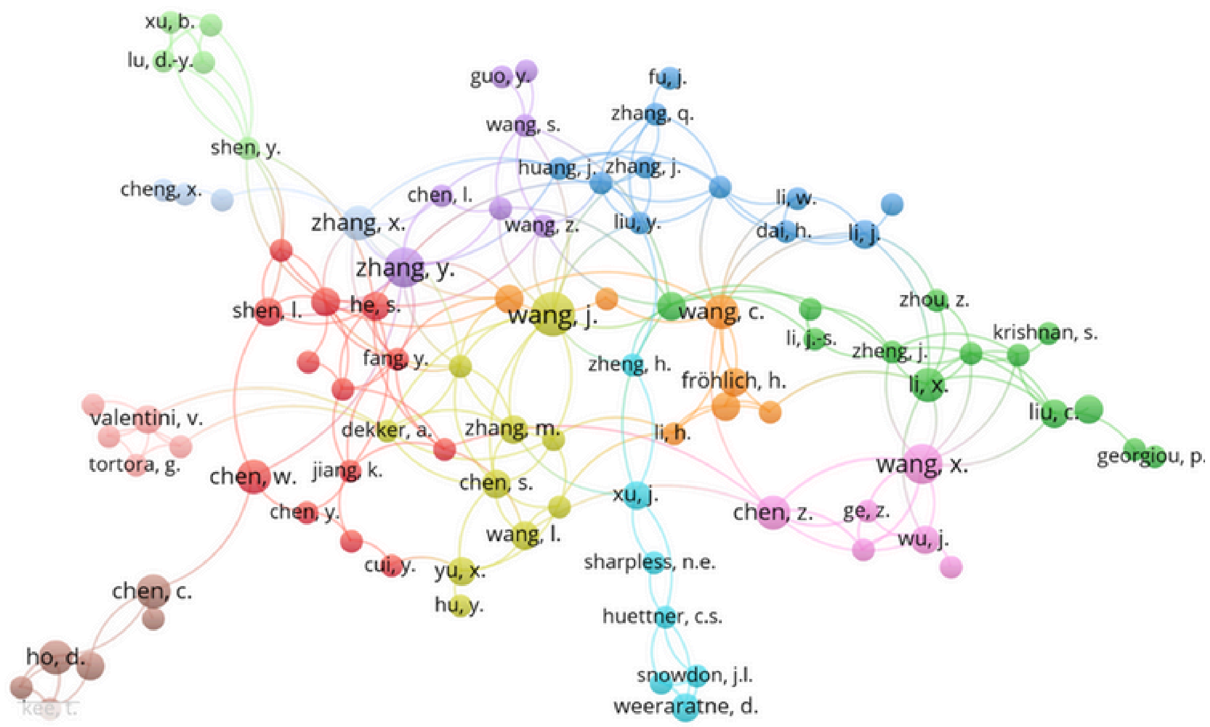

Figure 3. Co-authorship analysis.

Genomics and AI in personalized medicine

Genomic sequencing: AI significantly contributes to personalized medicine, particularly in genomics. Genomic sequencing involves scrutinizing an individual's DNA to pinpoint variations and mutations linked to diseases. Utilizing deep learning algorithms, AI models analyze extensive genomic datasets, identifying patterns and predicting disease risk based on genetic information [23,54]. For example, AI-powered tools can scrutinize cancer genomes, identifying specific mutations driving tumor growth. This information enables oncologists to customize treatment plans according to the unique genetic profile of a patient's cancer, resulting in more effective and personalized therapies [52,56,57]. Figure 4 shows the integrating AI for personalized medicine and disease prediction.

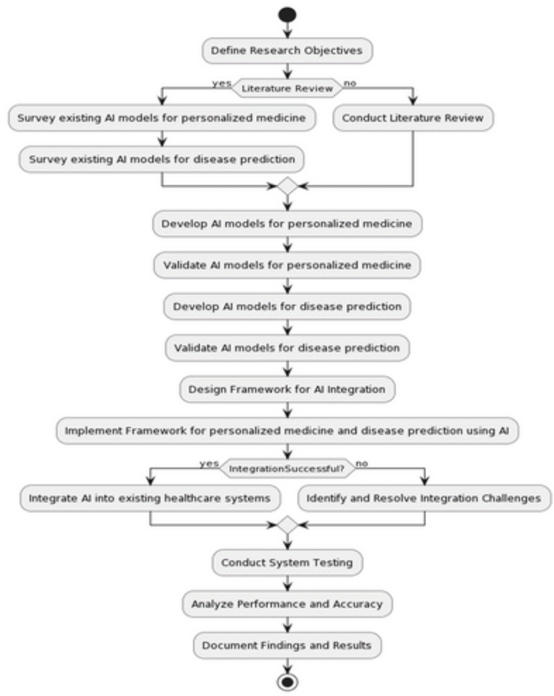

Figure 4. AI for personalized medicine and disease prediction.

https://doi.org/10.61577/abcb.2025.100005

Pharmacogenomics: Pharmacogenomics explores how an individual's genetic makeup influences their response to drugs. AI models analyze genetic data to predict a patient's response to specific medications, aiding clinicians in selecting the most effective and least harmful treatment. AI algorithms consider various genetic factors, including variations in drug metabolism enzymes and drug target receptors. By understanding how an individual's genes impact drug response, personalized medicine can minimize adverse effects and enhance treatment efficacy.

AI in cardiology

Cardiovascular risk prediction: In cardiology, AI is employed for personalized risk prediction and prevention. Machine learning models analyze diverse data sources, such as medical records, imaging data, and lifestyle information, to assess an individual's cardiovascular risk. These models identify patients at higher risk of developing heart diseases, enabling early intervention. For instance, AI algorithms can analyze cardiac imaging data to detect subtle abnormalities indicating an increased risk of heart disease. This information guides physicians in developing personalized preventive strategies, including lifestyle modifications or targeted medication [54,56].

Arrhythmia detection: AI models play a role in detecting and classifying cardiac arrhythmias. Based on deep learning techniques, these models analyze electrocardiogram (ECG) data to accurately identify irregular heart rhythms. This is crucial for personalized treatment, as different arrhythmias may require distinct therapeutic approaches [51,56].

AI in neurology

Alzheimer's disease prediction: In neurology, AI contributes to predicting and diagnosing diseases such as Alzheimer's. Machine learning algorithms analyze diverse data sources, including neuroimaging, genetic information, and clinical data, to identify patterns associated with Alzheimer's disease. Early detection is essential for personalized interventions in neurodegenerative diseases [53,55]. AI models predict the likelihood of developing Alzheimer's based on diverse factors, facilitating early interventions like lifestyle modifications and targeted therapies.

Stroke prediction and treatment optimization: AI is applied in predicting and optimizing treatments for stroke patients. Advanced imaging analysis using AI assesses the extent and location of brain damage caused by a stroke. This information helps clinicians tailor rehabilitation plans and select the most appropriate interventions for each patient, considering their unique neurological profile [54,56-60].

AI in oncology

Tumor profiling: In oncology, AI is extensively used for tumor profiling, involving the analysis of the molecular characteristics of tumors. AI models process complex genomic, transcriptomic, and proteomic data to identify specific alterations in cancer cells. Understanding the unique molecular signature of a tumor enables oncologists to personalize cancer treatment. For example, AI can predict a tumor's response to different chemotherapy drugs, facilitating the selection of the most effective and least toxic treatment for an individual patient.

Radiomics in cancer imaging: AI enhances radiomics, a field that extracts quantitative features from medical images, for personalized cancer treatment. AI algorithms analyze imaging data to identify subtle patterns not apparent to the human eye. This information aids in diagnosis, treatment planning, and monitoring the response to therapy.

AI in rheumatology

Disease activity prediction: In rheumatology, AI contributes to predicting disease activity in conditions like rheumatoid arthritis. Machine learning models analyze clinical and imaging data to assess inflammation severity and predict disease progression. This information guides rheumatologists in optimizing treatment plans for individual patients.

Personalized treatment strategies: AI assists in developing personalized treatment strategies in rheumatic diseases. By analyzing patient data, including genetic information, biomarkers, and response to previous treatments, AI models predict the most effective medications for an individual. This approach minimizes trial-and-error in finding suitable treatments, improving patient outcomes.

AI in psychiatry

Mental health prediction: AI plays a role in predicting mental health conditions based on various data sources, including patient history, genetic factors, and environmental influences [57-59]. Machine learning models identify patterns associated with conditions like depression, anxiety, and bipolar disorder. This personalized approach enables early intervention and the development of targeted treatment plans. For example, AI models predict an individual's response to different psychiatric medications, allowing psychiatrists to tailor medication regimens for optimal efficacy and minimal side effects.

Treatment response monitoring: AI is used to monitor and adjust treatment plans for psychiatric conditions. Continuously analyzing patient-reported data, such as mood changes and medication side effects, AI models provide real-time feedback to clinicians. This enables the optimization of treatment strategies, ensuring that patients receive personalized and effective mental health care. Table 1 shows the AI models for personalized medicine.

In the domain of autonomous healthcare, a suite of algorithms serves as the foundation of intelligent systems crafted to navigate and aid in the intricacies of medical decision-making. Among these, machine learning algorithms play a central role, showcasing prowess in recognizing patterns and offering predictions from data. For instance, supervised learning algorithms like Support Vector Machines (SVM) and Decision Trees excel in sorting tasks, assisting in diagnosing diseases based on patient data traits [55-58]. Meanwhile, unsupervised learning algorithms such as k-means clustering prove invaluable for revealing concealed structures within data, thereby facilitating patient categorization and anomaly detection, which are pivotal for early intervention in potential health concerns.

Deep learning, a subset of machine learning, has brought about a revolution in various healthcare domains, particularly in analyzing medical images and interpreting time-series data. Convolutional Neural Networks (CNNs) are crucial in accurately pinpointing irregularities in medical images, such as tumors in MRI scans, while Recurrent Neural Networks (RNNs) excel in scrutinizing sequential patient data to forecast outcomes and aid in devising treatment strategies. Natural Language Processing (NLP) algorithms play a crucial role in deciphering and producing human language, an essential element in healthcare where copious amounts of textual data exist in the form of clinical notes, medical literature, and

https://doi.org/10.61577/abcb.2025.100005

patient records [56-58]. NLP facilitates the extraction of relevant information from these sources, thereby assisting in diagnosis, recommending treatments, and enhancing communication between patients and virtual assistants.

Drawing inspiration from behavioral psychology, Reinforcement Learning (RL) algorithms empower systems to learn optimal decision-making strategies through interactions with their environment. In autonomous healthcare settings, RL finds applications in tailoring treatment plans, adjusting therapy dosages, and optimizing resource allocation within healthcare facilities [59,60]. Bayesian Networks, a variant of probabilistic graphical models, prove indispensable for representing uncertainty and causal connections among variables in healthcare data. They find utility in supporting diagnosis, assessing risks, and making medical decisions under conditions of uncertainty. Lastly, Genetic Algorithms, inspired by natural selection and genetics, are utilized to optimize parameters or features in healthcare systems. This encompasses tasks such as refining drug dosages, selecting features in medical imaging, and fine-tuning parameters in predictive models. Collectively, these algorithms constitute a robust arsenal for autonomous healthcare systems, empowering them to dissect complex data, make well-informed decisions, and ultimately enhance patient outcomes.

Algorithms Frequently Used in Artificial Intelligence

Following equations represent fundamental concepts and algorithms frequently used in artificial intelligence;

Logistic regression equation

$$P(Y=1)=\frac{1}{1+e^{-(mx+b)}}$$

Where,

$P(Y=1)$ Probability of the dependent variable being 1

e Euler's number (base of the natural logarithm)

m and b Parameters to be learned from the training data.

This method finds application in disease prediction, where it learns from patient data to estimate the likelihood of a patient having a specific disease based on their characteristics.

Neural network activation function (e.g., sigmoid)

$$\sigma(z)=\frac{1}{1+e^{-z}}$$

Where,

$\sigma(z)$ Sigmoid function output

z Weighted sum of inputs

In personalized medicine, this approach is instrumental in predicting patient outcomes or diagnosing diseases by analyzing input features like symptoms, genetic markers, or medical history.

Backpropagation update rule for weights (gradient descent)

$$W_{ij}=W_{ij}-\alpha\frac{\partial E}{\partial W_{ij}}$$

Where,

W_{ij} Weight between neuron i and neuron j

α Learning rate

$\frac{\partial E}{\partial W_{ij}}$ Partial derivative of the error with respect to the weight.

In the context of training neural networks for personalized medicine tasks, backpropagation plays a pivotal role. It involves adjusting weights iteratively using the gradient descent technique, thereby minimizing prediction errors and enhancing model performance.

Bayes' Theorem

$$P(A|B)=\frac{P(B|A)P(A)}{P(B)}$$

Where,

$P(A|B)$ Probability of event A given event B

$P(B|A)$ Probability of event B given event A

$P(A)$ and $P(B)$ Marginal probabilities of events A and B

Bayes' theorem facilitates disease prediction by incorporating new evidence (e.g., test results, patient symptoms) to update prior probabilities. This theorem calculates the probability of a patient having a disease by considering conditional and marginal probabilities.

K-Means clustering objective function

$$J=\sum_{i=1}^{k}\sum_{j=1}^{n}\left\|x_j-\mu_i\right\|^2$$

Where,

J Objective function (sum of squared distances)

k Number of clusters

μ_i Centroid of cluster i

x_j Data point j

K-means clustering groups patients based on similar characteristics, leveraging an objective function to assign data points to clusters. This method aids in devising personalized treatment plans or identifying high-risk patient groups.

Gaussian distribution probability density function

$$f(x|\mu,\sigma^2)=\frac{1}{\sqrt{2\pi\sigma^2}}exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

Where,

$f(x|\mu,\sigma^2)$ Probability density function of the Gaussian distribution

μ Mean of the distribution

σ^2 Variance of the distribution.

The Gaussian distribution models patient data attributes such as blood pressure or cholesterol levels, providing insights into normal ranges and outliers indicative of disease risk.

ReLU (Rectified Linear Unit) Activation Function

$$f(x)=max(0,x)$$

Where,

$f(x)$ Output of the ReLU activation function

x Input to the activation function

ReLU activation functions are employed in deep learning to extract features from medical imaging data or physiological signals, enhancing pattern recognition capabilities.

Softmax function (multiclass classification)

$$\text{softmax}(z)_i=\frac{e^{z_i}}{\sum_{j=1}^{K}e^{z_j}}$$

Where,

$\text{softmax}(z)_i$ Probability of class i in a multiclass classification

e^z Exponential of the input for class i

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$\sum_{j=1}^{K} e^{z_j}$ Sum of exponentials over all classes

Softmax is a valuable tool in multiclass disease classification tasks, offering probabilities for each disease class based on patient features.

Reinforcement learning - q-learning update rule

$$Q(s,a) = (1-\alpha)Q(s,a) + \alpha\left(R + \gamma\, max_{a'}\, Q\,(s',a')\right)$$

Where,

$Q(s,a)$Value of state-action pair (s,a)

α Learning rate

R Immediate reward

γ Discount factor

$max_{a'}\, Q\,(s',a')$ Maximum value of the next state-action pair

Q-learning optimizes treatment strategies by iteratively updating Q-values using immediate rewards and a discount factor. This approach learns the best actions (treatments) to maximize long-term health outcomes across different patient states.

PCA (principal component analysis) objective function

$$J = \frac{1}{m}\sum_{i=1}^{m}\left|\left|x^{(i)} - \bar{x}^{(i)}\right|\right|^2$$

Where,

J Objective function (mean squared reconstruction error)

m Number of data points

$x^{(i)}$Original data point

$\bar{x}^{(i)}$Reconstructed data point

PCA reduces dimensionality in patient data while retaining essential information, aiding in visualization, feature selection, or noise reduction through an objective function. Assessing the efficacy of predictive models on unfamiliar or unexplored data relies heavily on performance metrics. These metrics, widely utilized, encompass:

Accuracy: The proportion of correctly predicted outcomes to the total number of predictions.

Accuracy= TP+TN/TP+TN+FP+FN

Where,

true positive (TP), false positive (FP), false negative (FN), and true negative (TN).

Precision: The proportion of true positive predictions to all positive predictions, indicating the model's ability to avoid false positives.

Precision= TP/TP+FP

AI Models for Disease Prediction

AI has emerged as a revolutionary catalyst in reshaping healthcare, presenting groundbreaking solutions for forecasting, diagnosing, and treating diseases [58-66]. Within the domain of disease prediction, AI models have showcased extraordinary potential in various medical specialties, fundamentally altering our healthcare approach [60-62]. Table 1 shows the AI models for personalized medicine.

Cardiology

Cardiovascular diseases (CVDs) persist as a primary contributor to global morbidity and mortality. AI models play a pivotal role in foreseeing and preventing cardiovascular events by scrutinizing diverse datasets, including electronic health records (EHRs), medical imaging, and genetic information [67-72]. Machine learning algorithms, such as support vector machines and deep neural networks, excel in discerning patterns and risk factors associated with heart diseases [73-78].

Electrocardiogram (ECG) analysis

AI models proficiently analyze ECG data to predict cardiovascular events. Deep learning algorithms, including CNNs, exhibit high accuracy in detecting subtle abnormalities indicative of heart conditions. These models identify patterns in ECG signals that may elude human interpretation, facilitating early detection and intervention.

Risk stratification

AI contributes to risk stratification by amalgamating multiple patient variables. Predictive models consider diverse factors, such as age, gender, blood pressure, cholesterol levels, and lifestyle, to evaluate an individual's risk of developing cardiovascular diseases. This personalized approach enables clinicians to tailor preventive strategies for high-risk patients.

Oncology

AI has made substantial strides in oncology, augmenting early cancer detection, forecasting disease progression, and optimizing treatment plans [79-82]. The intricate nature of cancer datasets, encompassing genomic data, medical imaging, and clinical records, underscores the value of AI in extracting meaningful insights.

Radiomics and medical imaging

AI excels in analyzing medical imaging data, such as CT scans, MRIs, and mammograms, to identify early signs of cancer. Radiomics, a subfield extracting quantitative features from medical images, facilitates the development of predictive models for cancer detection and characterization. AI algorithms results in enhancing accuracy in diverse field [83-87].

Genomic analysis

The genomic landscape of cancer is intricate, with numerous genetic mutations influencing disease progression. AI models analyze large-scale genomic data to identify genetic markers associated with specific cancer types. This information contributes to predictive models for assessing cancer likelihood and tailoring treatment based on the individual's genetic profile.

Neurology

Neurological disorders present unique challenges due to the brain's complexity and diverse conditions. AI applications in neurology focus on predicting disease onset, tracking progression, and optimizing therapeutic interventions [88-93].

Neuroimaging

AI aids in neuroimaging data analysis, such as MRI and PET scans, for early detection of neurological disorders [94-100]. Pattern recognition such algorithms identify structural and functional abnormalities, aiding in predicting conditions like Alzheimer's disease, Parkinson's disease, and multiple sclerosis [100-105].

Table 1. AI models for personalized medicine.

Sr. No	Field	AI Model(s)	Application	Key Features	Data Types	Challenges and Considerations	References
1	Oncology	IBM Watson for Oncology, DeepMind's AlphaFold	Predicting optimal cancer treatments, identifying potential drug targets, protein structure prediction	Clinical decision support, drug discovery	Genomic data, clinical records, medical imaging	Interpretability, integration with healthcare systems	[20,30]

https://doi.org/10.61577/abcb.2025.100005

2	Cardiology	Echonous, Caption Health	Automated echocardiogram analysis, cardiac image interpretation	Real-time analysis, accuracy in detecting cardiac abnormalities	Echocardiograms, medical imaging	Limited labeled data, standardization of imaging protocols	[67,69,70]
3	Genetics	DeepVariant, Varient, GATK	Variant calling, genomic data analysis, identifying disease-associated genetic variations	High accuracy in variant calling, scalability	Genomic data, bioinformatics data	Data privacy, ethical considerations in genetic testing	[4,5]
4	Neurology	IBM Watson for Drug Discovery, Aidoc	Drug discovery for neurodegenerative diseases, automated detection of neurological abnormalities in medical imaging	Early diagnosis, personalized treatment plans	Medical imaging, clinical data	Limited labeled data for rare neurological conditions	[91-93]A
5	Radiology	Arterys, Zebra Medical Vision	Automated detection of abnormalities in medical images (X-rays, CT scans, MRI), early diagnosis of diseases	Speed and accuracy in image analysis	Medical imaging data	Integration with radiologist workflows, ethical use of AI in diagnostics	[23,26,27]
6	Pharmacogenomics	PREDICT, GeneSight	Predicting patient response to specific medications based on genetic information	Individualized treatment plans, improving drug efficacy	Genetic data, electronic health records	Limited understanding of gene-drug interactions, standardization of genetic testing	[4]
7	Immunology	ImmuneML, BenevolentAI	Identifying potential immunotherapies, analyzing immune system responses	Personalized immunotherapy, drug discovery	Immunological data, clinical records	Complexity of immune system interactions, limited understanding of individual variability	[13,17,19]
8	Infectious Diseases	BlueDot, Metabiota	Early detection of infectious disease outbreaks, predicting disease spread	Real-time monitoring, global health surveillance	Epidemiological data, travel patterns	Data integration, false positives/negatives in outbreak prediction	[9,11]
9	Rheumatology	Exagen Diagnostics, Arthritis.AI	Predicting disease progression, personalized treatment plans for autoimmune disorders	Early intervention, improving patient outcomes	Clinical data, imaging, genomic data	Heterogeneity in autoimmune diseases, long-term monitoring challenges	[21,26,29]
10	Dermatology	Aidoc, SkinVision	Automated analysis of skin lesions, early detection of skin cancers	Early diagnosis, reducing time to treatment	Dermatological images, patient history	Limited diversity in dermatological datasets, potential biases in image analysis	[27,36,69]
11	Psychiatry	Woebot, Wysa	AI-based mental health support, personalized therapy recommendations	Accessibility, continuous support	Text and voice data, user interactions	Ethical considerations in mental health AI, integration with clinical care	[50,76,89]

Electroencephalogram (EEG) analysis

EEG data, measuring brain electrical activity, can be challenging to interpret manually. AI models, particularly deep learning architectures, show promise in analyzing EEG patterns to predict seizures in epilepsy patients, enabling timely intervention and personalized treatment plans.

Infectious diseases

In the realm of infectious diseases, AI models contribute to predicting, monitoring, and managing outbreaks [106-111]. The capacity to analyze vast amounts of data, including epidemiological information, clinical records, and genomic sequences, empowers AI to offer insights for disease prevention and control.

Epidemic modeling

AI-driven epidemic models utilize real-time data to predict infectious disease spread. Machine learning algorithms analyze variables such as population density, travel patterns, and climate data to forecast outbreak trajectories. This information is invaluable for public health agencies in planning and implementing effective intervention strategies [112-116].

https://doi.org/10.61577/abcb.2025.100005

Diagnosis and surveillance

AI aids in the rapid and accurate diagnosis of infectious diseases by analyzing clinical data and diagnostic test results. Additionally, AI models monitor social media, news reports, and other sources for early indications of disease outbreaks, enabling timely response and containment efforts. Table 2 shows the AI models for disease prediction.

Table 2. AI models for disease prediction.

Sr. No	Disease Category	Medical Domain	AI Model	Key Features	Performance Metrics
1	Cancer	Oncology	Convolutional Neural Networks (CNN)	Image recognition, Tumor segmentation	Sensitivity, Specificity, ROC-AUC
2	Cardiovascular	Cardiology	Recurrent Neural Networks (RNN)	Time-series analysis of ECG data	Accuracy, F1 Score
3	Diabetes	Endocrinology	Support Vector Machines (SVM)	Feature selection, Glucose level prediction	Mean Absolute Error, Precision
4	Neurological	Neurology	Long Short-Term Memory Networks (LSTM)	EEG data analysis for seizure prediction	Sensitivity, Specificity
5	Infectious Diseases	Infectious Disease	Random Forests	Epidemiological data analysis, outbreak prediction	Sensitivity, Specificity
6	Respiratory	Pulmonology	Decision Trees	Spirometry data analysis for respiratory disease prediction	Accuracy, F1 Score

Framework for Personalized Medicine and Disease Prediction Using AI

This section delineates a comprehensive framework for the integration of AI in personalized medicine and disease prediction, encompassing data acquisition, integration, analysis, and clinical implementation. Figure 5 shows the framework for personalized medicine and disease prediction using AI.

Data acquisition

Initiating the framework involves the gathering of diverse and comprehensive data from various sources to construct a holistic patient profile [116-121]. This includes:

Genomic data

High-throughput sequencing technologies enable the extraction of an individual's entire genomic information. AI algorithms analyze this data to identify genetic variations associated with diseases, drug responses, and susceptibility.

Clinical data

EHRs provide a wealth of information on patients' medical history, diagnoses, treatments, and outcomes. AI systems can extract and analyze relevant clinical data to identify patterns and correlations.

Lifestyle and environmental data

Factors such as diet, physical activity, and environmental exposures contribute to an individual's health [122-127]. Wearable devices, sensors, and self-reported data can be integrated to provide a comprehensive understanding of lifestyle factors.

Omics data

Beyond genomics, other "omics" data, such as transcriptomics, proteomics, and metabolomics, offer insights into the molecular mechanisms underlying diseases. AI algorithms can integrate and analyze these multi-omics data for a more comprehensive understanding.

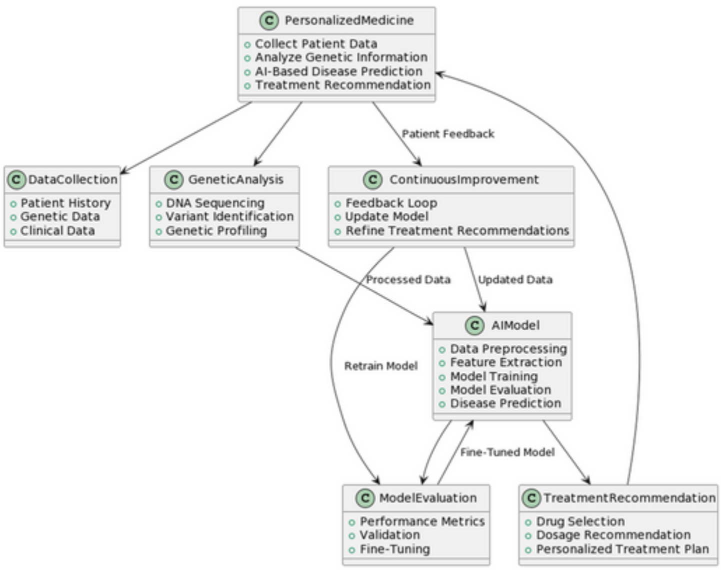

Figure 5. Framework for personalized medicine and disease prediction using AI.

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Where,

Data integration

Following data collection, the next step involves integrating the diverse datasets to create a unified and interoperable dataset [128-133]. Challenges such as data heterogeneity, privacy concerns, and standardization are addressed [130,134-138]. AI-powered tools, including natural language processing and data harmonization algorithms, play a crucial role in integrating disparate data sources and ensuring data quality.

Feature selection and dimensionality reduction

The integrated dataset may contain a large number of features, making it challenging to extract meaningful insights. AI algorithms, particularly machine learning techniques, are employed for feature selection and dimensionality reduction, identifying the most relevant features associated with disease prediction and treatment response, enhancing model interpretability and performance.

Disease prediction models

AI models, including machine learning and deep learning algorithms, are trained on the integrated dataset to predict disease susceptibility, progression, and treatment outcomes. These models consider genetic, clinical, lifestyle, and omics data to generate accurate and personalized predictions. Regular updates and retraining ensure that the models evolve with new data and knowledge.

Interpretability and explain ability

Addressing the "black box" nature of AI models, ensuring model interpretability and explain ability is crucial for successful implementation. AI tools that provide transparent insights into the decision-making process empower clinicians to make informed decisions based on the AI-generated predictions.

Clinical implementation

The ultimate goal is to translate AI-generated insights into clinical practice, necessitating collaboration between healthcare professionals, data scientists, and regulatory bodies. Integration with existing clinical workflows, adherence to ethical guidelines, and regulatory compliance are vital for the successful deployment of personalized medicine solutions.

Continuous learning and improvement

Recognizing the dynamic nature of medicine, the framework incorporates a continuous learning loop. AI models are updated and improved based on real-world outcomes and new data, ensuring that personalized medicine approaches remain current and effective over time [139-142].

Challenges of Integrating Artificial Intelligence for Personalized Medicine and Disease Prediction

AI into personalized medicine and disease prediction poses various challenges, spanning technical, ethical, regulatory, and societal domains [143-148]. The following are key obstacles in this endeavor.

Data privacy and security

Sensitive Information: Personalized medicine heavily relies on patient data, encompassing genetic information, medical records, and lifestyle data. Safeguarding the privacy and security of this sensitive information is imperative for establishing and retaining public trust [145-146].

Regulatory compliance

Adherence to data protection regulations (e.g., GDPR in Europe) adds complexity. AI systems must meet stringent standards to safeguard patient confidentiality.

Data quality and integration

Heterogeneous Data Sources: Integrating data from diverse sources like electronic health records, genetic databases, and patient-reported data is challenging due to differences in formats, standards, and quality.

Data bias

Biases in training data can result in skewed predictions (146,149-153). Ensuring representative training data is essential to the model's generalizability across diverse populations.

Interoperability

Integration with Existing Systems: Seamless integration with existing electronic health record (EHR) systems is crucial for implementing AI in healthcare settings. Achieving interoperability poses a significant challenge that requires attention for effective AI adoption.

Clinical validation and adoption

Lack of Clinical Evidence: Establishing the clinical validity and reliability of AI algorithms is crucial for gaining acceptance from healthcare professionals and regulatory bodies.

Physician acceptance

Healthcare providers may resist adopting AI tools without sufficient evidence of efficacy. Overcoming skepticism and ensuring AI complements clinical expertise is essential.

Regulatory challenges

Approval and Certification: AI-based medical tools must navigate complex regulatory pathways for approval [154-160]. Clear guidelines are necessary to streamline the approval process for AI in healthcare as the regulatory landscape evolves.

Ethical and legal concerns

Informed consent

Providing meaningful and informed consent for patients regarding the use of AI in personalized medicine is challenging. Patients need to comprehend the implications of AI-based predictions and treatments.

Liability

Determining liability in case of AI errors or adverse outcomes is a legal challenge that must be addressed to establish accountability.

Algorithm transparency and explain ability

Black Box Problem: Many AI models, particularly deep learning algorithms, are often perceived as "black boxes" with limited interpretability. Understanding and explaining AI model decisions are crucial for gaining trust from both healthcare professionals and patients.

Cost and resource constraints

Infrastructure and Training: Implementing AI necessitates

https://doi.org/10.61577/abcb.2025.100005

substantial resources, including robust computing infrastructure and ongoing training for healthcare professionals. The integration cost may pose a barrier, especially for smaller healthcare facilities.

Conclusions

In the quest to improve healthcare outcomes, the integration of AI has emerged as a transformative influence, reshaping the medical landscape toward a future marked by personalized medicine and advanced disease prediction. A prominent domain where AI is making substantial progress is personalized medicine. The traditional one-size-fits-all treatment approach is yielding to a more nuanced and individualized methodology, facilitated by powerful AI algorithms. Machine learning models, fed extensive datasets encompassing genetic, molecular, and clinical information, unravel intricate patterns underlying disease susceptibility and treatment response. Personalized medicine utilizes this information to tailor interventions, ensuring patients receive treatments optimized for their unique genetic makeup and physiological characteristics. Genomics, undergoing a paradigm shift with the advent of AI, plays a pivotal role in personalized medicine.

AI algorithms analyze genomic data on an unprecedented scale and speed, identifying genetic markers associated with diseases and contributing to the development of targeted therapies. Predicting an individual's predisposition to certain conditions enables proactive measures, transforming healthcare from reactive to preventive. Diagnostic imaging is another field where AI is making a lasting impact. Applying deep learning algorithms to medical imaging, such as radiology and pathology, demonstrates remarkable accuracy in identifying abnormalities. AI-powered diagnostic tools expedite the diagnosis process, enhance precision, reduce the margin for error, and ensure timely and effective interventions. The fusion of AI with diagnostic imaging promises early detection, a crucial factor in improving patient outcomes across various diseases.

In treatment planning and drug discovery, AI streamlines processes and expedites the development of novel therapies. AI algorithms analyzing vast databases propel drug repurposing, accelerating the drug development pipeline and potentially reducing associated costs. AI's influence extends beyond curative measures into predictive healthcare. Predictive analytics, fueled by machine learning algorithms, forecast disease trends and identify at-risk populations. Analyzing variables, including demographic data, environmental factors, and genetic predispositions, AI generates risk profiles for individuals and communities. This proactive approach enables healthcare providers to allocate resources efficiently, implement preventive measures, and mitigate the burden of diseases on individuals and healthcare systems.

EHRs is crucial for fostering seamless communication and collaboration among healthcare professionals. AI-driven EHR systems enhance data accuracy, accessibility, and facilitate real-time decision-making. Swiftly sifting through vast amounts of patient data enables healthcare providers to make informed decisions, leading to more effective and personalized care. The future of medicine lies at the intersection of human ingenuity and artificial intelligence, promising a healthcare landscape that is not only more advanced but also more compassionate and patient-centric.

Disclosure Statement

No potential conflict of interest was reported by the author.

References

1. Fritsch SJ, Blankenheim A, Wahl A, Hetfeld P, Maassen O, Deffge S, et al. Attitudes and perception of artificial intelligence in healthcare: A cross-sectional survey among patients. Digit Health. 2022;8:20552076221116772. https://doi.org/10.1177/20552076221116772
2. Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. Future Healthc J. 2019;6(2):94. https://doi.org/10.7861%2Ffuturehosp.6-2-94
3. Wen Z, Huang H. The potential for artificial intelligence in healthcare. J Commer Biotechnol. 2022;27(4). https://doi.org/10.5912/jcb1327
4. Abdelhalim H, Berber A, Lodi M, Jain R, Nair A, Pappu A, et al. Artificial intelligence, healthcare, clinical genomics, and pharmacogenomics approaches in precision medicine. Front genet. 2022;13:929736. https://doi.org/10.3389/fgene.2022.929736
5. Suwinski P, Ong C, Ling MH, Poh YM, Khan AM, Ong HS. Advancing personalized medicine through the application of whole exome sequencing and big data analytics. Front genet. 2019;10:49. https://doi.org/10.3389/fgene.2019.00049
6. Hassan M, Awan FM, Naz A, deAndrés-Galiana EJ, Alvarez O, Cernea A, et al. Innovations in genomics and big data analytics for personalized medicine and health care: A review. Int J Mol Sci. 2022;23(9):4645. https://doi.org/10.3390/ijms23094645
7. Vaz VM, Kumar L. 3D printing as a promising tool in personalized medicine. Aaps Pharmscitech. 2021;22:E1-20. https://doi.org/10.1208/s12249-020-01905-8
8. Silva-Spínola A, Baldeiras I, Arrais JP, Santana I. The road to personalized medicine in Alzheimer's disease: The use of artificial intelligence. Biomedicines. 2022;10(2):315. https://doi.org/10.3390/biomedicines10020315
9. Rezayi S, R Niakan Kalhori S, Saeedi S. Effectiveness of artificial intelligence for personalized medicine in neoplasms: a systematic review. Biomed Res Int. 2022;2022. https://doi.org/10.1155/2022/7842566
10. Cesario A, D'Oria M, Bove F, Privitera G, Boškoski I, Pedicino D, et al. Personalized clinical phenotyping through systems medicine and artificial intelligence. J Pers Med. 2021;11(4):265. https://doi.org/10.3390/jpm11040265
11. Hoshino I, Yokota H. Radiogenomics of gastroenterological cancer: The dawn of personalized medicine with artificial intelligence-based image analysis. Ann Gastroenterol Surg. 2021;5(4):427-435. https://doi.org/10.1002/ags3.12437
12. Lin B, Wu S. Digital transformation in personalized medicine with artificial intelligence and the internet of medical things. OMICS J Integr Biol. 2022;26(2):77-81. https://doi.org/10.1089/omi.2021.0037
13. Blasiak A, Khong J, Kee T. CURATE. AI: optimizing personalized medicine with artificial intelligence. SLAS Technology. 2020;25(2):95-105. https://doi.org/10.1177/2472630319890316
14. Toh TS, Dondelinger F, Wang D. Looking beyond the hype: applied AI and machine learning in translational medicine. EBioMedicine. 2019;47:607-615. https://doi.org/10.1016/j.ebiom.2019.08.027
15. Chavarriaga J, Moreno C. Precision Medicine, Artificial Intelligence, and Genomic Markers in Urology. Do we need to Tailor our Clinical Practice? Rev urol colomb. 2020;29(3):158-167. https://doi.org/10.1055/s-0040-1714148

https://doi.org/10.61577/abcb.2025.100005

16. Chang HY, Jung CK, Woo JI, Lee S, Cho J, Kim SW, et al. Artificial intelligence in pathology. J Pathol Transl Med. 2019;53(1):E1-E2. https://doi.org/10.4132/jptm.2018.12.16

17. Kruse TA, Larsen MJ, Tan Q, Andersen L, Thomassen M. Genomic medicine and artificial intelligence. Ugeskr Laeger. 2019;181(7A):V02190085.

18. Naaz S, Asghar A. Artificial intelligence, nano-technology and genomic medicine: The future of anaesthesia. J Anaesthesiol Clin Pharmacol. 2022;38(1):11. https://doi.org/10.4103%2Fjoacp.JOACP_139_20

19. Gulfidan G, Beklen H, Arga KY. Artificial intelligence as accelerator for genomic medicine and planetary health. OMICS J Integr Biol. 2021;25(12):745-749. https://doi.org/10.1089/omi.2021.0170

20. Quazi S. Artificial intelligence and machine learning in precision and genomic medicine. Medical Oncology. 2022;39(8):120. https://doi.org/10.1007/s12032-022-01711-1

21. Jin D, Harrison AP, Zhang L, Yan K, Wang Y, Cai J, et al. Artificial intelligence in radiology. Artif Intell Med. 2021;265-289. https://doi.org/10.1016/B978-0-12-821259-2.00014-4

22. Brady AP, Neri E. Artificial intelligence in radiology ethical considerations. Diagnostics. 2020;10(4):231. https://doi.org/10.3390/diagnostics10040231

23. Galán GC, Portero FS. Medical students' perceptions of the impact of artificial intelligence in Radiology. Radiología (English Edition). 2022;64(6):516-524. https://doi.org/10.1016/j.rxeng.2021.03.008

24. Gokdeniz ST, Kamburoğlu K. Artificial intelligence in dentomaxillofacial radiology. World J Radiol. 2022;14(3):55. https://doi.org/10.4329%2Fwjr.v14.i3.55

25. Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJ. Artificial intelligence in radiology. Nat Rev Cancer. 2018;18(8):500-510. https://doi.org/10.1038/s41568-018-0016-5

26. Van Leeuwen KG, de Rooij M, Schalekamp S, van Ginneken B, Rutten MJ. How does artificial intelligence in radiology improve efficiency and health outcomes? Pediatr. Radiol. 2022:1-7. https://doi.org/10.1007/s00247-021-05114-8

27. Van Leeuwen KG, Schalekamp S, Rutten MJ, van Ginneken B, de Rooij M. Artificial intelligence in radiology: 100 commercially available products and their scientific evidence. Eur Radiol. 2021;31:3797-3804. https://doi.org/10.1007/s00330-021-07892-z

28. Chang HY, Jung CK, Woo JI, Lee S, Cho J, Kim SW, et al. Artificial intelligence in pathology. J Pathol Transl Med. 2019;53(1):1. https://doi.org/10.4132/jptm.2018.12.16

29. Försch S, Klauschen F, Hufnagl P, Roth W. Artificial intelligence in pathology. Dtsch Arztebl Int. 2021;118(12):199. https://doi.org/10.3238%2Farztebl.m2021.0011

30. Niazi MK, Parwani AV, Gurcan MN. Digital pathology and artificial intelligence. Lancet Oncol. 2019;20(5):253-261. https://doi.org/10.1016/S1470-2045(19)30154-8

31. Jackson BR, Ye Y, Crawford JM, Becich MJ, Roy S, Botkin JR, et al. The ethics of artificial intelligence in pathology and laboratory medicine: principles and practice. Acad Pathol. 2021;8:2374289521990784. https://doi.org/10.1177/2374289521990784

32. Zhang T, Chen J, Lu Y, Yang X, Ouyang Z. Identification of technology frontiers of artificial intelligence-assisted pathology based on patent citation network. PloS one. 2022;17(8):0273355. https://doi.org/10.1371/journal.pone.0273355

33. Amboree TL, Montealegre JR, Fujimoto K, Mgbere O, Darkoh C, Wermuth PP. Exploring preventive healthcare in a high-risk vulnerable population. Int J Environ Res Public Health. 2022;19(8):4502. https://doi.org/10.3390/ijerph19084502

34. Batarseh FA, Ghassib I, Chong D, Su PH. Preventive healthcare policies in the US: solutions for disease management using Big Data Analytics. J Big Data. 2020;7(1):38. https://doi.org/10.1186/s40537-020-00315-8

35. Lin H, Xu M, Xie C. location and capacity planning for preventive healthcare facilities with congestion effects. J Ind Manag Optim. 2023;19(4). https://doi.org/10.3934/jimo.2022076

36. Nolan A, McCrory C, Moore P. Personality and preventive healthcare utilisation: Evidence from the Irish Longitudinal Study on Ageing. Prev Med. 2019;120:107-112. https://doi.org/10.1016/j.ypmed.2018.12.029

37. Ofoli JN, Ashau-Oladipo T, Hati SS, Ati L, Ede V. Preventive healthcare uptake in private hospitals in Nigeria: a cross-sectional survey (Nisa premier hospital). BMC Health Serv Res. 2020;20:1. https://doi.org/10.1186/s12913-020-05117-5

38. Zhang D, Xu Z, Yang Z, Zhou W, Cheung PM, Kam-pui Lee E, et al. Association of meaning in life with preventive healthcare use among Chinese adults: are there age and gender differences? BMC Public Health. 2022;22(1):2308. https://doi.org/10.1186/s12889-022-14699-0

39. Iqbal SM, Mahgoub I, Du E, Leavitt MA, Asghar W. Advances in healthcare wearable devices. NPJ Flex Electron. 2021;5(1):9. https://doi.org/10.1038/s41528-021-00107-x

40. Lee SM, Lee D. Healthcare wearable devices: an analysis of key factors for continuous use intention. Serv Bus. 2020;14(4):503-531. https://doi.org/10.1007/s11628-020-00428-3

41. Rha JY, Nam Y, Ahn SY, Kim J, Chang Y, Jang J, et al. What drives the use of wearable healthcare devices? A cross-country comparison between the US and Korea. Digit Health. 2022;8:20552076221120319. https://doi.org/10.1177/20552076221120319

42. Ali J, Jusoh A, Idris N, Airij AG, Chandio R. Wearable Devices in Healthcare Services. Bibliometrix Analysis by using R Package. iJOE. 2022;18(8). http://dx.doi.org/10.3991/ijoe.v18i08.31785

43. Kim E, Han S. Investigating the digital health acceptance of Korean baby boomers: Comparative study of telemedicine and wearable healthcare devices. Health policy techn. 2023;12(1):100727. https://doi.org/10.1016/j.hlpt.2023.100727

44. Kumar P, Chauhan S, Awasthi LK. Artificial intelligence in healthcare: review, ethics, trust challenges & future research directions. Eng Appl Artif Intell. 2023;120:105894. https://doi.org/10.1016/j.engappai.2023.105894

45. Saheb T, Saheb T, Carpenter DO. Mapping research strands of ethics of artificial intelligence in healthcare: a bibliometric and content analysis. Comput Biol Med. 2021;135:104660. https://doi.org/10.1016/j.compbiomed.2021.104660

https://doi.org/10.61577/abcb.2025.100005

46. Solanki P, Grundy J, Hussain W. Operationalising ethics in artificial intelligence for healthcare: A framework for AI developers. AI Ethics. 2023;3(1):223-240. https://doi.org/10.1007/s43681-022-00195-z

47. Küster D, Schultz T. Artificial intelligence and ethics in healthcare-balancing act or symbiosis? Bundesgesundheitsblatt Gesundheitsforschung Gesundheitsschutz. 2023. https://doi.org/10.1007/s00103-022-03653-5

48. Rogers WA, Draper H, Carter SM. Evaluation of artificial intelligence clinical applications: Detailed case analyses show value of healthcare ethics approach in identifying patient care issues. Bioethics. 2021;35(7):623-633. https://doi.org/10.1111/bioe.12885

49. Katirai A. The ethics of advancing artificial intelligence in healthcare: analyzing ethical considerations for Japan's innovative AI hospital system. Public Health Front. 2023;11:1142062. https://doi.org/10.3389/fpubh.2023.1142062

50. Mohammad Amini M, Jesus M, Fanaei Sheikholeslami D, Alves P, Hassanzadeh Benam A, Hariri F. Artificial Intelligence Ethics and Challenges in Healthcare Applications: A Comprehensive Review in the Context of the European GDPR Mandate. Mach learn knowl extr. 2023;5(3):1023-1035. https://doi.org/10.3390/make5030053

51. Rashid MB, Chow EK. Artificial intelligence-driven designer drug combinations: From drug development to personalized medicine. SLAS Technology. Translating Life Sciences Innovation. 2019;24(1):124-125. https://doi.org/10.1177/2472630318800774

52. CD milk. Artificial intelligence, radiology, precision medicine, and personalized medicine. Radiol Bras. 2019;52:7-8. https://doi.org/10.1590/0100-3984.2019.52.6e2

53. Egorov E, Pieters C, Korach-Rechtman H, Shklover J, Schroeder A. Robotics, microfluidics, nanotechnology and AI in the synthesis and evaluation of liposomes and polymeric drug delivery systems. Drug Deliv Transl Res. 2021;11:345-352. https://doi.org/10.1007/s13346-021-00929-2

54. Singh AV, Chandrasekar V, Paudel N, Laux P, Luch A, Gemmati D, et al. Integrative toxicogenomics: Advancing precision medicine and toxicology through artificial intelligence and OMICs technology. Biomed Pharmacother. 2023;163:114784. https://doi.org/10.1016/j.biopha.2023.114784

55. Koteluk O, Wartecki A, Mazurek S, Kołodziejczak I, Mackiewicz A. How do machines learn? artificial intelligence as a new era in medicine. J Pers Med. 2021;11(1):32. https://doi.org/10.3390/jpm11010032

56. Masood N, Wu SG. An era of personalized medicine in breast cancer: integrating artificial intelligence into practice. Front Oncol. 2023;13:1164808. https://doi.org/10.3389/fonc.2023.1164808

57. Denecke K, Baudoin CR. A review of artificial intelligence and robotics in transformed health ecosystems. Front Med. 2022;9:795957. https://doi.org/10.3389/fmed.2022.795957

58. Rashid J, Batool S, Kim J, Wasif Nisar M, Hussain A, Juneja S, et al. An augmented artificial intelligence approach for chronic diseases prediction. Public Health Front. 2022;10:860396. https://doi.org/10.3389/fpubh.2022.860396

59. Liu C, Jiao D, Liu Z. Artificial intelligence (AI)-aided disease prediction. BioInt. 2020;1(3):130-136. https://doi.org/10.15212/bioi-2020-0017

60. Ghaffar Nia N, Kaplanoglu E, Nasab A. Evaluation of artificial intelligence techniques in disease diagnosis and prediction. Discov Artif Intell. 2023;3(1):5. https://doi.org/10.1007/s44163-023-00049-5

61. Patil RR, Kumar S, Rani R. Comparison of Artificial Intelligence Algorithms in Plant Disease Prediction. Rev Intell Artif. 2022;36(2). https://doi.org/10.18280/ria.360202

62. Muneer S, Rasool MA. AA systematic review: Explainable Artificial Intelligence (XAI) based disease prediction. Int J of Adv Sci Comp and Eng. 2022;1(1):1-6.

63. Baashar Y, Alkawsi G, Alhussian H, Capretz LF, Alwadain A, Alkahtani AA, et al. Effectiveness of artificial intelligence models for cardiovascular disease prediction: network meta-analysis. Comput Intell Neurosci. 2022;2022.

64. Davagdorj K, Bae JW, Pham VH, Theera-Umpon N, Ryu KH. Explainable artificial intelligence based framework for non-communicable diseases prediction. IEEE Access. 2021;9:123672-123688. https://doi.org/10.1109/ACCESS.2021.3110336

65. Van Smeden M, Heinze G, Van Calster B, Asselbergs FW, Vardas PE, Bruining N, et al. Critical appraisal of artificial intelligence-based prediction models for cardiovascular disease. Eur Heart J. 2022;43(31):2921-2930. https://doi.org/10.1093/eurheartj/ehac238

66. Malibari AA. An efficient IoT-Artificial intelligence-based disease prediction using lightweight CNN in healthcare system. Meas: Sens. 2023;26:100695. https://doi.org/10.1016/j.measen.2023.100695

67. Johnson KW, Torres Soto J, Glicksberg BS, Shameer K, Miotto R, Ali M, et al. Artificial intelligence in cardiology. J Am Coll Cardiol. 2018;71(23):2668-2679. https://doi.org/10.1016/j.jacc.2018.03.521

68. Bonderman D. Artificial intelligence in cardiology. Wien Klin Wochenschr. 2017;129:866-868. https://doi.org/10.1007/s00508-017-1275-y

69. Itchhaporia D. Artificial intelligence in cardiology. Trends Cardiovasc Med. 2022;32(1):34-41. https://doi.org/10.1016/j.tcm.2020.11.007

70. Jaltotage B, Ihdayhid AR, Lan NS, Pathan F, Patel S, Arnott C, et al. Artificial intelligence in cardiology: an australian perspective. Heart Lung Circ. 2023;32(8):894-904. https://doi.org/10.1016/j.hlc.2023.06.703

71. Lopez-Jimenez F, Attia Z, Arruda-Olson AM, Carter R, Chareonthaitawee P, Jouni H et al. Artificial intelligence in cardiology: present and future. Elsevier Mayo Clin Proc. 2020;95(5):1015-1039. https://doi.org/10.1016/j.mayocp.2020.01.038

72. Karatzia L, Aung N, Aksentijevic D. Artificial intelligence in cardiology: Hope for the future and power for the present. Front cardiovasc med. 2022;9:945726. https://doi.org/10.3389/fcvm.2022.945726

73. Seetharam K, Balla S, Bianco C, Cheung J, Pachulski R, Asti D, et al. Applications of machine learning in cardiology. Cardiol Ther. 2022;11(3):355-368. https://doi.org/10.1007/s40119-022-00273-7

74. Arfat Y, Mittone G, Esposito R, Cantalupo B, De Ferrari GM, Aldinucci M. A review of machine learning for cardiology. Minerva Cardiol Angiol. 2021;70(1):1-75. https://dx.doi.org/10.23736/S2724-5683.21.05709-4

75. Petch J, Di S, Nelson W. Opening the black box: the promise and limitations of explainable machine learning in cardiology. Can J Cardiol. 2022;38(2):204-213. https://doi.org/10.1016/j.cjca.2021.09.004

https://doi.org/10.61577/abcb.2025.100005

76. Dudchenko A, Ganzinger M, Kopanitsa G. Machine learning algorithms in cardiology domain: A systematic review. Open Bioinform J. 2020;13(1). http://dx.doi.org/10.2174/1875036202013010025
77. Garcia-Canadilla P, Sanchez-Martinez S, Crispi F, Bijnens B. Machine learning in fetal cardiology: what to expect. Fetal Diagn Ther. 2020;47(5):363-372. https://doi.org/10.1159/000505021
78. Cuocolo R, Perillo T, De Rosa E, Ugga L, Petretta M. Current applications of big data and machine learning in cardiology. J Geriatr Cardiol: JGC. 2019;16(8):601. https://doi.org/10.11909%2Fj.issn.1671-5411.2019.08.002
79. Lin B, Tan Z, Mo Y, Yang X, Liu Y, Xu B. Intelligent oncology: the convergence of artificial intelligence and oncology. J Natl Cancer Cent. 2023;3(1):83-91. https://doi.org/10.1016/j.jncc.2022.11.004
80. Shimizu H, Nakayama KI. Artificial intelligence in oncology. Cancer Sci. 2020;111(5):1452-1460. https://doi.org/10.1111/cas.14377
81. Chua IS, Gaziel-Yablowitz M, Korach ZT, Kehl KL, Levitan NA, Arriaga YE, et al. Artificial intelligence in oncology: Path to implementation. Cancer Med. 2021;10(12):4138-4149. https://doi.org/10.1002/cam4.3935
82. Farina E, Nabhen JJ, Dacoregio MI, Batalini F, Moraes FY. An overview of artificial intelligence in oncology. Future Sci OA. 2022;8(4):FSO787. https://doi.org/10.2144/fsoa-2021-0074
83. Rane NL, Achari A, Choudhary SP, Mallick SK, Pande CB, Srivastava A, et al. A decision framework for potential dam site selection using GIS, MIF and TOPSIS in Ulhas river basin, India. J Clean Prod. 2023;423:138890. https://doi.org/10.1016/j.jclepro.2023.138890
84. Rane NL, Achari A, Saha A, Poddar I, Rane J, Pande CB, et al. An integrated GIS, MIF, and TOPSIS approach for appraising electric vehicle charging station suitability zones in Mumbai, India. Sustain Cities Soc. 2023;97:104717. https://doi.org/10.1016/j.scs.2023.104717
85. Gautam VK, Pande CB, Moharir KN, Varade AM, Rane NL, Egbueri JC, et al. Prediction of Sodium Hazard of Irrigation Purpose using Artificial Neural Network Modelling. Sustainability. 2023;15(9):7593. https://doi.org/10.3390/su15097593
86. Rane NL, Achari A, Kadam D. Evaluating the Selection Criteria of Formwork System (FS) for RCC Building Construction. Int J Eng Trends Technol. 2023;71(3):197-205. https://doi.org/10.14445/22315381/IJETT-V71I3P220
87. Liladhar Rane N, Achari A, Hashemizadeh A, Phalak S, Pande CB, Giduturi M, et al. Identification of sustainable urban settlement sites using interrelationship based multi-influencing factor technique and GIS. Geocarto Int. 2023;38(1):2272670. https://doi.org/10.1080/10106049.2023.2272670
88. Pedersen M, Verspoor K, Jenkinson M, Law M, Abbott DF, Jackson GD. Artificial intelligence for clinical decision support in neurology. Brain commun. 2020;2(2):fcaa096. https://doi.org/10.1093/braincomms/fcaa096
89. Amaro Junior E. Artificial intelligence and Big Data in neurology. Arq Neuro-Psiquiatr. 2022;80:342-347. https://doi.org/10.1590/0004-282X-ANP-2022-S139
90. Wiegand TL, Velezmoro LI, Jung LB, Wimbauer F, Dimitriadis K, Koerte IK. Artificial intelligence in neurology. Neurology. 2023;42(9):591-601. https://doi.org/10.1055/a-2050-0768
91. Vinny PW, Vishnu VY, Srivastava MP. Artificial Intelligence shaping the future of neurology practice. Med J Armed Forces India. 2021;77(3):276-282. https://doi.org/10.1016/j.mjafi.2021.06.003
92. Hillis JM, Bizzo BC. Use of artificial intelligence in clinical neurology. Semin Neurol. 2022;42(1):39-47. https://doi.org/10.1055/s-0041-1742180
93. Kedar S, Khazanchi D. Neurology education in the era of artificial intelligence. Curr Opin Neurol. 2023;36(1):51-58. https://doi.org/10.1097/WCO.0000000000001130
94. He X, Liu G, Zou C, Li R, Zhong J, Li H. Artificial intelligence algorithm-based MRI in evaluating the treatment effect of acute cerebral infarction. Comput Math Methods Med. 2022;2022. https://doi.org/10.1155/2022/7839922
95. Johnson PM, Recht MP, Knoll F. Improving the speed of MRI with artificial intelligence. Semin Musculoskelet Radiol. 2020;24(1):12-20. https://doi.org/10.1055/s-0039-3400265
96. Belue MJ, Turkbey B. Tasks for artificial intelligence in prostate MRI. Eur Radiol Exp. 2022;6(1):33. https://doi.org/10.1186/s41747-022-00287-9
97. Sunoqrot MR, Saha A, Hosseinzadeh M, Elschot M, Huisman H. Artificial intelligence for prostate MRI: open datasets, available applications, and grand challenges. Eur Radiol Exp. 2022;6(1):35. https://doi.org/10.1186/s41747-022-00288-8
98. Gullo RL, Marcus E, Huayanay J, Eskreis-Winkler S, Thakur S, Teuwen J, et al. Artificial intelligence-enhanced breast MRI: applications in breast cancer primary treatment response assessment and prediction. Invest Radiol. 2024;59(3):230-242. https://doi.org/10.1097/RLI.0000000000001010
99. Petrila O, Stefan AE, Gafitanu D, Scripcariu V, Nistor I. The Applicability of Artificial Intelligence in Predicting the Depth of Myometrial Invasion on MRI Studies - A Systematic Review. Diagnostics. 2023;13(15):2592. https://doi.org/10.3390/diagnostics13152592
100. Fritz B, Fritz J. Artificial intelligence for MRI diagnosis of joints: a scoping review of the current state-of-the-art of deep learning-based approaches. Skelet Radiol. 2022;51(2):315-329. https://doi.org/10.1007/s00256-021-03830-8
101. Rane NL, Jayaraj GK. Comparison of multi-influence factor, weight of evidence and frequency ratio techniques to evaluate groundwater potential zones of basaltic aquifer systems. Environ Dev Sustain. 2022;24(2):2315-2344. https://doi.org/10.1007/s10668-021-01535-5
102. Rane N. ChatGPT and Similar Generative Artificial Intelligence (AI) for Smart Industry: role, challenges and opportunities for industry 4.0, industry 5.0 and society 5.0. Challenges and Opportunities for Industry. 2023;4. https://dx.doi.org/10.2139/ssrn.4603234
103. Moharir KN, Pande CB, Gautam VK, Singh SK, Rane NL. Integration of hydrogeological data, GIS and AHP techniques applied to delineate groundwater potential zones in sandstone, limestone and shales rocks of the Damoh district, (MP) central India. Environ Res. 2023;228:115832. https://doi.org/10.1016/j.envres.2023.115832
104. Rane N. Transformers in Material Science: Roles, Challenges, and Future Scope. Challenges, and Future Scope. 2023. https://dx.doi.org/10.2139/ssrn.4609920
105. Rane N. Contribution of ChatGPT and other generative artificial intelligence (AI) in renewable and sustainable energy. 2023. https://dx.doi.org/10.2139/ssrn.4597674
106. Wong ZS, Zhou J, Zhang Q. Artificial intelligence for infectious disease big data analytics. Infect Dis Health. 2019;24(1):44-48. https://doi.org/10.1016/j.idh.2018.10.002

https://doi.org/10.61577/abcb.2025.100005

107. Cheng K, Li Z, He Y, Guo Q, Lu Y, Gu S, et al. Potential use of artificial intelligence in infectious disease: take ChatGPT as an example. Ann Biomed Eng. 2023;51(6):1130-1135. https://doi.org/10.1007/s10439-023-03203-3
108. Brownstein JS, Rader B, Astley CM, Tian H. Advances in Artificial Intelligence for infectious-disease surveillance. N Engl J Med. 2023;388(17):1597-1607. https://doi.org/10.1056/NEJMra2119215
109. Agrebi S, Larbi A. Use of artificial intelligence in infectious diseases. Artificial intelligence in precision health. 2020:415-438. https://doi.org/10.1016/B978-0-12-817133-2.00018-5
110. Smith KP, Kirby JE. Image analysis and artificial intelligence in infectious disease diagnostics. Clin Microbiol Infect. 2020;26(10):1318-1323. https://doi.org/10.1016/j.cmi.2020.03.012
111. Wong F, de la Fuente-Nunez C, Collins JJ. Leveraging artificial intelligence in the fight against infectious diseases. Science. 2023;381(6654):164-170. https://doi.org/10.1126/science.adh1114
112. Jiao Z, Ji H, Yan J, Qi X. Application of big data and artificial intelligence in epidemic surveillance and containment. Intell Med. 2023;3(01):36-43.
113. Lombardi R, Trequattrini R, Cuozzo B, Manzari A. Big data, artificial intelligence and epidemic disasters. A primary structured literature review. J Appl Decis Sci. 2022;15(2):156-180. https://doi.org/10.1504/IJADS.2022.121559
114. Yu J, Sun L. Design of Artificial Intelligence Epidemic Big Data Prevention and Control Early Warning System. Frontiers in Humanities and Social Sciences. 2022;2(9):141-145. https://doi.org/10.54691/fhss.v2i9.2119
115. MacIntyre CR, Lim S, Quigley A. Preventing the next pandemic: Use of artificial intelligence for epidemic monitoring and alerts. Cell Rep Med. 2022;3(12). https://doi.org/10.1016/j.xcrm.2022.100867
116. Yan-ping L, Ai-qin Q. Replace or create: Analysis of the Relationship between the Artificial Intelligence and Youth Employment in Post Epidemic Era. Procedia Comput Sci. 2022;202:217-222. https://doi.org/10.1016/j.procs.2022.04.029
117. Rane N. Role of ChatGPT and similar generative artificial intelligence (AI) in construction industry. 2023. https://dx.doi.org/10.2139/ssrn.4598258
118. Rane N. Enhancing the quality of teaching and learning through ChatGPT and similar large language models: challenges, future prospects, and ethical considerations in education. Future prospects, and ethical considerations in education. 2023. https://dx.doi.org/10.2139/ssrn.4599104
119. Rane N. Role and Challenges of ChatGPT and Similar Generative Artificial Intelligence in Finance and Accounting. 2023. https://dx.doi.org/10.2139/ssrn.4603208
120. Rane N. Role and challenges of ChatGPT and similar generative artificial intelligence in business management. 2023. https://dx.doi.org/10.2139/ssrn.4603227
121. Palanica A, Docktor MJ, Lieberman M, Fossat Y. The need for artificial intelligence in digital therapeutics. Digit Biomark. 2020;4(1):21-25. https://doi.org/10.1159/000506861
122. Zhang Y, Hu Y, Jiang N, Yetisen AK. Wearable artificial intelligence biosensor networks. Biosensors and Bioelectronics. 2023;219:114825. https://doi.org/10.1016/j.bios.2022.114825
123. Temsah MH, Jamal A, Aljamaan F, Al-Tawfiq JA, Al-Eyadhy A. ChatGPT-4 and the global burden of disease study: advancing personalized healthcare through artificial intelligence in clinical and translational medicine. Cureus. 2023;15(5). https://doi.org/10.7759/cureus.39384
124. Ganie SM, Malik MB. An ensemble machine learning approach for predicting type-II diabetes mellitus based on lifestyle indicators. Healthcare Analytics. 2022;2:100092. https://doi.org/10.1016/j.health.2022.100092
125. Xie Y, Lu L, Gao F, He SJ, Zhao HJ, Fang Y, et al. Integration of artificial intelligence, blockchain, and wearable technology for chronic disease management: a new paradigm in smart healthcare. Curr Med Sci. 2021;41:1123-1133. https://doi.org/10.1007/s11596-021-2485-0
126. Taj I, Zaman N. Towards industrial revolution 5.0 and explainable artificial intelligence: Challenges and opportunities. Int J Comput Digit Syst. 2022;12(1):295-320. https://dx.doi.org/10.12785/ijcds/120124
127. Hallak JA, Scanzera AC, Azar DT, Chan RP. Artificial intelligence in ophthalmology during COVID-19 and in the post COVID-19 era. Curr Opin Ophthalmol. 2020;31(5):447-453. https://doi.org/10.1097/ICU.0000000000000685
128. López-Martínez F, Núñez-Valdez ER, García-Díaz V, Bursac Z. A case study for a big data and machine learning platform to improve medical decision support in population health management. Algorithms. 2020;13(4):102. https://doi.org/10.3390/a13040102
129. Gautam N, Ghanta SN, Mueller J, Mansour M, Chen Z, Puente C, et al. Artificial Intelligence, Wearables and Remote Monitoring for Heart Failure: Current and Future Applications. Diagnostics. 2022;12(12):2964. https://doi.org/10.3390/diagnostics12122964
130. Gu C, Dai C, Shi X, Wu Z, Chen C. A cloud-based deep learning model in heterogeneous data integration system for lung cancer detection in medical industry 4.0. J Ind Inf Integr. 2022;30:100386. https://doi.org/10.1016/j.jii.2022.100386
131. Bukowski M, Farkas R, Beyan O, Moll L, Hahn H, Kiessling F, et al. Implementation of eHealth and AI integrated diagnostics with multidisciplinary digitized data: are we ready from an international perspective?. Eur Radiol. 2020;30:5510-5524. https://doi.org/10.1007/s00330-020-06874-x
132. Lin Y, Zhao X, Miao Z, Ling Z, Wei X, Pu J, et al. Data-driven translational prostate cancer research: from biomarker discovery to clinical decision. J Transl Med. 2020;18(1):119. https://doi.org/10.1186/s12967-020-02281-4
133. Rane N. Role and challenges of ChatGPT and similar generative artificial intelligence in human resource management. 2023. https://dx.doi.org/10.2139/ssrn.4603230
134. Rane N. Enhancing mathematical capabilities through ChatGPT and similar generative artificial intelligence: Roles and challenges in solving mathematical problems. 2023. https://dx.doi.org/10.2139/ssrn.4603237
135. Rane N. Transforming Structural Engineering through ChatGPT and Similar Generative Artificial Intelligence: Roles, Challenges, and Opportunities. Challenges, and Opportunities. 2023. https://dx.doi.org/10.2139/ssrn.4603242
136. Rane N. Roles and challenges of ChatGPT and similar generative artificial intelligence for achieving the sustainable development goals (SDGs). 2023. https://dx.doi.org/10.2139/ssrn.4603244
137. Rane NL. Multidisciplinary collaboration: key players in successful implementation of ChatGPT and similar generative artificial intelligence in manufacturing, finance, retail, transportation, and construction industry. https://doi.org/10.31219/osf.io/npm3d

https://doi.org/10.61577/abcb.2025.100005

138. Chiehfeng C, El-Wui L, Kuo KN, Ka-Wai T. The Times they Are a-Changin'–Healthcare 4.0 Is Coming!. J Med Syst. 2020;44(2). https://doi.org/10.1007/s10916-019-1513-0
139. Cepeda Zapata KA, Ward T, Loughran R, McCaffery F. Challenges Associated with the Adoption of Artificial Intelligence in Medical Device Software. AICS. Cham: Springer Nature Switzerland. 2022;163-174. https://doi.org/10.1007/978-3-031-26438-2_13
140. Eichler HG, Trusheim M, Schwarzer-Daum B, Larholt K, Zeitlinger M, Brunninger M, et al. Precision Reimbursement for Precision Medicine: Using Real-World Evidence to Evolve From Trial-and-Project to Track-and-Pay to Learn-and-Predict. Clin Pharmacol Ther. 2022;111(1):52-62. https://doi.org/10.1002/cpt.2471
141. Chander B. Advanced deep learning techniques and applications in healthcare services. Deep Learning for Personalized Healthcare Services. 2021;7:37.
142. Sun TQ, Medaglia R. Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. Gov Inf Q. 2019;36(2):368-383. https://doi.org/10.1016/j.giq.2018.09.008
143. Hulsen T. Explainable Artificial Intelligence (XAI) in Healthcare. 2023. https://doi.org/10.3390/ai4030034
144. Mudgal SK, Agarwal R, Chaturvedi J, Gaur R, Ranjan N. Real-world application, challenges and implication of artificial intelligence in healthcare: an essay. Pan Afr Med J. 2022;43. https://doi.org/10.11604%2Fpamj.2022.43.3.33384
145. Wen Z, Huang H. The potential for artificial intelligence in healthcare. J Commer Biotechnol. 2022;27(4). https://doi.org/10.5912/jcb1327
146. Chatterjee S, Dohan MS. Artificial intelligence for healthcare in India: policy initiatives, challenges, and recommendations. Int J Healthc Inf Syst Inform (IJHISI). 2021;16(4):1-1. https://doi.org/10.4018/IJHISI.20211001.oa17
147. Gerke S, Minssen T, Cohen G. Ethical and legal challenges of artificial intelligence-driven healthcare. Artificial intelligence in healthcare. Academic Press. 2020:295-336. https://doi.org/10.1016/B978-0-12-818438-7.00012-5
148. Rane N. Potential Role and Challenges of ChatGPT and Similar Generative Artificial Intelligence in Architectural Engineering. 2023. https://dx.doi.org/10.2139/ssrn.4607767
149. Rane N. Integrating Building Information Modelling (BIM) and Artificial Intelligence (AI) for Smart Construction Schedule, Cost, Quality, and Safety Management: Challenges and Opportunities. Cost, Quality, and Safety Management: Challenges and Opportunities. 2023. https://dx.doi.org/10.2139/ssrn.4616055
150. Patil DR, Rane NL. Customer experience and satisfaction: importance of customer reviews and customer value on buying preference. Int Res J Modern Eng Technol Sci. 2023;5(3):3437-3447. https://www.doi.org/10.56726/IRJMETS36460
151. Rane N. ChatGPT and similar Generative Artificial Intelligence (AI) for building and construction industry: Contribution, Opportunities and Challenges of large language Models for Industry 4.0, Industry 5.0, and Society 5.0. Opportunities and Challenges of Large Language Models for Industry. 2023;4. https://dx.doi.org/10.2139/ssrn.4603221
152. Rane N. Chatbot-Enhanced Teaching and Learning: Implementation Strategies, Challenges, and the Role of ChatGPT in Education. Challenges, and the Role of ChatGPT in Education. 2023. https://dx.doi.org/10.2139/ssrn.4603204
153. Amann J, Blasimme A, Vayena E, Frey D, Madai VI, Precise4Q Consortium. Explainability for artificial intelligence in healthcare: a multidisciplinary perspective. BMC Med Inform Decis Mak. 2020;20:1-9. https://doi.org/10.1186/s12911-020-01332-6
154. Roski J, Maier EJ, Vigilante K, Kane EA, Matheny ME. Enhancing trust in AI through industry self-governance. J Am Med Inform Assoc. 2021;28(7):1582-1590. https://doi.org/10.1093/jamia/ocab065
155. López DM, Rico-Olarte C, Blobel B, Hullin C. Challenges and solutions for transforming health ecosystems in low-and middle-income countries through artificial intelligence. Front Med. 2022;9:958097. https://doi.org/10.3389/fmed.2022.958097
156. Sharova DE, Zinchenko VV, Akhmad ES, Mokienko OA, Vladzymyrskyy AV, Morozov SP. On the issue of ethical aspects of the artificial intelligence systems implementation in healthcare. Digit diagn. 2021;2(3):356-368. https://doi.org/10.17816/DD77446
157. Hoch CC, Wollenberg B, Lüers JC, Knoedler S, Knoedler L, Frank K, et al. ChatGPT's quiz skills in different otolaryngology subspecialties: an analysis of 2576 single-choice and multiple-choice board certification preparation questions. Eur Arch Otorhinolaryngol. 2023;280(9):4271-4278. https://doi.org/10.1007/s00405-023-08051-4
158. Bisoyi A. Ownership, liability, patentability, and creativity issues in artificial intelligence. Inf Secur J A Glob. 2022;31(4):377-386. https://doi.org/10.1080/19393555.2022.2060879
159. Cummings M. Rethinking the maturity of artificial intelligence in safety-critical settings. AI Mag. 2021; 42(1):6-15.
160. Nurmaini S. The artificial intelligence readiness for pandemic outbreak COVID-19: Case of limitations and challenges in Indonesia. Com Eng App-Journal. 2021;10(1):9-19. https://doi.org/10.18495/comengapp.v10i1.353

https://doi.org/10.61577/abcb.2025.100005