



Towards Intelligent Healthcare: A Study of AI Applications, Challenges, and Future Trends

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Abstract: Artificial Intelligence (AI) is rapidly reshaping modern healthcare systems by enabling intelligent data processing, improving diagnostic precision, and supporting clinical decision-making. With the growth of electronic health records (EHRs), medical imaging, and wearable technologies, healthcare institutions are generating vast amounts of heterogeneous data that require advanced analytical techniques. AI technologies, including machine learning, deep learning, and natural language processing, provide powerful tools to extract meaningful insights from such data. This paper presents a comprehensive and structured review of AI in healthcare, focusing on system architectures, core enabling technologies, real-world applications, and emerging challenges. It highlights recent advancements such as explainable AI, federated learning, and blockchain-integrated healthcare systems. Furthermore, critical concerns related to data privacy, bias, interpretability, and regulatory compliance are examined in detail. The study concludes that while AI significantly enhances healthcare efficiency, accuracy, and accessibility, its successful adoption depends on the development of transparent, ethical, and clinically validated systems.

Keywords: Artificial Intelligence, Healthcare Systems, Deep Learning, Clinical Decision Support, Explainable AI, Smart Healthcare

INTRODUCTION

Artificial Intelligence (AI) has evolved from a conceptual framework into a transformative technology with far-reaching implications in healthcare. The rapid growth of digital healthcare infrastructure—including electronic health records (EHRs), imaging systems, genomic databases, and IoT-enabled medical devices—has created an environment where AI can be effectively utilized to enhance clinical outcomes and operational efficiency. Modern healthcare systems generate massive volumes of structured and unstructured data, which traditional analytical approaches struggle to process efficiently. AI addresses this limitation by enabling scalable, automated, and intelligent data analysis [1][2]. Recent advancements in deep learning and predictive analytics have demonstrated that AI models can achieve diagnostic accuracy comparable to healthcare professionals, particularly in medical imaging and disease prediction tasks. AI-based systems have shown high performance in detecting abnormalities in radiological images and identifying disease patterns, significantly reducing diagnostic errors and improving early detection [2] [3]. These capabilities support a transition from reactive healthcare toward proactive and predictive healthcare systems driven by data analytics [13].

In addition to clinical applications, AI is transforming healthcare management by optimizing workflows, reducing operational costs, and enhancing resource allocation. AI-driven decision support systems assist clinicians by analyzing patient history, clinical guidelines, and real-time data, enabling evidence-based treatment planning [3][6]. Moreover, the integration of AI with wearable devices allows continuous monitoring of patient health, improving chronic disease management and reducing hospital admissions [7][13]. Despite these advancements, several challenges hinder the widespread adoption of AI in healthcare. Data privacy and security remain critical concerns due to the sensitive nature of medical information. Traditional centralized AI models increase the risk of data breaches, whereas federated learning enables decentralized model training without sharing raw data [8][9]. Additionally, the lack of interpretability in complex AI models limits clinical trust, necessitating the adoption of explainable AI techniques to improve transparency [10][11].

AI HEALTHCARE SYSTEM ARCHITECTURE

AI-based healthcare systems follow a structured multi-layered architecture designed to support efficient data processing and decision-making. The architecture represented in Fig.1. follows a generalized AI healthcare pipeline consisting of data acquisition, preprocessing, model development, decision-making, and application deployment stages, as commonly described in healthcare analytics literature [3][5][13].



Fig.1 Architecture Flow

The data layer includes Electronic Health Records (EHRs), medical imaging, wearable sensors, genomic data, and laboratory reports. These datasets are heterogeneous and require robust integration mechanisms [3][13]. The preprocessing layer ensures data quality through cleaning, normalization, transformation, and feature extraction. Techniques such as dimensionality reduction improve model efficiency [3]. The model layer consists of machine learning and deep learning algorithms for classification and prediction. Federated learning enhances privacy by enabling decentralized training across institutions [8][9]. The decision layer interprets outputs into actionable insights such as diagnosis and risk scores. Explainable AI techniques improve transparency and trust [10][11]. The application layer integrates AI into real-world systems such as Clinical Decision Support Systems (CDSS), telemedicine, and remote monitoring. Blockchain technologies further enhance data security and integrity [14].

LITERATURE REVIEW

The body of literature on Artificial Intelligence in healthcare has evolved significantly over the past decade, transitioning from theoretical exploration to practical and large-scale clinical deployment. Early foundational studies primarily focused on validating the feasibility of applying machine learning and deep learning techniques in medical diagnostics. These studies demonstrated that deep neural networks could achieve performance comparable to trained clinicians, particularly in image-based diagnosis tasks such as radiology and dermatology, thereby establishing AI as a reliable clinical support tool [1][2].

As research progressed, attention shifted toward addressing real-world challenges associated with deploying AI systems in healthcare environments. One of the most critical issues identified in the literature is the management of sensitive patient data. Traditional AI models rely on centralized data storage, which introduces significant risks related to privacy, security breaches, and regulatory non-compliance. To address these concerns, federated learning (FL) has emerged as a promising solution that enables decentralized model training across multiple institutions without requiring data sharing. In this paradigm, models are trained locally, and only model updates are communicated, thereby preserving patient confidentiality while still enabling collaborative learning [8] [9].

Another important research direction is the need for transparency and interpretability in AI systems. Many advanced AI models, particularly deep learning architectures, operate as “black boxes,” making it difficult for clinicians to understand the reasoning behind predictions. This lack of interpretability reduces trust and limits adoption in critical healthcare settings. To overcome this limitation, Explainable Artificial Intelligence (XAI) has gained significant attention. Techniques such as feature importance analysis, saliency maps, and model-agnostic explanation methods (e.g., LIME and SHAP) provide insights into model behavior, thereby improving clinical trust and accountability [10] [11]. In addition to privacy and interpretability, data security and integrity have emerged as key research concerns. With the increasing use of cloud-based healthcare systems and interconnected medical devices, ensuring secure data exchange is essential. Blockchain technology has been proposed as a solution for maintaining secure and tamper-proof healthcare records. Blockchain-based systems provide decentralized data storage with transparency and traceability, enabling secure sharing of electronic health records (EHRs) across institutions [14].

Furthermore, recent studies highlight the integration of AI with the Internet of Medical Things (IoMT), which has enabled real-time health monitoring and predictive analytics. Wearable devices and smart sensors continuously generate physiological data that can be analyzed using AI models to detect anomalies and predict potential health risks. This approach is particularly effective in managing chronic diseases and improving healthcare accessibility in remote and underserved regions [7][13]. Overall, the literature clearly indicates a shift from accuracy-focused AI models to systems that prioritize privacy, explainability, scalability, and security. The convergence of federated learning, explainable AI, blockchain, and IoMT represents a multidisciplinary approach aimed at developing trustworthy and deployable healthcare solutions.



Table 1: Overview of existing approaches literature

Ref	Focus Area	Key Contribution
[4]	Machine Learning in Healthcare	Early review of ML techniques for medical data analysis
[6]	Clinical Decision Support	AI-based CDSS benefits, risks, and implementation strategies
[7]	IoMT & Wearables	Remote patient monitoring using wearable sensors
[8]	Federated Learning	Concept and applications of privacy-preserving AI
[9]	Federated Learning	Challenges and scalability in distributed AI systems
[10]	Explainable AI	Causability and interpretability in medical AI
[11]	Interpretable ML	Foundations of explainable and interpretable AI
[12]	Medical Data Learning	Representation learning for healthcare data
[13]	Big Data in Healthcare	Challenges and solutions in healthcare analytics
[14]	Blockchain Healthcare	Secure medical data sharing using blockchain

Table 1 highlights a shift from accuracy-focused models to privacy-aware, explainable, and scalable AI systems, reflecting the growing need for trustworthy and deployable healthcare solutions.

CORE AI TECHNOLOGIES

Artificial Intelligence in healthcare is driven by a combination of advanced computational techniques that enable the processing and analysis of complex, high-dimensional medical data. These technologies form the foundation of intelligent healthcare systems, supporting tasks such as diagnosis, prediction, treatment planning, and patient monitoring. The most significant AI technologies applied in healthcare include Machine Learning, Deep Learning, Natural Language Processing, Computer Vision, and Explainable Artificial Intelligence, each contributing uniquely to different aspects of healthcare transformation.

Machine Learning (ML) plays a central role in healthcare analytics by enabling systems to learn patterns from historical data and make predictions without explicit programming. In clinical environments, ML algorithms are widely used for disease prediction, patient risk stratification, and treatment outcome forecasting. Supervised learning models are commonly applied for classification tasks such as identifying patients at risk of chronic diseases, while unsupervised learning techniques help uncover hidden patterns in large-scale healthcare datasets. The increasing availability of electronic health records (EHRs) has significantly enhanced the performance and scalability of ML models, enabling more accurate and data-driven clinical decision-making [3][13]. Moreover, ML techniques are increasingly being integrated with healthcare workflows to support early diagnosis and preventive care. Machine learning techniques for healthcare data analysis and disease prediction have been extensively studied in early research, demonstrating their effectiveness in classification and prediction tasks in healthcare [4].

Deep Learning (DL), a specialized subset of machine learning, has revolutionized healthcare by enabling automatic feature extraction from raw data. Deep neural networks, particularly Convolutional Neural Networks (CNNs), are extensively used in medical imaging applications such as tumor detection, radiology analysis, and pathology classification. These models can learn complex representations directly from image data, eliminating the need for manual feature engineering. Studies have demonstrated that deep learning models can achieve performance levels comparable to or exceeding those of human experts in specific diagnostic tasks [2][3]. In addition to imaging, architectures such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are used for analyzing sequential data, including patient monitoring and time-series health data. The integration of advanced deep learning architectures has further enhanced the ability to process multimodal healthcare data, improving predictive accuracy and clinical



reliability [1][13]. Deep learning techniques are widely applied to electronic health records (EHRs) for tasks such as representation learning, clinical outcome prediction, and decision support. These approaches enable the extraction of complex patterns from high-dimensional healthcare data, thereby improving the accuracy and efficiency of clinical analytics [12].

Computer Vision (CV), closely associated with deep learning, focuses on enabling machines to interpret and analyze visual data. In healthcare, computer vision techniques are widely used for processing medical images such as X-rays, CT scans, MRIs, and ultrasound images. These systems can automatically detect abnormalities, segment regions of interest, and assist clinicians in diagnosis and treatment planning. For example, computer vision models are applied in oncology for tumor detection and in ophthalmology for identifying retinal diseases. The integration of computer vision with real-time imaging systems has also enabled advancements in robotic-assisted surgery, where AI assists surgeons in performing precise and minimally invasive procedures [2][3].

Explainable Artificial Intelligence (XAI) has emerged as a critical component for the adoption of AI in healthcare. While advanced AI models provide high accuracy, their lack of interpretability poses challenges in clinical settings where transparency and accountability are essential. XAI techniques aim to make AI models more interpretable by providing insights into how decisions are made. Methods such as feature importance analysis, saliency maps, and model-agnostic approaches (e.g., LIME and SHAP) are increasingly used to explain predictions. The integration of XAI with healthcare systems improves trust among clinicians and ensures compliance with regulatory requirements, thereby facilitating wider adoption of AI technologies [10][11]. Overall, the integration of these core AI technologies enables the development of robust and intelligent healthcare systems capable of improving diagnostic accuracy, enhancing patient care, and supporting data-driven decision-making.

APPLICATIONS OF AI IN HEALTHCARE

Artificial Intelligence has emerged as a transformative force in healthcare by enabling a wide range of data-driven applications that improve diagnostic accuracy, treatment efficiency, and healthcare management. Unlike traditional systems, AI-driven solutions can process vast amounts of heterogeneous medical data in real time, thereby supporting clinicians in making informed and timely decisions. The application of AI spans multiple domains (Fig. 2), including medical imaging, clinical decision support, drug discovery, remote monitoring, and personalized medicine, each contributing significantly to the evolution of intelligent healthcare systems.

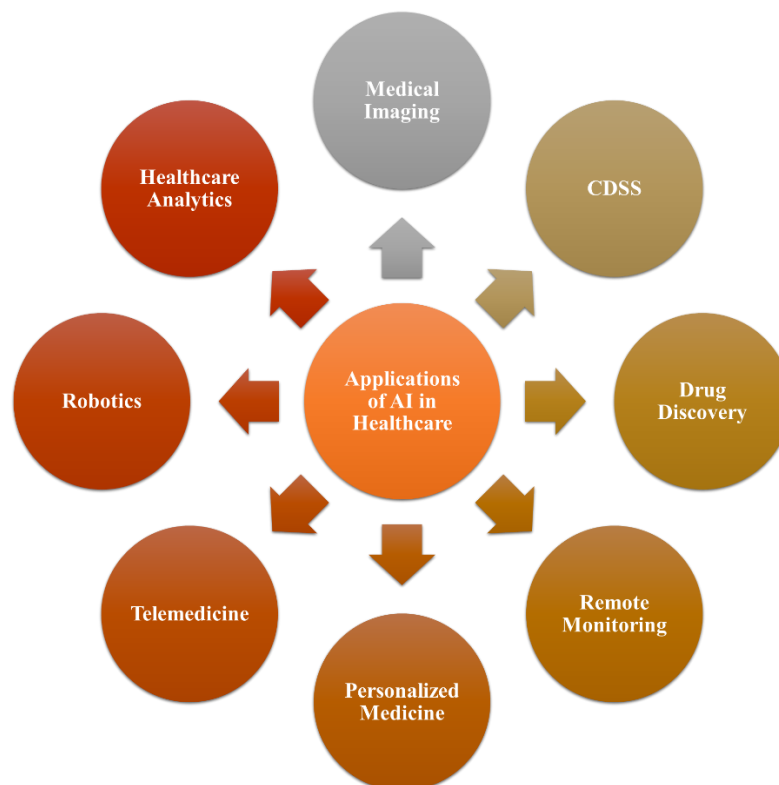


Fig. 2 Applications of AI in healthcare



One of the most prominent applications of AI in healthcare is medical imaging and diagnostics, where deep learning techniques-particularly Convolutional Neural Networks (CNNs)-are widely used to analyze radiological images such as X-rays, CT scans, and MRI scans. These models automatically learn hierarchical features from raw image data and can detect abnormalities such as tumors, fractures, and infectious diseases with high precision. Studies have demonstrated that AI-based diagnostic systems can achieve performance comparable to expert clinicians, particularly in dermatology and radiology tasks [2][3]. Furthermore, AI systems reduce the workload on radiologists by automating routine image analysis, enabling faster diagnosis and improving clinical workflow efficiency. The integration of AI in imaging also supports early disease detection, which is critical for improving patient outcomes and reducing mortality rates [1].

Another critical application area is Clinical Decision Support Systems (CDSS), where AI plays a vital role in assisting healthcare professionals in diagnosis and treatment planning. AI-driven CDSS integrate patient data, clinical guidelines, and historical medical records to generate evidence-based recommendations. These systems leverage machine learning algorithms to predict disease progression, identify high-risk patients, and suggest optimal treatment strategies. By reducing variability in clinical decisions and minimizing human error, AI-based CDSS enhance the quality and consistency of healthcare delivery [6]. Additionally, these systems support personalized treatment planning by analyzing patient-specific data, thereby improving therapeutic outcomes and resource utilization [3].

AI has also significantly impacted drug discovery and pharmaceutical research, a domain traditionally characterized by high costs and long development cycles. Machine learning and deep learning models are capable of analyzing complex biological datasets, identifying drug-target interactions, and predicting the efficacy of potential compounds. This accelerates the drug development process by reducing the need for extensive laboratory experiments and clinical trials. AI-driven approaches have been particularly effective in identifying novel therapeutic candidates and optimizing drug design, especially for complex diseases such as cancer and neurological disorders [3]. Moreover, AI enables simulation-based testing and predictive modeling, which further enhances the efficiency and success rate of drug discovery pipelines.

The integration of AI with remote patient monitoring systems represents another significant advancement in modern healthcare. With the widespread adoption of wearable devices and IoMT technologies, continuous monitoring of physiological parameters such as heart rate, blood pressure, glucose levels, and oxygen saturation has become feasible. AI algorithms analyze this real-time data to detect anomalies and predict potential health risks before they become critical. This proactive approach enables early intervention, reduces hospital readmissions, and improves chronic disease management [7] [13]. Remote monitoring systems are particularly beneficial for elderly patients and individuals with long-term health conditions, as they provide continuous care without requiring frequent hospital visits.

Another emerging and highly impactful application is personalized and precision medicine, where AI is used to tailor treatment strategies based on individual patient characteristics. By analyzing large-scale datasets that include genetic information, clinical history, lifestyle factors, and environmental influences, AI models can identify patterns that support customized treatment planning. This approach ensures that patients receive therapies that are most effective for their specific conditions, thereby improving treatment outcomes and minimizing adverse effects. AI-driven precision medicine represents a shift from generalized healthcare approaches to patient-centric care, which is a key objective of modern healthcare systems [1][13].

AI is also transforming healthcare administration and operational management by improving hospital workflows, resource allocation, and scheduling processes. Machine learning techniques enable the analysis of historical and real-time data to support predictions of patient admission rates and optimization of staffing requirements. These capabilities help healthcare institutions reduce operational costs while maintaining high-quality patient care. Additionally, AI-powered systems can automate administrative tasks such as billing, documentation, and record management, thereby reducing the workload on healthcare professionals and allowing them to focus on clinical activities [5].

In the domain of telemedicine and virtual healthcare, AI has enabled the development of intelligent systems that facilitate remote diagnosis and consultation. AI-powered platforms analyze patient symptoms, medical history, and real-time data to provide preliminary assessments and assist healthcare providers during virtual consultations. This is particularly beneficial in rural and underserved regions where access to healthcare facilities is limited. The combination of AI and telemedicine enhances accessibility, reduces healthcare disparities, and ensures timely medical intervention [7] [13].

Furthermore, AI plays a crucial role in robotic-assisted surgery and smart medical devices, where it enhances precision and reduces human error. AI-integrated robotic systems assist surgeons in performing complex procedures with high accuracy, enabling minimally invasive surgeries and faster recovery times [3]. These systems utilize real-time data and



advanced imaging techniques to guide surgical actions, thereby improving patient safety and clinical outcomes [3]. The integration of AI in surgical robotics represents a significant advancement in modern healthcare technology.

Another important application area is healthcare data analytics and predictive modeling, where AI is used to analyze large-scale datasets to identify trends, predict disease outbreaks, and support public health decision-making. By leveraging big data analytics, AI systems can provide insights into population health, enabling early detection of epidemics and effective healthcare planning. These capabilities are essential for managing large-scale health crises and improving overall healthcare system resilience [13].

Overall, the applications of AI in healthcare demonstrate its potential to revolutionize the entire healthcare ecosystem. From diagnosis and treatment to administration and research, AI enables more efficient, accurate, and personalized healthcare services. However, the successful implementation of these applications requires addressing challenges related to data privacy, interpretability, and regulatory compliance, as discussed in subsequent sections.

AI IN CLINICAL TRIALS AND RESEARCH

Artificial Intelligence is significantly transforming clinical trials and biomedical research by improving efficiency, accuracy, and scalability. Traditional clinical trials are often time-consuming, expensive, and resource-intensive, with challenges related to patient recruitment, data management, and outcome analysis. AI addresses these limitations by automating and optimizing various stages of the clinical trial lifecycle. One of the most critical challenges in clinical trials is patient recruitment, which involves identifying eligible participants from large and diverse populations. AI-based systems can analyze electronic health records (EHRs) and clinical databases to match patients with specific trial criteria, significantly reducing recruitment time and improving trial efficiency. This automated screening process enhances the likelihood of successful trial completion while minimizing manual effort [3] [12].

AI also plays a vital role in data analysis and real-time monitoring during clinical trials. Machine learning models can process large volumes of patient data to identify patterns, detect anomalies, and predict clinical outcomes. This enables early identification of adverse drug reactions and potential risks, thereby improving patient safety and reducing trial failures. Additionally, AI-driven predictive analytics can optimize trial design by identifying appropriate patient cohorts and treatment strategies [3] [13]. Another important contribution of AI is in enabling collaborative research through federated learning. In this approach, multiple healthcare institutions can collaboratively train AI models without sharing sensitive patient data. This ensures data privacy while enabling large-scale data analysis and improving model generalization. Federated learning is particularly valuable in healthcare research, where strict data protection regulations often limit data sharing across institutions [8] [9].

Furthermore, AI supports precision medicine research by analyzing genomic, clinical, and lifestyle data to identify biomarkers and predict patient responses to specific treatments. This enables the development of targeted therapies that improve treatment effectiveness and reduce side effects. AI-driven approaches are particularly beneficial in oncology and rare disease research, where individualized treatment strategies are essential [1] [13]. Overall, AI is accelerating the pace of biomedical research and transforming clinical trials by enhancing efficiency, improving accuracy, and enabling data-driven innovation.

AI IN PATIENT CARE

Artificial Intelligence is playing a transformative role in improving patient care by enabling continuous monitoring, enhancing accessibility, and supporting clinical decision-making. AI-driven healthcare systems are designed to provide patient-centric care that is proactive, personalized, and efficient. One of the most impactful applications of AI in patient care is telemedicine and remote healthcare services. AI-powered platforms enable patients to consult healthcare providers remotely, reducing the need for physical visits. These systems analyze patient data in real time and provide diagnostic recommendations, thereby improving the efficiency of virtual consultations. This is particularly beneficial in rural and underserved areas, where access to healthcare facilities is limited [7] [13].

AI is also widely used in remote patient monitoring systems, where wearable devices continuously collect physiological data such as heart rate, blood pressure, and glucose levels. AI algorithms analyze this data to detect anomalies and predict potential health risks, enabling early intervention. This approach is especially effective in managing chronic diseases and improving long-term patient outcomes [7] [13]. Another significant application is robotic-assisted surgery, where AI enhances surgical precision and reduces human error. AI-powered robotic systems assist surgeons in performing complex



procedures with high accuracy, enabling minimally invasive surgeries and faster recovery times. These systems integrate real-time data and advanced imaging technologies to improve surgical outcomes and patient safety [3].

AI also contributes to patient care through virtual health assistants and chatbots, which provide continuous support to patients. These systems can answer medical queries, schedule appointments, and provide medication reminders, thereby improving patient engagement and adherence to treatment plans. By automating routine interactions, AI reduces the workload on healthcare professionals and enhances overall healthcare efficiency [12]. In addition, AI plays a crucial role in elderly and assisted care, where intelligent monitoring systems track patient activities and detect emergencies such as falls. These systems provide real-time alerts to caregivers, ensuring timely medical intervention and improving the quality of life for elderly patients [7]. Overall, AI enhances patient care by enabling continuous monitoring, improving accessibility, and supporting personalized healthcare services.

CHALLENGES AND ISSUES

Despite its transformative potential, the adoption of AI in healthcare is associated with several critical challenges that must be addressed to ensure safe and effective implementation. One of the most significant challenges is data privacy and security. Healthcare data is highly sensitive, and centralized AI systems increase the risk of data breaches and unauthorized access. Emerging technologies such as federated learning and blockchain provide solutions by enabling secure and decentralized data processing, thereby reducing privacy risks [8] [14]. Another major issue is the lack of interpretability in AI models. Many advanced algorithms operate as “black boxes,” making it difficult for clinicians to understand how decisions are generated. This lack of transparency reduces trust and limits the adoption of AI systems in clinical practice. Explainable AI techniques are being developed to address this challenge by providing interpretable insights into model behavior [10] [11]. Bias and fairness also pose significant concerns, as AI models trained on biased datasets can produce inaccurate or discriminatory outcomes. Ensuring diversity in training data and implementing fairness-aware algorithms are essential for developing ethical and trustworthy AI systems [10] [11].

In addition, regulatory and legal challenges create barriers to AI adoption. Healthcare systems must comply with strict regulations to ensure patient safety, data protection, and clinical reliability. The absence of standardized guidelines for AI implementation further complicates the approval and deployment of AI systems [6]. Finally, integration challenges arise when incorporating AI into existing healthcare infrastructure. Implementing AI requires substantial investment in technology, training, and system redesign, which may not be feasible for all healthcare organizations. Additionally, integrating AI into clinical workflows requires careful alignment with existing systems and practices to ensure effective adoption [5] [6].

CONCLUSION AND FUTURE SCOPE

Artificial Intelligence is transforming healthcare by improving diagnostic accuracy, enhancing patient care, and optimizing clinical workflows. This study presented a comprehensive analysis of AI technologies, architectures, applications, and challenges, highlighting the significant impact of AI on modern healthcare systems. While AI offers numerous benefits, its successful adoption depends on addressing critical challenges such as data privacy, interpretability, bias, and regulatory compliance. Developing transparent, ethical, and clinically validated AI systems is essential to ensure trust and reliability in healthcare applications.

Looking forward, the future of AI in healthcare is highly promising. One of the most significant trends is the advancement of precision medicine, where AI enables personalized treatment strategies based on genetic, clinical, and lifestyle data. This approach improves treatment outcomes and reduces adverse effects [1] [13]. The integration of AI with IoMT and wearable technologies is expected to further enhance real-time health monitoring and predictive analytics, enabling early detection of diseases and proactive healthcare management [7] [13]. Additionally, the adoption of federated learning will support privacy-preserving collaborative research across healthcare institutions, enabling large-scale AI applications without compromising data security [8] [9]. Explainable AI will continue to play a critical role in improving transparency and trust, making AI systems more acceptable to clinicians and patients. Furthermore, advancements in robotic systems and automation are expected to enhance surgical precision and healthcare delivery.

In the long term, AI-driven predictive healthcare systems will shift the paradigm from reactive treatment to preventive care, significantly improving patient outcomes while reducing healthcare costs.



REFERENCES

- [1]. E. J. Topol, "High-performance medicine: the convergence of human and artificial intelligence," *Nature Medicine*, vol. 25, no. 1, pp. 44–56, 2019. <https://doi.org/10.1038/s41591-018-0300-7>
- [2]. Andre Esteva, A. Robicquet, B. Ramsundar et al., "A guide to deep learning in healthcare," *Nature Medicine*, vol. 25, no. 1, pp. 24–29, 2019. <https://doi.org/10.1038/s41591-018-0316-z>
- [3]. Riccardo Miotto, F. Wang, S. Wang, X. Jiang, and J. T. Dudley, "Deep learning for healthcare: review, opportunities and challenges," *Briefings in Bioinformatics*, vol. 19, no. 6, pp. 1236–1246, 2018. <https://doi.org/10.1093/bib/bbx044>
- [4]. M. Chen, Y. Hao, K. Hwang, L. Wang, and L. Wang, "Disease prediction by machine learning over big data from healthcare communities," *IEEE Access*, vol. 5, pp. 8869–8879, 2017. <https://doi.org/10.1109/ACCESS.2017.269444>
- [5]. Thomas Davenport and R. Kalakota, "The potential for artificial intelligence in healthcare," *Future Healthcare Journal*, vol. 6, no. 2, pp. 94–98, 2019. <https://doi.org/10.7861/futurehosp.6-2-94>
- [6]. R. T. Sutton, D. Pincock, D. C. Baumgart et al., "An overview of clinical decision support systems: benefits, risks, and strategies for success," *NPJ Digital Medicine*, vol. 3, no. 17, 2020. <https://doi.org/10.1038/s41746-020-0221-y>
- [7]. S. Majumder, T. Mondal, and M. J. Deen, "Wearable sensors for remote health monitoring," *IEEE Sensors Journal*, vol. 21, no. 1, pp. 216–232, 2021. <https://doi.org/10.1109/JSEN.2020.3012318>
- [8]. Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated machine learning: Concept and applications," *ACM Transactions on Intelligent Systems and Technology*, vol. 10, no. 2, 2019. <https://doi.org/10.1145/3298981>
- [9]. P. Kairouz, H. B. McMahan, B. Avent et al., "Advances and open problems in federated learning," *Foundations and Trends in Machine Learning*, vol. 14, no. 1–2, pp. 1–210, 2021. <https://doi.org/10.1561/22000000083>
- [10]. A. Holzinger, G. Langs, H. Denk, K. Zatloukal, and H. Müller, "Causability and explainability of artificial intelligence in medicine," *WIREs Data Mining and Knowledge Discovery*, vol. 12, no. 2, 2022. <https://doi.org/10.1002/widm.1312>
- [11]. Finale Doshi-Velez and Been Kim, "Towards a rigorous science of interpretable machine learning," arXiv:1702.08608, 2017.
- [12]. B. Shickel, P. J. Tighe, A. Bihorac, and P. Rashidi, "Deep EHR: A survey of recent advances in deep learning techniques for electronic health record (EHR) analysis," *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 5, pp. 1589–1604, 2018. <https://doi.org/10.1109/JBHI.2017.2767063>
- [13]. M.-H. Kuo, T. Sahama, A. W. Kushniruk, E. M. Borycki, and D. K. Grunwell, "Health big data analytics: Current perspectives, challenges and potential solutions," *International Journal of Big Data Intelligence*, vol. 1, no. 2, pp. 114–126, 2014. <https://doi.org/10.1504/IJBDI.2014.063835>
- [14]. A. Azaria, A. Ekblaw, T. Vieira, and A. Lippman, "MedRec: Using blockchain for medical data access and permission management," *Proceedings of IEEE Open & Big Data Conference*, 2016.