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Exploring the Key Supports and Industry Adaptation Strategies of Artificial Intelligence Technology in Medical Data Applications

Chenxi Zhang*

Roche Diagnostics (Shanghai) Limited, Shanghai, 200335, China

**Author to whom correspondence should be addressed.*

Abstract: With the rapid evolution of artificial intelligence (AI) technologies, the medical industry is undergoing a profound transformation driven by data intelligence. As the foundational element for intelligent diagnosis, precision prevention, and public health governance, medical data is characterized by massive volume, complex structure, diverse sources, high dimensionality, strong privacy, and high timeliness. Traditional data analysis methods are no longer sufficient to meet the comprehensive requirements of data security, intelligent processing, and decision support. Through techniques such as machine learning, deep learning, natural language processing, and multimodal fusion, AI provides robust technical support for medical data cleaning, governance, mining, and application. At the data level, intelligent algorithms enable the standardization, structuring, and interoperability of medical data, promoting information sharing across medical systems. At the model level, AI supports auxiliary diagnosis and precision treatment through image recognition, medical record analysis, and knowledge graph construction. At the system level, intelligent decision-support platforms continuously enhance the efficiency and accuracy of healthcare services. However, the widespread adoption of AI in medicine still faces challenges such as privacy protection, data security, model interpretability, and the lack of unified industry standards. Based on a systematic review of AI's key supporting technologies in medical data processing and application, this paper focuses on the compliance challenges and adaptation strategies during industry integration and proposes an adaptation framework centered on "technological trustworthiness, data security, and industry collaboration." The study provides theoretical and practical insights for promoting the standardized and sustainable development of AI in the healthcare industry.

Keywords: Algorithmic support; Artificial intelligence; Data governance; Industry adaptation; Medical data; Privacy protection

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1. Introduction

Against the backdrop of rapid advancements in information technology, artificial intelligence (AI) is reshaping the healthcare industry's operational models and innovation pathways at an unprecedented pace. As the core resource of modern healthcare systems, medical data holds immense knowledge value and decision-making potential. Its scale and complexity continue to grow with the proliferation of multimodal data sources such as medical imaging, electronic health records (EHRs), wearable devices, and genomics. Traditional data processing methods, constrained by limited computing power, inefficient algorithms, and inconsistent data quality, struggle to handle the diversity, unstructured nature, high dimensionality, and real-time requirements of medical data. Consequently, AI offers revolutionary solutions for medical data collection, management, analysis, and application, driving the transition from experience-based to data-driven and intelligent healthcare.

In recent years, intelligent healthcare systems powered by machine learning, deep learning, and natural language processing have achieved remarkable success in areas such as image diagnosis, medical record analysis, drug discovery, and health management. By building models capable of identifying image anomalies, automatically extracting clinical features, and generating diagnostic suggestions, AI significantly improves the accuracy and efficiency of healthcare services. Nevertheless, the integration of AI in medical practice still faces major challenges. Medical data is inherently sensitive and private, involving personal health records, clinical diagnoses, and physiological parameters, thus requiring strict adherence to data security and regulatory compliance. Additionally, discrepancies in data standards, collection methods, and system architectures among institutions have created "data silos," hindering AI model generalization and interoperability. More critically, the lack of model interpretability and the emergence of ethical risks limit the clinical reliability and public acceptance of AI applications.

Therefore, this paper aims to systematically explore the key technical supports and industry adaptation strategies of AI in medical data applications. From the technical perspective, it analyzes the role of AI in data governance, intelligent modeling, and system integration; from the industry perspective, it examines adaptation pathways in privacy protection, standard formulation, and policy regulation. By synthesizing representative case studies and real-world practices, this paper seeks to reveal both the opportunities and bottlenecks of medical AI development, providing theoretical foundations and practical references for building a "secure, interpretable, and scalable" intelligent healthcare ecosystem in the future.

1.1. Types and characteristics of medical data

Medical data is the most fundamental, complex, and valuable information resource within the modern healthcare system, encompassing patients' physiological attributes, disease information, treatment processes, and health management data. It is characterized by multi-source heterogeneity and dynamic variability. Broadly, medical data can be categorized into three types: structured, semi-structured, and unstructured data. Structured data includes standardized information stored in EHRs, such as laboratory test results, medication records, and surgical data, typically organized in tabular form for easy statistical analysis and modeling. Semi-structured data originates from medical imaging, laboratory reports, and sensor outputs, while somewhat standardized, they still require algorithmic interpretation and feature extraction. Unstructured data, which constitutes the majority of medical information, includes physician notes, nursing records, voice consultations, and genomic sequences [1].

These data are complex and information-dense, often containing implicit medical insights, making them prime targets for AI-driven analysis. Medical data also exhibits several unique characteristics compared to data from other industries. It is high-dimensional and complex, as a single patient may generate data across multiple institutions and devices over time. It is highly private and sensitive, involving personal and genetic information whose leakage can lead to severe ethical and legal consequences. It is also real-time and dynamic, especially with the widespread use of wearable and IoT-based health monitoring devices that continuously generate time-series data for real-time diagnosis and intervention [2]. Lastly, heterogeneity and lack of standardization remain significant barriers, as variations in data formats and terminologies across hospitals prevent seamless data sharing and integration.

Overall, the diversity and complexity of medical data present both opportunities and challenges for AI applications. Achieving secure, standardized, and semantically interoperable data integration is fundamental to enabling AI-driven healthcare. Building unified data governance frameworks and multimodal fusion mechanisms is thus essential to unlocking the full potential of medical big data for intelligent diagnosis, precision medicine, and public health management [3].

1.2. Practical demands of medical data applications

With the acceleration of healthcare digitalization and intelligent transformation, the role of medical data has expanded from basic information recording to driving clinical decision-making, disease prediction, health management, and policy formulation. AI technologies have greatly enhanced the value of medical data by enabling precise, efficient, and evidence-based decision-making across the entire healthcare system. In clinical diagnosis and decision support, AI assists physicians in handling increasing case volumes and complex disease types by analyzing medical images, text records, and laboratory data. Deep learning-based image recognition systems have achieved high accuracy in detecting lung nodules, breast cancer, and brain lesions, reducing radiologists' workload and improving diagnostic consistency [4].

In disease prediction and personalized treatment, AI leverages longitudinal health records to identify chronic disease risks, high-risk patient groups, and potential complications, enabling early intervention and precision care. Particularly in genomics and drug development, AI helps discover correlations between molecular structures and clinical outcomes, supporting personalized medication and targeted therapy strategies. In public health management and resource allocation, large-scale data analysis enables real-time disease monitoring and epidemic forecasting. AI models analyze epidemiological and hospital data to guide policy-making, optimize resource distribution, and improve emergency response efficiency [5]. For instance, during infectious disease outbreaks, AI can model transmission patterns and optimize vaccine distribution strategies, reducing response times and enhancing control measures. Finally, in healthcare service optimization, AI-driven data analytics can streamline hospital operations, reduce waiting times, and lower administrative costs. Insurers also use AI for fraud detection and claim verification, improving financial transparency and efficiency.

In summary, the practical demands for medical data applications extend beyond technical innovations, they represent a systemic integration of technology, governance, and ethics. As data volumes grow and privacy requirements tighten, the future of healthcare data applications must prioritize security, compliance, and intelligent interconnectivity, enabling AI to drive sustainable development in precision and smart healthcare [6].

2. Key technical supports of AI in medical data

2.1. Data processing and intelligent governance

Data processing and governance form the foundation of AI-driven medical data applications. High-quality data ensures the reliability of algorithmic models, while the heterogeneity, noise, and sensitivity of medical data demand rigorous standards for accuracy, completeness, and compliance. AI transforms data management from static storage to dynamic, intelligent governance, laying the groundwork for feature extraction, model training, and clinical decision-making. AI-powered algorithms automate data cleaning and quality control by identifying outliers, missing values, and duplicates [7]. Machine learning can impute missing test results or detect abnormal patterns through clustering. For unstructured data like physician notes or radiology reports, natural language processing (NLP) and optical character recognition (OCR) enable semantic extraction and medical terminology standardization, greatly enhancing processing efficiency.

In data standardization and structural modeling, AI supports semantic mapping and interoperability using medical ontologies, standardized coding systems (e.g., ICD-10, SNOMED CT), and HL7/FHIR frameworks. For instance, in EHR governance, AI can automatically align synonymous clinical terms under unified taxonomies, reducing manual annotation and improving data integration accuracy. AI also enables multimodal data fusion and feature extraction, integrating imaging, textual, genomic, and physiological data through embedding and attention mechanisms. Combining CT image features with clinical text can improve diagnostic precision, while integrating genomic and drug-response data aids personalized treatment recommendations [8]. Furthermore, intelligent data governance platforms based on AI and big data architectures (e.g., Spark, Hadoop, Data Lakes) support distributed storage, rapid retrieval, and dynamic visualization. Differential privacy, federated learning, and encryption-based techniques enable secure model training and cross-institution collaboration without exposing raw data.

Overall, intelligent data governance defines the reliability and interpretability of AI systems in healthcare. The future trend will emphasize standardization, automation, security, and collaboration, ensuring full lifecycle management and value maximization of medical data for intelligent healthcare ecosystems [9].

2.2. Algorithmic and model evolution

The evolution of algorithms and models is the core driver of AI-powered healthcare. From early rule-based and statistical methods to deep learning, reinforcement learning, and large-scale models, AI continues to push the boundaries of data analysis, transitioning from "data availability" to "intelligent usability." Traditional machine learning algorithms, such as logistic regression, decision trees, random forests, and support vector machines, remain valuable for structured data analysis due to their simplicity and interpretability. For example, logistic regression has been widely applied in cardiovascular risk prediction, while decision trees are effective in identifying critical diagnostic variables. However, these models struggle with high-dimensional, unstructured medical data, limiting their applicability. With advances in computational power, deep learning has become the dominant paradigm in medical AI.

Convolutional neural networks (CNNs) excel in medical image analysis, achieving diagnostic accuracy comparable to expert radiologists in detecting lung nodules or breast tumors. Recurrent neural networks (RNNs) and long short-term memory (LSTM) models effectively capture temporal dynamics in patient monitoring data, while generative adversarial networks (GANs) enhance image quality and augment training datasets. Recently, transformer-based large language models (LLMs) and multimodal architectures have driven cross-domain integration in medical AI. Models such as BioBERT, ClinicalBERT, and Med-PaLM leverage self-attention mechanisms to perform complex semantic understanding in medical text, achieving breakthroughs in report summarization, automated coding, and clinical question answering.

Multimodal models that combine imaging, text, and genomic data support integrated diagnostic reasoning and explainable decision-making. Additionally, reinforcement learning (RL) is being applied in adaptive clinical decision-making, such as dynamic treatment planning and ICU intervention strategies. RL models learn optimal policies from feedback, enabling AI to make patient-specific, context-aware decisions in real time. As model sophistication grows, challenges in interpretability, fairness, and safety become more prominent. Explainable AI (XAI) methods such as LIME, SHAP, and attention heatmaps help clinicians visualize the reasoning behind model predictions, improving trust and clinical adoption. Lightweight and federated learning approaches further support privacy-preserving and resource-efficient AI deployment. In essence, medical AI is evolving from task-driven to cognition-driven intelligence, from unimodal to multimodal learning, and from opaque to interpretable decision-making. The integration of biomedical knowledge with next-generation AI models will transform AI from a data analysis tool into a core driver of medical innovation, enabling precision medicine, smart hospitals, and data-driven public health governance [10].

3. Industry adaptation and compliance challenges

The widespread application of AI to medical data brings unprecedented opportunities to medical research, clinical decision-making, and public health management, while simultaneously posing dual challenges of industry adaptation and safety compliance. Healthcare is a highly regulated, high-risk sector: its data involves not only personal privacy and life-and-death decisions, but also public safety and ethical baselines. Consequently, AI deployment in medical scenarios must proceed under the preconditions of safeguarding data security, upholding ethical principles, and complying with industry standards. As AI algorithms grow more complex and medical data more diverse, issues surrounding data protection, algorithmic transparency, model interpretability, and regulatory compliance have become increasingly prominent, now key factors constraining the healthy development of medical AI. For instance:

(1) Data privacy and security are the foremost challenges facing medical AI. Medical data typically contains personally identifiable information, clinical records, genetic information, and social-behavioral attributes. Once leaked, such data may inflict serious harm on individual privacy and trigger a broader crisis of public trust. Traditional anonymization and de-identification techniques have become less reliable in the face of AI models' re-identification capabilities, even as cross-institutional data-sharing needs continue to rise. To address this tension, the field has introduced differential privacy, homomorphic encryption, and federated learning to enable model training and knowledge sharing without exposing raw data. These methods help balance "data utilization" and "privacy protection," offering technically viable routes for inter-institutional collaboration and regional healthcare integration. Nevertheless, privacy protection is not only a technical problem but also one of governance and liability. Clear delineation of data-use boundaries and responsibility among hospitals, technology firms, and regulators still requires systematic governance frameworks and legal mechanisms;

(2) Algorithm interpretability and model trustworthiness are central obstacles to clinical adoption. Unlike industrial predictions, medical decisions directly affect patient safety; clinicians and patients alike need to understand the basis of AI recommendations. Yet many deep learning models remain "black boxes," with complex internal computations that resist direct explanation. In response, researchers have advanced XAI frameworks, such as feature-weight visualizations and attention heatmaps, to illuminate model reasoning. These techniques allow clinicians to more intuitively comprehend recommended diagnostic or treatment plans, thereby improving trust and real-world uptake. In addition, AI models are susceptible to dataset bias

during training, which can lead to misleading predictions or fairness problems. For example, imbalanced representation of sex, age, or region can induce algorithmic discrimination. Algorithm governance therefore must rest on principles of fairness, transparency, and ethical controllability;

(3) Lagging legal frameworks and industry standards also pose major hurdles. Although many countries have released AI-related policies and ethics guidelines, regulatory systems tailored to medical AI remain incomplete. In China, the Data Security Law, Personal Information Protection Law, and Cybersecurity Law provide a foundational legal framework for handling medical data, while documents such as the Ethical Norms for Artificial Intelligence and the Regulation on the Supervision and Administration of Medical Devices set forth high-level requirements for AI in medicine. In practice, however, questions remain unresolved: when should an AI system be classified as a "medical device," how should it pass registration and approval, and how should re-validation proceed after algorithmic updates? Internationally, the U.S. FDA has introduced a "Predetermined Change Control Plan" for adaptive AI/ML-based medical devices, and the EU's AI Act adopts a risk-based regulatory approach. These developments provide useful references for establishing tiered oversight in China. Going forward, medical AI will need to integrate policy design with standardization efforts to build a full life-cycle compliance mechanism that spans R&D, testing, clinical validation, and scaled deployment;

(4) Ethics review and social responsibility cannot be overlooked. Applying AI in healthcare is as much an ethical exercise as a technical innovation. Key questions include whether clinicians can independently evaluate algorithmic recommendations, whether automation weakens clinician-patient communication, and how to allocate responsibility in cases of AI-induced misdiagnosis. Medical AI should adhere to the principles of "human-centeredness, decision support, and non-replacement of physicians," cultivating human-AI collaborative care models. Medical institutions should establish ethics review committees to conduct risk assessments and ethical reviews before use, ensuring alignment between technological innovation and patient rights.

Overall, industry adaptation and compliance are the critical thresholds for translating medical AI from laboratory research to clinical routine. Only by clarifying legal boundaries, strengthening data security, enhancing algorithmic transparency, and improving ethical oversight can we build a secure, trustworthy, and sustainable medical-AI ecosystem. In the future, medical AI should be guided by "safety and trust, unified standards, and clear accountability," balancing public interest with technological innovation to advance a high-quality, high-reliability digital transformation of healthcare.

4. Typical cases and industry practices of medical AI

4.1. An adaptation framework for sustainable medical AI adoption

Based on the challenges discussed, the successful and sustainable adoption of AI in healthcare is contingent on a comprehensive adaptation framework. We propose a framework centered on three core, interdependent pillars: Technological Trustworthiness, Data Security & Governance, and Industry & Ethical Collaboration.

(1) Pillar 1 (technological trustworthiness): This pillar addresses the technical reliability and robustness of AI models. It moves beyond simple accuracy metrics to integrate the development of XAI, enabling clinicians to understand and scrutinize the reasoning behind AI-generated recommendations. It also mandates robust methodologies for bias detection and mitigation to ensure fairness across diverse patient

populations. Finally, it calls for rigorous, transparent validation processes to confirm model performance and safety before initial deployment and during its clinical lifecycle;

(2) Pillar 2 (data security & governance): This pillar forms the foundation of patient trust and legal compliance, addressing the high-privacy nature of medical data. It encompasses the technical implementation of Privacy-Preserving Technologies (PPTs), such as federated learning, differential privacy, and homomorphic encryption, to allow for model training without exposing raw data. This is coupled with the organizational adoption of data interoperability standards (e.g., HL7/FHIR) and the establishment of clear governance protocols that align with national and international regulations;

(3) Pillar 3 (industry & ethical collaboration): This pillar focuses on the human and systemic integration of AI, ensuring technology serves, rather than dictates, clinical practice. It requires the active, early involvement of institutional ethics committees to review AI tools. It promotes the cultivation of "human-in-the-loop" collaborative care models, where AI functions as a decision-support tool to augment clinician expertise, not replace it. Eventually, it calls for cross-institutional collaboration among hospitals, technology firms, and regulatory bodies to co-develop unified standards, validation benchmarks, and best practices.

The application of AI in medical data has steadily progressed from laboratory research to clinical practice, yielding a multi-dimensional, multi-scenario landscape of deployment. Its value lies not only in improving diagnostic accuracy and operational efficiency but also in driving the shift toward intelligent, personalized, and fine-grained models of care. Today, AI has achieved notable results in medical imaging diagnostics, electronic medical record (EMR) analysis, clinical decision support, drug discovery, and public-health management, producing a number of representative use cases.

In intelligent imaging diagnostics, deep learning has catalyzed a transformation in image analysis. China's "Tencent Miying" platform, for example, uses CNNs to automatically detect pulmonary nodules on CT scans and assess malignancy. According to publicly reported clinical validations, its nodule-detection accuracy in lung-cancer screening reaches 94.7%, with reading efficiency 3.5× that of traditional manual workflows. Similarly, the U.S. "IDx-DR" system, cleared by the FDA in 2018, can screen for diabetic retinopathy without an ophthalmologist present; clinical trials reported 87% sensitivity and 90% specificity. These outcomes demonstrate that AI imaging systems can play a stable role in early disease screening, reducing clinician workload and improving equity of access in primary care. In intelligent EMR processing and decision support, natural language processing (NLP) is reshaping clinical text structuring and knowledge management. Alibaba Health's "Yizhilu" platform, built on large-scale EMR corpora and knowledge graphs, performs semantic analysis for auto-coding, symptom-disease association mining, and diagnostic recommendations. Reported results in tertiary hospitals indicate a 30% reduction in physician documentation time, with recommendation accuracy exceeding 92%, markedly improving both documentation and decision efficiency.

Internationally, IBM's Watson for Oncology integrates global oncology cases and treatment evidence to recommend personalized therapy. At Korea's National Cancer Center, its recommendations reportedly achieved 96% concordance with expert panels; in some breast and lung cancer cases, AI-suggested regimens outperformed routine human choices, highlighting AI's potential in precision oncology. AI has also delivered strong results in public-health management and epidemic control. During COVID-19, platforms such as Baidu Health and Ping An Good Doctor used AI to analyze massive streams of outbreak data in real time for trend forecasting and hotspot identification. For instance, Baidu Health's AI platform combined LSTM models with epidemiological features to forecast one-week case increases with prediction error within 5%, supporting timely, evidence-based policy measures.

Meanwhile, reinforcement-learning-based logistics optimization improved emergency supply routing, boosting response efficiency by approximately 40%. In drug discovery and clinical trials, AI substantially shortens molecular design and screening cycles. Insilico Medicine applied GANs and reinforcement learning to design a novel anti-fibrosis candidate, completing the path from target discovery to lead identification in just 46 days, compared with 2–3 years on average via traditional pipelines. AI thus both reduces R&D cost and improves candidate success rates, strengthening the foundations of precision and personalized medicine as shown in **Table 1**.

While these cases are highly promising, it is important to approach their reported metrics with academic caution. The high-performance figures (e.g., 94.7% accuracy or 96% concordance) are often derived from controlled, internal validations or specific clinical trials using curated datasets. The challenge of generalizing this performance to diverse, real-world clinical settings, with different patient populations, equipment variations, and workflow pressures, remains significant. Therefore, independent, third-party validation and continuous post-deployment monitoring are critical steps to confirm the real-world efficacy, safety, and equity of these commercial systems.

Table 1. Representative medical-AI applications and their outcomes

Case name	Application area	Core techniques	Key metrics	Reported outcomes
Tencent Miying (China)	Medical imaging diagnostics	Convolutional neural networks	Detection accuracy (94.7%)	3.5× faster reading; supports early lung-cancer screening
IDx-DR (USA)	Diabetic retinopathy screening	Convolutional neural networks	Sensitivity (87%), Specificity (90%)	FDA-cleared; enables screening without an on-site ophthalmologist
Yizhilu (Alibaba Health)	EMR text analysis	NLP + knowledge graph	Recommendation accuracy (92%)	Physician documentation time reduced by 30%; higher structuring
Watson for Oncology (IBM)	Treatment decision support	Knowledge reasoning + retrieval	Concordance with experts (96%)	Improves personalized oncology decisions
Baidu Health AI Platform	Epidemic forecasting & control	LSTM + reinforcement learning	Forecast error ≤ (5%)	Policy response times shortened by 40%; more targeted measures
Insilico Medicine	Drug discovery	GAN + reinforcement learning	Design cycle (46 days)	~60% R&D cost reduction; faster lead generation

In sum, these cases demonstrate AI's enabling power across the full lifecycle of medical data, from image recognition to record analysis, from disease prediction to drug discovery, while also revealing practical hurdles in data sharing, safety compliance, interpretability, and the generalizability of performance from trials to routine practice. As algorithms continue to evolve and oversight improves, AI will play an increasingly profound role in healthcare, accelerating the transition from experience-based to intelligent medicine.

5. Conclusion

AI has undeniably become a core driver of medical-data intelligence, reshaping modern healthcare through advances in data governance, analytical modeling, and clinical decision support. However, this paper argues that translating AI's potential into routine, equitable, and safe clinical practice is not merely a technical challenge. Its success is contingent on the deliberate implementation of a robust, multi-faceted adaptation framework. The path forward requires a unified strategy built on the three pillars we have proposed: Technological Trustworthiness (ensuring models are fair, interpretable, and validated), Data Security & Governance (protecting patient privacy while enabling compliant interoperability), and Industry & Ethical Collaboration (keeping clinicians and ethical oversight at the center of development). By moving beyond isolated technological advancements and focusing on this integrated framework, the healthcare industry can build a truly secure, trustworthy, and sustainable intelligent ecosystem that elevates quality, efficiency, and equity in tandem.

Disclosure statement

The authors declare no conflict of interest.

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