



Transforming healthcare through artificial intelligence: From technical foundations to clinical implementation and global governance

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Abstract

Artificial intelligence (AI) has become a powerful system which transforms healthcare organizations throughout the entire world. The study presents a thorough examination of healthcare AI systems which shows their complete technological structure and clinical deployment methods and their operational difficulties and their management systems. The document establishes clear connections between artificial intelligence and its subfields which include machine learning and deep learning and generative AI by showing their separate operational roles in medical environments. The study presents medical AI through two operational tracks which handle both administrative work and patient care delivery while analyzing seven essential technological areas that include operational AI and large language models and ambient listening systems and digital health assistants and genomic AI and imaging diagnostics and predictive analytics. The research study evaluates AI applications in disease prevention and diagnostic accuracy and personalized treatment and drug discovery and hospital management and public health surveillance through international studies and healthcare practice examples. The research shows that AI systems bring multiple advantages to healthcare operations yet various essential obstacles prevent their complete implementation throughout the entire healthcare sector. The research shows multiple important barriers which prevent AI systems from achieving full implementation in healthcare organizations because medical professionals and patients doubt their capabilities and these systems create unexplainable results and their performance changes over time and their implementation needs advanced infrastructure and their integration into medical workflows proves challenging. The research establishes the clinical adoption funnel framework while it studies ethical standards which healthcare providers need to follow when using AI systems for patient care. The Global Initiative on Artificial Intelligence for Health (GI-AI4H) serves as a collaborative governance system which the World Health Organization leads with its international partners to promote ethical and fair AI deployment. The research shows that AI technology has the ability to enhance healthcare operations through better service delivery and improved patient access and higher quality care but the system needs strong management systems and ongoing model assessment and human-AI teamwork and fair distribution of digital healthcare facilities to achieve its goals.

Keywords: Artificial intelligence, healthcare, machine learning, generative ai, clinical implementation, medical ethics, health governance

Introduction

The healthcare system faces major structural problems which include ongoing medical staff shortages and unequal access to excellent healthcare services and extended drug development timelines and excessive clinical paperwork and inefficient diagnostic systems (Rajkomar *et al.*, 2019) ^[11]. The World Health Organization shows that medical facilities in five global regions lack specialized doctors and advanced diagnostic equipment while remote primary medical centers fail to perform initial screenings for cancer and chronic diseases (World Health Organization [WHO], 2024). The population aging process together with increasing chronic disease cases has created a rising need for people to receive ongoing health tracking and customized medical care. The medical system which treats diseases after they appear struggles to meet today's health requirements (Topol, 2019) ^[19]. The healthcare industry has experienced a major breakthrough through artificial intelligence technology which includes machine learning and deep learning and generative AI systems. The healthcare industry now uses artificial intelligence through its complete technical system which includes medical AI as a fundamental component. The system contains separate technical units which perform particular functions within their designated operational range to create the base

structure for intelligent medical treatment (Singhal *et al.*, 2025) ^[17]. Medical AI in industrial practice has developed two main operational areas which include hospital administrative functions and medical service delivery to patients. The administrative track provides workers with a safe environment to complete their tasks because it allows fast landings at low risk which helps cut down on the need for multiple registrations and insurance claims processing and medical record organization. The clinical track operates under severe monitoring which establishes a high entry barrier yet maintains its main purpose to enhance medical diagnosis accuracy and develop better treatment strategies and protect patient survival (Ramachandran, Kamath, & Shabaraya, 2023) ^[12]. Medical AI has reached full development in medical image diagnosis and chronic disease remote monitoring and drug molecular screening and related areas. Medical image AI represents approximately 80% of all AI medical devices which global regulatory agencies have approved for certification because it demonstrates its clinical usefulness (Esteva *et al.*, 2017) ^[6].

Medical AI stands as a probabilistic system which operates independently from the deterministic framework that traditional medical software follows. The clinical diagnosis and treatment process faces potential safety threats because

of three main problems which include algorithmic black boxes and content hallucinations and data drift (Takita *et al.*, 2025) ^[18]. Medical AI deployment faces multiple barriers because different regions have different infrastructure levels and clinical processes do not match and people doubt AI medical systems and regulatory frameworks need improvement which creates a clear "clinical adoption funnel" (Char *et al.*, 2018) ^[11]. The international community has created ethical standards for medical AI which they use to support an international governance network that protects medical equity together with patient rights and technological progress in healthcare. This study takes the whole industrial chain of healthcare as the research scope, combs the technical hierarchy of medical AI in detail, analyzes typical application scenarios and practical effects at home and abroad, discusses the core risks and landing barriers of technology, and expounds the ethical norms and global governance system of medical AI. Combined with the perspective transformation of all participants in the industrial chain, it summarizes the transformation path of intelligent medical treatment, aiming to provide theoretical reference and practical guidance for the standardized application and sustainable development of AI in the global healthcare industry.

Hierarchical Technical System of Medical Artificial Intelligence

Medical AI is a nested technical system from broad to narrow scope. General artificial intelligence is the overall framework, which contains machine learning; machine learning includes deep learning; generative AI is the cutting-edge branch of deep learning. Each technical layer has independent technical characteristics and functional advantages, and realizes differentiated value in different medical scenarios (Russell & Norvig, 2021) ^[15]. The hierarchical relationship and application characteristics of each technology are analyzed as follows.

1. General Artificial Intelligence (AI): The Overall Framework of Intelligent Healthcare

General artificial intelligence is defined as a computer system that can independently complete work that originally relies on human intelligence, and it is the general term for all intelligent technologies in the healthcare field (Amisha *et al.*, 2019) ^[3]. The application scope of general AI in healthcare covers all links from patient admission to hospital operation management, including outpatient registration robots, voice medical record recording systems, surgical auxiliary robots, remote diagnosis platforms, hospital automatic scheduling systems and chronic disease remote monitoring devices. The core goal of general AI is to replace humans to complete repetitive, high-load and standardized medical work, and solve the long-standing pain points such as shortage of global medical staff and cumbersome medical processes (Secinaro *et al.*, 2021) ^[16]. In terms of hospital operation, the automatic scheduling system based on general AI can dynamically allocate medical staff according to the flow of outpatients and emergency patients, avoid manpower surplus or shortage; the patient risk classification screening tool can complete the initial screening of patients with different severity, reduce the pressure of primary medical staff and shorten the waiting time of patients. In the patient service link, the remote monitoring device for chronic diseases can collect

real-time physiological data such as blood pressure and blood sugar of patients at home, and feed back abnormal indicators to medical staff in a timely manner to realize continuous off-hospital care. As the most basic underlying technology of intelligent medical treatment, general AI has the widest landing scope and the lowest technical threshold. It does not involve complex data feature recognition, and mainly relies on preset logical frameworks to realize process automation. It is the first choice for primary medical institutions and small and medium-sized hospitals to carry out intelligent transformation.

2. Machine Learning (ML): The Core Subset of AI Realizing Autonomous Data Learning

Machine learning is the key branch of general AI and the basic technology supporting modern medical diagnosis (Rajkomar *et al.*, 2019) ^[11]. Different from traditional computer programs that need humans to write all judgment rules line by line, the core feature of machine learning is that the system can summarize rules independently and optimize judgment models continuously by learning from massive medical data without manual setting of all logic. In clinical diagnosis, machine learning models have been widely used in the screening of chronic diseases and infectious diseases. For example, the detection system for diabetic retinopathy trains the model through tens of thousands of patient examination reports and fundus images, and can independently distinguish the characteristics of healthy fundus and lesion fundus to identify early lesions (Abràmoff *et al.*, 2018) ^[11]. The tuberculosis recognition model based on voice data takes a large number of cough sounds and symptom data of patients as training samples, and can identify latent infected persons through sound characteristics, which is suitable for large-scale screening in remote areas with insufficient medical resources. In hospital operation management, machine learning analyzes historical data such as annual outpatient flow, seasonal epidemic rules and hospital revenue and expenditure to realize financial forecasting, outpatient peak prediction and flexible manpower allocation. This technology effectively alleviates the financial pressure and manpower imbalance of medical institutions, and provides data support for the scientific operation of hospitals. Machine learning is the transition link between general AI and in-depth intelligent diagnosis, and it is also the most widely used core technology in current clinical auxiliary diagnosis.

3. Deep Learning (DL): Neural Network Technology for Identifying Complex Medical Data

Deep learning is a special branch of machine learning, which simulates the structure of human brain neurons and builds a multi-layer neural network architecture to process high-dimensional and complex data (Esteva *et al.*, 2017) ^[6]. Medical fields contain a large number of unstructured complex data such as medical images, gene sequences and physiological waveforms. These data have complex features and numerous hidden information which are difficult to summarize manually by humans. Deep learning relies on multi-layer neural networks to extract features layer by layer, breaking the limitations of manual identification. Medical image interpretation is the most mature application scenario of deep learning. X-ray, computed tomography (CT) and magnetic resonance imaging (MRI) have huge data volume and tiny early lesion features that are easy to be

ignored by human eyes. Convolutional Neural Networks (CNN), a classic model of deep learning, can capture subtle lesion information such as small tumors and vascular lesions layer by layer, realizing early screening of major diseases such as lung cancer and stroke (Takita *et al.*, 2025) ^[18]. In addition, deep learning can also interpret genome data, automatically analyze electrocardiogram waveforms and simulate the molecular structure of drugs. In the field of new drug research and development, the traditional R&D cycle of a new drug is more than 10 years with huge capital investment. Deep learning simulates the interaction between drug molecules and human proteins, quickly screens potential effective compounds and predicts drug side effects, which greatly shortens the pre-clinical experimental cycle and R&D cost (Singhal *et al.*, 2025) ^[17]. Deep learning has become the core technical pillar of precision medicine and innovative drug research and development, and it is also the mainstream technology of high-end medical AI devices certified by global regulatory agencies.

4. Generative AI: Frontier Branch for Creating New Medical Content

Generative AI is the innermost subset of deep learning and one of the fastest-growing technical directions in medical AI in recent years (Morley *et al.*, 2020) ^[19]. Different from discriminant AI which is only used for data classification and identification, generative AI has the ability to generate new content independently according to input information, and the output forms include text, images, audio and molecular structure models. Large Language Models (LLMs) represented by BioGPT and medical professional generative models are the main technical carriers of generative AI in the medical field (Luo *et al.*, 2022) ^[8]. In clinical documentation, generative AI voice assistants can synchronously record doctor-patient consultation content, automatically generate standardized medical records, inspection summaries and discharge reports, reducing the time of doctors' document work by about 40% and effectively alleviating the occupational burnout of clinical medical staff (Yang *et al.*, 2022) ^[21]. In the auxiliary diagnosis link, inputting patients' medical history and test data, generative AI can integrate massive medical literature and put forward multiple sets of reference treatment plans to assist doctors in formulating individualized treatment courses. In public health and medical education, generative AI can generate popular science pictures and texts on disease health education and multi-language remote diagnosis questionnaires to bridge the gap of medical resources in remote areas. In the field of scientific research, it can simulate lesion development images and new drug molecular structures to provide new research tools for cancer treatment and drug R&D (Amatriain, 2023) ^[2]. Generative AI has expanded the application boundary of medical AI from data identification to content creation, and has become an efficient collaborative tool for medical staff.

Dual-Track Application Model of Medical AI: Administrative Operation and Clinical Care

Medical AI technology has developed two main application areas during its industrial growth which now include administrative operations and clinical healthcare services. The two tracks operate under different risk levels and they require different timeframes for implementation and they need different evaluation metrics and they serve distinct

operational roles to create a complete intelligent medical ecosystem (Roszkowska & Filipowicz-Chomko, 2026).

1. Administrative Operation Track: Low-Risk and Quick-Return Scenarios

Medical AI operates through the administrative operation track which serves as its "hidden return on investment track" because it covers hospital revenue cycle management and patient consultation and appointment services and document classification processes. The track operates without direct clinical diagnosis and treatment interference because it presents minimal application risks and achieves fast implementation timelines. Most projects show their cost savings and operational improvements through AI technology during the first few weeks of deployment which makes this field attractive for worldwide medical organizations to adopt AI systems (Rieke *et al.*, 2020) ^[20]. The administrative track contains three essential modules which form its basic structure. First, insurance claim verification and financial management; Hospital insurance declaration depends on human workers to perform manual inspections, which leads to numerous rejected claims because staff members fail to notice important details. AI technology performs automatic medical record comparisons with inspection items and insurance clauses which help hospitals reduce their rejection rates while maintaining their financial stability. The system operates to manage patient services. AI technology enables patients to register automatically through online systems while also providing appointment rescheduling and smart answers to standard medical questions which reduce their wait time for phone calls and in-person queueing. Third, document and information classification; Generative AI systems process large numbers of consultation emails and medical documents for classification purposes while they automatically organize information which prevents service interruptions because of information buildup. The administrative track evaluation system requires organizations to monitor their expenses and operational efficiency by tracking three main performance indicators which consist of labor cost reduction for individual operations and patient waiting time reduction and insurance rejection rate reduction. Because it does not involve the safety of patients, it does not need long-term clinical verification, and the investment recovery cycle is short. Hospitals need to start their intelligent transformation process through this particular stage.

2. Clinical Care Track: High-Risk and High-Value Core Medical Scenarios

The clinical care track directly faces patients' diagnosis and treatment, covering auxiliary diagnosis, radiotherapy adjustment, early warning of critical illnesses and other links. This track is the core value carrier of medical AI to "save lives", with high technical threshold and application risks (Topol, 2019) ^[19]. Since the output results of AI will directly affect the formulation of treatment plans, all AI products on the clinical track need to pass strict regulatory review and long-term clinical data verification, and the landing cycle ranges from several months to several years. The key application scenarios of the clinical track are divided into three categories. First, intelligent auxiliary diagnosis; AI analyzes CT, X-ray and blood test data to capture early lesion features that are difficult for human

eyes to find, and improve the accuracy of diagnosis of cancer, stroke and other major diseases. Second, adaptive radiotherapy; The AI system dynamically adjusts the radiation dose according to the tumor location and physical characteristics of patients, killing lesion tissues while protecting normal human tissues and reducing treatment side effects. Third, early warning of critical illnesses; for sepsis, acute heart disease and other rapidly progressive fatal diseases, AI monitors vital signs in real time, sends out early warnings before the condition deteriorates, and seizes the golden time for first aid. The evaluation standards of the clinical track are all around patients' health quality, including diagnostic accuracy, long-term survival rate of patients and emergency response time. Although the landing difficulty of the clinical track is high, it is the key to improve the overall medical quality and reduce the mortality rate of patients, and it is also the core direction of the long-term development of medical AI.

3. Collaborative Mechanism of Dual Tracks

The administrative operation track and clinical care track function as supportive elements which work together to form a unified system (Li & Liu, 2025)^[7]. The administrative AI system helps medical staff by cutting down their document work and operational duties so doctors can spend their time in direct patient care. The clinical AI system delivers better diagnosis results which lead to better treatment options while it decreases the costs that doctors must pay and the paperwork requirements which stem from incorrect diagnoses and extended treatment periods. The hospital transformation process follows a step-by-step approach which starts with administrative AI deployment for cost reduction and data collection and technical skill development before moving to clinical AI product advancement after clinical testing. The hospital administration track creates immediate financial advantages which improve hospital operations through better efficiency. The clinical track achieves its fundamental medical purpose by safeguarding patient health and preserving their lives throughout the long term. The two tracks need to develop together because this approach will maintain intelligent medical ecosystem stability through sustainable operations.

Seven Mainstream Technical Directions of Intelligent Medical Treatment

Based on the underlying AI technology system and dual-track application model, the current intelligent healthcare industry has derived seven mainstream technical directions of covering hospital operation, clinical documentation, image diagnosis, precision treatment and public health prediction. These technologies are interconnected and share data, forming a full-coverage intelligent medical solution (Amisha *et al.*, 2019)^[3].

1. Operational AI: Optimizing Hospital Logistics and Manpower Allocation

Operational AI is the most easily deployed technology in medical AI, focusing on solving the three major problems of hospital daily administration, financial management and manpower scheduling. Its core modules include automatic registration and appointment, insurance claim verification and dynamic manpower planning. Traditional hospitals have long been plagued by cumbersome administrative processes. Manual processing of appointment changes, document

verification and manpower scheduling not only consumes a lot of labor costs, but also easily leads to unreasonable allocation of medical resources. Operational AI builds models based on historical data such as annual outpatient flow, emergency peak and seasonal epidemic rules, realizes automatic triage of patient appointments and intelligent reply to online consultation. In terms of financial management, it automatically checks insurance documents to reduce the error rate of manual work. In terms of manpower allocation, it predicts manpower gaps in advance according to the changing rules of patient flow, and flexibly deploys doctors and nurses to avoid manpower imbalance. This technology has low deployment risk and obvious short-term benefits, and has been widely used in primary medical institutions and chain hospital groups around the world.

2. Generative AI and Large Language Models (LLMs): Underlying Technology for Clinical Documentation

Generative AI and large language models are the fastest-growing technical fields in medical AI in recent years, with two core values: automatic generation of clinical documents and construction of intelligent consultation assistants (Singhal *et al.*, 2025)^[17]. Clinical documentation is a heavy burden for clinical doctors. Statistics show that doctors spend nearly two hours sorting out medical records for every hour of consultation, which is an important cause of occupational burnout. After training with massive medical literature and standardized medical record data, large language models can sort out consultation information in real time and generate standardized medical records, discharge summaries and test reports, greatly shortening the time of document work. At the same time, LLMs support multi-language and local dialect intelligent consultation assistants, answering patients' questions about medication, disease health education and medical process 24 hours a day, diverting mild consultation demands in outpatient departments. In addition, generative AI is also widely used in pharmaceutical R&D, medical teaching and public health publicity, and it has become a universal underlying technology connecting all medical scenarios.

3. Ambient Listening Technology: Real-Time Voice Recording to Reduce Documentation Burden

Ambient listening technology is the extended landing application of large language models, which focuses on real-time transcription of doctor-patient consultation dialogue, and fundamentally solves the problem of excessive documentation work of medical staff (Yang *et al.*, 2022)^[21]. Different from the traditional AI medical record tools that require manual input or post-recording sorting, the ambient listening system runs silently during the whole consultation process without interfering with doctor-patient communication. It automatically extracts key information such as patients' chief complaints, symptoms, examination results and medication plans, and sorts them into structured electronic medical records. After the consultation, the first draft of medical records is completed synchronously, eliminating the overtime work of doctors sorting out reports after work. This technology has a particularly prominent effect in high-flow scenarios such as primary clinics, physical examination centers and emergency departments. It returns doctors' energy to the core work of diagnosis and treatment, and effectively improves the quality of doctor-patient communication.

4. Agentic AI and Digital Health Assistants: Continuous Health Management Robots

Agentic AI (multi-agent AI) integrates multiple automation systems and hospital electronic health records (EHR) to build an all-in-one digital health assistant, which is responsible for initial information collection of patients, triage of mild and severe cases and long-term home management of chronic diseases (Rieke *et al.*, 2020) ^[13]. When patients are admitted to the hospital, the intelligent robot guides them to independently fill in basic information, medical history and allergy history, and automatically synchronizes the data to the electronic medical record system to complete initial triage, saving the queuing time of manual filling. For patients with chronic diseases such as hypertension and diabetes, the digital health assistant tracks physiological data such as blood pressure and blood sugar for a long time, regularly pushes medication and rehabilitation reminders, and sends alarm information to attending doctors when indicators are abnormal, realizing seamless connection between in-hospital treatment and home care. Compared with a single dialogue robot, agentic AI has the capabilities of cross-system data access, independent risk judgment and cross-scenario resource coordination, and is the core technology to realize continuous personal health management.

5. Genomic AI: Realizing Gene-Driven Precision Medicine

Genomic AI combines artificial intelligence with human genome data to break the traditional standardized treatment mode and formulate exclusive treatment plans according to individual gene characteristics (Rajkomar *et al.*, 2019) ^[11]. Human genome data is huge and complex. It used to take gene experts several weeks to interpret a single sample, which was difficult to popularize in conventional diagnosis and treatment. Genomic AI quickly analyzes gene sequences, identifies genetic disease risks and tumor mutation sites, and judges patients' tolerance and therapeutic response to specific drugs. For the same type of cancer patients, different gene mutation types correspond to completely different targeted drugs and immunotherapy schemes. Genomic AI can quickly match the most suitable treatment plan, reduce the side effects of ineffective medication and improve the cure rate. In the field of preventive medicine, genomic AI predicts the risk of genetic diseases such as cancer and cardiovascular diseases through gene screening, and carries out intervention in advance to realize the transformation of medical treatment from "treating diseases" to "preventing diseases". With the reduction of gene detection cost and the improvement of AI analysis ability, large-scale precision medicine will gradually become popular.

6. AI-Driven Imaging Diagnosis System: The First Line of Defense for Early Screening of Severe Diseases

Medical image diagnosis is the field with the largest number of certified AI products by global regulatory agencies, accounting for about 80% of all medical AI devices (Esteva *et al.*, 2017) ^[6]. X-ray, CT and MRI images contain tiny early lesions that are easy to be ignored by human eyes. The deep learning model trained by millions of confirmed images can automatically mark suspicious masses, nodules and bleeding points, quantify the size of lesions and

malignant risk levels. In the screening of lung cancer, breast cancer and stroke, the detection accuracy of AI image system is comparable to that of senior specialist physicians. It acts as a "second reader" to recheck all images after the initial diagnosis by doctors unify the judgment standards of the whole hospital and reduce missed diagnosis caused by human fatigue. For primary medical institutions in remote areas lacking radiologists, the AI image system is equivalent to a portable specialist consultant, which greatly narrows the gap of early screening resources for severe diseases between urban and rural areas and seizes the golden period for treatment.

7. Predictive Analytics Technology: Dynamic Optimization of Medical Resource Allocation

Predictive analytics AI integrates hospital-wide medical data, patients' vital signs and epidemiological information to predict patients' health risks and hospital resource demands in advance (Beam & Kohane, 2018) ^[4]. In clinical treatment, the system monitors the vital signs of inpatients in real time, predicts sudden crises such as sepsis, postoperative complications and acute heart disease, and enables medical staff to intervene before the condition deteriorates. In hospital operation, it predicts the peak of outpatient and emergency department visits based on historical data, and deploys beds, testing equipment and first-aid manpower in advance to solve the problems of emergency department congestion and bed shortage. In the field of public health, predictive analytics combines regional medical data, climate information and satellite remote sensing data to predict regional health risks such as influenza and nutritional crises, helping health departments to deploy epidemic prevention resources in advance. This technology realizes the dynamic optimal allocation of medical resources and is an important technical support for the overall operation of medical institutions and regional public health prevention and control.

Inherent Risks of Medical AI and Clinical Landing Barriers

Medical AI is essentially a probabilistic evolutionary system, which is fundamentally different from traditional deterministic medical software. Its unique operating mechanism brings inherent clinical risks. At the same time, affected by infrastructure, workflow and user trust, medical AI faces multiple barriers from laboratory research to large-scale clinical popularization (Char *et al.*, 2018) ^[1].

1. Essential Differences between Medical AI and Traditional Medical Software

Traditional medical software belongs to a deterministic system. After inputting fixed information, it will always output unique results according to pre-set program logic, and the operation path is completely predictable and traceable. For example, the traditional registration system and test report calculation software will not have output deviation as long as the input data remains unchanged. Engineers can reshuffle all operation logic of the program. Medical AI is a probabilistic and continuously evolving system. Even if the same patient data is input, the model may produce multiple different output results, and even "hallucinate" false information that does not exist (Takita *et al.*, 2025) ^[18]. Medical AI summarizes rules through learning from massive data rather than relying on pre-

written logic. Each inference is based on probability judgment, and the internal operation path is complex and difficult to fully interpret. With the iteration of the model and the change of training data distribution, the judgment results of the same sample by AI may also change, which is the essential difference between medical AI and traditional software, and also the root of clinical risks.

2. Three Core Inherent Risks of Medical AI

Deep learning models and large language models operate through their own unique system which people identify as a "black box". AI systems in medical diagnosis create obstacles because their developers and clinical staff members lack comprehensive understanding of the entire diagnostic process (Morley et al., 2020) ^[9]. Medical personnel lack the ability to verify which lung nodule malignant risk assessments and genome data interpretations by AI stem from actual lesion characteristics versus random data interruptions. The process of identifying problem sources becomes complicated when the output shows abnormal results. The black box problem makes clinicians unable to fully trust AI's judgment results, which restricts its application in high-risk diagnosis and treatment links. The medical language model which generates text shows hallucination as its primary operational failure. The system creates fake medical information by generating test results and drug side effects and complete patient medical records which do not exist in reality (Luo et al., 2022) ^[8]. The system creates false pulmonary nodules when users enter basic cough symptoms while it also generates unverified drug interaction information. Medical doctors who fail to check their results will produce wrong data that leads to wrong medical decisions which endangers patient lives. Clinical documentation along with auxiliary diagnosis through generative AI systems becomes dangerous because they create hallucinations which lead to safety threats. The actual clinical information from real patients keeps changing through time. The training data from previous years will not match current medical environments because new virus subtypes appear and doctors must treat both uncommon diseases and the different body types which people from various ethnic backgrounds possess (Rieke et al., 2020) ^[13]. AI models will lose their ability to make correct decisions at a slow rate when time progresses. The disease screening model which started as dependable will generate numerous false negatives and incorrect results but the system lacks the ability to detect when its performance starts to deteriorate. Medical AI systems face an ongoing risk because their data patterns change unexpectedly which requires continuous data refreshes and model adaptation processes.

3. Four Barriers of Medical AI Clinical Adoption Funnel

The "clinical adoption funnel" theory divides the medical AI implementation process into four distinct stages which show the progressive development of its landing process. The process of technology popularizes only when all links in the chain function correctly because any single break will cause the entire system to fail. Many AI models which show strong performance during lab testing become unusable for standard medical practice because their development process leads to operational failures (Li & Liu, 2025) ^[7]. The first stage of the funnel is to confirm whether the AI product matches the real pain points of clinical scenarios.

Research and development teams focus their efforts on achieving maximum algorithm performance with laboratory data instead of addressing the actual requirements of medical practice. Medical personnel will eventually stop using products which demonstrate excellent technical performance but fail to provide useful clinical applications. Medical staff can adopt AI tools which decrease their work responsibilities while boosting diagnostic speed and solving medical service shortages. The initial phase of technology landing exists as the starting point for this process. Medical AI functions through three essential components which include standardized electronic medical records and high-resolution image storage systems and fast internal network transmission capabilities. Primary hospitals together with remote medical facilities continue to operate with physical medical documents and outdated diagnostic devices which produce unorganized and incomplete information that prevents AI systems from working properly. The operation of AI requires technical specialists to perform routine model corrections while they protect data security during their maintenance work. The absence of necessary hardware and software and technical staff members creates a direct obstacle which prevents technology from reaching clinical practice.

Medical AI products fail to reach their final stages because of this crucial link in the process. The medical staff maintains a busy schedule because they work in a fast-paced clinical environment which prevents them from spending time on operating complex auxiliary systems. The AI system demands multiple software openings during independent operation which forces staff members to duplicate patient data entry and perform additional system operations which increases their work duties. Medical AI products that reach maturity need to establish connections with hospital electronic medical record systems to perform automated data synchronization and provide direct access to analysis results through a single interface while preserving all existing medical procedures. The final stage of the funnel requires medical personnel and patients to develop trust in AI systems through three essential requirements which exist in this phase. The product should help users reduce their workload instead of making their tasks more difficult. Medical legal systems together with safety guarantees need full establishment to show how AI recommendations and medical decisions from doctors should share responsibility. AI systems operate with complete transparency because their judgment systems and clinical validation datasets become accessible to the public. Medical treatment is related to life and health. The implementation of AI tools in clinical practice will succeed when they operate transparently through secure systems which provide functional solutions for user trust development.

Ethical Guidelines and Global Collaborative Governance of Medical AI

To standardize the development of medical AI, avoid technical risks and realize the equity of medical resources, the international community has formulated unified ethical guidelines for medical AI and built a global collaborative governance system led by international organizations, forming a multi-dimensional governance system combining ethics, supervision and international cooperation (WHO, 2024).

1. Six Core Ethical Principles for Medical AI

Medical AI needs to collect a large amount of patients' medical records, images, genes and physiological data. Before using personal health information, it is necessary to clearly inform patients of the purpose of data use, storage period and potential risks, and obtain voluntary and explicit authorization. At the same time, no matter what diagnosis and treatment suggestions AI puts forward, the final decision right of medication, operation and treatment plan belongs to doctors and patients. AI is only used as a reference auxiliary tool, and it is forbidden for the system to automatically execute medical disposal to protect patients' right to choose independently. Safety is the bottom line of the medical industry. All medical AI products must pass strict regulatory review and complete clinical trials to verify their accuracy and stability before being put into clinical use. During the operation of the system, regular quality control shall be carried out to track problems such as model misjudgment, hallucination and data drift, and the model shall be corrected in a timely manner. Once potential safety hazards are found, the system shall be suspended or recalled immediately to minimize the risk of patient injury. It is required that the R&D team completely records the source of training data, algorithm judgment logic, error range and potential defects of AI products. When doctors or patients question the diagnostic basis of AI, the system can clearly explain the reasoning process to solve the black box problem. For large-scale public health AI systems, the operation mechanism shall be publicly disclosed in advance, and opinions from all sectors shall be collected to avoid the technical standards being unilaterally formulated by enterprises.

Set up human supervision nodes in all links of data labeling, model training, clinical use and result review to clarify the responsibility attribution of developers, hospital operators and reviewing doctors when AI causes medical accidents. At the same time, improve the complaint, correction and compensation channels to ensure that patients can safeguard their legitimate rights and interests when they suffer from misdiagnosis caused by AI errors. In the process of model training, diversified data samples from different regions, ethnic groups and economic groups are used to eliminate algorithm bias caused by single training data, and avoid different diagnostic accuracy of AI for different groups. At the same time, reduce the use threshold of AI products, and rely on remote medical AI systems to enable medical institutions in remote and resource-poor areas to obtain the same level of diagnostic capacity as high-level hospitals, narrowing the gap of health resources between regions. Optimize the energy consumption of AI servers and reduce the energy loss caused by large-scale medical data operation to realize environmental sustainability. Rely on AI to automate document work and divert patient flow, alleviate the overwork and loss of medical staff, maintain the long-term stability of medical manpower, and realize the balanced development of technology, human resources and the environment.

2. Global Collaborative Governance Framework: GI-AI4H Initiative

The World Health Organization (WHO) together with the International Telecommunication Union (ITU) and the World Intellectual Property Organization (WIPO) have established the Global Initiative for Artificial Intelligence

for Health (GI-AI4H) to address worldwide challenges which include medical AI regulatory differences and algorithmic discrimination and unequal access to technology through international organizational partnerships. WHO maintains control over medical AI standards which include clinical application specifications and medical safety standards and ethical guidelines to verify that all technical systems maintain their focus on patient cares. The International Telecommunication Union (ITU) works toward digital infrastructure development and technical standardization by creating standardized medical data transmission protocols. Moreover, it change medical equipment operation systems and AI core technical requirements to solve the problem of incompatible systems in different countries. Medical data and algorithm models fall under WIPO jurisdiction because this organization manages intellectual property rights which safeguard R&D personnel interests while serving public health requirements. Medical AI governance unites three organizations which work together to develop a single global oversight system.

Most of the existing medical AI models are trained based on European and American population data, which have obvious Western-centric biases and low recognition accuracy for tropical diseases and local genetic diseases in developing regions. The GI-AI4H initiative executes two fundamental cooperation programs which serve developing nations through their first program to localize data by gathering domestic patient information for regional medical database development and algorithm correction and their second program to build local abilities through medical AI R&D training for local professionals who will create AI solutions that match domestic healthcare requirements. The GI-AI4H framework unifies worldwide regulatory and technical standards which decrease international medical technology company expenses while enabling faster adoption of remote medical care through AI drug development services and cross-border medical treatment. The program uses local data with trained experts to stop algorithms from discriminating against vulnerable populations while preventing AI technology from making health disparities worse and working to achieve equal access to top medical care worldwide.

Transformation Thinking and Implementation Path of All Participants in the Industrial Chain

The comprehensive popularization of medical AI cannot rely solely on technical R&D. Clinical medical staff, hospital managers, technical developers and regulatory authorities need to change their traditional thinking and cooperate with each other to promote the digital transformation of the healthcare industry in an all-round way (Topol, 2019) ^[19].

1. Clinical Physicians and Medical Researchers: Human-Machine Collaborative Diagnosis and Research

For front-line clinicians and medical researchers, the core thinking transformation is to change from "manually completing all diagnosis and research work independently" to the collaborative mode of "human professional judgment as the core and AI responsible for massive data processing". AI will not replace doctors, but undertake repetitive work such as image reading and document sorting, freeing doctors' energy for doctor-patient communication and

complex disease decision-making. In clinical work, AI completes the initial screening of medical images and automatic generation of medical records, providing objective data support for doctors' diagnosis. In scientific research, AI shortens the R&D cycle of new drugs and the analysis cycle of epidemiological data, and promotes the progress of medical research. On the basis of making full use of AI tools, clinicians always adhere to the principle of human final decision-making to ensure the safety and rationality of diagnosis and treatment plans.

2. Hospital and Medical Enterprise Managers: Taking AI as an Operational Lever

Medical institution managers need to abandon the idea of regarding AI as an additional technical cost, and recognize that AI is a core lever to optimize operational efficiency, control costs and improve service quality. Relying on operational AI to reduce administrative labor costs and insurance rejection rates; relying on predictive analysis technology to optimize the allocation of medical resources and improve patient satisfaction; relying on clinical AI to improve the overall medical level of hospitals. Managers establish a data-driven strategic thinking, incorporate AI layout into the long-term development plan of the organization, and formulate phased promotion strategies combining administrative track and clinical track according to the actual situation of the hospital, so as to realize the win-win of social value and operational benefits.

3. Technical Developers, Industry Consultants Regulatory, and Policy Makers

Technical developers change from developing a single independent AI model to building an integrated platform centered on generative AI, realizing the interconnection and joint analysis of image data, text medical records, gene sequences and physiological waveforms. The R&D focus shifts from simply pursuing algorithm accuracy to adapting to clinical workflows, simplifying operation steps and realizing seamless docking with existing hospital systems. Industry consultants need to master both medical professional knowledge and AI technology capabilities, assist medical institutions in evaluating technical solutions, planning infrastructure, and solving problems such as data privacy and algorithm bias, to avoid blind investment and resource waste.

Regulators and policy makers have developed AI systems to operate as governance tools which restrict technological development. The system depends on AI to evaluate medical policy execution results through dynamic assessment, which also predicts public health crisis risks including infectious diseases and nutritional deficiencies, such as infectious diseases and nutritional crises. At the same time, establish a strict algorithm review mechanism, detect and correct algorithm bias in a timely manner, formulate unified safety and ethical standards for medical AI, and balance technological innovation and public health security.

Conclusions

Artificial intelligence has comprehensively penetrated into all links of the global healthcare industry. From the hierarchical technical system of general AI, machine learning, deep learning to generative AI, to the dual-track application model of administrative operation and clinical

care, medical AI has formed a complete industrial system. At present, medical AI has achieved remarkable results in alleviating the shortage of medical staff, optimizing medical processes, accelerating new drug R&D and promoting the popularization of precision medicine. Medical image AI, generative AI documentation systems and predictive analysis tools have become standard configurations of many medical institutions, effectively improving the overall operational efficiency and clinical diagnosis level of the medical industry. However, the development of medical AI still faces multiple challenges. The probabilistic characteristics of the system lead to potential safety risks such as hallucination and data drift; the gaps in regional infrastructure make it difficult for AI to be popularized in remote and underdeveloped areas; the disconnection between technical products and clinical workflows restricts the application effect of technology; the imperfect trust mechanism and regulatory system also become obstacles to the large-scale promotion of medical AI. To solve these problems, the whole industry needs to work together: R&D institutions optimize algorithm performance and enhance the interpretability and stability of models; medical institutions improve supporting infrastructure and promote the seamless integration of AI and clinical work; regulatory authorities and international organizations improve ethical norms and governance systems to standardize the application of technology.

In the future, the development of medical AI will present three major trends. First, full-process integrated application: AI will run through the whole chain of disease prevention, diagnosis, treatment, rehabilitation and chronic disease management, realizing the transformation of medical treatment from passive treatment to active prevention. Second, the popularization of large-scale precision medicine: the combination of genomic AI and clinical data will make personalized treatment no longer exclusive to a few people, and benefit all groups. Third, further promotion of global medical equity, relying on remote medical AI and localized technical transformation, the gap of medical resources between regions will be further narrowed, and the goal of global equitable health will be gradually realized. As a transformative technology, artificial intelligence is reshaping the development pattern of the healthcare industry. Under the guidance of ethical norms and global governance mechanisms, adhering to the human-machine collaborative development model, continuously breaking through technical and application barriers, medical AI will surely release greater value, and make greater contributions to protecting human health and promoting the sustainable development of global public health.

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