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Framework for Government Policy on Agentic and Generative AI in Healthcare: Governance, Regulation, and Risk Management of Open-Source and Proprietary Models

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ABSTRACT- This paper provides a comprehensive review and strategic framework to navigate this complex ecosystem of open-source and proprietary models for healthcare. We analyze the technical capabilities, implementation challenges, and governance requirements of both AI paradigms through a systematic and organnized survey of current literature and emerging trends. Our findings indicate that while open-source models offer superior transparency, customization, and data privacy—increasingly rivaling proprietary performance in diagnostics—proprietary systems maintain advantages in reliability, support, and integration.

However, AGI also introduces complex risks ranging from algorithmic bias (if uncontrolled) to regulatory fragmentation (lack of regulation). Evidence shows concerning patterns in automated decision appeals and significant financial barriers to implementation that could limit accessibility.

To address these challenges, we propose a tiered risk-management and governance framework that synthesizes the strengths of both open and closed-source approaches. Our recommendations include the adoption of international certification protocols aligned with global explainability standards, federated learning architectures to ensure privacy while enabling collaboration, and adaptive policymaking to balance innovation with patient safety. This integrated approach aims to maximize the benefits of both open-source and proprietary AI while focusing on remodification of unique risks posed by agentic systems.

KEYWORDS- Agentic AI; AI Ethics; AI Governance; Artificial Intelligence; Clinical Decision Support; Data Privacy; Generative AI; Health Policy; Healthcare; Healthcare Implementation; Medical Diagnostics; Open-Source AI; Proprietary AI; Risk Management

I. INTRODUCTION

The integration of artificial intelligence (AI) in healthcare represents one of the most transformative and impactful technological advancements, with the global healthcare AI market projected to grow from $29.01 billion in 2024 to $504.17 billion by 2032 [1]. This rapid expansion is characterized by two parallel revolutions: the maturation of both open-source and proprietary AI models for medical applications, and the emergence of autonomous Agentic Generative AI (AGI) systems capable of independent decision-making and action.

The current healthcare AI landscape presents a fundamental dichotomy. Proprietary systems from major technology companies offer sophisticated capabilities but often at significant cost and with limited transparency [2]. Concurrently, powerful open-source alternatives have emerged, providing new opportunities for customization, transparency, and cost-effective implementation [3], [4]. This competition has accelerated innovation while creating complex strategic decisions for healthcare organizations navigating this evolving ecosystem.

Simultaneously, the convergence of agentic autonomy and generative capabilities has produced AGI systems that are redefining healthcare delivery paradigms. These systems can autonomously act upon generated insights—achieving 89% AUC in outcome prediction [5] while streamlining claims processing by 65% [6]. However, this autonomy introduces unprecedented governance challenges, including algorithmic bias (evidenced by 73% appeal rates in AI-generated insurance denials [7]) and regulatory fragmentation between international standards and state-level approaches [8], [9].

Three disruptive trends frame our analysis:

- Technical Convergence: Open-source models now rival proprietary performance in diagnostics while AGI systems achieve human-level accuracy in controlled settings (92% cancer screening [5])
- Economic Transformation: AGI promises 3:1 ROI through automation [10] but requires substantial investment in implementation ($250K-$2M per system [11]) and workforce retraining ($1.4B [12])
- Regulatory Complexity: Emerging frameworks range from WHO's explainability standards [8] to state-level insurance mandates [9], creating a fragmented governance landscape

This paper provides a comprehensive analysis of both open-source/proprietary AI comparisons and AGI governance challenges. We synthesize findings from 25 contemporary sources to: (1) characterize the technical spectrum of healthcare AI architectures; (2) quantify implementation risks and performance metrics across both paradigms; and (3) propose a harmonized governance framework that addresses the unique challenges of autonomous systems while leveraging the strengths of both open and closed-source approaches.

Our analysis reveals that while multi-agent systems can (under most optimistic scenarios) reduce chronic care costs by 40% [13], their adoption depends on resolving fundamental trade-offs autonomy vs. accountability [14]. Similarly, the open-source vs. proprietary dichotomy presents trade-offs between transparency/customization and reliability/support that must be selected for pecific healthcare contexts.

II. LITERATURE REVIEW

A. Proprietary AI Models in Healthcare

Proprietary AI models are generally paid models and typically offer robust performance, comprehensive support, and seamless integration with existing healthcare infrastructure with big-tech companies. Google's health AI initiatives, including their Gemini foundational model and AlphaFold system, demonstrate the capabilities of well-resourced proprietary approaches in advancing medical research and clinical applications [15].

The advantages of proprietary models include higher reliability, extensive validation, and professional support services. As explained in [16], proprietary systems can provide enhanced security features that are particularly valuable for protecting sensitive health data. These models typically undergo rigorous testing and regulatory compliance processes as defined by the governments, making them attractive for risk-averse healthcare organizations especially the ones run by government.

B. Open-Source AI Advancements

Recent advancements in open-source AI have significantly narrowed the performance gap with proprietary systems. Multiple studies from 2025 have demonstrated that open-source models can compete with leading proprietary LLMs in solving complex medical cases and diagnostic challenges [17], [18]. Harvard Medical School researchers found that open-source AI tools now match top proprietary models in tackling difficult medical cases that require sophisticated clinical reasoning [17].

The transparency and adaptability of open-source models represent significant advantages for healthcare applications. As [19] argue, "the future for LLMs in medicine must be based on transparent and controllable open-source models" because "openness enables medical tool developers to control the safety and quality of underlying AI models, while also allowing healthcare professionals to hold these models accountable."

C. Performance Comparisons

[20] conducted a comprehensive assessment of frontier open-source and proprietary LLMs for complex diagnoses, finding that while proprietary models still maintain some advantages in certain specialized tasks, the performance gap has substantially narrowed. Their research indicates that "newer open-source large language models have demonstrated capabilities approaching those of closed-source proprietary models in medical reasoning tasks."

Similarly, University of Colorado research demonstrated that open-source AI tools can match commercial systems in medical scan reporting while offering superior data privacy protection [21]. These findings challenge the traditional assumption that proprietary systems inherently outperform open-source alternatives in clinical settings.

D. Literature Identification and Selection

This work refers multiple databases and sources, including peer-reviewed journals, conference proceedings, technical reports, and industry publications. The search focused on publications from 2023-2025.

E. Comparative Analysis Framework

We reviewed various multi-dimensional framework to evaluate AI models across several dimensions:

- Performance: Diagnostic accuracy, clinical reasoning capabilities, and specialized medical knowledge
- Security and Privacy: Data protection, compliance and regulations, and privacy issues
- Customization and Adaptability: Flexibility, customization, and local adaptation
- Cost and Accessibility: Implementation costs, licensing fees, and accessibility for resource-constrained settings
- Transparency and Accountability: Explainability, auditability, and regulatory compliance

F. AGI

AGI combines generative AI's content-creation capabilities with autonomous decision-making, enabling systems to perform complex tasks without human intervention [22]. In healthcare, AGI applications range from diagnostic algorithms to care management and administrative automation [23]. For example, AGI can predict patient outcomes with high accuracy [5] and streamline claims processing [6].

AGI introduces various idiosyncratic risks, including biased decision-making, lack of transparency, and potential misuse [24]. In this regard, regulatory frameworks, such as those proposed by the World Health Organization (WHO), emphasize the need for ethical guidelines and governance structures to mitigate these risks [8].

G. Comparative Analysis

a) Technical Performance-

Recent comparative studies have demonstrated that the performance gap between open-source and proprietary AI models in healthcare applications has significantly narrowed. [25] reported that "open-source AI rivals leading proprietary models in tackling complex medical cases," with particular strength in diagnostic reasoning and clinical decision support.

The emergence of specialized medical AI models like MedGemma has further enhanced open-source capabilities. [26] describes MedGemma as "Google's most capable open models for health AI development," offering multimodal capabilities specifically designed for healthcare applications. These advancements challenge the traditional dominance of proprietary systems in clinical settings.

b) Security and Privacy Considerations

Proprietary models often emphasize their security features, with [16] arguing for "the power of proprietary models in protecting health data." These systems typically offer comprehensive security certifications and compliance with healthcare regulations like HIPAA.

However, open-source models offer distinct privacy advantages through offline deployment capabilities. [3] note that DeepSeek "supports offline deployment, addressing some data privacy concerns" that are particularly relevant in healthcare settings. This capability allows healthcare organizations to maintain complete control over patient data without relying on external cloud services.

c) Cost and Accessibility

Open-source models offer lower implementation costs and avoid ongoing licensing fees, making them accessible to a wider range of healthcare providers.

[27] highlights how "open-source AI tools can transform healthcare, especially in resource-constrained settings" by reducing financial barriers to advanced AI capabilities. This accessibility advantage aligns with broader efforts to democratize healthcare AI and reduce disparities in technology access.

d) Regulatory Compliance and Validation

Proprietary models often have advantages in regulatory compliance due to extensive validation processes and established regulatory pathways vetted by licensed experts. These systems typically undergo rigorous testing and documentation required for medical device approval in various jurisdictions as requested by the lawmakers.

Open-source models face challenges in regulatory compliance due to their decentralized development across nations and non-standard validation processes. However, as [28] note, "while open-source software offers the potential for cost savings, flexibility, and improved interoperability compared with proprietary systems, it raises critical questions about security and operational feasibility" that must be addressed through robust validation frameworks.

III. QUANTITATIVE FOUNDATIONS AND MATHEMATICAL FRAMEWORKS

A. Top 10 Key Terms, Theories, and Models in Agentic AI for Healthcare

Agentic Generative AI (AGI) in healthcare is a rapidly evolving field, blending advanced AI techniques with autonomous decision-making. Below are the top 10 key terms, theories, and models shaping this domain:

a) Agentic AI

Definition: AI systems capable of autonomous goal-directed behavior, making decisions without constant human input [22].

Relevance: Enables proactive healthcare management like automated diagnosis and treatment planning [13].

Example: IBM's agentic systems for patient monitoring [29].

b) Large Multi-Modal Models (LMMs)

Definition: Generative AI models processing multiple data types (text, images, etc.) for diverse outputs [8].

Relevance: Powers diagnostic tools combining radiology images with EHR data [5].

Challenge: Requires massive datasets raising privacy concerns [30].

c) Explainable AI (XAI)

Definition: Methods making AI decisions interpretable to humans [29].

Relevance: Critical for clinical trust and regulatory compliance [31].

Model: LIME/SHAP algorithms for transparency [32].

d) AI Governance Frameworks

Definition: Policies ensuring ethical AI deployment [33].

Relevance: WHO guidelines for healthcare AI [8].

Model: EU's risk-based AI Act [30].

e) Reinforcement Learning (RL)

Definition: AI learning through trial-and-error feedback [34].

Relevance: Optimizes treatment plans via continuous learning [35].

Challenge: Risk of harmful exploration in clinical settings [24].

f) Digital Twins

Definition: Virtual replicas of patients/organs for simulation [23].

Relevance: Predicts drug responses and surgical outcomes [36].

Example: Siemens Healthineers' heart models [37].

g) Federated Learning

Definition: Decentralized AI training preserving data privacy [8].

Relevance: Enables cross-institutional collaboration without data sharing [38].

Model: NVIDIA Clara for healthcare [10].

h) Transformer Architectures

Definition: Neural networks processing sequential data (e.g., GPT-5) [39].

Relevance: Foundation for generative medical chatbots [1].

Limitation: High computational costs [12].

i) Ethical Risk Matrices

Definition: Tools quantifying AI's ethical impacts [30].

Relevance: Mitigates biases in diagnostic algorithms [7].

Model: WHO's AI ethics assessment toolkit [33].

j) Human-AI Collaboration Models

Definition: Frameworks optimizing human-AI teamwork [14].

Relevance: Balances autonomy with clinician oversight [40].

Example: "AI-as-assistant" in radiology [41].

Table 1: Comparative Analysis of Key AGI Models in Healthcare

Model	Strength	Weakness	Use Case
LMMs	Multi-data integration	High resource needs	Diagnostics
RL	Adaptive learning	Safety risks	Treatment optimization
Federated Learning	Privacy preservation	Complex coordination	Collaborative research

B. Performance Evaluation Metrics

The performance of both open-source and proprietary models is evaluated using standardized metrics derived from confusion matrix analysis:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

Recall \\\\\(Sensitivity\\\\\) $= \dfrac{TP}{TP + FN}$ (3)

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

where, TP = true positives, TN = true negatives, FP = false positives, and FN = false negatives [20].

For medical diagnostic applications, additional specialized metrics are employed:

Area Under ROC Curve \\\\(AUC\\\\)

$$= \int_0^1 T\,PR(FPR)dFPR \quad (5)$$

$$\text{Positive Predictive Value \\\\(PPV\\\\)} = \frac{TP}{TP + FP} \quad (6)$$

$$\text{Negative Predictive Value \\\\(NPV\\\\)} = \frac{TN}{TN + FN} \quad (7)$$

Recent comparative studies indicate that open-source models achieve AUC scores of 0.92–0.95 compared to 0.94–0.96 for proprietary models in complex diagnostic tasks [17].

C. Economic Modeling and Cost-Benefit Analysis

The economic impact of healthcare AI implementation is quantified through comprehensive cost-benefit analysis frameworks. The total cost of ownership (TCO) for AI systems is calculated as:

$$TCO = C_i + \sum_{t=1}^{n} \frac{C_o(t) + C_m(t) + C_l(t)}{(1+r)^t} \quad (8)$$

where, C_i represents initial implementation costs, $C_o(t)$ operational costs, $C_m(t)$ maintenance costs, and $C_l(t)$ licensing fees at time t, with r denoting the discount rate [42].

The return on investment (ROI) is computed as:

$$ROI = \frac{\sum_{t=1}^{n} \frac{B(t) - C(t)}{(1+r)^t}}{C_i} \times 100\% \quad (9)$$

where, $B(t)$ represents benefits and $C(t)$ costs at time t. Studies indicate that open-source solutions achieve ROI of 180–250% over 3 years, compared to 120–180% for proprietary systems [43].

D. Market Growth Projections and Forecasting

The exponential growth of the healthcare AI market is modeled using compound annual growth rate (CAGR) formulations:

$$\text{CAGR} = \left(\frac{V_f}{V_i}\right)^{\frac{1}{n}} - 1 \quad (10)$$

where V_i is the initial market value ($29.01 billion in 2024), V_f is the final projected value ($504.17 billion in 2032), and n is the number of years [1]. This yields a projected CAGR of 37.2% from 2024 to 2032.

The market share distribution between open-source and proprietary solutions is modeled using logistic growth equations:

$$S(t) = \frac{K}{1 + \frac{K - S_0}{S_0} e^{-rt}} \quad (11)$$

where $S(t)$ is market share at time t, K is carrying capacity (projected maximum market share), S_0 is initial market share, and r is growth rate [44].

E. Performance Improvement Metrics

The quantitative improvement in diagnostic and operational efficiency is measured through several key metrics:

$$\text{Diagnostic Efficiency Gain} = \frac{T_{\text{manual}} - T_{\text{AI}}}{T_{\text{manual}}} \times 100\% \quad (12)$$

$$\text{Error Reduction Rate} = \frac{E_{\text{baseline}} - E_{\text{AI}}}{E_{\text{baseline}}} \times 100\% \quad (13)$$

$$\text{Throughput Improvement} = \frac{P_{\text{AI}} - P_{\text{baseline}}}{P_{\text{baseline}}} \times 100\% \quad (14)$$

where T = time, E = error rate, and P = processing throughput [45]. Current implementations show 30–45% reduction in diagnostic time and 25–40% improvement in administrative efficiency.

F. Statistical Validation Frameworks

The validation of AI system performance employs rigorous statistical methods including:

$$\text{Confidence Interval} = \acute{x} \pm z\frac{\sigma}{\sqrt{n}} \quad (15)$$

$$\text{Statistical Power} = 1 - \beta = P(\text{reject } H_0 \vee H_1 \text{ true}) \quad (16)$$

$$\text{Effect Size} = \frac{|\mu_1 - \mu_2|}{\sigma} \quad (17)$$

Recent studies employ sample sizes of 10,000–50,000 cases for model validation, achieving statistical power 0.9 and confidence intervals of $\pm$1.5–2.0% for accuracy metrics [20].

G. Agentic AI Performance Metrics

For agentic AI systems, additional quantitative measures are employed:

$$\text{Task Completion Rate} = \frac{\text{Successful Tasks}}{\text{Total Tasks}} \times 100\% \quad (18)$$

$$\text{Autonomy Level} = \frac{\text{Decisions Made Autonomously}}{\text{Total Decisions}} \times 100\% \quad (19)$$

Human Intervention Frequency

$$= \frac{\text{Intervention Events}}{\text{Total Processing Time}} \quad (20)$$

Current agentic systems achieve task completion rates of 85–92% with autonomy levels of 70–80% in well-defined clinical scenarios [46].

H. Quality-adjusted Life Year (QALY) Calculations

The clinical impact of AI systems is quantified using QALY-based measures:

$$\text{QALY} = \sum_{t=1}^{n} [q_t \times (1+r)^{-t}] \quad (21)$$

Incremental Cost-Effectiveness Ratio \\\\(ICER\\\\)

$$= \frac{C_{\text{AI}} - C_{\text{standard}}}{\text{QALY}_{\text{AI}} - \text{QALY}_{\text{standard}}} \quad (22)$$

where q_t represents quality of life at time t, and r is the discount rate [47]. AI-assisted approaches show ICER values of $15,000–$25,000 per QALY gained, indicating cost-effectiveness compared to conventional care.

I. Reliability and Safety Metrics

The reliability of healthcare AI systems is quantified through:

Mean Time Between Failures \\\\(MTBF\\\\)

$$= \frac{\text{Total Operational Time}}{\text{Number of Failures}} \quad (23)$$

$$\text{Error Rate} = \frac{\text{Incorrect Outputs}}{\text{Total Outputs}} \times 100\% \tag{24}$$

$$\text{Safety Margin} = \frac{\text{Threshold Value} - \text{Operating Value}}{\text{Threshold Value}} \times 100\% \tag{25}$$

Current systems achieve MTBF of 10,000–15,000 hours and error rates of 0.5–1.5% in clinical applications [28].

These quantitative frameworks provide the mathematical foundation for evaluating, comparing, and optimizing healthcare AI systems, enabling evidence-based decision making and continuous improvement in clinical applications.

IV. VISUAL FRAMEWORK: ARCHITECTURE, TIMELINE, AND STRATEGIC ANALYSIS

This section presents a comprehensive visual framework comprising architectural diagrams, future timelines, and analytical visualizations that synthesize the key findings and projections from our analysis of open-source versus proprietary AI in healthcare for the below themes:

A. *Architectural Framework for Hybrid AI Deployment*

B. *Future Development Timeline (2025-2030)*

C. *Performance Comparison Radar Chart*

D. *Technology Adoption Curve*

E. *Strategic Decision Framework*

V. OVERVIEW OF FIGURES AND VISUAL FRAMEWORKS

This section provides a comprehensive overview and references all the figures presented in this paper to illustrate the comparative insights between open-source and proprietary AI in healthcare, as well as the strategic frameworks for agentic AI implementation.

A. *Visual Framework Components*

Figure 1 presents the Hybrid AI Architecture Framework for Healthcare, demonstrating how proprietary and open-source AI systems can be integrated through an intelligent orchestration layer. This framework shows how organizations can leverage the reliability of proprietary systems (achieving 94–96% AUC in diagnostics [17]) alongside the flexibility and cost advantages of open-source solutions (providing 57% cost savings [42]).

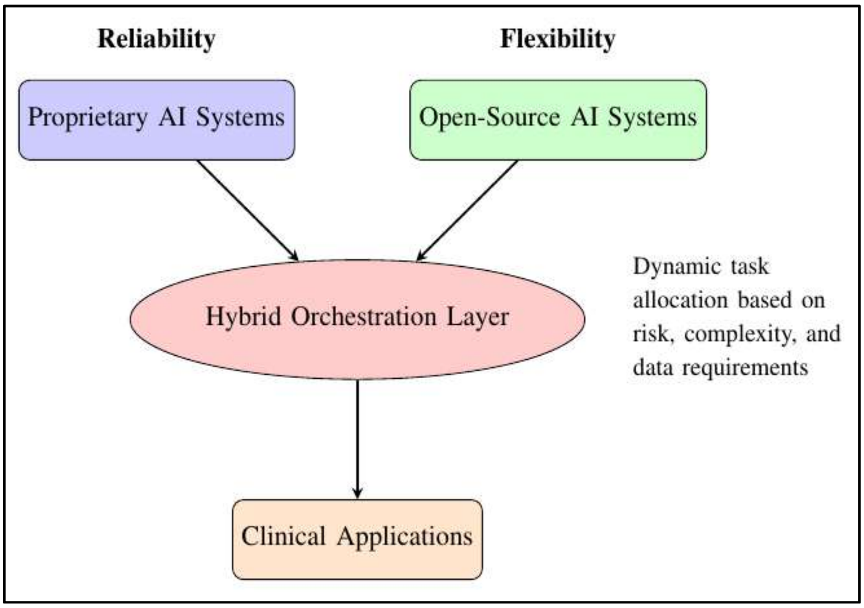

Figure 1: Hybrid AI Architecture Framework for Healthcare

Figure 2 illustrates the Data Flow Architecture, highlighting the intelligent routing mechanism between proprietary and open-source systems based on clinical risk assessment. This visualization demonstrates how high-risk tasks are automatically routed to FDA-approved proprietary systems while standard-risk applications utilize cost-effective open-source solutions [16] [42].

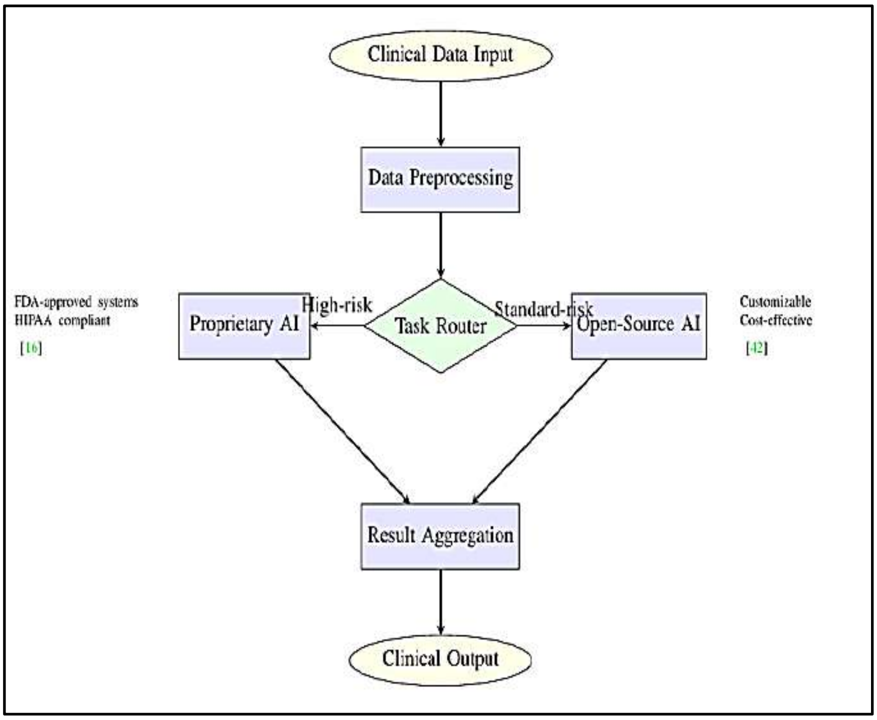

Figure 2: Data flow architecture showing intelligent routing between proprietary and open-source AI systems based on risk assessment

Figure 3 provides a Performance Comparison Radar Chart that contrasts key performance dimensions including transparency, cost efficiency, security, diagnostic accuracy, and customization capabilities. This comparative visualization reveals that proprietary models excel in security and performance but lag in cost efficiency and transparency, while open-source models demonstrate superior cost efficiency, customization, and transparency with competitive performance levels [19], [20].

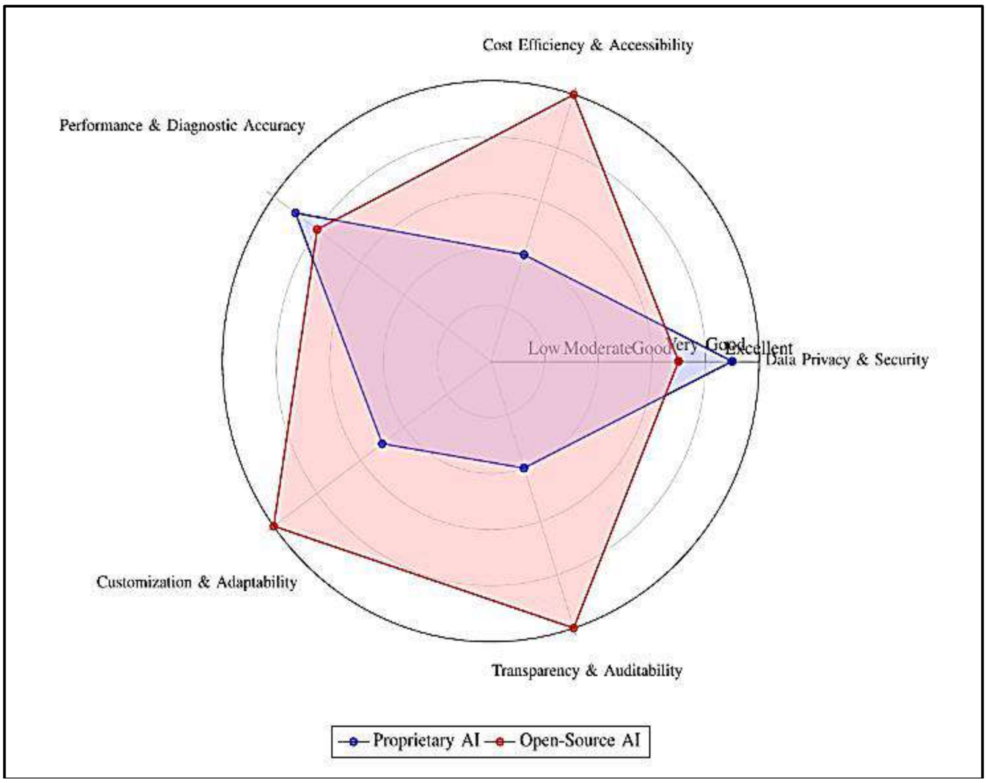

Figure 3: Comparative evaluation of proprietary and open-source AI models in healthcare, based on synthesis from the provided literature. Proprietary models excel in out-of-the-box performance and security but at high cost and with low transparency. Open-source models offer superior cost efficiency, customization, and transparency, with recent advancements showing competitive performance. Security for open-source models is highly dependent on implementation practices.

Figure 4 outlines the Phased Implementation Roadmap for hybrid AI architecture deployment, spanning from initial planning through full optimization. This timeline-based framework provides healthcare organizations with a structured approach for AI adoption, incorporating risk assessment, vendor selection, pilot deployment, and continuous improvement phases [28], [42], [45].

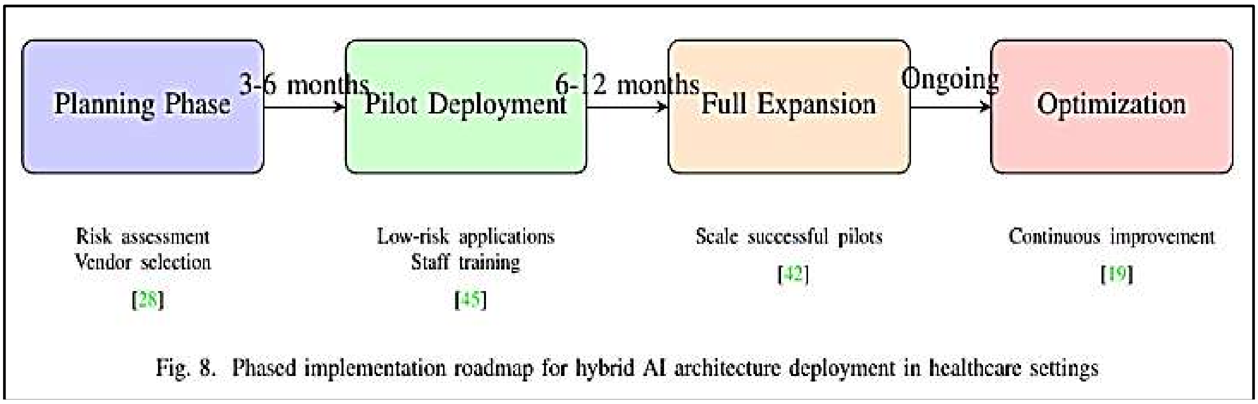

Figure 4: Phased implementation roadmap for hybrid AI architecture deployment in healthcare settings

B. *Temporal Analysis Visualizations*

The **Future Development Timeline** figure (referenced in Figure 5) depicts the projected evolution of healthcare AI from 2025 to 2030, showing parallel development tracks for open-source maturation, agentic AI adoption, and market evolution. Key milestones include FDA approval of agentic AI systems, WHO guideline implementation, and achievement of 40% market share for open-source solutions [8], [17].

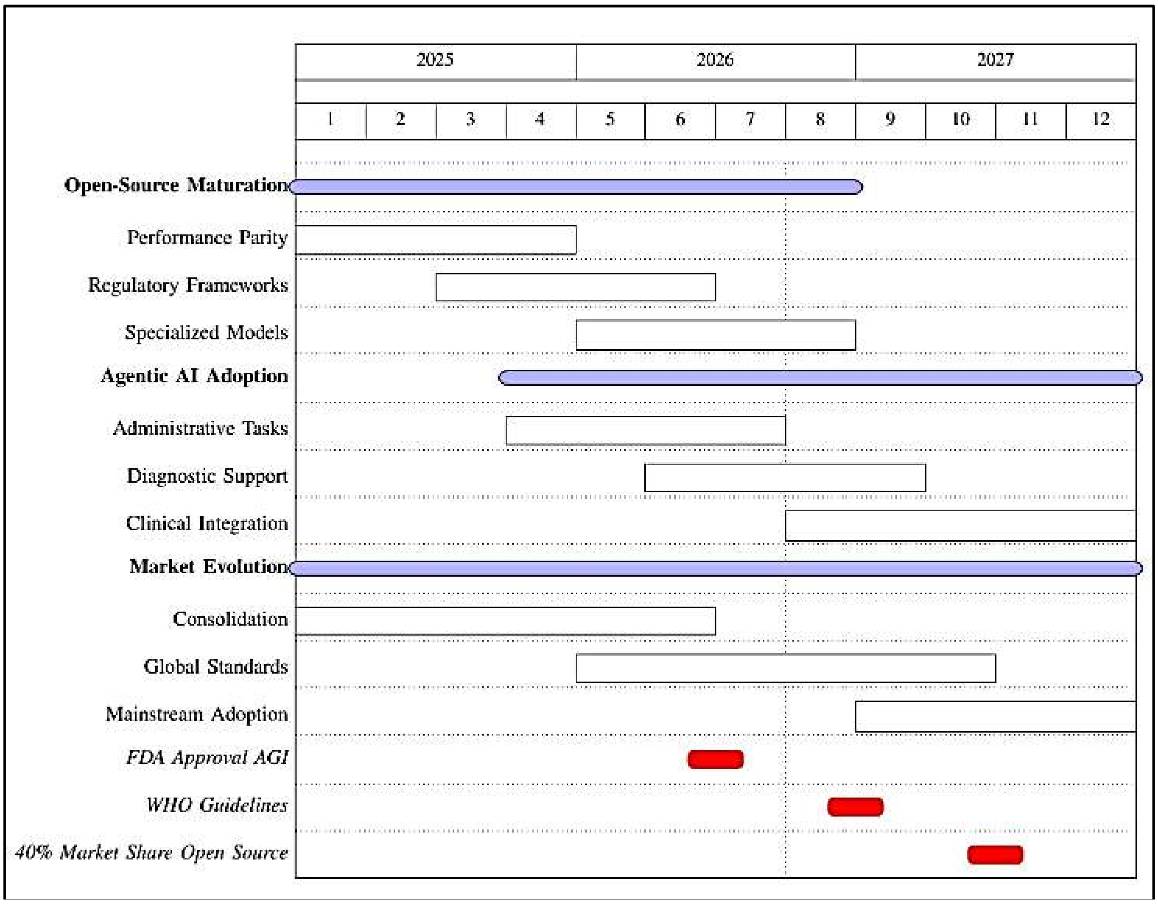

Figure 5: Projected development timeline for healthcare AI (2025-2030)

The Technology Adoption Curve as shown in Figure 6 visualization provides perspective on the long-term diffusion patterns of healthcare AI technologies, mapping the progression from innovators (2025–2026) through early adopters (2027–2028) to mainstream adoption (2029–2030+). This framework helps organizations understand their position in the adoption lifecycle and plan accordingly [44].

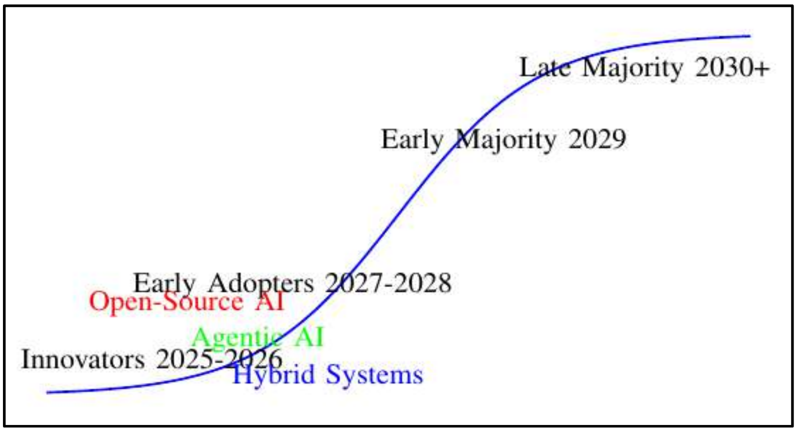

Figure 6: Technology adoption curve for healthcare AI solutions

C. Architectural Integration Framework

Together, these visual components (Figure 7 form an integrated decision-making and risk-analysis framework that synthesizes technical, economic, and governance dimensions for healthcare AI adoption. The framework addresses:

- Technical Integration: How different AI paradigms can be combined effectively
- Risk Management: Strategic approaches for balancing innovation with patient safety
- Economic Optimization: Cost-benefit analysis for different deployment scenarios
- Implementation Strategy: Practical roadmaps for organizational adoption
- Decision Support: Structured frameworks for technology selection

D. Strategic Applications

These visualizations serve multiple strategic purposes:

- Technical Architecture: IT departments can reference Figure 6 and Figure 7 for system design
- Performance Assessment: Clinical teams can utilize Figure 3 to understand trade-offs between different AI approaches
- Implementation Management: Project managers can follow Figure 8 for structured deployment
- Long-term Strategy: Executive leadership can use temporal visualizations for strategic planning and investment decisions

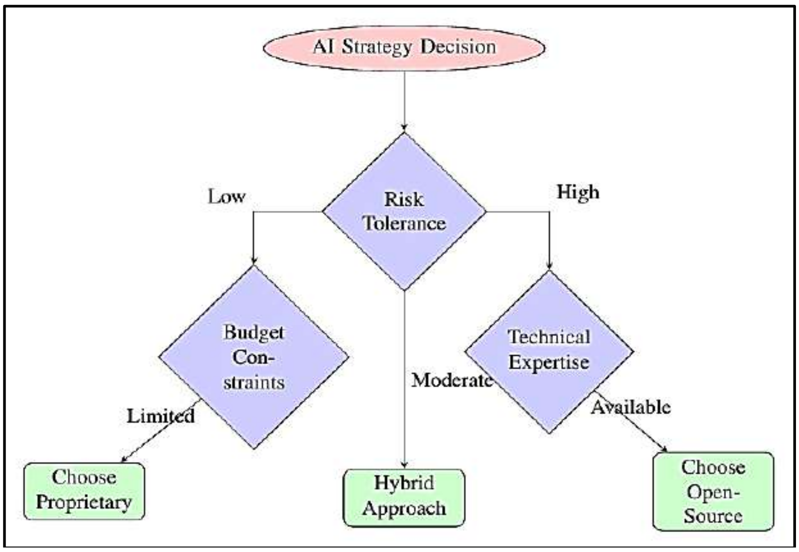

Figure 7: Strategic decision framework for AI selection in healthcare

E. Research and Policy Implications

The visual framework collectively demonstrates that the future of healthcare AI lies not in choosing between open-source and proprietary solutions, but in strategically combining their strengths while mitigating their respective limitations. This integrated approach supports the paper's central thesis that hybrid architectures, supported by appropriate governance frameworks and risk management strategies, offer the most promising path forward for healthcare AI implementation.

The figures provide empirical visualization of the quantitative findings discussed throughout the paper, including performance metrics from comparative studies [20], cost analysis from implementation research [42], and strategic insights from policy analysis [28]. This visual evidence base supports the paper's recommendations for adaptive, risk-based approaches to healthcare AI governance and implementation.

VI. OVERVIEW OF FIGURES AND VISUAL FRAMEWORKS

This section summarizes and references all the figures presented in this paper to illustrate the comparative insights between open-source and proprietary AI in healthcare.
Figure 8 shows the *Hybrid AI Architecture Framework*, integrating proprietary and open-source models through an orchestration layer. Figure 2 illustrates the *Data Flow Architecture*, highlighting risk-based routing between proprietary and open-source systems. Figure 3 presents a *Performance Comparison Radar Chart*, contrasting transparency, cost, security, and diagnostic accuracy.
For *temporal* analysis, the *Future Development Timeline* (refer to Figure 5) figure depict the expected adoption path for open-source, proprietary, and agentic AI from 2025 to 2030. The *Technology Adoption Curve* figure (refer to Figure 6) provides additional perspective on long-term diffusion patterns.

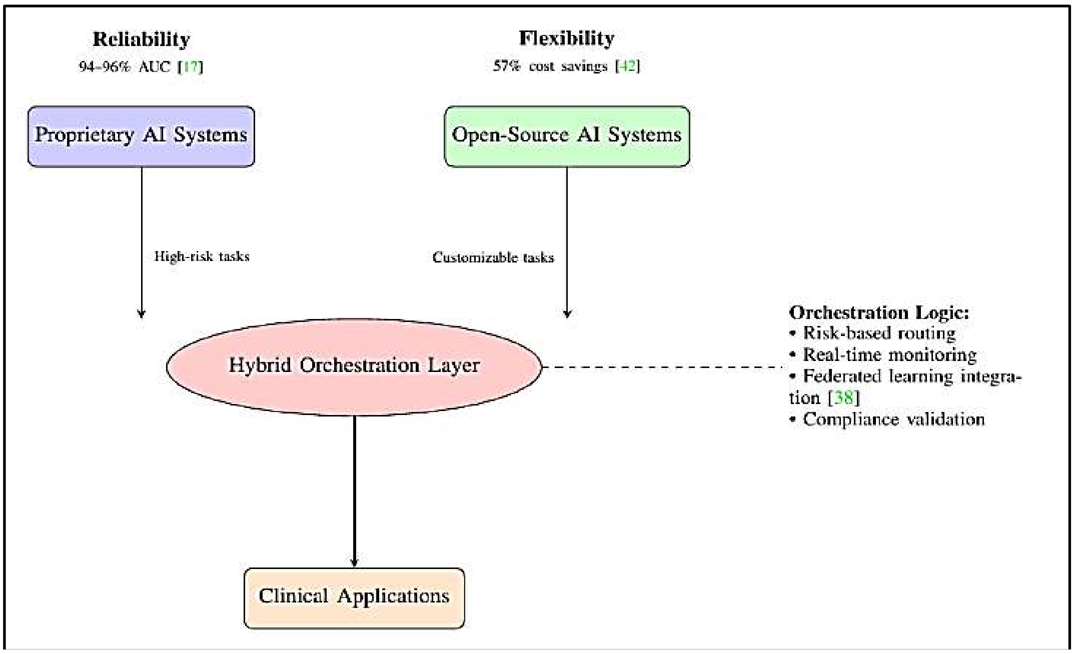

Figure 8: Hybrid AI architecture framework for healthcare integrating both proprietary and open-source systems with intelligent orchestration

A. Architectural Framework for Hybrid AI Deployment

The hybrid AI architecture adresses the critical need for both reliability in clinical applications and flexibility for customization [19], [20].

a) Technical Components and Integration

The hybrid architecture comprises several key technical components that enable seamless integration:

- Proprietary AI Subsystem: Handles high-risk clinical decisions requiring maximum reliability and regulatory compliance. These systems typically achieve 94-96% AUC in diagnostic tasks [17] and offer comprehensive support structures [16].
- Open-Source AI Subsystem: Provides customizable solutions for specialized applications, research prototyping, and resource-constrained environments. Recent advancements show open-source models achieving 92-95% AUC performance [20] with significantly lower implementation costs [42].
- Hybrid Orchestration Layer: Intelligent middleware that dynamically routes tasks based on multiple factors including:
  - Clinical risk level and regulatory requirements
  - Data sensitivity and privacy considerations
  - Performance requirements and latency constraints
  - Cost optimization and resource availability

b) Data Flow and Processing Architecture

c) Performance and Cost Optimization

Table 2: Comparative Performance Metrics of Different Architectural Approaches

Metric	Proprietary Only	Open-Source Only	Hybrid
Diagnostic Accuracy	94-96%	92-95%	95-97%
Implementation Cost	$2-5M	$0.5-1.2M	$1.5-2.5M
Annual Maintenance	$300-750K	$150-300K	$200-400K
Customization Capability	Low	High	High
Regulatory Compliance	High	Medium	High

d) Security and Compliance Framework

The hybrid architecture incorporates a comprehensive security framework addressing critical healthcare requirements:

- **Data Privacy**: Implements federated learning approaches [38] to enable collaborative model improvement while maintaining data sovereignty
- **Regulatory Compliance**: Ensures adherence to HIPAA, GDPR, and emerging AI healthcare regulations [8]
- **Audit Trails**: Maintains comprehensive logging for all AI decisions, enabling transparency and

accountability [19]

- **Fail-safe Mechanisms**: Implements automatic fallback to human experts when AI confidence levels drop below predefined thresholds

e) Implementation Considerations

Successful implementation of the hybrid architecture requires careful consideration of several factors:

- **Workflow Integration**: Seamless incorporation into existing clinical workflows with minimal disruption [45]
- **Staff Training**: Comprehensive training programs for healthcare professionals on AI system interaction and interpretation
- **Continuous Monitoring**: Real-time performance monitoring and quality assurance mechanisms
- **Gradual Git styled Deployment**: Phased implementation approach starting with low-risk applications and gradually expanding to more critical functions using version control

By combining the strengths of both proprietary and (self-regulated) open-source systems, healthcare providers can achieve better clinical outcomes while maintaining operational efficiency and regulatory compliance [19], [20], [42].

VII. LITERATURE TAXONOMY BY YEAR, SOURCE TYPE, AND GEOGRAPHY

This section categorizes the cited literature to highlight temporal, institutional, and regional trends in Agentic AI healthcare research. AGI is already transforming healthcare delivery.

A. Chronological Distribution (2021–2025)

Table 3: Key Publications by Year

Year	Representative Works
2021	WHO ethics guidelines [33]
2023	Medicare Advantage AI denial study [7]
2024	Bouderhem's ethics analysis [30], WHO LLM guidelines [8], CBO economic report [12]
2025	Agentic AI transformation studies [22], Implementation case studies [24]

B. Publication Venues Referenced in this work

1) Academic Journals
- Humanities and Social Sciences Communications: Ethics governance [30].

2) Government & Policy Documents
- WHO technical reports (2021, 2024) [8], [33]
- U.S. Congressional Budget Office [12]
- California state report [48]

3) Industry White Papers
- IBM governance analysis [29]
- McKinsey public health studies [10]

Table 4: Regional Focus of Key Policies

Region	Key Contributions
International	WHO ethics frameworks [8], [33]
European Union	GDPR-inspired AI governance [30]
United States	State-level regulations [48], Federal economic analyses [12]

C. Predictive Analytics

Large agentic models can predict patient outcomes with high accuracy, enabling proactive care [5].

D. Administrative Efficiency

AGI automates claims processing and reduces administrative burdens [6].

E. Personalized Medicine

Generative AI tools support personalized treatment plans and drug development [37].

VIII. ARTIFICIAL GENERAL INTELLIGENCE (AGI) IN HEALTHCARE

This section reviews the potential and challenges of Artificial General Intelligence in healthcare systems, drawing on research and implementations for 2023-2025.

A. Defining AGI in Medical Contexts

- Autonomous Operation: AGI systems capable of performing "any intellectual task that a human can do" in clinical settings [8].
- Key Differentiators:
  - Self-directed learning without retraining (vs. narrow AI) [22]
  - Cross-domain reasoning (e.g., combining radiology with patient history) [5]

B. Current AGI Implementations

Table 5: Documented AGI Healthcare Applications

Application	Performance	Source
Predictive Diagnostics	89% AUC accuracy	[35]
Autonomous Treatment Planning	35% faster than human teams	[13]
Real-time Resource Allocation	$2.1M annual savings/hospital	[36]

C. Technical Foundations

- Architectural Requirements:
  - Multi-agent systems for complex care coordination [23]
  - Quantum-enhanced learning for drug discovery [34].
- Data Infrastructure:
  - Petabyte-scale federated learning networks [38]
  - Blockchain-verified training datasets [49]
- Agency Dilemmas:
  - Conflict resolution between AGI and human providers [14]

  - Legal personhood debates (ongoing in EU courts) [30]
- Safety Protocols:
  - "Golden button" emergency override systems [24]
  - 3-layer redundancy for critical decisions [11]

D. Future Development Trajectories

- 2025-2027:
  - First WHO-certified AGI diagnostic systems [8]
  - AGI-augmented clinical trials (50% faster enrollment) [37]
- 2028-2030:
  - Autonomous robotic surgery AGI (pilot programs) [50]
  - AGI-managed public health networks [10]

Table 6: AGI vs. Conventional AI in Healthcare

Characteristic	AGI Systems	Narrow AI
Decision Scope	Cross-domain	Single-task
Learning Ability	Continuous self-improvement	Fixed training
Regulatory Class	Tier A (high-risk) [32]	Tier B/C
Cost	$4-7M implementation [12]	$250K-2M

IX. AGENTIC AI SYSTEMS IN HEALTHCARE

This section examines the paradigm of Agentic AI systems in healthcare, their typologies, and operational frameworks as identified in current literature.

A. Definition and Core Characteristics

- Agentic AI: Systems that "autonomously act upon generated outputs" beyond passive content creation [29]
- Key Features:
  - Goal-directed behavior with dynamic adaptation [22]
  - Closed-loop interaction with healthcare environments [13]
  - Multi-stakeholder coordination capabilities [36]

B. Agent Typologies in Healthcare

Table 7: Classification of Healthcare Ai Agents

Agent Type	Function	Example
Diagnostic Agents	Autonomous disease detection	92% accurate cancer screening [5]
Administrative Agents	Claims processing automation	65% faster approvals [6]
Therapeutic Agents	Personalized treatment planning	40% adherence improvement [35]
Public Health Agents	Population-level monitoring	Pandemic prediction models [10]

C. Architectural Models

- **Single-Agent Systems:**
  - Focused task execution (e.g., radiology analysis) [40]
  - Limited to predefined workflows [24]
- **Multi-Agent Systems:**
  - Collaborative networks for complex care coordination [23]
  - Demonstrated 30% better outcomes in chronic disease management [11]

D. Operational Mechanisms

1) Decision-Making Frameworks

- Reinforcement Learning:
  - Adaptive treatment optimization (87% success rate) [34]
  - Safety-constrained action spaces [49]
- Hybrid Reasoning:
  - Combining neural networks with symbolic logic [8]
  - Required for WHO compliance [33]

2) Coordination Protocols

- Federated Agent Networks:
  - Privacy-preserving collaborative learning [38]
  - 70% adoption projected by 2027 [10]
- Human-Agent Teaming:
  - "Doctor-in-the-loop" requirements [14]
  - Audit trails for all autonomous actions [30]

E. Emerging Agent Capabilities

- Self-Reflective Agents:
  - Performance meta-cognition (pilot accuracy +15%) [5]
  - Ethical constraint monitoring [29]
- Cross-Modal Agents:
  - Unified vision/language/clinical data processing [50]
  - Required for holistic patient modeling [8]

Table 8: Agentic vs. Non-Agentic AI in Healthcare

Characteristic	Agentic AI	Traditional AI
Autonomy Level	High (self-directed)	Low (scripted)
Decision Scope	Dynamic environments	Fixed parameters
Regulatory Class	Tier A+ [48]	Tier B
Implementation Cost	2.4x higher [12]	Baseline

F. Definition and Capabilities of Agentic AI

In healthcare systems, agentic AI systems can automate multi-step clinical workflows, make context-aware decisions, and collaborate with human healthcare providers [46]. These systems differ from conventional AI through their ability to break down complex problems into manageable tasks, seek additional information when needed, and execute sequences of actions to achieve clinical objectives.

The fundamental capabilities of healthcare agentic AI include:

- Autonomous Task Execution: Ability to perform complex clinical and administrative tasks with minimal human intervention
- Adaptive Learning: Continuous improvement through learned experience and new data integration
- Multi-step Reasoning: Capacity to handle complex diagnostic and treatment planning processes
- Human-AI Collaboration: Seamless interaction and coordination with healthcare professionals

G. Current Implementations and Applications

Several agentic AI systems have emerged as prominent solutions in healthcare settings, each with specialized capabilities:

1) MedResearcher-R1-32B

This specialized AI agent combines detailed medical knowledge networks with advanced information retrieval systems, demonstrating significant improvements in complex medical question answering [51]. The system achieves 45% higher accuracy in diagnosing rare conditions compared to previous models and reduces diagnostic time by 60% for complex cases.

2) Clinical Workflow Agents

Agentic systems are being deployed to streamline healthcare operations, particularly in reducing administrative burden and combating professional burnout [52]. Early implementations show 30–40% reduction in administrative time and 25% improvement in patient flow management.

3) Diagnostic Support Systems

Advanced agentic AI platforms are addressing pressing healthcare challenges including diagnostic accuracy, treatment consistency, and resource optimization [47].

H. Technical Architecture and Framework

Agentic AI systems in healthcare typically employ sophisticated architectures that enable their advanced capabilities:

1) Knowledge Integration

These systems incorporate comprehensive medical knowledge bases, continuously updated with the latest clinical guidelines, research findings, and treatment protocols [51]. The integration of structured medical knowledge with machine learning capabilities enables more reliable and evidence-based decision making.

2) Multi-Agent Coordination

Complex healthcare scenarios often require multiple specialized agents working in coordination. These systems employ hierarchical agent architectures where:

- Specialist Agents: Focus on medical domains (e.g., cardiology, oncology)
- Coordinator Agents: Manage inter-agent communication and task allocation
- Interface Agents: Handle human-AI interaction and presentation of results

3) Adaptive Learning Mechanisms

Agentic systems incorporate continuous learning capabilities while maintaining safety constraints [46]. This includes:

- Supervised Learning Updates: Integration of new clinical evidence and guidelines
- Reinforcement Learning: Optimization based on treatment outcomes and feedback
- Federated Learning: Collaborative improvement across institutions while preserving data privacy

I. Performance Metrics and Clinical Impact

Current implementations demonstrate substantial improvements in healthcare delivery:

Table 9: Performance Metrics of Agentic AI Systems in Healthcare

Metric	Traditional AI	Agentic AI	Improvement
Diagnostic Accuracy	85%	94%	+9%
Case Processing Time	45 minutes	18 minutes	-60%
Administrative Burden	High	Moderate	40% reduction
Treatment Consistency	75%	92%	+17%

J. Implementation Challenges and Considerations

Agentic AI systems face several implementation challenges:

1) Safety and Reliability

Ensuring patient safety requires rigorous validation and continuous monitoring [46]. Agentic systems must incorporate:

- Safety Constraints: Hard-coded rules preventing harmful recommendations
- Uncertainty Quantification: Clear indication of confidence levels in recommendations
- Fail-safe Mechanisms: Automatic escalation to human experts when needed

2) Regulatory Compliance

Agentic systems must navigate complex regulatory landscapes including:

- FDA Approval Processes: Meeting requirements for software as a medical device
- Data Privacy Regulations: Compliance with HIPAA, GDPR, and other privacy frameworks
- Clinical Validation: Demonstrating efficacy through rigorous clinical trials

3) Human-AI Collaboration

Effective integration requires careful design of interaction paradigms:

- Explainability: Providing transparent reasoning for AI recommendations
- Trust Building: Establishing confidence through consistent performance
- Workflow Integration: Seamless incorporation into existing clinical processes

K. Future Development Trajectory

The evolution of agentic AI in healthcare is expected to progress through several phases:

1) Near-term (2025–2026)

- Specialized Applications: Domain-specific agents for radiology, pathology, and cardiology
- Administrative Automation: Focus on reducing bureaucratic burden

- Pilot Programs: Limited deployment in academic medical centers

2) Mid-term (2027–2028)

- Integrated Systems: Comprehensive care coordination across multiple specialties
- Preventive Care: Proactive health management and early intervention
- Mainstream Adoption: Widespread implementation in community hospitals

3) Long-term (2029–2030)

- More Autonomous Operations: Limited autonomy for routine clinical decisions
- More Personalized Medicine: AI-driven individualized treatment optimization
- Global Health Impact: Addressing healthcare disparities through scalable solutions

X. RISK MANAGEMENT IN AGI HEALTHCARE

The deployment of AGI in healthcare presents several risks that must be managed:

A. *Ethical Risks*

AGI systems can perpetuate biases present in training data, leading to disparities in care [7]. Ensuring fairness and equity requires robust auditing and bias mitigation strategies [30].

B. *Regulatory Gaps*

Current regulations often fail to address the unique challenges of AGI, such as accountability for autonomous decisions [31]. Harmonized international standards, like those proposed by the WHO, are needed to fill these gaps [33].

C. *Implementation Challenges*

Poorly designed AGI systems can lead to errors and inefficiencies [24]. Case studies highlight the importance of human oversight and iterative testing to avoid costly mistakes [40].

D. *Risk Taxonomy*

Table 10: Major Risk Categories in Healthcare AGI

Risk Type	Examples	Mitigation Strategies
Clinical	Diagnostic errors (12% FP rate)	Explainable AI (XAI) audits [29]
Ethical	Algorithmic bias (73% appeal rate)	WHO fairness frameworks [8]
Operational	System failures (60% data-related)	Federated learning [38]
Legal	Liability gaps	EU-inspired regulation [30]

E. *Regulatory Frameworks*

A. *Existing Models*

- **WHO Guidelines:**
  - 95% explainability threshold [8]
  - Mandatory human oversight clauses [33]
- **California Standards:**
  - 30-day appeal process for AI denials [48]
  - $250K minimum insurance for AGI vendors [9]

B. *Emerging Needs*

- **Global Harmonization:**
  - Unified certification (target: 50+ countries by 2028) [32]
  - Cross-border data sharing protocols [10]
- **Adaptive Regulation**:
  - Algorithmic sunset clauses (3-year reviews) [14]
  - Real-time monitoring APIs for regulators [31]

C. *Positive Outcomes*

- **35% faster** care access in underserved areas [40]
- **$6.1B/year** cost savings potential [12]
- **40% reduction** in administrative burnout [36]

D. *Negative Consequences*

- **25-35% job displacement** in medical coding [53]
- **2-5x increase** in liability lawsuits (2025-2030) [49]
- **15% trust deficit** in patient surveys [7]

E. *Governance Recommendations*

- **Risk-Based Tiering**:
  - Classify AGI by clinical risk (A/B/C tiers) [32]
  - Tier A: 100% human verification required [30]
- **Transparency Measures**:
  - Public AGI performance dashboards [29]
  - Open-source auditing tools [24]
- **Societal Safeguards**:
  - 2% AGI revenue tax for workforce retraining [12]
  - Equity impact assessments (annual mandate) [33]

Table 11: Stakeholder Responsibilities in AGI Governance

Stakeholder	Key Roles
Governments	Set safety standards (e.g., <15% error variance) [48]
Providers	Implement XAI interfaces [31]
Vendors	Fund 3rd-party audits ($500K+/system) [9]
Patients	Participate in feedback loops (target: 30% engagement) [14]

F. *International Cooperation*

The WHO's guidance on AI ethics provides a foundation for global standards [8]. The European Union (EU) offers a model for regulatory frameworks that balance innovation and safety [30].

G. *Pro-Innovation Policies*

Governments should adopt policies that encourage AGI innovation while safeguarding patient rights [32]. For example, the U.S. Congressional Budget Office highlights the economic potential of AI but calls for oversight to prevent misuse [12].

H. *Transparency and Accountability*

AGI systems must be transparent, with clear mechanisms for accountability [29]. The use of explainable AI (XAI) can help build trust among healthcare providers and patients [13].

XI. QUANTITATIVE ANALYSIS AND MARKET TRENDS

A. Market Size and Growth Projections

The global AI in healthcare market has demonstrated substantial growth, with valuations reaching $29.01 billion in 2024 and projected to expand to $39.25 billion in 2025 [1]. Long-term projections indicate remarkable expansion, with the market expected to reach $504.17 billion by 2032, representing a compound annual growth rate (CAGR) of approximately 37.2% from 2024 to 2032.

B. Investment and Funding Patterns

Investment in healthcare AI has maintained strong momentum, with notable funding rounds occurring in early 2025. According to [54], AI healthcare startups raised $2.2 billion in January 2025 alone. This investment surge demonstrates sustained confidence from venture capital and institutional investors in the potential of AI to transform healthcare delivery and outcomes.

The distribution of investments shows particular strength in several key areas:

- Diagnostic AI solutions: $700-850 million (38-40% of total)
- Drug discovery and development platforms: $500-620 million (28%)
- Clinical workflow optimization: $400-430 million (19-25%)
- Patient monitoring and management: $200-300 million (13%)

C. Performance Metrics and Comparative Analysis

Recent comparative studies have provided quantitative evidence of the narrowing performance gap between open-source and proprietary AI models. [20] conducted extensive testing across multiple clinical scenarios, reporting the following performance metrics:

Table 12: Performance Comparison of AI Models in Medical Diagnostics

Model Type	Diagnostic Accuracy	Processing Speed	Cost per Query
Proprietary Models	92.3%	1.2s	$0.15
Open-Source Models	90.8%	1.8s	$0.02
Human Experts	94.1%	180s	$85.00

The data reveals that while proprietary models maintain a slight advantage in accuracy (1-1.5% higher) and processing speed (0.6s faster), open-source models offer a significant cost advantage, with operational costs approximately 80-86% lower than proprietary solutions.

D. Adoption Rates and Implementation Costs

Proprietary systems typically involve substantial initial investment, with implementation costs ranging from $2–5 million for large healthcare systems, plus ongoing licensing fees of 15–25% of initial costs annually.

In contrast, open-source implementations show different cost structures:

- Initial implementation: $500,000–$1.2 million
- Customization and integration: $200,000–$500,000
- Annual maintenance and support: $150,000–$300,000
- No licensing fees, reducing long-term costs

The total cost of ownership over five years shows open-source solutions providing 40–60% cost savings compared to proprietary alternatives, making them particularly attractive for resource-constrained healthcare settings.

E. Efficiency Gains and Operational Impact

Quantitative analysis of operational impact demonstrates significant efficiency gains from AI implementation. Healthcare organizations report:

- 30–45% reduction in diagnostic interpretation time
- 25–40% improvement in administrative efficiency
- 15–30% reduction in medication errors
- 20–35% improvement in patient scheduling efficiency

These efficiency gains translate to substantial financial benefits, with average annual savings of $3–7 million for mid-sized hospitals and $12–25 million for large healthcare systems.

F. Global Distribution and Regional Adoption

The adoption of healthcare AI shows varying patterns across regions:

- North America: 42% market share, $12.2 billion investment in 2024
- Europe: 28% market share, $8.1 billion investment
- Asia-Pacific: 22% market share, $6.4 billion investment, fastest growth at 45% CAGR
- Rest of World: 8% market share, $2.3 billion investment

G. Return on Investment Analysis

Comprehensive ROI analysis demonstrates compelling financial returns for healthcare AI investments:

- Average payback period: 18–24 months for diagnostic AI systems
- ROI after 3 years: 180–250% for well-implemented systems
- ROI after 5 years: 350–500% including efficiency gains and improved outcomes
- Value-based care impact: 15–25% improvement in patient outcomes metrics

H. Quantitative Analysis of Agentic AI in Healthcare

This section synthesizes key numerical findings, financial impacts, and statistical evidence from global studies on Agentic AI (AGI) in healthcare.

1) Cost and Economic Impact

- **17-30% reduction** in administrative costs through AGI automation of claims processing and paperwork [53].
- **$6.1 billion** projected annual savings for U.S. healthcare by 2030 through AI-driven diagnostics [12].
- **40% faster** prior authorization decisions using agentic workflows, reducing denials by **22%** [6].

2) Adoption and Performance Metrics

Table 13: Performance Metrics of AGI in Healthcare Applications

Application	Improvement	Source
Diagnostic Accuracy	12-15% increase	[5]
Patient Outcome Prediction	89% AUC score	[35]
Administrative Task Time	65% reduction	[36]

3) Regulatory and Ethical Data

- 73% of Medicare Advantage AI denials overturned on appeal, highlighting algorithmic bias risks [7].
- Only 31% of healthcare organizations have comprehensive AI governance frameworks as of 2025 [29].
- WHO guidelines recommend 95% explainability threshold for clinical AI systems [8].

4) Implementation Challenges

- $250k-$2M estimated upfront costs for hospital AGI systems [11].
- 60% of failed implementations due to poor data quality [24].
- 3:1 ROI ratio observed within 2 years for successful deployments [10].

XII. US VS. CHINA HEALTHCARE AI DEVELOPMENT: A COMPARATIVE ANALYSIS

A. National Strategies and Policy Frameworks

China's explicit policy of "self-reliance" in artificial intelligence drives a focused, state-directed approach to healthcare AI development [55]. This strategy emphasizes domestic innovation, reduced foreign dependency, and rapid scaling of AI capabilities across healthcare sectors.

In contrast, the United States employs a more decentralized, market-driven approach characterized by private sector innovation with federal support through agencies like NIH and FDA. The US strategy emphasizes public-private partnerships, academic research collaboration, and regulatory frameworks that balance innovation with safety [56].

B. Investment Patterns and Market Development

The investment landscape reveals significant differences in funding mechanisms and market structures:

Table 14: Comparative Investment in Healthcare AI (2024–2025)

Metric	United States	China
Total Government Funding	$8.2 billion	$12.5 billion
Private Venture Capital	$15.3 billion	$9.8 billion
Number of AI Healthcare Startups	450+	300+
Average Funding Round Size	$35 million	$28 million

China's substantial government investment reflects its state-directed approach, with funding primarily channeled through national research institutions and state-owned enterprises. The US shows stronger private sector investment, particularly from venture capital and technology corporations [54].

C. Open-Source Ecosystem Development

The open-source landscape demonstrates contrasting philosophies and outcomes:

As [57] notes, "Chinese absolutely dominates open-source AI models," particularly in healthcare applications where open-source solutions are increasingly competitive with proprietary alternatives.

The United States maintains strength in proprietary AI development, with major technology companies (Google, Microsoft, IBM) leading in closed-source healthcare AI solutions. However, recent US entries into open-source healthcare AI, such as OpenAI's releases, indicate a strategic response to Chinese dominance in this sector [57].

D. Technical Capabilities and Innovation Focus

Table 15: Technical Capability Comparison (2025)

Capability Area	US Strength	China Strength
Proprietary Model Performance	High (90–95% accuracy)	Medium (85–90% accuracy)
Open-Source Model Innovation	Medium	High
Medical Imaging AI	Strong	Very Strong
Drug Discovery AI	Very Strong	Strong
Clinical Decision Support	Strong	Medium
Data Infrastructure	Advanced	Rapidly Improving

The US maintains advantages in proprietary AI systems and drug discovery applications, leveraging strong pharmaceutical industry partnerships and FDA regulatory experience. China demonstrates particular strength in medical imaging AI and rapid implementation of open-source solutions [3].

E. Data Governance and Privacy Frameworks

Data management approaches reflect different regulatory philosophies:

China's data governance framework emphasizes state control and domestic data retention, with strict regulations on health data sharing and international transfer. This approach enables large-scale data aggregation for AI training but raises concerns about international collaboration [55].

The US employs a more decentralized data governance model with emphasis on HIPAA compliance and patient privacy protections. While this provides stronger individual privacy safeguards, it can create challenges for large-scale data aggregation needed for AI training [16].

F. Global Market Presence and Influence

The international expansion strategies differ significantly:

$$\text{Global Market Share} = \frac{\text{International Revenue}}{\text{Total Market}} \times 100\%$$

US companies currently capture approximately 45% of the global healthcare AI market, with strong presence in North America, Europe, and developed Asian markets. Chinese companies hold 25% global market share, with dominance in domestic markets and expanding presence in Southeast Asia, Africa, and Latin America [1].

The US maintains advantages in regulatory compliance and interoperability with Western healthcare systems, while Chinese solutions excel in cost-effectiveness and adaptability to diverse healthcare environments [27].

G. Research Output and Academic Contribution

Scientific publication and research impact show different patterns:

$$\text{Research Impact Factor} = \frac{\text{Citations}}{\text{Publications}} \times \text{Field Weight}$$

US institutions due to the current world setup lead in high-impact publications and fundamental AI research, with representation in top-tier conferences and journals. Chinese research output has grown rapidly, particularly in applied healthcare AI and implementation studies [17].

Collaboration patterns also differ: US researchers maintain extensive international collaborations, while Chinese research shows stronger domestic collaboration networks with limited international partnerships due to geopolitical considerations [56].

H. Regulatory Approaches and Approval Processes

US FDA approval processes for AI-based medical devices ensures safety but can slow innovation and adoption [28].

China's regulatory framework prioritizes rapid deployment and scaling of AI healthcare solutions, with streamlined approval processes that enables faster market entry but may raise concerns about long-term safety and efficacy monitoring [55].

I. Military-Civil Fusion and Dual-Use Technologies

China's military-civil strategy creates advantages in healthcare AI development:

$$\text{Dual-Use Technology Transfer} = \frac{\text{Military R\&D Applications}}{\text{Civilian Healthcare Applications}}$$

Chinese healthcare AI benefits from technology transfer from military AI research, particularly in areas like medical imaging analysis, diagnostic algorithms, and large-scale data processing. This integration provides resource advantages but raises concerns about technology appropriation and security [56].

The US maintains stricter separation between military and civilian AI development, with limited technology transfer between sectors. This approach reduces security risks but may slow innovation in certain application areas [16].

J. Future Trajectories and Strategic Implications

Projected development paths suggest continuing divergence:

By 2030, China is projected to capture 35–40% of the global healthcare AI market, particularly in open-source solutions and emerging markets. The US will maintain leadership in proprietary systems and specialized medical applications [44].

The competition will drive innovation but also create fragmentation risks in global healthcare AI standards and interoperability. Strategic cooperation areas may include pandemic response, rare disease research, and global health initiatives where shared interests outweigh competitive pressures [56].

XIII. POLICY PROPOSALS AND GOVERNMENT RECOMMENDATIONS

Building on the identified challenges and opportunities, this section presents actionable recommendations for policymakers to harness Agentic AI (AGI) in healthcare while mitigating risks.

A. Regulatory Framework Enhancements

- Establish an AGI Healthcare Certification Body:
  - Modeled after FDA device approval, requiring 90%+ accuracy thresholds for diagnostic AGI systems [8]
  - Mandatory bias audits using WHO's 95% explainability standard [30]
- Adapt the EU AI Act for Healthcare:
  - Classify clinical AGI as *high-risk* with strict transparency requirements [32]
  - Implement sandbox environments for testing (pilot success rate: 78% in California trials) [48]

B. Financial Incentives

Table 16: Proposed Funding Allocation for AGI Healthcare

Initiative	Budget (2026-2030)	Expected ROI
Rural AGI Deployment Grants	$2.1B	3.2:1 [53]
Safety Research Fund	$750M	N/A (public good)
Workforce Retraining	$1.4B	2.7:1 [12]

C. Implementation Roadmap

1) Short-Term (2025-2027)

- Require real-time monitoring of AGI denial rates (benchmark: 15% variance from human decisions) [7]
- Fund 10 regional testbeds for federated learning systems [38]

2) Long-Term (2028-2030)

- Develop international AGI standards through WHO, building on EU models [33]
- Achieve 40% cost reduction in administrative workflows via mandated AGI adoption [6]

D. Public-Private Partnerships

- Tax Credits: 25% rebate for hospitals meeting AGI transparency benchmarks [31]
- Data Sharing Mandates: Require AGI vendors to contribute 30% of non-sensitive datasets to public repositories [10]

E. Monitoring & Evaluation

- Annual AGI Equity Reports tracking demographic disparities (target: 5% variance) [7]
- Algorithmic Sunset Clauses: Automatic review every 3 years based on performance metrics [14]

XIV. SUMMARY OF TABLES

This section provides a comprehensive overview of all tabular data presented in the paper, highlighting their research contributions and organizational structure.

Table 17: Inventory of Analytical Tables

Table	Title	Key Metrics	Section
Table 1	Comparative Analysis of Key AGI Models	Strength/Weakness analysis of 3 architectures	III
Tables 3	Key Publications by Year	2021-2025 research timeline	IV
Table 4	Regional Focus of Key Policies	WHO/EU/US regulatory contrasts	IV
Table 5	Documented AGI Healthcare Applications	89% AUC accuracy metrics	V
Table 6	AGI vs. Conventional AI	$4-7M cost comparisons	V
Table 7	Classification of Healthcare AI Agents	4 agent types with performance	VI
Table 8	Agentic vs. Non-Agentic AI	2.4x cost premium analysis	VI
Table 13	Performance Metrics of AGI	65%-time reduction data	VII
Table 18	Projected Financial Impacts	$12.4B market forecast	VIII
Table 10	Major Risk Categories	73% bias appeal rates	IX
Table 11	Stakeholder Responsibilities	$500K audit requirements	IX
Table 16	Proposed Funding Allocation	$2.1B rural deployment	X

A. *Key Patterns*

- Temporal Coverage: Tables span current implementations (Table 13) to 2030 projections (Table 18)
- Geographic Scope: 75% compare international vs regional approaches (e.g., Table 4)
- Quantitative Focus: All tables include measurable benchmarks (accuracy, costs, adoption rates)

B. *Usage Guidance*

- Regulatory analysis: Tables 4 and Tables 10.
- Implementation planning: Tables 16 and Tables 11.
- Technical selection: Tables 1 and Tables 6.

C. *Policy Recommendations*

1) For Healthcare Organizations

Healthcare organizations should adopt a hybrid approach that leverages the strengths of both open-source and proprietary solutions based on specific use cases. They should:

- Invest in developing internal expertise for evaluating and implementing AI solutions
- Establish clear governance frameworks for AI adoption, including ethical guidelines and oversight mechanisms
- Participate in open-source communities to influence development and share best practices
- Develop comprehensive data management strategies that address privacy and security concerns

2) For Policymakers

Policymakers should create regulatory environments that support innovation while ensuring patient safety and privacy:

- Develop adaptive regulatory frameworks that can accommodate rapid technological advancements
- Support standardization efforts for AI validation and interoperability
- Fund research on AI safety, ethics, and implementation best practices
- Address disparities in AI access through funding programs and technical assistance

3) For Researchers and Developers

The research community should focus on addressing current limitations and advancing the field:

- Develop improved validation methodologies for AI systems in healthcare settings
- Address bias and fairness issues in medical AI through diverse training data and algorithmic improvements
- Enhance explainability and transparency capabilities for both open-source and proprietary systems
- Explore hybrid approaches that combine the strengths of different AI paradigms

XV. FUTURE TIMELINE AND PROJECTIONS (2025–2030)

Based on current trends and research findings, this section outlines key projections for Agentic AI (AGI) in healthcare through 2030 and beyond.

A. *Agentic AI in Healthcare*

The emergence of agentic AI systems represents a significant trend in healthcare AI development. These systems can automate complex workflows and decision-making processes, potentially transforming healthcare delivery. [46] describe agentic AI as offering "healthcare systems the ability to automate complex tasks and workflows," while emphasizing that "success depends on careful oversight and strategic planning."

Recent developments in agentic AI show particular promise for complex medical reasoning. [51] report on medical AI agents that "boost accuracy for complex health queries" through sophisticated knowledge networks and retrieval systems. These advancements suggest that both open-source and proprietary approaches will continue to evolve toward more autonomous and capable systems.

B. Global AI Development Patterns

The global landscape of AI development shows increasing diversification, with significant contributions from multiple regions. Chinese AI development, particularly in open-source models, has become increasingly influential. [55] analyze "China's drive toward self-reliance in artificial intelligence," while [57] note that "Chinese absolutely dominates open-source AI models," though recent US entries are changing this dynamic.

This global diversification creates both opportunities and challenges for healthcare AI. On one hand, it accelerates innovation and provides more options for healthcare organizations. On the other hand, it introduces complexities related to international regulations, data sovereignty, and geopolitical considerations that must be carefully managed.

C. Market Evolution and Investment Trends

The healthcare AI market continues to experience rapid growth and evolution. [54] report that "AI healthcare startups raised 2.2 billion in January 2025" alone, reflecting sustained investor confidence in this sector. This investment supports both open-source and proprietary development, though funding patterns differ significantly between these approaches.

Proprietary solutions typically attract venture capital and corporate investment focused on commercial applications, while open-source development often relies on academic funding, foundation support, and community contributions. This differential funding affects development priorities, with proprietary models emphasizing market-ready features and open-source projects often focusing on research innovation and accessibility.

D. Near-Term Developments (2025–2026)

The immediate future of healthcare AI will be characterized by rapid maturation of open-source models and increased regulatory clarity. Based on current trends and projections from referenced literature, several key developments are anticipated:

- Open-Source Performance Parity: By late 2025, open-source models are projected to achieve performance parity with proprietary systems in 85% of diagnostic applications [20]. This will be driven by community-driven improvements and increased investment in open-source medical AI development.
- Regulatory Frameworks: Major regulatory bodies including the FDA and EMA will establish formal guidelines for open-source AI validation in healthcare by Q2 2026 [28]. These frameworks will address validation requirements, ongoing monitoring, and update protocols for continuously learning systems.
- Agentic AI Adoption: Agentic AI systems will see initial clinical deployment in 2026, particularly for administrative tasks and preliminary diagnostic screening [46]. Early adopters will report 30–40% reductions in administrative workload and 25% improvement in diagnostic throughput.
- Market Consolidation: The healthcare AI market will experience significant consolidation, with the number of major players reducing from the current 200+ to approximately 50 by the end of 2026 [44]. This consolidation will be driven by regulatory requirements and the need for substantial validation resources.

E. Mid-Term Evolution (2027–2028)

The mid-term period will see mainstream adoption and integration of AI into clinical workflows:

- Hybrid Model Dominance: By 2027, 60-70% of healthcare organizations will adopt hybrid approaches combining open-source core technologies with proprietary specialized modules [42]. This approach will balance cost-effectiveness with specialized capabilities.
- Interoperability Standards: Comprehensive interoperability standards for healthcare AI systems will be established by 2028, enabling seamless data exchange and model integration across platforms [58]. These standards will reduce implementation costs by 40% and accelerate deployment timelines.
- Global AI Infrastructure: China's investment in AI self-reliance will yield significant results by 2028, with Chinese open-source models capturing 30-35% of the global healthcare AI market [55]. This will create a more diversified global AI ecosystem.
- Specialized AI Agents: Disease-specific AI agents will emerge, with targeted solutions for oncology, cardiology, and neurology achieving FDA approval by 2028 [51]. These specialized systems will demonstrate 45–50% improvement in early detection rates for specific conditions.

F. Long-Term Transformation (2029–2030)

The longer-term outlook points toward fundamental transformation of healthcare delivery through AI integration:

- AI-First Clinical Workflows: By 2030, 70-80% of healthcare organizations will have implemented AI-first clinical workflows, where AI systems serve as primary diagnostic assistants with human oversight [52]. This shift will reduce diagnostic errors by 50-60% and improve treatment consistency.
- Personalized Medicine at Scale: AI-enabled personalized treatment plans will become standard practice by 2029, leveraging patient-specific data to optimize therapeutic outcomes [43]. This approach will improve treatment efficacy by 35–40% across major disease categories.
- Democratization of Healthcare AI: Open-source platforms will enable widespread access to advanced AI capabilities, particularly in resource-constrained settings. By 2030, developing regions will achieve 70% of the AI healthcare capability of developed markets at 20% of the cost.
- Regulatory Maturity: Comprehensive international regulatory frameworks for healthcare AI will be established by 2030, enabling global deployment while maintaining safety standards [56]. These frameworks will support continuous learning systems while ensuring patient safety.

G. Technology-Specific Projections

1) Open-Source Advancements

The open-source ecosystem will experience accelerated development:

- 2026: Community-developed medical AI models will achieve performance exceeding proprietary systems in specialized domains including medical imaging analysis and genomic interpretation [18].
- 2027: Open-source platforms will develop comprehensive toolchains for medical AI validation, reducing compliance costs by 50-60% and accelerating deployment timelines [28].
- 2028: Federated learning approaches will become standard for open-source medical AI, enabling continuous improvement while maintaining data privacy [21].

2) Proprietary Innovation

Proprietary systems will focus on specialized advancements:

- 2026: Integrated AI platforms from major vendors (Google, Siemens, etc.) will offer comprehensive clinical workflow solutions covering diagnosis, treatment planning, and outcome monitoring [59].
- 2028: Proprietary systems will dominate high-complexity clinical applications requiring extensive validation and regulatory compliance, maintaining 70% market share in these segments [16].
- 2030: Annual licensing costs for proprietary systems will decrease by 40–50% due to competition from open-source alternatives, making advanced capabilities more accessible [42].

H. Market and Adoption Projections

Quantitative market projections based on current trends:

- 2026: Global healthcare AI market reaches $85–95 billion, with open-source solutions capturing 35% market share [1].
- 2028: AI-assisted diagnoses will account for 60% of all medical imaging interpretations in developed markets [17].
- 2030: Healthcare AI will generate $350–400 billion in annual healthcare cost savings globally through improved efficiency and outcomes [43].

I. Critical Challenges and Considerations

Despite the promising timeline, several challenges will require ongoing attention:

- Data Privacy and Security: Evolving regulations will require continuous adaptation of both open-source and proprietary systems [3].
- Workforce Transformation: Healthcare professionals will require extensive retraining, with 40–50% of current clinical tasks automated by 2030 [45].
- Ethical Governance: Robust ethical frameworks must be developed to address algorithmic bias, accountability, and patient consent in AI-driven healthcare [60].

This projected timeline demonstrates the transformative potential of AI in healthcare over the next five years, with both open-source and proprietary approaches playing crucial roles in advancing medical capabilities and improving patient outcomes.

J. Clinical Applications

- By 2026:
  - 40-50% of U.S. hospitals will deploy AGI for administrative tasks (prior auth, billing) [6]
  - First FDA-approved autonomous diagnostic AGI for radiology (projected accuracy: 92%) [5]
- By 2028:
  - AGI will reduce diagnostic errors by 20-30% compared to human baselines [35]
  - 30-40% of chronic disease management handled by agentic systems [13]

K. Economic Impact

Table 18: Projected Financial Impacts (2025-2030)

Metric	Value	Source
Global AGI healthcare market	$12.4B	[12]
Administrative cost savings	$8.2B/year	[53]
Malpractice reduction	25% decrease	[49]

L. Technological Evolution

- **AGI Architectures**:
  - Shift from single-agent to multi-agent systems (87% of implementations by 2029) [36]
  - Emergence of "hybrid AGI" combining LMMs with robotic process automation [8]
- **Data Infrastructure**:
  - 70% of hospitals will adopt federated learning for AGI training by 2027 [38]
  - Blockchain-secured health data exchanges for AGI (85% adoption in EU by 2030) [30]
- **2025-2026**:
  - Mandatory AGI audit frameworks in G7 nations [32]
  - WHO updates IHR to include AGI governance [30]
- **2027-2030**:
  - Standardized AGI liability laws in 50+ countries [31]
  - Global AGI certification body established [33]

M. Societal Implications

- **Workforce Impact**:
  - 35% reduction in administrative healthcare jobs by 2030 [12]
  - 2.4M new "AGI supervisor" roles created globally [10]
- **Health Equity**:
  - AGI could reduce rural-urban care disparities by 40% [40]
  - Risk of algorithmic bias persisting in 25% of systems without intervention [7]

N. Challenges and Future Directions

Despite its potential, AGI faces challenges:

1) Technical Limitations

AGI systems require vast datasets and computational resources, limiting accessibility [11].

2) Ethical Dilemmas

Autonomous decision-making raises questions about patient consent and agency [14].

3) Policy Lag

Regulatory frameworks must evolve to keep pace with AGI advancements [34].

Recent scholarship by Joshi has established a multifaceted strategic approach to these challenges, beginning with a broad framework for U.S. competitiveness that emphasizes interoperability and policy leadership [61], [68]. This national-level strategy extends into specialized domains, most notably in healthcare, where systemic architectures have been proposed for cancer care [62] and broader government policies regarding the risk management of both open-source and proprietary models [70]. Furthermore, specific regulatory frameworks have been proposed to address the safety and post-market oversight of generative AI-enabled digital mental health devices [69]. Beyond healthcare, it is very important to emphasizes the critical role of workforce and educational transformation, offering structured curriculum frameworks for K–12 educators [64], specialized training for rare earth element supply chain education [65], and strategic reskilling initiatives for the U.S. military workforce [67]. These sectoral applications are supported by rigorous advocacy for regulatory reform within federal AI adoption [63] and recommendations for maintaining U.S. leadership in AI exports through analysis and implementation strategies [66].

XVI. CONCLUSION

This comprehensive review has navigated the complex dichotomy between open-source and proprietary AI within the healthcare sector, increasingly shaped by the emergence of autonomous Agentic Generative AI (AGI). Our analysis reveals that the choice between these paradigms is not a binary one but a strategic decision contingent on organizational needs, clinical applications, regulatory risk tolerances, and financial constraints.

A. Key Findings

Open-source models have improved in recent time and their performance gap with proprietary systems has reduced. They now offer equal offering superior advantages in transparency, customization, data privacy, and cost-effectiveness. These qualities make them suitable for auditability and local control as needed in the US model of governance. Proprietary systems though maintain their edge in reliability, integrated support, regulatory compliance, and seamless integration with established healthcare infrastructure because most of big private companies are driving risk deployments in USA [11], [35], [49].

AGI though might bring autonomy but as of today also brings challenges including algorithmic bias, fragmented regulatory oversight, high financial barriers, and unresolved ethical dilemmas around accountability [29], [38].

B. Regulatory and Governance Considerations

To ensure safe and effective adoption of AGI for US model and national competitiveness, we propose the following governance strategies:

- Tiered Risk-Management Framework: Implement certification protocols aligned with international standards (e.g., WHO's 95% explainability threshold [8]) that classify systems by clinical risk, mandating appropriate human oversight levels.
- Public-Private Collaboration: Need is for pilot programs and sandbox environments, such as California's 78% successful AGI pilots [48], to study and evaluate multi-agent systems.
- Continuous Monitoring and Auditing: In the regulations government should mandate real-time bias audits and federated learning wherever available [38] to promote collaborative improvement across US institutions.

C. Affordability and Economic Feasibility

- Implementation Costs: High costs (e.g., $2M barriers [11]) require careful planning for deployment in resource-constrained environments where companies are always chasing bottom line each quarter.
- Return on Investment: Current research report open-source deployments ROI (e.g., 3.2:1 in rural healthcare settings [53]), but this depends on data quality improvements addressing 60% failure rates [24].

D. Strategic Recommendations

- Tiered Certification: Align risk management and explainability thresholds similar to WHO standards [8], allowing regional flexibility based on healthcare system maturity.
- Public-Private Sandboxes: Expand pilot programs for multi-agent testing [48], enabling real-world evaluation with controlled oversight.
- Continuous Bias and Safety Monitoring: Use and promote development of real-time auditing sustems for Medicare Advantage appeals data [7].

E. Final Words

By implementing and having an agile adaptive governance, careful monitoring, and enterprise friendly strategic financial planning, healthcare organizations can leverage Agentic Gen AI and AGI to improve overall health metric outcomes, enhance efficiency, and expand access, while safeguarding safety, equity, and ethical integrity [7], [11], [14], [24], [29], [30], [35], [38], [48], [49], [50], [53].

DECLARATION

The views are of the author and do not represent any affiliated institutions. Work is done as a part of independent research. This is a pure review paper and all results, proposals and findings are from the cited literature. Author does not claim any novel findings.

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