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Review Article

Application of Artificial Intelligence Enabled Targeted Clinical Diagnosis and Treatment

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Abstract

Diagnosis and treatment, the core pillars of the clinical healthcare system, remain critical to safeguarding patient health. The long-accumulated clinical expertise in these areas demonstrates significant value in preventing and treating major diseases. Traditional clinical diagnosis and treatment practices face several core challenges, including inefficient data processing, inadequate standardization of diagnosis and treatment aligned with standardized intelligent diagnosis and treatment models, and insufficient personalized adaptation, which are increasingly exposed by the pressing need for precise, efficient, and personalized medicine. With its targeted breakthroughs and mature applications in medical data processing and intelligent decision-making modeling, AI technology has emerged as the only viable and indispensable core technological solution to overcome these challenges. This paper examines how AI tackles these issues by focusing on the core challenges of traditional clinical diagnosis and treatment systems, including data processing efficiency, standardization of diagnosis and treatment, and personalized adaptation capabilities. It systematically expounds how artificial intelligence (AI) technologies—including federated learning architectures, multimodal data processing technology (for integrating multi-source heterogeneous medical data), and personalized modeling technologies—can specifically address these challenges and create clinical value. Meanwhile, it analyzes the practical challenges faced by AI in clinical applications, such as the balance between data privacy and quality, insufficient interpretability, ambiguous definition of ethical responsibilities, and commercialization difficulties. Beyond these hurdles, this paper concludes by outlining future development pathways, including advancing multimodal data processing technology, building trustworthy systems, promoting ecological collaboration, and expanding universal access. It ultimately demonstrates how AI can drive high-quality healthcare development (laying the groundwork for digital therapeutics via personalized interventions) and provides a roadmap for medical system upgrades.

Keywords: clinical diagnosis and treatment; personalized adaptation; federated learning; standardized intelligent diagnosis and treatment models; multimodal data processing technology; multi-source heterogeneous medical data; digital therapeutics

Introduction

Today's healthcare landscape demands precision, efficiency, and personalized treatment, but traditional clinical models are struggling to keep up due to limitations in data utilization, decision-making efficiency, and individualized adaptation1. For instance, traditional clinical models are limited to integrating only 1-2 types of modal data, such as text-based medical records and basic laboratory tests, whereas the integration rate of multimodal data, including imaging, genetic, and wearable device data, remains below 15%2, leaving significant data value untapped. To overcome these challenges, artificial intelligence (AI) is emerging as a pivotal force in reshaping clinical paradigms, leveraging its unique strengths in data analysis, pattern recognition, and dynamic decision-making. The following analysis will first dissect the inherent limitations of traditional clinical care models, then delve into how AI technology provides targeted solutions to these pain points through specialized applications3.

1.Analysis of the Practical Limitations of Traditional Clinical Practice Models

Within the global healthcare system, traditional diagnostic and treatment models serve as the foundational framework. However, their inherent reliance on human labor, coupled with limitations in resource allocation and data processing, exposes multidimensional shortcomings when addressing complex medical needs. This makes them ill-suited to meet

modern medicine's pursuit of efficiency, precision, and universal accessibility4.

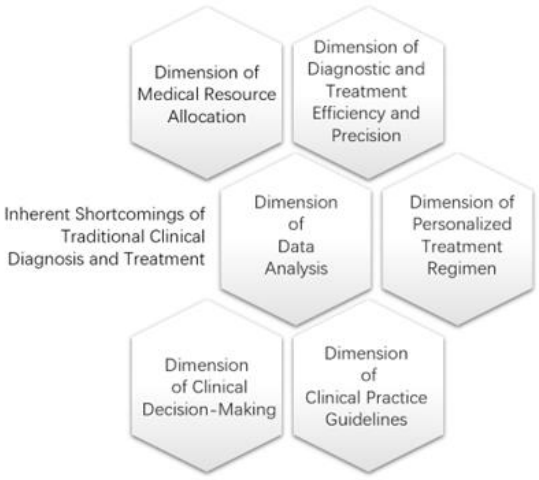

Figure 1: Core Limitations of Traditional Clinical Diagnosis and Treatment[5]

3.1 From the Perspective of Medical Resource Allocation

The “siphoning effect” of high-quality medical resources is a universal challenge worldwide. According to a 2024 report by the World Health Organization (WHO)6, high-income countries account for 72% of the world's total medical resources, while low-income countries hold only 4.5%. The disparity in per capita healthcare expenditure reaches a staggering 55-fold difference7.

This global imbalance in medical resource distribution also manifests as pronounced “centralization” within individual nations8: High-tier hospitals, leveraging their resource concentration advantages, often concentrate over 80% of a nation's senior physicians, advanced equipment, and core diagnostic expertise. Conversely, primary healthcare facilities commonly face challenges such as insufficient physician qualifications, limited case experience, and outdated equipment. This directly results in a severe mismatch between primary care capabilities and patient needs9.

In sub-Saharan Africa, healthcare resource scarcity leads to preventable disease mortality rates 40% higher than in high-income regions10. Even in Europe and the United States with relatively well-developed healthcare systems, patients in remote rural areas often require lengthy referrals to urban central hospitals for basic care. This not only increases healthcare costs but also risks worsening conditions due to delayed treatment, perpetuating a vicious cycle where “greater resource concentration leads to weaker primary care.”

3.2 In terms of diagnostic efficiency and precision

With the widespread adoption of medical imaging and genetic testing technologies, medical data is growing exponentially. Traditional models heavily rely on individual physician expertise, yet human processing capacity has reached a global bottleneck when confronting the rapidly expanding volume of multimodal data in modern medicine11.

WHO statistics indicate that the annual growth rate of global medical imaging examinations reached 15% in 202312. Imaging data such as CT and MRI scans account for over 80% of total medical data. A single chest CT scan can generate 300-500 images13, while a comprehensive genetic sequencing report contains millions of data points. Even dedicating their full attention, physicians struggle to achieve rapid and thorough interpretation of all this data.

Simultaneously, processing multidimensional patient data—such as medical history, laboratory indicators, and medication responses—requires manually integrating information scattered across disparate systems. This process is not only time-consuming but also prone to diagnostic errors due to information omissions. Under prolonged high-intensity workloads, the global rate of manual misdiagnosis for early-stage tumors and other minute lesions can reach 15%-20%14.Even in developed regions like Europe and the United States, manual image interpretation carries an 8%-12% risk of missed diagnoses. In low- and middle-income countries, constrained by physician experience and limited equipment resolution, the rate of missing such subtle lesions can exceed 30%15.

Whether due to inefficient, time-consuming data processing or the risk of missed diagnoses caused by fatigue, these factors fundamentally sever the link between “real-time condition monitoring” and “treatment plan adjustments,” ultimately making the dynamic, precise management of chronic diseases a significant challenge16.

3.3 Regarding the degree of treatment plan personalization

Traditional diagnostic and treatment models remain constrained by a "group experience-oriented" core logic17.Standardized protocols based on authoritative clinical guidelines overlook the dynamic variations in patients' genetics, physiological states, and living conditions. This limitation is particularly pronounced in global cancer and chronic disease treatment18.

Take cancer treatment as an example: patients with the same cancer type and stage exhibit significant variations in response to chemotherapy and targeted therapies due to differences in genetic profiling, immune status, and lifestyle habits19.Traditional protocols can only prescribe medications based on clinical guideline recommendations. Data from the National Cancer Institute indicates that traditional approaches achieve an overall response rate of just 35% for advanced solid tumor patients. 28% of patients receive ineffective treatment due to failure to identify drug resistance genes beforehand20. Moreover, reliance on delayed imaging assessments for efficacy evaluation often delays timely adjustments.

Furthermore, in chronic disease management, traditional models fail to capture real-time fluctuations in blood glucose and blood pressure, nor can they integrate dietary and exercise data to develop personalized intervention plans. This limitation profoundly impacts the 1.3 billion hypertensive and 500 million diabetic patients globally—failing to accurately monitor critical data like nocturnal hypertension and postprandial glucose spikes21. hypertension patients' nighttime medication needs remain inadequately addressed, and diabetes patients'

glycemic control rates (HbA1c < 7%) fall below 50%. This "lagging" and "static" shortfall represents the critical bottleneck constraining the quality improvement of precision chronic disease management.

2.Targeted Application of Artificial Intelligence in Clinical Diagnosis and Treatment

Artificial intelligence, with its core capabilities of autonomous evolution through deep learning, parallel processing of massive datasets, and precise integration of multimodal information, precisely addresses the shortcomings of traditional diagnosis and treatment22. It is not merely a technical add-on but fundamentally aligns with the limitations of conventional medical practices, serving as the pivotal solution to overcome these challenges23.

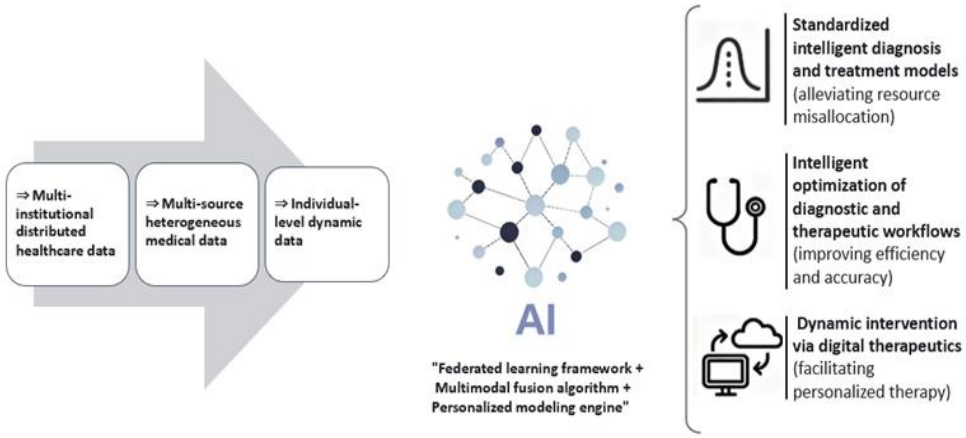

Figure 2: AI-Driven Solutions for Clinical Diagnosis and Treatment Bottlenecks

4.1 Federated Learning Enables Standardized Intelligent Diagnosis and Treatment Models—Addressing Imbalances in High-Quality Healthcare Resource Allocation

Artificial intelligence provides the algorithmic framework and technological foundation for constructing standardized intelligent diagnosis and treatment models. As a key branch technology, federated learning addresses the challenge of medical data silos through distributed collaborative training under privacy protection, enabling secure cross-institutional data reuse24. This empowers models to enhance their generalization capabilities and clinical adaptability under unified standards. Its core logic is as follows:

Standardized intelligent diagnosis and treatment models (hereafter referred to as "diagnosis models") serve as the core technological vehicle for addressing capacity gaps at the grassroots level25. They are defined as AI models constructed based on multicenter evidence-based medical data, capable of generating personalized clinical decision outputs. This model must satisfy two core characteristics: First, "standardization"—meaning the model training data covers standardized diagnostic and therapeutic cases from tertiary hospitals, and the generated medication recommendations and risk warnings must demonstrate≥90% consistency26 with clinical guidelines and expert consensus. Second,"intelligence"—the model dynamically adjusts decisions based on individual patient characteristics rather than mechanically applying group guidelines27.

Federated learning, as a distributed machine learning technology28,provides critical support for constructing clinical decision models. Its core logic enables collaborative training of multi-center medical data while ensuring data privacy and compliance. The specific implementation path is as follows:

1. Data Collaboration Layer: Organized around "tertiary hospitals + primary care institutions" as collaborative units, tertiary hospitals provide high-quality annotated data while primary care institutions contribute real-world data from local patients[29]. All institutions store data locally without transferring raw data across organizations.

2. Model Training Layer: Adopts an iterative "local training-parameter aggregation-global update" model—each institution trains an initial model using local data, uploading only model parameters to the federated learning center server; The server aggregates and optimizes parameters via encryption algorithms, generates a global model, and distributes it back to institutions to complete one training cycle[30]. After 10-15 iterations, the model adapts to clinical scenarios across different regions and healthcare levels.

3. Model Validation Layer: Multi-center clinical validation ensures the model achieves≥88% accuracy[31] in medication recommendations for primary care patients and ≥85% sensitivity in complication alerts, meeting practical primary care needs.

The scarcity of primary care data and the difficulty in disseminating high-quality clinical expertise—resulting from the "centralization" of medical resources—fundamentally stem from the contradiction between data silos and insufficient standardized clinical capabilities32. Federated learning enables distributed collaborative training under privacy protection. This approach preserves AI's advantage in processing massive datasets while overcoming compliance and security barriers to cross-institutional data transfer. It facilitates secure collaboration between tertiary hospitals' high-quality data resources and primary care's real-world data, thereby advancing the development of standardized intelligent diagnosis and treatment models. This shifts AI technology from "point applications" to "holistic empowerment," precisely addressing primary care's urgent need for standardized clinical capabilities.

The underlying logic and technical pathways of federated learning enabling standardized intelligent diagnosis and treatment models have been thoroughly validated through collaborative research among multiple scientific teams and medical institutions both domestically and internationally, yielding a series of practical outcomes with clinical application value. For instance, teams including Tencent's Tianyan Lab33, Peking University Health Science Center, and Ruijin Hospital have respectively developed standardized intelligent models for stroke prediction, pediatric pneumonia assessment, and rare disease diagnosis using federated learning. While safeguarding data privacy, these models

achieved prediction/diagnostic accuracy rates as high as 98.7%, significantly reducing misdiagnosis rates at primary care levels and outperforming single-center models. Institutions like the U.S. SIIM, France's Owkin, and the UK's NHS leveraged federated learning frameworks to integrate multi-center medical data34, successfully developing intelligent models for renal cell carcinoma segmentation, breast cancer recurrence prediction, and cardiovascular disease screening. These advancements significantly improved diagnostic consistency, predictive AUC values, and screening efficiency, providing efficient solutions for cross-institutional collaborative diagnosis and treatment35.

The aforementioned "federated learning-enabled standardized intelligent diagnosis and treatment models" represent a typical practical pathway for AI technology to address the imbalance in the distribution of high-quality medical resources36. This is not the sole model for AI's participation in balancing healthcare resource allocation. AI can also contribute through establishing "AI pre-screening + expert remote precision diagnosis" systems, developing portable diagnostic devices with embedded AI, and building AI-driven physician training systems37. Though these approaches differ in implementation, they all leverage AI as a bridge to break down barriers between high-quality resources and grassroots needs, collectively expanding more feasible pathways for universal access to healthcare resources.

4.2 AI Multimodal Data Processing Empowers Diagnostic and Treatment Process Optimization—Breaking Through Bottlenecks in Efficiency and Accuracy

As a vital branch of artificial intelligence, AI multimodal data processing leverages core technologies such as deep learning and cross-modal fusion to break down modal barriers between different types of medical data38. Through precise integration and efficient analysis, it provides critical support for enhancing the efficiency and precision of diagnostic and treatment processes, specifically addressing core bottlenecks in traditional medical models. Its technical logic and implementation pathways are detailed below:

Multimodal data processing constitutes a comprehensive technological framework encompassing "image recognition, temporal prediction, and multi-source data fusion," centered on two key technologies:

First, CNN-based image analysis technology simulates the human visual system through convolutional neural networks to automatically extract pathological features from medical images39—such as pulmonary nodules <5mm in diameter or microaneurysms in diabetic retinopathy—processing 20-50 times faster than manual methods while adapting to diverse imaging devices via transfer learning.

Second, RNN/Transformer-based time-series data processing technology captures fluctuation patterns in continuous monitoring data across the temporal dimension40. It predicts indicator trends over the next 4-24 hours, achieving 30%-50% higher prediction accuracy than traditional statistical methods. Both technologies share the common feature of "eliminating the need for manual annotation of all data." They reduce data dependency through semi-supervised learning, making them suitable for scenarios with scarce medical data41.

In the field of imaging screening, AI systems developed through multi-center collaboration can simultaneously process multiple modalities of medical images, automatically annotate suspicious lesion areas, and reduce the average processing time per image from tens of minutes to minutes. This significantly lowers the rate of missed early-stage diagnoses, providing primary care institutions with standardized imaging diagnostic support tools. For instance, Google Health's AI for breast cancer screening, developed using CNNs42, can simultaneously process mammography and ultrasound images while automatically labeling suspicious lesions. In primary care hospitals across Europe and the US, this system reduced single-image processing time from 20 minutes to 1 minute, lowering the early breast cancer missed diagnosis rate from 18% to 7%43. A domestic team's "Diabetic Retinopathy AI Screening System," compatible with fundus cameras in primary hospitals, allows image uploads via mobile devices. The AI outputs "no lesions/mild/moderate/severe" diagnoses within 30 seconds, boosting primary care fundus screening efficiency tenfold and expanding annual coverage from 5,000 to 50,000 individuals.

In chronic disease dynamic management, mainstream intelligent platforms integrate multidimensional time-series data—including physiological metrics and lifestyle habits—to automatically generate personalized health recommendations and proactively alert users to potential indicator abnormalities44. This significantly enhances patient self-management efficiency and physicians' clinical coordination capabilities. For instance, Livongo's diabetes management platform leverages RNN technology to integrate continuous glucose monitoring data, dietary logs, and exercise metrics. It automatically generates "high GI food avoidance lists" and "post-meal exercise recommendations," while providing 6-hour advance warnings for "potential post-breakfast blood glucose exceeding 8.3 mmol/L the following day." This approach increased timely intervention rates for abnormal blood glucose from 35% to 82%, enabling physicians to manage 150 patients monthly compared to the previous 5045.

AI multimodal data processing technology encompasses capabilities like image analysis and time-series prediction. It enables "minute-level integration + precise identification": For medical imaging, it automatically screens for anomalies frame by frame, processing 20 times faster than manual methods while reducing missed diagnoses by 60%46.For chronic disease time-series data, it correlates diet, exercise, and indicator fluctuations in real time, issuing risk alerts 4-6 hours in advance and automatically generating preliminary analysis reports. This technological empowerment shifts clinical workflows from "human-driven" to "AI-assisted." Physicians no longer need to handle tedious data processing, freeing them to focus on treatment decisions. Individual patient consultations are reduced to under 5 minutes, while early anomaly detection accuracy surpasses 90%47.

It should be clarified that AI multimodal data processing is not the sole AI pathway for enhancing clinical efficiency. Multiple AI technologies are synergistically advancing clinical care from diverse dimensions48. For instance, deep learning-based clinical decision support systems uncover implicit correlations within vast electronic health records, providing multidimensional treatment references for complex diseases. Natural language processing technology automatically extracts key information from electronic medical records and organizes it structurally, significantly reducing physicians' administrative workload while enhancing the utilization efficiency of medical record data. Reinforcement learning technology simulates the long-term effects of different treatment plans49, providing dynamic decision support for optimizing personalized treatment strategies for chronic diseases like cancer. These technologies complement and synergize with multimodal data processing techniques, collectively building an intelligent diagnosis and treatment ecosystem. This ecosystem delivers diversified solutions for advancing precision and efficiency in clinical practice[50].

4.3 AI Personalized Modeling Empowers Dynamic Intervention in Digital Therapeutics—Addressing Shortcomings in Treatment Personalization

As a vital application branch of artificial intelligence, AI personalized modeling leverages core technologies such as user profiling, real-time data mining, and dynamic decision algorithms to empower digital therapeutics with precise dynamic interventions51. This approach specifically addresses the lack of personalization in traditional treatment plans, laying the groundwork for subsequent in-depth exploration of its technical pathways and practical value. Its technical logic and implementation pathways are detailed below52:

AI personalized modeling constitutes a proprietary predictive and intervention model technology system centered on individual data53, with the core objective of transcending reliance on group statistical patterns to achieve precise individual adaptation. This system primarily relies on three key technologies: Reinforcement learning optimizes intervention strategies through a "trial-and-error-feedback" mechanism, enhancing patient treatment adherence; Natural language processing technology enables deep analysis of patient text and voice data, accurately identifying cognitive distortions and potential psychological issues with emotional judgment accuracy exceeding 85%54; multimodal interaction technology integrates biofeedback with VR/AR environments, enabling real-time linkage between physiological signals and intervention measures. These technologies all revolve around individual data, ensuring models precisely match each patient's specific needs.

Digital therapy dynamic intervention55represents a novel, real-time data-driven treatment paradigm characterized by "dynamicity" and "actionability." Serving as a critical data gateway and intervention vehicle for AI personalized modeling, it fulfills three key functions: comprehensively collecting multidimensional patient data including genetic profiling, health metrics, and treatment task completion; translating AI model predictions into actionable interventions such as medication reminders and customized dietary plans; and continuously gathering feedback data to support iterative model optimization, ensuring treatment plans dynamically adjust to patient status56.

AI personalized modeling and digital therapeutics achieve deep synergistic empowerment through a closed-loop mechanism of "data collection-model prediction-intervention adjustment-feedback optimization." AI personalized modeling provides precise decision support for digital therapeutics by mining individual data to predict patient responses to different treatment plans. Digital therapeutics, in turn, supply continuous data streams and practical scenarios to AI models, translating model predictions into concrete therapeutic actions while feeding back data to optimize the models57. This synergy liberates treatment plans from reliance on traditional group guidelines, achieving the personalized treatment goal of "one plan per person with real-time dynamic adjustments."

In practical clinical applications, this collaborative model has demonstrated significant value across multiple domains. For instance, MedTech's diabetes digital therapeutics platform deployed in Hainan uses AI algorithms to analyze multidimensional patient data—including blood glucose and dietary patterns—to generate personalized management plans. By establishing a tripartite coordination system linking patients, physicians, and specialists, the platform increased fasting blood glucose compliance rates among managed diabetes patients in the pilot region by 18.63%58.

The synergistic model of AI personalized modeling and digital therapy dynamic intervention fundamentally resolves the core pain point of traditional treatment schemes being "one size fits all." Traditional approaches, often based on group statistical patterns, struggle to accommodate individual patient differences, leading to inconsistent treatment outcomes. This collaborative model centers on individual data, achieving precise alignment between treatment plans and patient characteristics through AI model predictions59 and digital therapy interventions. Whether tailoring medication regimens based on genetic variations or adjusting rehabilitation plans according to behavioral data, this approach ensures targeted and effective treatment, completely addressing the shortcomings of traditional treatment plans in personalized adaptation.

This collaborative model is not the sole pathway for AI to address the personalized treatment gap. AI can also achieve this goal through: - Providing personalized diagnostic and treatment references via deep learning clinical decision systems - Supporting targeted therapies with AI-assisted genetic testing - Delivering real-time intervention recommendations through wearable devices and AI early warning systems - Expanding personalized treatment coverage via AI telemedicine platforms These complementary approaches collectively build a diversified AI-driven personalized healthcare technology ecosystem.

4.Existing Challenges and Future Directions

5.1 The Dual Constraints of Data Quality and Privacy Protection

The multimodal nature of medical data leads to heterogeneous formats and inconsistent standards. A significant portion of real-world data suffers from missing values and noise interference. Professional annotation requires substantial medical resources, further exacerbating the scarcity of high-quality training data. Simultaneously, regulations like GDPR[60] and the Personal Information Protection Law impose stringent compliance requirements across data collection, transmission, and utilization. While anonymization and de-identification techniques mitigate privacy risks, they may compromise certain data values. Furthermore, inadequate cross-institutional data-sharing mechanisms, coupled with data silos created by healthcare institutions for security and competitive reasons, hinder AI models' access to large-scale generalized data[61]. This severely constrains model performance enhancement and scenario adaptability.

5.2 Insufficient Clinical Interpretability Hinders Practical Implementation

Current mainstream deep learning models are predominantly "black box" systems, lacking human-understandable logical chains in their decision-making processes. In clinical settings, AI may accurately identify lesions or recommend treatment plans but cannot clearly articulate the basis for its judgments—for example, it cannot explain why a particular drug class is prioritized or the logical connection between a specific imaging feature and a disease62. This ambiguity not only diminishes clinicians' trust in AI tools but also fails to meet healthcare's core requirements for traceable and verifiable diagnostic processes. Particularly in diagnosing complex conditions, where physicians bear legal and medical responsibility for decisions, AI's "black box" nature hinders its integration into core clinical workflows. Consequently, many technically mature AI products63 remain confined to supplementary reference roles, struggling to achieve widespread clinical adoption.

5.3 Ethical Risks and the Practical Dilemma of Defining Responsibility

Ethical controversies surrounding AI applications in healthcare are increasingly prominent, with the primary issue being ambiguous liability. When AI diagnoses result in misdiagnoses, missed diagnoses, or recommended treatment plans lead to medical disputes, the lack of clear legal frameworks and industry standards for allocating responsibility among developers, healthcare institutions, and treating physicians creates significant challenges in dispute resolution. Second, algorithmic bias may exacerbate healthcare inequities64: if training data exhibits demographic representativeness bias, AI diagnostic accuracy may significantly decline for specific groups—such as higher misdiagnosis rates among rare disease patients or elderly populations. Furthermore, unclear boundaries for AI autonomous decision-making, coupled with overreliance on AI, may erode physicians' clinical judgment capabilities. This raises ethical concerns about "technological dependency," potentially disrupting traditional doctor-patient relationships and medical liability frameworks.

5.4 Commercialization Faces Multiple Practical Barriers

The commercialization of AI medical products is constrained by multiple stages including R&D, validation, and monetization. During the R&D phase, products must undergo rigorous clinical trials to validate efficacy and safety. For instance, the FDA requires[65]prospective controlled studies, which not only span several years but also demand substantial investments in data collection, sample recruitment, and outcome analysis. Market access is complicated by inconsistent medical regulatory

standards across countries and regions, requiring products to adapt to multiple compliance requirements and further increasing R&D costs and time. Regarding monetization models, hospitals' willingness to pay is directly influenced by insurance policies and departmental budgets. Most AI products remain excluded from insurance reimbursement lists, forcing medical institutions to bear procurement and operational costs independently, which dampens purchasing enthusiasm[66].Simultaneously, quantifying the value of AI healthcare products remains challenging. Demonstrating their impact on clinical efficiency and patient outcomes through straightforward cost-benefit data is difficult, further hindering commercialization efforts.

Over the next 5-10 years, AI healthcare will steadily advance toward greater precision, reliability, and accessibility by addressing these existing challenges. Technologically, multimodal fusion will emerge as a core development direction. By integrating diverse data sources—including text, imaging, genomic information, and physiological signals—it will enable more comprehensive patient profiling. This will elevate AI from single-function assistance to end-to-end clinical decision support, achieving intelligent coverage across the entire chain from disease screening and diagnosis to treatment and rehabilitation management.

4.Conclusion

As the healthcare sector undergoes a critical transition toward precision, efficiency, and personalization, artificial intelligence has emerged as the core engine driving this change through breakthrough applications in balanced resource allocation, optimized diagnostic workflows, and personalized interventions. This approach tackles deep-seated challenges in traditional models, including imbalanced resource allocation, insufficient efficiency and accuracy, and inadequate personalized adaptation, and provides viable solutions for upgrading global healthcare systems universally and intelligently through technical pathways like federated learning, multimodal data processing, and personalized modeling.

However, dual constraints on data quality and privacy protection, insufficient clinical interpretability, and the challenge of defining ethical responsibilities remain tangible barriers to the large-scale implementation of AI in healthcare. Moving forward, a dual-pronged approach of “technological breakthroughs + ecosystem co-creation” is essential. On one hand, technological and institutional innovations must be strengthened across dimensions like algorithmic explainability, data governance systems, and ethical regulatory frameworks. On the other hand, deep collaboration among medical institutions, technology companies, and regulatory bodies must be fostered to continuously expand the application boundaries of AI healthcare while ensuring safety and compliance. Only through this approach can the true potential of artificial intelligence be unleashed, propelling clinical diagnosis and treatment from an “experience-driven” to a “data-intelligence-driven” paradigm shift. This will ultimately achieve universal access to healthcare resources, comprehensive improvements in treatment quality, and personalized safeguarding of patient health, laying a solid foundation for building the next-generation intelligent healthcare ecosystem.

5.Disclaimer

The authors declare no competing financial interests.

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