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A Review of Artificial Intelligence Applications in Healthcare: Clinical Value and Primary Care Adaptation Challenges

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Abstract. Artificial intelligence (AI) has developed rapidly in recent years and is reshaping diagnostic and therapeutic approaches in healthcare. This paper systematically reviews AI applications in three typical scenarios: medical image recognition, electronic health record (EHR) analysis, and personalized health management. It summarizes representative technologies, performance benchmarks, and typical systems, and compares their clinical value. Focusing on primary care institutions, the paper identifies key adaptation challenges in deploying AI diagnostic systems, which arise from three dimensions: data (e.g., sample bias, insufficient annotation quality), technical (e.g., lack of computational resources, non-uniform interfaces), and user (e.g., low physician trust, lack of training). To address these, the paper proposes three optimization directions: developing lightweight, offline-capable AI models; adopting federated learning for cross-institutional training; and establishing human–AI collaborative workflows. This paper may serve as a reference for promoting AI implementation in disease screening, risk warning, and health management in primary healthcare settings.

Keywords: Artificial intelligence, Medical imaging, Electronic health records, Personalized health management, Primary care adaptation

1. Introduction

In recent years, AI technologies such as deep learning and NLP have been widely applied in healthcare [1]. In medical image recognition, AI has achieved expert-level performance in tasks like lung nodule detection and fundus disease diagnosis [2]. In EHR analysis, AI supports disease prediction and readmission risk assessment [3]. In personalized health management, AI-driven systems aid chronic disease care [4]. Overall, AI is transforming healthcare.

However, a central contradiction has emerged: while AI performs well in high-level hospitals, it faces implementation difficulties in resource-limited primary care settings. A 2025 WHO report noted challenges including legal uncertainty, insufficient funding, and weak infrastructure [5]. International studies show that AI models trained on urban hospital data often degrade in rural or community settings due to differences in disease spectrum and population characteristics [6]. In China, primary care institutions also suffer from limited data, poor hardware, and a shortage of professionals [7, 8].

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To address these issues, this paper has three objectives: to summarize AI applications in the three domains; to compare AI systems across accuracy, explainability, real-time performance, and workflow integration; and to focus on adaptation challenges in primary care, proposing optimization strategies including lightweight models, federated learning, and human–AI collaboration. This paper aims to promote equitable and effective AI implementation in resource-limited environments.

2. AI Applications and validation in healthcare

2.1. Medical image recognition and diagnosis

2.1.1. Core technologies: Deep learning architectures (UNet, ResNet, etc.)

Medical image recognition is one of the most mature application scenarios of AI in healthcare. Deep learning, particularly convolutional neural networks (CNNs), has fundamentally transformed the way medical images are analyzed [1]. Among the various architectures, the UNet model, with its symmetric encoder-decoder structure and skip connections, has become the benchmark for medical image segmentation, enabling precise localization while preserving spatial information [2]. Subsequent variants such as ResUNet and AttentionUNet have further improved convergence stability and segmentation accuracy [9]. Collectively, these technologies support multiple computer-aided diagnosis (CAD) tasks, including pulmonary nodule detection, breast cancer screening, and fundus disease classification [10].

2.1.2. Typical applications: Pulmonary nodule detection and diabetic retinopathy screening

AI systems have been successfully applied to detect diseases from medical images. In lung cancer screening, deep learning algorithms assist in detecting pulmonary nodules and distinguishing benign from malignant lesions [2]. A meta-analysis of 26 studies (over 2.39 million exams) reported that CNN models achieved a pooled sensitivity of 0.93, specificity of 0.95, and AUC of 0.98 for pulmonary nodule detection [11]. Another meta-analysis found a pooled sensitivity of 0.87, specificity of 0.87, and SROC of 0.93 for lung cancer diagnosis [12]. However, factors such as data source and population source may cause performance decline across institutions, highlighting the need for multicenter external validation [11].

In diabetic retinopathy (DR) screening, AI algorithms have demonstrated robust capabilities [13]. A real-world study of 842 participants reported a sensitivity of 82.2%, specificity of 97.0%, and AUC of 0.90 for referable DR in primary care. The ungradable image proportion was 20.8% by manual grading versus 9.4% by AI [14]. Another large-scale study (over 15,000 photographs) reported 98.6% accuracy, 96.7% sensitivity, and 99.8% specificity [15]. These applications illustrate AI's generalizability across different disease types.

2.1.3. Clinical validation: Performance metrics and comparative studies

Multiple AI systems have been developed for medical image analysis. For segmentation, UNet with a ResNet50 backbone achieves superior mIoU scores on multi-organ benchmarks. For classification, ResNet and its deeper variants are widely adopted due to their ability to mitigate vanishing gradients. Combining ResNet with UNet generally outperforms simpler designs, especially in challenging tasks like mass segmentation in dense breast tissue or small liver lesion detection.

Clinical validation has progressed from single-center retrospective studies to multicenter prospective validation. The MultiXpert system achieved a 13.9%–22.6% AUC improvement over

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traditional single-center models on data from ten hospitals [16]. A collaborative study published in Nature Medicine reported an RCT using over ten million ocular images to build the multimodal foundation model EyeFM, which improved ophthalmic diagnostic capabilities for primary care and specialist physicians across Asia, North America, Europe, and Africa [17].

Notably, system performance varies across datasets and disease types; no single architecture universally outperforms others. Thus, AI model selection should be guided by specific clinical requirements and data characteristics.

2.2. Electronic health record analysis

2.2.1. Natural language processing methods for unstructured EHR data

Electronic health records contain rich but often underutilized clinical data [3]. A substantial portion of this information exists in the form of unstructured free text, including discharge summaries, progress notes, and radiology reports. Natural language processing techniques have been developed to extract structured information from these texts. Specific methods include named entity recognition, relation extraction, and text classification. Pretrained language models, when fine-tuned on large-scale clinical text corpora, have significantly improved the efficiency of mining useful information from EHRs [7].

2.2.2. Predictive analytics: Disease risk and readmission prediction

NLP-based EHR analysis has been widely applied to disease risk prediction, readmission assessment, and medication recommendation. For example, AI models can predict cardiovascular event risk within the next year [3]. In readmission assessment, models using discharge summaries can identify high-risk patients for early intervention [3]. Medication recommendation systems can flag potential adverse drug reactions or suggest alternative therapies [7].

A representative case is DeepPatient, which uses deep neural networks to learn patient feature representations from large-scale EHR data and predict the risk of multiple diseases [3]. MedBERT, pretrained on Chinese medical text based on the BERT architecture, has achieved leading performance on named entity recognition and relation extraction tasks [7]. These systems demonstrate the feasibility of transforming unstructured clinical text into actionable knowledge for clinical decision support.

2.3. Personalized health management

2.3.1. Intelligent health monitoring and chronic disease management

AI-driven personalized health management is a rapidly developing application direction in recent years. Leveraging wearable devices and intelligent analytics platforms, AI systems enable remote monitoring and proactive intervention for population health. In the domain of chronic disease management, such as diabetes care, an ongoing open-label, multicenter, non-inferiority randomized controlled trial is comparing a fully automated AI-driven digital diabetes prevention program against a traditional human coach program, involving 368 participants with prediabetes, to validate the scalability and cost-effectiveness of AI in chronic disease management [18].

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2.3.2. AI-driven health education and emotional support

Generative AI and large language models are transforming traditional models of health education and emotional support. In the domain of outpatient service optimization, the Personalized Intelligent Outpatient Reception System (PIORS) developed by the team at Fudan University integrates a large language model-based triage nurse function. Evaluation results demonstrate that the PIORS system outperforms the current state-of-the-art model, GPT-4o, and better aligns with human preferences and clinical needs [19].

2.4. Comparison of major application effects of AI in healthcare

To facilitate a horizontal comparison of key indicators across the three types of applications, this paper summarizes and compares them from seven dimensions: core tasks, representative technologies, accuracy, explainability, real-time performance, maturity, and major challenges. The results are presented in Table 1.

Table 1. Comparison of major application effects of AI in healthcare

Evaluation Dimension	Medical Image Recognition	EHR Analysis	Personalized Health Management
Core Tasks	Lesion detection and segmentation, disease classification	Risk prediction, readmission assessment, medication recommendation	Health monitoring, chronic disease management, health education
Representative Technologies	CNN, UNet, ResNet, MultiXpert	BERT, DeepPatient, MedBERT	Large language models, wearable devices
Accuracy	High (lung nodule detection sensitivity 0.93 [11])	Moderate to high (AUC approximately 0.75–0.85)	Moderate (lack of gold standard)
Explainability	Moderate (e.g., attention maps)	Low to moderate	Moderate
Real-time Performance	High (seconds-level)	Low	Moderate
Maturity	High (multiple products approved)	Moderate	Moderate
Major Challenges	Cross-center generalization, technical heterogeneity [11]	Data privacy, unstructured data processing	User adherence, outcome validation

2.5. Summary

This chapter has summarized the major achievements of AI in medical image recognition, EHR analysis, and personalized health management. In medical image recognition, AI has achieved high diagnostic accuracy, with meta-analyses supporting its use as a clinical assistive tool for tasks such as pulmonary nodule detection. In EHR analysis, NLP techniques are progressively unlocking the value of unstructured data. In personalized health management, generative AI and large language models are enhancing chronic disease management and health education; however, current evidence remains primarily exploratory, and more RCTs are needed to provide high-level support. These findings lay the foundation for examining adaptation challenges in primary care settings in subsequent chapters.

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3. Adaptation challenges for AI deployment in primary care

3.1. Data-related challenges

When primary care institutions deploy AI systems, data-level challenges are the most fundamental. The first issue is sample bias. Most AI models are trained on data from tertiary hospitals, where the disease spectrum, patient demographics, and equipment types often differ substantially from those in primary care communities [10]. For instance, pulmonary nodule detection models trained on tertiary hospital data (mostly early screening cases) may encounter advanced-stage patients with obvious symptoms in primary care, leading to marked performance degradation [10]. International studies have similarly confirmed this phenomenon [6].

The second issue is data annotation quality. Primary care institutions generally lack specialized radiologists and pathologists capable of fine-grained data annotation. Deep learning models require large volumes of high-quality annotated data for robust learning. However, clinical annotations in primary care are often inconsistent, incomplete, or erroneous, impeding effective supervised learning [10]. Even deployed AI systems often fail due to non-uniform data formats and missing key fields in primary care settings.

3.2. Technical and infrastructure barriers

Infrastructure-related issues are equally concerning. High-performance deep learning models typically require GPU acceleration, yet many primary care centers cannot guarantee stable network connectivity or basic power supply [8]. This hardware gap causes AI systems that work well in tertiary hospitals to become sluggish, delayed, or fail entirely in primary care settings.

System integration presents another major challenge. AI diagnostic tools must interface with existing HIS, PACS, and other platforms for automated data flow. However, information systems in primary care institutions are often outdated, lack standardized interfaces, and suffer from poor cross-vendor compatibility, resulting in high deployment costs and long implementation cycles [8]. Even when primary care facilities obtain AI system authorization, they often shelve them due to unresolved technical integration.

From a global perspective, a WHO survey of 50 European countries found that 86% identified legal uncertainty and regulatory lag as primary barriers to AI application, while 78% considered insufficient funding a major issue [5]. This demonstrates that technology and funding bottlenecks are common challenges faced by primary care settings across different countries.

3.3. User trust and literacy levels

User-level challenges center on two aspects: trust and operational training. Primary care physicians generally lack basic knowledge of AI, including its principles, advantages, and limitations. This often leads to two extreme scenarios: excessive reliance on AI, abandoning its own clinical judgment, or complete distrust of AI, viewing it as an unnecessary interference [7]. Neither attitude enables effective use of AI systems.

The lack of operational training exacerbates the problem. Most vendors provide only simple product manuals, lacking customized training programs for primary care workflows [9]. When physicians encounter system errors or abnormal results, they often do not know how to respond, leading to discontinued use or incorrect operation. The WHO report notes that lack of AI literacy investment for healthcare workers may further exacerbate inequalities in healthcare resource

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distribution [5]. International scholars have also emphasized that AI application in rural healthcare must be integrated with personnel training and social support systems; technology alone is insufficient [6].

4. Optimization pathways and solutions

4.1. Developing lightweight and deployment-friendly models

To address limited hardware conditions in primary care, developing lightweight, offline-capable AI models is the primary optimization direction. Techniques such as model pruning, quantization, and knowledge distillation can compress large GPU-dependent models to run on ordinary CPUs or mobile devices, adapting to primary care hardware [10]. These models also enable offline inference, resolving network instability issues.

Recent successful explorations include the MultiXpert system developed by Li Hai's team at the Hefei Institutes of Physical Science, Chinese Academy of Sciences, which achieves "zero-shot" intelligent diagnosis of chest X-rays. On multi-center data from ten hospitals, it achieved a 13.9%–22.6% AUC improvement over traditional single-center models [16], demonstrating strong cross-center generalization. Baichuan Intelligent Technology's open-source medical enhancement model, Baichuan-M2, has undergone an extreme lightweight design for private deployment, running on a single RTX 4090 GPU after quantization, significantly lowering hardware investment thresholds. These examples indicate that lightweight models are technically feasible for deployment in primary care settings.

4.2. Leveraging federated learning for shared model utilization

Federated learning addresses the problems of small data volumes and uneven distribution in primary care settings. It allows multiple institutions to collaboratively train a shared model without data leaving local sites, protecting patient privacy while improving model generalizability [20].

For primary care, federated learning is particularly valuable. A single facility cannot independently train a high-performance model due to limited data. However, through federated learning, multiple primary care institutions can jointly train with higher-level hospitals, sharing knowledge without disclosing data [20]. This approach also mitigates sample bias—data from different regions and institution levels enables the model to learn broader disease spectra and population characteristics, improving robustness in primary care deployment.

Additionally, federated learning addresses regulatory requirements such as the Personal Information Protection Law, which imposes strict restrictions on cross-institutional data flow. The principle of "data stays in place, the model moves" aligns well with this policy direction [20].

4.3. Establishing human-AI collaborative workflows

Beyond technical solutions, workflow redesign is equally critical. Establishing a human-AI collaborative model of "AI pre-screening + physician review" does not replace physicians but rather has AI handle routine, repetitive tasks while referring suspicious or complex cases for focused physician review [8]. This model reduces primary care physician burden while retaining final decision-making authority in human hands, thereby enhancing physician acceptance and willingness to use AI.

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High-level evidence has confirmed the clinical value of human-AI collaboration. A collaborative study by Professor Tien Yin Wong's team (Tsinghua) and Professor Bin Sheng's team (Shanghai Jiao Tong), published in Nature Medicine, reported a randomized controlled trial. The team constructed a multimodal ophthalmic imaging foundation model, EyeFM, using over ten million ocular images and multimodal data. They validated the model's ability to enhance diagnostic capabilities for multiple ophthalmic diseases among primary care and specialist physicians across Asia, North America, Europe, and Africa. This study provides the first high-level evidence in AI medical research demonstrating that foundation models can empower both primary care and specialist diagnosis, proving the generalizability of the human-AI collaborative model across diverse global healthcare settings [17].

4.4. The role of policy support and capacity building

The optimization of technology and workflows requires institutional support and talent development. Policy support is critical. The WHO calls on countries to formulate national AI strategies aligned with public health goals; invest in an "AI-ready workforce"; strengthen systematic AI training; ensure transparent public engagement; and improve data governance and ethical safeguards [5, 6]. Without clear legal standards and funding, clinicians will remain cautious, and primary care institutions will lack incentives to introduce AI [5].

For capacity building, stratified training should be designed based on physicians' needs. Basic training should cover AI principles, system operation, and error identification. Advanced training can incorporate explainable AI techniques (e.g., attention maps) to help physicians understand model conclusions and establish appropriate trust [9]. The Multi-Glau system uses Grad-CAM to improve acceptance of AI-assisted diagnosis among physicians at all levels [13].

In summary, lightweight models address "whether AI can be used," federated learning addresses "whether AI works well," human-AI collaboration addresses "whether AI is willingly used," and policy support with capacity building provides institutional safeguards and talent support. Together, these four dimensions form a systematic solution for empowering primary care with AI.

5. Conclusion

This paper reviewed AI applications in medical image recognition, EHR analysis, and personalized health management, and compared their clinical value. AI has made substantial progress in assisted diagnosis and health management, especially in high-level hospitals. However, in primary care, significant challenges remain: data-level issues (sample bias, low annotation quality), infrastructure limitations (insufficient computing, integration difficulties), and user-level barriers (low trust, lack of training). To address these, this paper proposes three directions: lightweight offline-capable models, privacy-preserving techniques like federated learning, and human-AI collaborative workflows.

A limitation is that this paper is based on existing literature without primary experimental data. Future research should include prospective evaluations in real-world primary care, along with policy design, field studies, and controlled trials to validate the proposed strategies.

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