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Perspective

Next-generation agentic AI for transforming healthcare

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ABSTRACT

Artificial Intelligence (AI) is transforming the healthcare landscape, yet many current applications remain narrowly task-specific, constrained by data complexity and inherent biases. This paper explores the emergence of next generation "agentic AI" systems, characterized by advanced autonomy, adaptability, scalability, and probabilistic reasoning, which address critical challenges in medical management. These systems enhance various aspects of healthcare, including diagnostics, clinical decision support, treatment planning, patient monitoring, administrative operations, drug discovery, and robotic-assisted surgery. Powered by multimodal AI, agentic systems integrate diverse data sources, iteratively refine outputs, and leverage vast knowledge bases to deliver context-aware, patient-centric care with heightened precision and reduced error rates. These advancements promise to enhance patient outcomes, optimize clinical workflows, and expand the reach of AI-driven solutions. However, their deployment introduces ethical, privacy, and regulatory challenges, emphasizing the need for robust governance frameworks and interdisciplinary collaboration. Agentic AI has the potential to redefine healthcare, driving personalized, efficient, and scalable services while extending its impact beyond clinical settings to global public health initiatives. By addressing disparities and enhancing care delivery in resource-limited environments, this technology could significantly advance equitable healthcare. Realizing the full potential of agentic AI will require sustained research, innovation, and cross-disciplinary partnerships to ensure its responsible and transformative integration into healthcare systems worldwide.

1. Introduction

The rapid advancement of artificial intelligence (AI) is reshaping global healthcare, positioning digital technologies as integral to modern medical systems. We are entering an 'agentic era,' characterized by AI agent systems capable of autonomous functionality, advanced reasoning, and dynamic human–AI interactions. These advancements are driven by the integration of Multimodal Large Language Models (MLLMs) with other sophisticated AI systems, as demonstrated by AI assistants like OpenAI's ChatGPT (based on GPT-4), Google's Gemini (built on the Gemini 1.5 model), and Microsoft's Copilot (which utilizes GPT-4 and other AI models).

AI's relationship with healthcare spans decades, from personalized care to drug discovery,[1,2] beginning with pioneering rule-based systems in the 1970s, such as MYCIN,[3] INTERNIST-1, and QMR,[4] DXplain,[5] which addressed diagnostic challenges but struggled with the growing complexity of medical knowledge. By the late 1990s, the advent of larger healthcare datasets, improved computational capacity, and advanced machine learning (ML) algorithms marked a shift to data-driven approaches.[6] This collaboration between ML researchers and medical professionals fostered clinically relevant automation.[7] The rise of deep learning (DL) in the 2000s further accelerated progress, particularly in medical imaging, where convolutional neural networks (CNNs) enabled accurate anomaly detection, image segmentation, and classification.[8–12] These innovations significantly improved diagnostic precision and prognostic predictions.

Despite these breakthroughs, AI integration in healthcare faces challenges beyond medical data complexity, including interoperability with clinical workflows, regulatory constraints, and integration with medical devices.[13,14] Healthcare applications demand accuracy, reliability, and context-aware reasoning to ensure patient safety. While current AI systems excels in large-scale pattern recognition,[15] they still face challenges in higher-level reasoning and decision-making.[16] To address these complexities, AI agents designed for decision support can offer a solution, provided they are integrated with evidence-based strategies to ensure reliability and transparency in healthcare applications.

AI agents extend beyond traditional rule-based systems by dynamically optimizing workflows, adapting to tasks with minimal human intervention, and integrating with specialized AI models. Depending on

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their architecture, these agents can operate independently or collaborate within multi-agent frameworks to address complex workflows.[17] Their applications span healthcare domains, from diagnostics to drug discovery, demonstrating their transformative potential in advancing global healthcare (detailed in Section 2).

1.1. Traditional AI agents vs. agentic AI systems

Traditional AI agents, as classified in,[18,19] fall into six categories:

Simple Reflex Agents: Operate on condition–action rules without memory.

Model-Based Reflex Agents: Extend reflex agents with an internal model that updates based on past percepts.

Goal-Based Agents: Plan and execute actions to achieve specified objectives.

Utility-Based Agents: Use utility functions to choose actions that maximize expected utility, managing conflicting goals.

Learning Agents: Continuously improve strategies based on new experiences.

Problem-Solving Agents: Employ search algorithms to achieve desired outcomes.

Traditional AI agents typically utilize rule-based systems, heuristic-driven ML, and, in some cases, reinforcement learning (RL) for decision optimization, each optimized for predefined objectives. In healthcare, these approaches have been applied to clinical decision support, diagnostics, and treatment planning, but they often struggle with adaptability in dynamic healthcare settings. In contrast, agentic AI advances these paradigms by incorporating adaptive architectures that enhance decision-making autonomy and flexibility. By enabling AI agents to generalize across diverse healthcare tasks—such as personalized treatment optimization and autonomous medical imaging analysis—these advancements represent progress toward more versatile AI systems, aligning with long-term goals in Artificial General Intelligence (AGI) research.

Table 1 summarizes the differences between traditional and agentic AI in healthcare. An illustrative application is the AI healthcare agent (Fig. 1), which serves as a hub for processing data from medical databases, electronic health records (EHRs), medical scans, and neural networks. By generating prompts and offering insights, these agents support high-stakes decision-making in clinical settings, showcasing the transformative potential of agentic AI in healthcare and beyond.

1.2. Technical overview of agentic AI

Agentic AI systems often integrate pretrained DL encoders for processing multimodal data, such as images and text, though alternative approaches exist. These encoded representations are processed by a central LLM, which functions as the reasoning and decision-making core of the agent. Commonly employed open-source LLMs in this domain include LLaMA,[20] Falcon[21] and Vicuna,[22] which have been pretrained on large-scale datasets. The openness of these models allows researchers to develop their own AI agents with greater transparency and a deeper understanding of their internal reasoning and decision-making processes. In contrast, proprietary LLMs such as the ChatGPT models and Gemini, while often delivering highly optimized performance and broader support, offer minimal transparency regarding their internal decision-making procedure.

Key mechanisms leveraged by these central LLMs include advanced reasoning techniques, such as chain-of-thought (CoT),[23] reasoning and acting (ReAct),[24] tree of thought (ToT).[25] These techniques enhance reasoning and decision-making through structured decomposition, logical inference, and contextual understanding.

A critical advantage of agentic AI lies in its modularity and adaptability, allowing seamless integration of LLMs, DL models, and other specialized AI components. This modular architecture supports scalability, enhances flexibility in adapting to evolving tasks, and enables deployment across diverse application domains, including autonomous systems, scientific research, and complex decision-making frameworks.

Table 1
Key Differences Between Traditional AI Agents and Agentic AI in healthcare.

Aspect	Traditional AI agent	Agentic AI
Reasoning Approach	Use domain specific algorithms (e.g., RL, finite state machines). Example: A rule-based chatbot that answers predefined medical FAQs.	Natural language-based reasoning, primarily leverage LLMs. Example: An AI assistant that engages in open-ended medical Q&A and explains conditions based on patient history.
Domain Flexibility	Optimized for a specific task or environment. Example: Optimized for specific tasks such as structured report generation or rule-based classification.	Adaptable to multiple tasks using zero/few-shot learning or dynamic prompt engineering. Example: Can summarize radiology reports and also assist in diagnostic support.
Decision Structure	Rule-based, with a predefined set of actions and goals. Example: An AI system that follows fixed guidelines for triaging emergency cases.	Capable of self-directed sub-goals and iterative planning (e.g., language-based reasoning models). Example: An AI agent that dynamically adjusts triage decisions based on patient data and evolving symptoms.
Data & Training	Domain-specific datasets. Example: AI trained only on structured EHR data.	Utilizes large-scale pretraining over vast corpora; can generalize or specialize with minimal updates (few-shot). Example: AI trained on diverse medical texts, adapting quickly to new diseases and guidelines.
Tool Integration	Limited. Example: A standalone AI tool for detecting anomalies in CT scans.	Dynamically calls external APIs, knowledge bases, ML, DL, MLLMs. Example: An AI system that integrates with hospital systems, lab results, and medical literature to provide comprehensive diagnostic insights.
Explanations	Transparent in symbolic systems; moderate interpretability in RL. Example: A decision tree model explaining why a drug is recommended.	Largely blackbox, though techniques for interpretability are emerging. Example: Agentic AI system suggesting treatments based on DL patterns, with efforts to explain its reasoning using attention maps or counterfactual analysis.
Primary Use Cases	Robotics, rule-based decision-making, industrial control systems. Example: A robotic system following predefined surgical procedures.	Unlimited Example: AI-driven virtual assistants for patient monitoring, adaptive treatment planning, personalized medicine, and robotic surgery and many more.

2. Significance of AI agents in healthcare

Recent advances in AI-related medical technologies have fueled unprecedented growth in healthcare data. Between 2011 and 2018, medical image datasets grew by three- to ten-fold, with annual increases of 21–32 % across various imaging modalities.[26] The proliferation of mobile applications, cloud computing, wearable devices, and big-data analytics has further expanded data sources, enabling personalized medicine and real-time health monitoring.[27] Despite these advancements, the healthcare sector faces a projected shortfall of 18 million workers by 2030, particularly in low-income regions.[28,29] AI agents can help mitigate this gap by integrating advanced ML, DL, natural language processing (NLP), and computer vision technologies, automating administrative tasks, enhancing diagnostics, and improving workflow

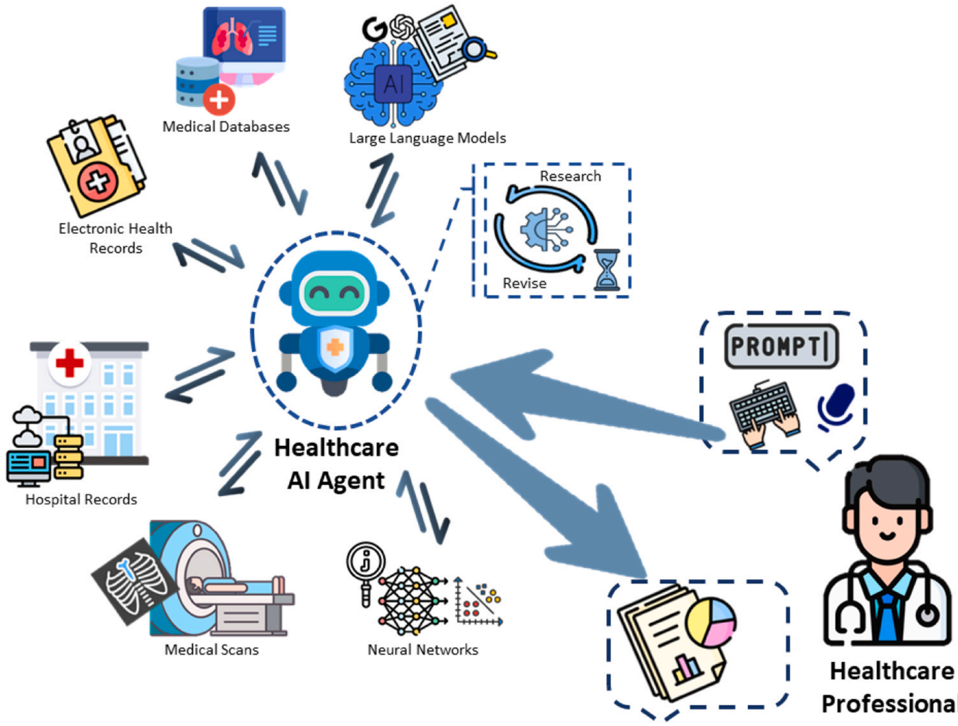

Fig. 1. Healthcare AI agent: Integrating multimodal data for collaborative clinical decision making.

efficiency.

2.1. Features of agentic AI in healthcare

Fig. 2 illustrates the key features that make agentic AI technologies well-suited for healthcare environments.

Autonomy: AI agents function independently, making decisions based on predefined goals and real-time data inputs. In radiology, for instance, an AI agent can autonomously analyze scans, select diagnostic algorithms, and generate preliminary reports. In multilingual settings, the agent can detect the need for translation and invoke appropriate tools, reducing manual intervention and expediting workflows.

Adaptability: Unlike traditional AI models that are typically optimized for specific tasks, agentic AI dynamically adjusts to new data and evolving clinical needs. For example, an AI agent trained on X-ray analysis can fine-tune itself to process MRI or CT scans, ensuring continued relevance as imaging modalities evolve.

Scalability: By leveraging cloud infrastructures and federated learning, agentic AI can handle vast and heterogeneous data in real time. This capability is critical for applications like telemedicine, where large-scale data analysis must be performed without compromising speed or accuracy.

Probabilistic Decision-Making: AI agents use iterative reasoning, continuously updating their predictions based on new data, contextual knowledge, and feedback loops. For instance, an AI agent might initially diagnose pneumonia but revise it to tuberculosis after incorporating epidemiological data and lab results.

These features collectively enable agentic AI to provide robust,

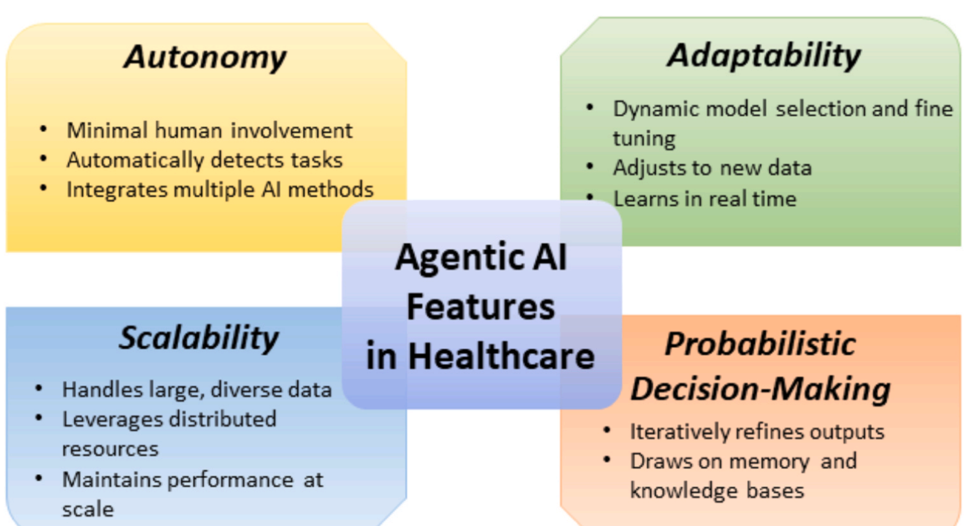

Fig. 2. Key agentic AI features in healthcare.

efficient, and context-aware solutions across diverse healthcare settings.

2.2. Core functional domains of AI agents in healthcare

As illustrated in Fig. 3, healthcare-focused AI agents can be categorized into several core functional domains, including diagnosis, clinical decision support, treatment and patient care, patient engagement and monitoring, operations and administration, drug discovery and research, and robot-assisted surgery. The following subsections describe how AI and AI agents are applied within each of these domains in healthcare.

2.2.1. AI agents in diagnosis

Modern diagnostic workflows rely heavily on AI for medical image analysis and predictive analytics. The growing volume of imaging data and complexity of EHRs can overwhelm clinicians, but AI helps alleviate these burdens,[30,31] reducing cognitive load and enhancing patient safety.[32,33]

AI integration with medical imaging is transforming diagnostics by improving accuracy. In radiology, AI enhances diagnostic accuracy through anomaly detection,[34,35] lesion segmentation,[36–38] classification.[39] DL technologies like CNNs and vision transformers (ViTs) optimize workflows within PACS for modalities such as CT, MRI, X-ray, and pathological imaging, while maintaining patient data confidentiality.[40] Additionally, AI uses MLLMs to integrate radiological and clinical data, supporting diagnoses and automating report generation.[41–44]

Beyond radiology, AI excels in analyzing pathology images, enhancing cancer detection and microscopic diagnoses.[45]

A recent study[46] explores the role of text-only AI agents in assisting radiologists with brain MRI differential diagnosis. A comparison between LLM-assisted agents and conventional internet search workflows showed that AI-assisted diagnoses had higher accuracy (61.4 % vs. 46.5 %), though there was no significant difference in interpretation time or confidence levels. Integrating medical images into a MLLM could potentially eliminate the need for manual descriptions of imaging findings, further enhancing diagnostic efficiency. For accurate diagnosis image analysis is a key criterion. Med-Flamingo[47] is a multimodal few-shot AI agent designed for medical diagnosis, using 2D images and text to assist clinicians. It outperforms existing models in diagnostic accuracy by up to 20 %. Beyond 2D imaging, M3D-LaMed[48] is an MLLM designed for 3D medical image analysis, integrating text-based data to enhance diagnostic tasks. By leveraging a pre-trained 3D vision encoder and an efficient 3D spatial pooling perceiver, M3D-LaMed improves diagnosis for complex 3D medical images like CT and MRI scans, representing a significant advancement in AI-assisted medical diagnosis.

The integration of AI agents into imaging workflows has the potential to optimize operations, enhance diagnostic accuracy, and streamline processes. In radiology, AI agents can interface with PACS to automate quality assurance, manage data transfers, and execute DL and ML algorithms for image analysis. These agents flag abnormalities for review while maintaining patient privacy through de-identification and can operate in the background, continuously analyzing imaging data, generating preliminary reports, and proposing diagnoses using MLLMs. By combining computational efficiency with radiologists' expertise, AI agents improve accuracy, reduce uncertainty, and save time and resources.

Beyond diagnostics, AI agents advance predictive analytics and personalized care by analyzing EHRs, imaging, genomics, and wearable

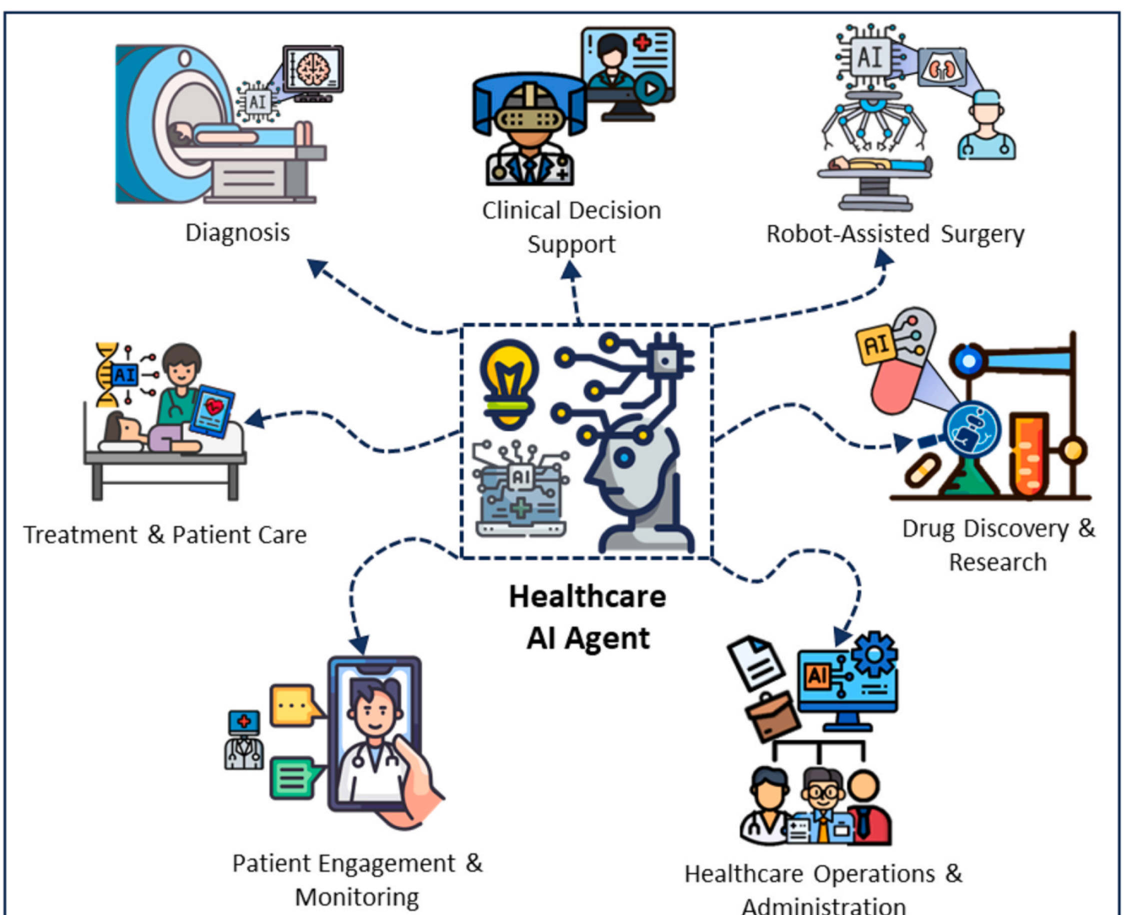

Fig. 3. Key applications of AI agent in healthcare industry.

device data. They identify subtle disease indicators, such as early signs of diabetes,[49,50] cardiovascular conditions,[51] or cancer,[52] enabling early detection, optimized resource allocation, and improved patient outcomes. AI agents also enhance prognosis by forecasting disease trajectories, modeling progression, and tailoring treatment plans.[53–56] These insights help physicians anticipate complications and adjust therapies proactively.

For effective integration, AI agents must embed seamlessly into clinical workflows and patient environments. In clinical settings, they provide real-time data and actionable insights, while on the patient side, wearables equipped with AI monitor health metrics and offer personalized recommendations, bridging clinical care and daily life. Additionally, AI agents serve as educational tools, creating interactive learning modules, quizzing students on realistic cases[57,58] and supporting clinical decision-making, resource management, and healthcare professional training.

2.2.2. AI agents in clinical decision support systems

AI can be seamlessly integrated into clinical decision support systems (CDSS) to enhance patient care.[59,60,54] By analyzing EHRs, clinical data, genomic data, behavioral data, and administrative data,[14] AI systems summarize key findings, establish connections using LLMs, access medical databases, generate reminders, and facilitate collaboration. These capabilities improve diagnoses, reduce misdiagnoses, and ease clinicians' workloads through automation and task prioritization.

The incorporation of healthcare AI agents into CDSS accessible via mobile devices as standalone tools or part of a multi-agent system represents a major advancement. Unlike traditional CDSS, where tasks such as information retrieval and summarization are performed manually or in separate steps, AI agents can execute these processes cohesively and adaptively. They refine outputs by evaluating individual AI module results,[61] delivering more precise and reliable clinical insights.

Vision-Language Models (VLMs) integrate LLMs with medical imaging, aiding clinicians in interpreting images and generating structured reports.[62] A study explored the use of AI-driven VLMs in radiology, identifying key applications such as draft report generation, augmented report review, visual search and querying, and patient imaging history highlights. The findings suggest that AI-assisted report generation and visual search functionalities can improve workflow efficiency, reduce cognitive burden, and enhance diagnostic accuracy. However, the study highlights the need for explainability, seamless workflow integration, and clinician oversight to ensure AI-generated insights are clinically reliable and interpretable. Another VLM, LLaVA-Med, an AI agent, was trained using a large-scale biomedical dataset from PubMed Central and GPT-4-based instruction tuning to support biomedical image interpretation, clinical reporting, and medical visual question answering (VQA).[63] The study demonstrated that LLaVA-Med outperforms previous state-of-the-art models on standard biomedical VQA datasets, proving its efficacy in assisting radiologists and clinicians.

As the first AI agent in medical imaging that dynamically plans, executes, and adapts using external computational tools, VoxelPrompt[61] breaks free from rigid, single-task models. It outperforms specialized segmentation models on 13/17 anatomical structures, surpasses conventional vision models on 23 different brain regions, and achieves 89 % accuracy in pathology characterization—matching expert classifiers while handling a broader range of tasks that helps clinical decision making. Another practical example the study[64] surpasses traditional AI by acting as an intelligent agent named LLMSeg that fuses textual clinical data with imaging, enabling precise 3D contouring. This approach achieves superior accuracy with significantly less data, maintaining robust performance even data-insufficient settings where conventional AI struggles. By leveraging LLMs, AI agents enhance efficiency and adaptability in clinical settings, improving automated report generation, decision support, and disease characterization.

Despite significant advancements in agentic AI for CDSS, many AI-driven decision support systems remain at the research level and have yet to achieve widespread clinical adoption. A study[65] address this challenge by proposing a systematic AI support framework that considers key dimensions such as disease, data, technology, user groups, validation, decision-making, and maturity, emphasizing a structured approach to improving the real-world integration of AI in healthcare.

As AI agents continue to evolve, human-centered AI design and regulatory considerations will be critical for ensuring trust, usability, and compliance in CDSS. The integration of AI-powered decision support systems in radiology and other medical domains has the potential to revolutionize diagnostics, reduce clinician workload, and improve patient outcomes.

2.2.3. AI agents in treatment and patient care

AI has transformative potential in treatment and patient care through advanced functionalities. DL and ML models enable personalized medicine by analyzing genomics and clinical data to create tailored treatment plans,[66] simulate drug responses,[67] and optimize chemotherapy and radiation therapy protocols for maximum efficacy.[68] DL also contributes to therapeutic optimization.[69] Radiomics combined with AI further enhances treatment planning,[70] while AI embedded in medical devices ensures precision monitoring, reduces errors, and enables remote and in-hospital patient surveillance. These systems alert caregivers to critical changes and assist first responders with real-time, context-specific guidance during emergencies.[71,72]

The study[73] presents AgentClinic, an AI agent that simulates doctor-patient interactions, autonomously collecting patient information, making diagnostic decisions, and recommending treatments. AgentClinic actively engages with patients through dialogue, requests medical tests, and adapts its questioning strategies in real time, mimicking human clinical decision-making. The study highlights how these AI-driven agentic interactions influence patient engagement and monitoring, particularly in shaping patient compliance, trust in AI recommendations, and follow-up willingness.

Currently, AI technologies for treatment operate as standalone algorithms tailored to specific datasets and tasks. Transitioning to AI agents allows for seamless integration with existing models, databases, and other AI modules, improving efficiency. In patient care, traditional semi-autonomous AI modules often result in fragmented workflows and errors. AI agents overcome these challenges by integrating smoothly into healthcare systems. They analyze genomic profiles and patient histories to recommend personalized treatments, validate these with extensive databases, and optimize therapy plans by simulating complications and alerting clinicians proactively.

2.2.4. AI agents in patient engagement and monitoring

AI plays a transformative role in patient engagement and monitoring, leveraging advanced technologies to enhance care. In remote monitoring, AI analyzes data from wearables and home-based devices, such as cameras and sensors, to track vital signs and detect abnormalities in real time.[74] Virtual health assistants and chatbots provide symptom checks, automated triage, and scheduling guidance, reducing the workload of healthcare professionals.[75,76] However, many chatbots are limited by the size and heterogeneity of their training datasets, which restrict adaptability. On telehealth platforms, AI improves video consultation scheduling and performs real-time patient data analysis, enabling efficient and personalized virtual care.[77,78]

Recent study[79] presents Agent Hospital, an AI agent system that enhances patient engagement by simulating interactive doctor-patient interactions in a virtual hospital. LLM agents autonomously manage triage, consultation, and follow-ups, engaging patient agents through dynamic dialogues, medical examinations, and feedback loops. The study highlights how AI agents track patient responses, adapt decisions based on evolving symptoms, and influence follow-up adherence, demonstrating their potential in proactive healthcare monitoring.

To overcome the limitations of traditional AI systems, AI agents seamlessly integrate into healthcare systems and devices. Paired with wearables and home monitoring tools, AI agents continuously analyze health data, alert caregivers when needed, and provide patients with emergency instructions. Virtual health agents on mobile platforms guide users through symptom assessments, triage, and scheduling, while aligning appointments with personal calendars for a smooth healthcare experience. On telehealth platforms, AI agents optimize schedules, analyze patient data during video calls, and support clinicians with advanced features like real-time language translation and sign language interpretation using DL and NLP. These capabilities ensure accessibility, efficiency, and precision in patient engagement and monitoring, bridging cutting-edge technology with personalized care.

AI conversational agents have emerged as valuable tools for mental health monitoring and patient engagement. A notable example is Woebot, an AI-powered chatbot that dynamically enhances user engagement by actively analyzing emotional states through NLP and delivering context-aware, empathic responses in real time.[80] Another study evaluates the use of LLM agent in mental health support,[81] revealing biases in empathy and response quality across different demographic groups. While LLMs like GPT-4 can enhance patient engagement by encouraging behavior change, the study highlights the need for bias mitigation strategies to ensure equitable and ethical deployment in clinical settings.

The AI agent tailors therapeutic content by continuously adapting its dialogue based on user inputs, fostering an interactive and personalized support system. Through proactive daily check-ins and automated mood tracking, monitors user sentiment, detects fluctuations in emotional well-being, and delivers targeted interventions to promote self-reflection, emotional awareness, and sustained participation. This underscores the potential of AI agents to serve as engaging, scalable, and readily available platforms for continuous patient engagement and monitoring, augmenting and complementing traditional therapeutic methods.

2.2.5. AI agents in healthcare operations and administration

DL and ML technologies enhances healthcare operations through advanced data analysis, task automation, and predictive modeling.[82–85] In workflow optimization, AI streamlines triage in emergency departments, automates patient flow and bed allocation,[86] facilitates language translation and disability support,[87] and provides virtual assistance for training and management of healthcare staff.[88] In billing and coding, AI automates claim processing, verifies insurance details,[89] and detects fraudulent activities.[90] Predictive analytics further optimize scheduling and resource management by improving staff rostering, operating room planning, and resource allocation.[91]

AI agents enhance healthcare operations by integrating with hospital systems, optimizing workflows, and reducing administrative burdens. In emergency rooms, they monitor real-time data to prioritize patients, manage bed assignments, and coordinate transfers. Leveraging LLMs, AI agents support communication through language translation and disability accommodations. They also assist healthcare staff with training, updated protocols, and best practices. In financial operations, AI agents automate billing, claims verification, and fraud detection, reducing administrative burdens. For scheduling, they analyze staffing needs, optimize rosters, plan surgeries, and forecast resources, dynamically adjusting to maintain operational efficiency and ensure high-quality patient care. A practical example of AI agent integration in healthcare operations is NYUTron,[92] the first clinically deployed AI agent used in real-world hospital settings. Embedded within NYU Langone Health's EHR system, NYUTron assists physicians and administrators by predicting hospital readmission risk, length of stay, in-hospital mortality, and insurance claim denials, showcasing how AI agents can enhance decision-making and streamline healthcare operations. Another practical example of AI agent integration in healthcare operations is GPT4DFCI,[93] an institute-wide AI deployment at Dana-Farber Cancer Institute. Designed as a secure, HIPAA-compliant AI system, GPT4DFCI supports research, clinical documentation, and administrative workflows while addressing challenges in data privacy, regulatory compliance, and ethical governance. This initiative demonstrates how AI agents can be safely integrated into healthcare institutions to enhance efficiency while maintaining strict oversight and responsible AI use.

2.2.6. AI agents in drug discovery and research

Advancements in AI are revolutionizing drug discovery by enhancing efficiency and precision. In drug candidate screening, AI-powered high-throughput screening rapidly analyzes vast compound libraries, while molecular modeling predicts interactions with biological targets, narrowing down potential candidates.[94] These models require extensive datasets and expert domain knowledge for effective training and evaluation.[95] In clinical trial optimization, AI analyzes patient data to improve recruitment, designs adaptive protocols based on emerging data, and refines parameters to boost success rates.[96,97] Additionally, AI processes large-scale genomic data to identify genetic markers, enabling precision therapeutics tailored to individual profiles.[98,99] These innovations shorten discovery timelines, reduce costs, and advance personalized medicine.

AI agents further accelerate drug discovery by automating complex workflows and reducing errors. In candidate screening, agents conduct high-throughput experiments, run molecular simulations, and analyze results to identify promising compounds. For clinical trials, they leverage EHRs and genomic databases to recruit suitable participants, streamline processes, and adapt protocols in real time. In genomics, AI agents analyze sequencing data, detect disease-linked mutations, and propose personalized therapies. Integrated with lab instruments, data platforms, and clinical systems, AI agents automate decision-making, enhance accuracy, and expedite the development of safe, effective treatments.

In a recent study,[100] a multi-agent AI system named DrugAgent was designed to automate ML programming for drug discovery. By integrating domain-specific knowledge with AI-driven model selection, it enhances key tasks such as ADMET prediction, drug-target interaction analysis, and molecular optimization. Unlike traditional non-agentic methods, which require manual coding and expert intervention, DrugAgent autonomously generates, tests, and refines ML models, significantly improving efficiency and reducing errors. The model achieved an F1 score of 0.92 in drug absorption prediction, demonstrating its ability to optimize predictive models for pharmaceutical research.

Beyond ML-driven drug discovery, agentic AI systems are transforming biomedical research by autonomously generating, refining, and validating scientific hypotheses, thereby saving significant time. The AI co-scientist[101] exemplifies this shift by leveraging self-improving, multi-agent reasoning to advance drug repurposing, novel drug target discovery, and antimicrobial resistance research. The AI co-scientist identified repurposed drug candidates for acute myeloid leukemia (AML), for novel target discovery, it proposed epigenetic regulators for liver fibrosis, refining hypotheses through expert feedback and experimental validation. Additionally, it independently hypothesized a bacterial gene transfer mechanism, aligning with unpublished microbiological findings, showcasing its autonomous reasoning and discovery capabilities. By integrating human in the loop (HITL) collaboration, the AI co-scientist ensures expert alignment while continuously evolving through a self-improving feedback loop, marking a new era of AI-empowered scientific discovery in drug development. These examples highlights how AI agents can streamline drug development, reduce human workload, and accelerate pharmaceutical innovation.

2.2.7. AI agents in robot-assisted surgery

AI-guided robot-assisted surgery marks a new era in medicine, enhancing precision, accuracy, and safety in complex procedures.[102,103] By integrating advanced imaging, sensor data, ML, and robotics, AI systems enable surgical robots to perform tasks with exceptional precision. AI-driven navigation and instrument guidance allow real-time interpretation of patient anatomy, adaptation to subtle movements, and optimal instrument positioning, reducing invasiveness and minimizing risks. These advancements support surgeons in planning, executing, and refining interventions, improving outcomes and expanding minimally invasive surgery possibilities.

AI agents embedded in robotic systems orchestrate these capabilities by analyzing data from endoscopic cameras, sensors, and preoperative imaging to chart precise surgical paths and guide instruments in real time. During surgery, they monitor critical parameters, detect complications, and alert the team if intervention is needed. AI agents assist decision-making, provide dynamic feedback, and automate tasks like suturing or tissue manipulation under supervision. With continuous learning from operations, these agents refine their models, enhancing robotic performance and advancing safer, more efficient, and personalized surgical care.

In a recent study[104] highlights the emergence of AI-agent surgical assistance, introducing multi-agent AI systems that simulate surgical roles, enhance decision-making, and optimize workflow coordination. These intelligent systems leverage LLMs and memory-augmented AI to provide real-time guidance, anticipate procedural steps, and facilitate seamless team collaboration. Expanding on this, SUFIA,[105] an LLM-driven robotic assistant agent, translates natural language commands into high-level surgical plans and low-level control actions. It integrates real-time perception modules for dynamic adaptation and ensures safety via a HITL mechanism. In simulated experiments, SUFIA achieved a 100 % success rate in needle lifting and 90 % in needle handover, while in physical trials, success rates were 100 % and 50 %, respectively. These results highlight agentic AI's potential to enhance surgical dexterity, optimize workflow, and support autonomous yet supervised robotic interventions. Operating within an interactive environment, these AI agents refine surgical strategies, assist with intraoperative navigation, and adapt dynamically to evolving scenarios. By enhancing precision, safety, and efficiency, agent-driven approaches in robotic surgery broaden the scope of automation, paving the way for more autonomous, adaptive surgical systems in the future.

Table 2 shows the categorization of AI agent types in healthcare, along with key applications, users, and technologies that are associated with each type.

3. Challenges and recommendations for agentic AI in healthcare

Implementing agentic AI systems in healthcare presents several critical challenges that must be addressed for successful integration and safe deployment.

3.1. Model availability and data privacy

One of the most critical challenges in healthcare AI is the availability of diverse, high-quality data for train AI models.[106] Data availability is restricted by regulatory barriers, fragmented healthcare infrastructures, and stringent privacy requirements. Furthermore, medical records contain unstructured text and sensitive data, necessitating the use of Explainable AI (XAI) to ensure compliance with strict medical regulations.

Recent research highlights the importance of fine-tuning LLMs to extract structured knowledge from pathology reports while maintaining interpretability and compliance with evolving regulatory standards. In this context, a study[107] applied the Bidirectional Encoder Representations from Transformers (BERT) model to the medical domain, enabling the generation of decision scores and improving pathology report annotations. By analyzing the resulting contextual embeddings, the study provides valuable insights into the organization of diagnostic information, enhancing alignment with clinical workflows and enabling integration with imaging data. While LLMs improve structured knowledge extraction, privacy-enhancing technologies, such as federated learning[108] and differential privacy,[109] are emerging solutions, but their implementation is resource-intensive and technically complex. Additionally, ensuring data traceability and compliance with evolving regulatory frameworks, such as the European In Vitro Diagnostic Regulation (IVDR), is essential for AI adoption in medical diagnostics.[110]

Bias in AI-driven healthcare models can lead to discriminatory decisions, disproportionately affecting underrepresented groups. Addressing this requires diverse data curation, bias mitigation, and continuous fairness evaluations in clinical settings. Addressing this challenge requires diverse dataset curation, bias-mitigation techniques in model training, and ongoing fairness evaluations in real-world clinical deployments.

3.2. Regulatory and compliance complexity

Healthcare regulations lag behind the rapid advancements in AI technology. In agentic AI models, continuous learning, which adapts based on new data, poses unique challenges to regulatory approval processes, as their performance and risk profiles may evolve over time. Additionally, LLMs present risks of hallucinating information,[111] potentially leading to clinical errors. Under IVDR, AI-driven diagnostics must demonstrate scientific validity, analytical robustness, and clinical

Table 2
Categorization of AI agent types in healthcare with key applications, users, and technologies.

AI agents	Key applications	Healthcare categories	Main users	Key AI technologies
Image base agents	Disease diagnosis, early detection, report generation	Diagnosis, Clinical decision support	Radiologists, Doctors	Computer vision (CNNs, ViTs), MLLMs for image-text integration
predictive analytics agents	Risk prediction, disease progression forecasting, patient outcomes	Clinical Decision Support, Treatment and Patient Care, Drug Discovery & Research	Doctors, Care Teams	Predictive Modeling, including supervised ML, ensemble methods, and time-series analysis
Conversational agents	Symptom checking, patient triage, virtual consultations	Patient Engagement and Monitoring	Patients, General Practitioners	NLP, Dialogue Systems, Pretrained LLMs
NLP agents	Processing clinical notes, summarizing EHRs, extracting insights	Operations and Administration, Clinical Decision Support	Medical Coders, Analysts	NLP, Pretrained LLMs
Rule base agents	Following clinical guidelines, alerting for drug interactions	Clinical Decision Support	Doctors, Pharmacists	Rule-Based Reasoning, leveraging logic programming, expert rules, knowledge graphs
Hybrid agents	Combining imaging, text, video, and predictive analytics for decisions	Clinical Decision Support, Diagnosis, Robot-Assisted Surgery	Doctors, Radiologists, Surgeons	Multimodal Learning
ML agents	Disease classification, anomaly detection, treatment planning	Diagnosis, Treatment and Patient Care, Drug Discovery & Research	Data Scientists, Doctors	ML/DL algorithms, RL
Expert system agents	Emulating clinical expertise for diagnosis and planning	Treatment and Patient Care, Clinical Decision Support, Robot-Assisted Surgery	Specialists, Researchers, Surgeons	Knowledge-based systems, rule-based systems
Recommender agents	Suggesting diagnostic tests, personalized treatments	Treatment and Patient Care, Clinical Decision Support	Doctors, Care Teams	Collaborative filtering, recommendation systems, RL

reliability to meet compliance standards.[110] Establishing robust validation and monitoring frameworks for these evolving systems is critical to ensuring patient safety. As a best practice, continuous model validation and performance monitoring should be conducted. Furthermore, surveillance protocols must be introduced specifically for these AI models to track decision-making accuracy.

3.3. Integration with healthcare workflows

Seamlessly incorporating agentic AI into existing clinical workflows is a formidable challenge. Many healthcare institutions rely on legacy EHRs and operational systems that are not designed to accommodate novel AI tools. Successful integration requires addressing these technical constraints through change management, user training, and iterative collaboration between clinicians, IT teams, and AI developers. Furthermore, as highlighted in AI-supported medical imaging, explainability and causability are key factors in ensuring trust and adoption among healthcare professionals, allowing them to understand and validate AI-driven recommendations.[110]

A lack of trust and acceptance among clinicians and patients remains a major barrier to AI adoption in healthcare. To address this, AI agentic models should undergo rigorous real-world validation, and healthcare professionals should receive structured training on AI-assisted decision-making. Explainability mechanisms, such as interpretable AI models and confidence scores, can also improve clinician trust and enable informed decision-making.

3.4. Resource and infrastructure limitations

Deploying agentic AI systems at scale requires significant computational resources and infrastructure. Many resource-constrained settings, such as rural clinics, lack the hardware and connectivity needed to run advanced AI systems. Moreover, the energy demands of LLMs raise sustainability concerns.[112] Optimizing AI systems for low-resource environments is essential for equitable access to their benefits.

High implementation costs remain a major challenge, especially for small hospitals and clinics with limited budgets. To promote equitable AI adoption, scalable and cost-effective AI solutions—such as open-source medical AI models, cloud-based AI platforms, and public-private funding initiatives can help reduce the financial burden while ensuring accessibility.

3.5. Adversarial weaknesses

AI systems in healthcare are vulnerable to adversarial attacks,[113] where maliciously crafted inputs can manipulate their outputs. This poses significant risks in AI agents, particularly in high-stakes scenarios such as diagnostics, treatment planning, and robot-assisted surgeries. Developing robust defenses and conducting rigorous testing against these threats are critical for ensuring reliability. Strengthening AI defenses will not only protect patient outcomes but also foster trust in the adoption of agentic AI across healthcare applications.

3.6. Ethical and legal responsibilities

The autonomy of agentic AI and complexity of the data[65] in healthcare raises significant ethical and legal concerns, particularly regarding liability for adverse outcomes. Assigning responsibility for AI-related medical errors is complex due to the opaque nature of many AI models. Establishing liability frameworks and standardized accountability measures is essential for ethical AI deployment.[114] The lack of transparency in how AI systems generate medical recommendations makes it difficult to assign accountability in cases of misdiagnosis or inappropriate treatment suggestions.[115]

To address these challenges, legal frameworks and governance mechanisms must be established to define clear accountability structures. Regulatory bodies, such as the EU AI Act[116] and FDA[117] emphasis rigorous documentation, monitoring, and human oversight to ensure accountability. Furthermore, the agentic AI models outputs should have a explainability mechanism, such as confidence score and interpretable outputs, that helps the clinicians understand and validate the outcome.

3.7. Human oversight and AI governance

Another major challenge in deploying agentic AI in healthcare is the diminishing feasibility of human oversight, particularly as AI models become more complex and autonomous. The opacity of these models and the scale at which AI systems operate make real-time human monitoring increasingly difficult. Recent studies highlight the need for hybrid oversight mechanisms, incorporating HITL frameworks, rule-based interventions, and XAI to maintain regulatory compliance and trust in AI-driven decisions.[118] However, challenges such as automation bias, oversight fatigue, and regulatory gaps complicate governance efforts, necessitating interdisciplinary solutions that balance autonomy with liability.

While agentic AI presents significant challenges in healthcare, addressing these issues through robust governance, transparency, and clinician collaboration will enable safer and more effective AI-driven healthcare solutions. By integrating ethical oversight, regulatory adaptability, and technical innovations, AI can transform patient care while maintaining high standards of safety and accountability.

4. Future directions for agentic AI in healthcare

Agentic AI in healthcare is still in its early stages, requiring rigorous development to ensure its safety, reliability, and seamless integration into healthcare management and clinical practice. The next phase of agentic AI will be driven by advancements in self-evolving AI architectures, multimodal integration, and real-time adaptability, enabling these systems to assist clinicians rather than replace them. As AI continues to evolve at an unprecedented pace, its adoption in healthcare is expected to expand significantly in the coming years.[94]

A key research priority will be the development of Generalist AI Agents capable of performing complex, multidisciplinary tasks with minimal human intervention. Few-shot and self-supervised learning techniques will play a crucial role in enabling these models to rapidly adapt to new medical scenarios while reducing dependence on large, annotated datasets. However, the central challenge remains: how can these technological advancements be effectively integrated into daily clinical workflows?

To address this, hybrid human-AI collaboration frameworks will continue to evolve, fostering deeper physician-AI interaction while ensuring trust, interpretability, and accountability. Explainable AI and ethical AI governance will remain focal areas, with an increasing emphasis on auditability, transparency, and regulatory oversight to mitigate risks in clinical decision-making. Moreover, the rapid advancements in open-source LLMs[119] and reasoning mechanisms will drive the next milestone in the evolution of agentic AI, enhancing its reasoning capabilities and contextual understanding in healthcare applications.

A key direction for future work in agentic AI is transforming its reactive nature into a proactive one. This shift will enable AI agents to engage more effectively with clinicians and patients, bridge knowledge gaps, and suggest optimal workflows.

From an implementation standpoint, edge AI solutions will facilitate real-time AI inference on medical devices, reducing reliance on centralized cloud-based infrastructure and improving AI accessibility in resource-limited environments. Additionally, federated learning and blockchain are poised to revolutionize secure, decentralized medical data sharing, ensuring interoperability while preserving patient privacy.

In the long term, agentic AI will likely evolve into universal AI healthcare ecosystems, where AI seamlessly integrates with EHRs, imaging platforms, and robotic systems to enable proactive, personalized, and preventive medicine. However, realizing this vision will require sustained interdisciplinary collaboration among AI researchers, clinicians, and policymakers to ensure that agentic AI remains ethical, transparent, clinically reliable, and aligned with patient-centered care.

5. Conclusion

The emergence of agentic AI, powered by advancements in MLLMs, represents a transformative milestone in the healthcare industry. This technology has the potential to revolutionize modern healthcare by addressing longstanding challenges associated with complex and diverse medical data. The autonomy and human-like reasoning capabilities of agentic AI systems can mitigate inefficiencies and augment decision-making, paving the way for more precise diagnostics, personalized treatment plans, and enhanced healthcare administration.

To fully realize its potential, collaboration between healthcare professionals and computer scientists is essential. Such interdisciplinary efforts can ensure that agentic AI solutions are aligned with clinical workflows and optimized for real-world application. These systems can support a wide range of use cases, from diagnosis and treatment planning to robotic-assisted surgeries and administrative automation. Agentic AI can be deployed in various configurations, including private hospital-owned systems, public inter-hospital networks, or clinician-specific tools, offering flexibility and adaptability to different healthcare settings.

Importantly, this technology holds promise for bridging healthcare disparities, particularly in low-resource environments. By enhancing clinician efficiency and diagnostic accuracy, agentic AI can significantly improve patient outcomes even in underprivileged areas. However, the current developmental stage of agentic AI also brings challenges, particularly its "blackbox" nature and unpredictable behaviors. Rigorous research is necessary to address these concerns, including robust validation, interpretability, and transparency in AI decision-making.

Additionally, the integration of agentic AI into healthcare must be guided by strategic legal frameworks and ethical standards to ensure patient safety and societal trust. As we enter the "agentic era," the adoption of these next-generation AI systems offers a promising future for digital healthcare, with the potential to redefine patient care and operational efficiency at a global scale.

Ethical Approval

This article does not contain any studies with human participants or animals performed by the author.

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Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used ChatGPT to assist with language editing. After using this tool, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of Competing Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

1. Hirani R, et al. Artificial intelligence and healthcare: a journey through history, present innovations, and future possibilities. Art. no. 5 *Life*. May 2024;14(5). https://doi.org/10.3390/life14050557.
2. Jiang F, et al. Artificial intelligence in healthcare: past, present and future. *Stroke Vasc Neurol*. Dec. 2017;2(4). https://doi.org/10.1136/svn-2017-000101.
3. van Melle W. MYCIN: a knowledge-based consultation program for infectious disease diagnosis. *Int J Man-Mach Stud*. May 1978;10(3):313–322. https://doi.org/10.1016/S0020-7373(78)80049-2.
4. Miller RA, McNeil MA, Challinor SM, et al. The INTERNIST-1/QUICK medical reference project—status report. *West J Med*. Dec. 1986;145(6):816–822.
5. Barnett GO, Cimino JJ, Hupp JA, Hoffer EP. DXplain: an evolving diagnostic decision-support system. *JAMA*. Jul. 1987;258(1):67–74. https://doi.org/10.1001/jama.1987.03400010071030.
6. Kaul V, Enslin S, Gross SA. History of artificial intelligence in medicine. *Gastrointest Endosc*. Oct. 2020;92(4):807–812. https://doi.org/10.1016/j.gie.2020.06.040.
7. Patel VL, et al. The coming of age of artificial intelligence in medicine. *Artif Intell Med*. May 2009;46(1):5–17. https://doi.org/10.1016/j.artmed.2008.07.017.
8. Yin J, Ngiam KY, Teo HH. Role of artificial intelligence applications in real-life clinical practice: systematic review. *J Med Internet Res*. Apr. 2021;23(4), e25759. https://doi.org/10.2196/25759.
9. Tang Y-X, et al. Automated abnormality classification of chest radiographs using deep convolutional neural networks. *Npj Digit Med*. May 2020;3(1):1–8. https://doi.org/10.1038/s41746-020-0273-z.
10. Truhn D, Schrading S, Haarburger C, et al. Radiomic versus convolutional neural networks analysis for classification of contrast-enhancing lesions at multiparametric breast MRI. *Radiology*. Feb. 2019;290(2):290–297. https://doi.org/10.1148/radiol.2018181352.
11. Bernal J, et al. Deep convolutional neural networks for brain image analysis on magnetic resonance imaging: a review (C) *Artif Intell Med*. Apr. 2019;95:64–81. https://doi.org/10.1016/j.artmed.2018.08.008.
12. Yamashita R, Nishio M, Do RKG, Togashi K. Convolutional neural networks: an overview and application in radiology. Art. no. 4 *Insights Imaging*. Aug. 2018;9(4). https://doi.org/10.1007/s13244-018-0639-9.
13. Miotto R, Wang F, Wang S, et al. Deep learning for healthcare: review, opportunities and challenges. *Brief Bioinf*. Nov. 2018;19(6):1236–1246. https://doi.org/10.1093/bib/bbx044.
14. Bertl M, et al. Challenges for AI in Healthcare Systems. In: Steffen B, ed. *Bridging the Gap Between AI and Reality*. Cham: Springer Nature Switzerland; 2025:165–186. https://doi.org/10.1007/978-3-031-73741-1_11.
15. Holzinger A, Saranti A, Angerschmid A, et al. Toward human-level concept learning: pattern benchmarking for AI algorithms. *Patterns*. Jul. 2023;4(8), 100788. https://doi.org/10.1016/j.patter.2023.100788.
16. Peters U. Explainable AI lacks regulative reasons: why AI and human decision-making are not equally opaque. *AI Ethics*. Aug. 2023;3(3):963–974. https://doi.org/10.1007/s43681-022-00217-w.
17. Mehandru N, Miao BY, Almaraz ER, et al. Evaluating large language models as agents in the clinic. *Npj Digit Med*. Apr. 2024;7(1):1–3. https://doi.org/10.1038/s41746-024-01083-y.
18. Russell SJ, Norvig P. *Artificial intelligence: a modern approach*. Third edition, Global edition. Prentice Hall series in artificial intelligence. Boston Columbus Indianapolis: Pearson; 2016.
19. Petrova-Dimitrova VS. Classifications of intelligence agents and their applications. Art. no. 1, 2022, Accessed: Jan. 15 *J Fundam Sci Appl*. 2025;28(1). ⟨https://journals.tu-plovdiv.bg/index.php/journal/article/view/559⟩. Art. no. 1, 2022, Accessed: Jan. 15.
20. H. Touvron *et al.*, LLaMA: Open and Efficient Foundation Language Models. Feb. 27, 2023, *arXiv*: arXiv:2302.13971. doi: 10.48550/arXiv.2302.13971.
21. E. Almazrouei *et al.*, The Falcon Series of Open Language Models. Nov. 29, 2023, *arXiv*: arXiv:2311.16867. doi: 10.48550/arXiv.2311.16867.
22. L. Zheng *et al.*, Judging LLM-as-a-Judge with MT-Bench and Chatbot Arena. Dec. 24, 2023, *arXiv*: arXiv:2306.05685. doi: 10.48550/arXiv.2306.05685.
23. J. Wei *et al.*, Chain-of-Thought Prompting Elicits Reasoning in Large Language Models. Jan. 10, 2023, *arXiv*: arXiv:2201.11903. doi: 10.48550/arXiv.2201.11903.
24. "[2210.03629] ReAct: Synergizing Reasoning and Acting in Language Models." Accessed: Mar. 11, 2025. [Online]. Available: ⟨https://arxiv.org/abs/2210.03629⟩.

25. S. Yao *et al.*, Tree of Thoughts: Deliberate Problem Solving with Large Language Models. Dec. 03, 2023, *arXiv*: arXiv:2305.10601. doi: 10.48550/arXiv.2305.10601.
26. Kiryati N, Landau Y. Dataset growth in medical image analysis research. Art. no. 8 *J Imaging*. Aug. 2021;7(8). https://doi.org/10.3390/jimaging7080155.
27. Matengo W, Otsieno E, Wanjiru K. Big data analytics in healthcare. In: Chaari L, ed. *Digital Health in Focus of Predictive, Preventive and Personalised Medicine*. Cham: Springer International Publishing; 2020:129–138. https://doi.org/10.1007/978-3-030-49815-3_15.
28. Refsum C, Britnell M. *The missing millions: leadership and the global workforce crisis in healthcare*. *Research Handbook on Leadership in Healthcare*. Edward Elgar Publishing; 2023:75–99. Accessed: Jan. 12, 2025. [Online]. Available: ⟨https://www.elgaronline.com/edcollchap/book/9781800886254/book-part-9781800886254-12.xml⟩.
29. Unige, Healthcare Human Resource Shortfall in Vietnam Compared to Select Countries in Asean. Archives Des Sciences. Accessed: Jan. 12, 2025. [Online]. Available: ⟨https://unige.org/volume-74-issue-3-2024/healthcare-human-resource-shortfall-in-vietnam-compared-to-select-countries-in-asean-2/⟩.
30. Ng KH, Faust O, Sudarshan V, Chattopadhyay S. Data overloading in medical imaging: emerging issues, challenges and opportunities in efficient data management. *J Med Imaging Health Inf*. Aug. 2015;5(4):755–764. https://doi.org/10.1166/jmihi.2015.1449.
31. Keni S. Evaluating artificial intelligence for medical imaging: a primer for clinicians. *Br J Hosp Med*. Jul. 2024;85(7):1–13. https://doi.org/10.12968/hmed.2024.0312.
32. Nijor S, Gokcen E, Lad N. Patient safety issues from information overload in electronic medical records: a systematic review. *Res Sq*. Apr. 21, 2020. https://doi.org/10.21203/rs.3.rs-23424/v1.
33. Nijor S, Rallis G, Lad N, Gokcen E. Patient safety issues from information overload in electronic medical records. *J Patient Saf*. Sep. 2022;18(6), e999. https://doi.org/10.1097/PTS.0000000000001002.
34. Raghavendra U, et al. Brain tumor detection and screening using artificial intelligence techniques: current trends and future perspectives. *Comput Biol Med*. Sep. 2023;163, 107063. https://doi.org/10.1016/j.compbiomed.2023.107063.
35. Khan MdSI, et al. Accurate brain tumor detection using deep convolutional neural network. *Comput Struct Biotechnol J*. Jan. 2022;20:4733–4745. https://doi.org/10.1016/j.csbj.2022.08.039.
36. Weikert T, Akinci D'Antonoli T, Bremerich J, et al. Evaluation of an AI-powered lung nodule algorithm for detection and 3D segmentation of primary lung tumors, 2019 *Contrast Media Mol Imaging*. 2019;1:1545747. https://doi.org/10.1155/2019/1545747.
37. Karunanayake N, Lohitvisate W, Makhanov SS. Artificial life for segmentation of fusion ultrasound images of breast abnormalities. *Pattern Recognit*. Nov. 2022;131, 108838. https://doi.org/10.1016/j.patcog.2022.108838.
38. Karunanayake N, et al. Dual-stage AI model for enhanced CT imaging: precision segmentation of kidney and tumors. Art. no. 1 *Tomography*. Jan. 2025;11(1). https://doi.org/10.3390/tomography11010003.
39. Kumar S, Mankame DP. Optimization driven deep convolution neural network for brain tumor classification. *Biocybern Biomed Eng*. Jul. 2020;40(3):1190–1204. https://doi.org/10.1016/j.bbe.2020.05.009.
40. Kondylakis H, et al. Documenting the de-identification process of clinical and imaging data for AI for health imaging projects. *Insights Imaging*. May 2024;15(1):130. https://doi.org/10.1186/s13244-024-01711-x.
41. Hiredesai AN, Martinez CJ, Anderson ML, et al. Is artificial intelligence the future of radiology? Accuracy of ChatGPT in radiologic diagnosis of upper extremity bony pathology, 15589447241298982 *Hand N Y N*. Dec. 2024. https://doi.org/10.1177/15589447241298982.
42. Huppertz MS, et al. Revolution or risk?-Assessing the potential and challenges of GPT-4V in radiologic image interpretation. *Eur Radio*. Oct. 2024. https://doi.org/10.1007/s00330-024-11115-6.
43. Cámara J, Troya J, Burgueño L, Vallecillo A. On the assessment of generative AI in modeling tasks: an experience report with ChatGPT and UML. *Softw Syst Model*. Jun. 2023;22(3):781–793. https://doi.org/10.1007/s10270-023-01105-5.
44. Tanno R, et al. Collaboration between clinicians and vision–language models in radiology report generation. *Nat Med*. Nov. 2024:1–10. https://doi.org/10.1038/s41591-024-03302-1.
45. Wang S, et al. Artificial intelligence in lung cancer pathology image analysis. Art. no. 11 *Cancers*. Nov. 2019;11(11). https://doi.org/10.3390/cancers11111673.
46. Kim SH, et al. Human-AI collaboration in large language model-assisted brain MRI differential diagnosis: a usability study. *Eur Radio*. Mar. 2025. https://doi.org/10.1007/s00330-025-11484-6.
47. M. Moor *et al.*, Med-Flamingo: a Multimodal Medical Few-shot Learner. Jul. 27, 2023, *arXiv*: arXiv:2307.15189. doi: 10.48550/arXiv.2307.15189.
48. Bai F, Du Y, Huang T, et al. M3D: advancing 3D medical image analysis with multi-modal large language models. Mar. 31. *arXiv: arXiv*. 2024;2404:00578. https://doi.org/10.48550/arXiv.2404.00578.
49. Mohsen F, Al-Absi HRH, Yousri NA, et al. A scoping review of artificial intelligence-based methods for diabetes risk prediction. *Npj Digit Med*. Oct. 2023;6(1):1–15. https://doi.org/10.1038/s41746-023-00933-5.
50. Huang Y-J, Chen C, Yang H-C. AI-enhanced integration of genetic and medical imaging data for risk assessment of Type 2 diabetes. *Nat Commun*. May 2024;15(1):4230. https://doi.org/10.1038/s41467-024-48618-1.
51. Deepa DrR, Sadu VB, C PG, Sivasamy DrA. Early prediction of cardiovascular disease using machine learning: unveiling risk factors from health records. *AIP Adv*. Mar. 2024;14(3), 035049. https://doi.org/10.1063/5.0191990.
52. Ayoub C, et al. Multimodal fusion artificial intelligence model to predict risk for MACE and myocarditis in cancer patients receiving immune checkpoint inhibitor therapy. *JACC Adv*. Jan. 2025;4(1), 101435. https://doi.org/10.1016/j.jacadv.2024.101435.
53. Swan M, Kido T, Roland E, dos Santos RP. AI Health Agents: Pathway2vec, ReflectE, category theory, and longevity. Art. no. 1 *Proc AAAI Symp Ser*. May 2024;3(1). https://doi.org/10.1609/aaaiss.v3i1.31249.
54. Yang X. The applications of artificial intelligence in personalized medicine. *Appl Comput Eng*. Aug. 2024;71:47–51. https://doi.org/10.54254/2755-2721/71/20241625.
55. Zhang H, Xi Q, Zhang F, et al. Application of deep learning in cancer prognosis prediction model, 15330338231199287 *Technol Cancer Res Treat*. Jan. 2023;22. https://doi.org/10.1177/15330338231199287.
56. Iqbal MJ, et al. Clinical applications of artificial intelligence and machine learning in cancer diagnosis: looking into the future. *Cancer Cell Int*. May 2021;21(1):270. https://doi.org/10.1186/s12935-021-01981-1.
57. Hu X, et al. Interpretable medical image Visual Question Answering via multi-modal relationship graph learning. *Med Image Anal*. Oct. 2024;97, 103279. https://doi.org/10.1016/j.media.2024.103279.
58. Bai M, Yu X, Wang Y, et al. Enhancing pixel-level analysis in medical imaging through visual instruction tuning: introducing PLAMi. *Vis Comput*. 2024. https://doi.org/10.1007/s00371-024-03742-3.
59. Labkoff S, et al. Toward a responsible future: recommendations for AI-enabled clinical decision support. *J Am Med Inform Assoc*. Nov. 2024;31(11):2730–2739. https://doi.org/10.1093/jamia/ocae209.
60. Finkelstein J, Gabriel A, Schmer S, et al. Identifying facilitators and barriers to implementation of AI-assisted clinical decision support in an electronic health record system. *J Med Syst*. Sep. 2024;48(1):89. https://doi.org/10.1007/s10916-024-02104-9.
61. A. Hoopes, V.I. Butoi, J.V. Guttag, and A.V. Dalca, VoxelPrompt: A Vision-Language Agent for Grounded Medical Image Analysis. Oct. 10, 2024, *arXiv*: arXiv:2410.08397. doi: 10.48550/arXiv.2410.08397.
62. N. Yildirim *et al.*, Multimodal Healthcare AI: Identifying and Designing Clinically Relevant Vision-Language Applications for Radiology. presented at the PROCEEDINGS OF THE 2024 CHI CONFERENCE ON HUMAN FACTORS IN COMPUTING SYTEMS, CHI 2024, 2024. doi: 10.1145/3613904.3642013.
63. Li C, et al. *LLaVA-med: training a large language-and-vision assistant for biomedicine in one day. in Proceedings of the 37th International Conference on Neural Information Processing Systems, in NIPS '23*. Red Hook, NY, USA: Curran Associates Inc; Dec. 2023:28541–28564.
64. Oh Y, et al. LLM-driven multimodal target volume contouring in radiation oncology. *Nat Commun*. Oct. 2024;15(1):9186. https://doi.org/10.1038/s41467-024-53387-y.
65. Bertl M, Ross P, Draheim D. Systematic AI support for decision-making in the healthcare sector: obstacles and success factors. *Health Policy Technol*. Sep. 2023;12(3), 100748. https://doi.org/10.1016/j.hlpt.2023.100748.
66. Koumakis L. Deep learning models in genomics; are we there yet? *Comput Struct Biotechnol J*. Jan. 2020;18:1466–1473. https://doi.org/10.1016/j.csbj.2020.06.017.
67. Golriz Khatami S, Mubeen S, Bharadhwaj VS, et al. Using predictive machine learning models for drug response simulation by calibrating patient-specific pathway signatures. *Npj Syst Biol Appl*. Oct. 2021;7(1):1–9. https://doi.org/10.1038/s41540-021-00199-1.
68. Kang J, Schwartz R, Flickinger J, Beriwal S. Machine learning approaches for predicting radiation therapy outcomes: a clinician's perspective. *Int J Radiat Oncol*. Dec. 2015;93(5):1127–1135. https://doi.org/10.1016/j.ijrobp.2015.07.2286.
69. Mason DM, et al. Optimization of therapeutic antibodies by predicting antigen specificity from antibody sequence via deep learning. *Nat Biomed Eng*. Jun. 2021;5(6):600–612. https://doi.org/10.1038/s41551-021-00699-9.
70. Zhang X, et al. Deep learning with radiomics for disease diagnosis and treatment: challenges and potential. *Front Oncol*. Feb. 2022;12. https://doi.org/10.3389/fonc.2022.773840.
71. Nova SN, Rahman MdS, Hosen ASMS. Deep learning in biomedical devices: perspectives, applications, and challenges. In: Kaiser MS, Mahmud M, Al Mamun S, eds. *Rhythms in Healthcare*. Singapore: Springer Nature; 2022:13–35. https://doi.org/10.1007/978-981-19-4189-4_2.
72. Muhammad Arslan M, Yang X, Zhang Z, et al. Advancing healthcare monitoring: integrating machine learning with innovative wearable and wireless systems for comprehensive patient care. *IEEE Sens J*. Sep. 2024;24(18):29199–29210. https://doi.org/10.1109/JSEN.2024.3434409.
73. "AgentClinic: a multimodal agent benchmark to evaluate AI in simulated clinical environments." Accessed: Mar. 12, 2025. [Online]. Available: ⟨https://arxiv.org/html/2405.07960v1⟩.
74. Shaik T, et al. Remote patient monitoring using artificial intelligence: current state, applications, and challenges. *WIREs Data Min Knowl Discov*. 2023;13(2), e1485. https://doi.org/10.1002/widm.1485.
75. Nadarzynski T, Miles O, Cowie A, Ridge D. Acceptability of artificial intelligence (AI)-led chatbot services in healthcare: a mixed-methods study, 2055207619871808 *Digit Health*. Jan. 2019;5. https://doi.org/10.1177/2055207619871808.
76. Catherine AT, Towfek SK, A. Abdelhamid A. An overview of the evolution and impact of chatbots in modern healthcare services. Dec. 2023 *Mesop J Artif Intell Health*. 2023:71–75. https://doi.org/10.58496/MJAIH/2023/014.
77. Christopoulou SC. Machine learning models and technologies for evidence-based telehealth and smart care: a review. Art. no. 1 *BioMedInformatics*. Mar. 2024;4(1). https://doi.org/10.3390/biomedinformatics4010042.

78. Andrikopoulou E. Chapter 13 - The rise of AI in telehealth. In: Freeman AM, Bhatt AB, eds. *Emerging Practices in Telehealth*. Academic Press; 2023:183–207. https://doi.org/10.1016/B978-0-443-15980-0.00011-9.
79. J. Li *et al.*, Agent Hospital: A Simulacrum of Hospital with Evolvable Medical Agents. Jan. 17, 2025, *arXiv*: arXiv:2405.02957. doi: 10.48550/arXiv.2405.02957.
80. Fitzpatrick KK, Darcy A, Vierhile M. Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (Woebot): a randomized controlled trial. *JMIR Ment Health*. Jun. 2017;4(2), e7785. https://doi.org/10.2196/mental.7785.
81. S. Gabriel, I. Puri, X. Xu, *et al*, Can AI Relate: Testing Large Language Model Response for Mental Health Support. Oct. 07, 2024, *arXiv*: arXiv:2405.12021. doi: 10.48550/arXiv.2405.12021.
82. Ahmed Z, Mohamed K, Zeeshan S, Dong X. Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine. Jan. 2020 *Database*. 2020:baaa010. https://doi.org/10.1093/database/baaa010.
83. Alowais SA, et al. Revolutionizing healthcare: the role of artificial intelligence in clinical practice. *BMC Med Educ*. Sep. 2023;23(1):689. https://doi.org/10.1186/s12909-023-04698-z.
84. Aminizadeh S, et al. Opportunities and challenges of artificial intelligence and distributed systems to improve the quality of healthcare service. *Artif Intell Med*. Mar. 2024;149, 102779. https://doi.org/10.1016/j.artmed.2024.102779.
85. Patil S, Shankar H. Transforming healthcare: harnessing the power of AI in the modern era. Art. no. 2 *Int J Multidiscip Sci Arts*. Apr. 2023;2(2). https://doi.org/10.47709/ijmdsa.v2i1.2513.
86. Rathore Y, Sinha U, Haladkar JP, et al. Optimizing patient flow and resource allocation in hospitals using AI. *2023 Int Conf Artif Intell Innov Healthc Ind (ICAIIHI)*. Dec. 2023:1–6. https://doi.org/10.1109/ICAIIHI57871.2023.10489698.
87. Bahrami S, Rubulotta F. Artificial intelligence-driven translation tools in intensive care units for enhancing communication and research. Art. no. 1 *Int J Environ Res Public Health*. Jan. 2025;22(1). https://doi.org/10.3390/ijerph22010095.
88. Gonzalez-Garcia A, Pérez-González S, Benavides C, et al. Impact of artificial intelligence–based technology on nurse management: a systematic review. *J Nurs Manag*. 2024;2024(1):3537964. https://doi.org/10.1155/2024/3537964.
89. Vaithiyalingam G. Bridging the gap: AI, automation, and the future of seamless healthcare claims processing. Art. no. 2 *Afr J Artif Intell Sustain Dev*. Jul. 2022;2(2). Art. no. 2.
90. Kapadiya K, et al. Blockchain and AI-empowered healthcare insurance fraud detection: an analysis, architecture, and future prospects. *IEEE Access*. 2022;10:79606–79627. https://doi.org/10.1109/ACCESS.2022.3194569.
91. Prabhod KJ. The role of artificial intelligence in reducing healthcare costs and improving operational efficiency. Art. no. 2 *Q J Emerg Technol Innov*. Apr. 2024;9(2). Art. no. 2.
92. Jiang LY, et al. Health system-scale language models are all-purpose prediction engines. *Nature*. Jul. 2023;619(7969):357–362. https://doi.org/10.1038/s41586-023-06160-y.
93. "GPT-4 in a Cancer Center — Institute-Wide Deployment Challenges and Lessons Learned | NEJM AI." Accessed: Mar. 12, 2025. [Online]. Available: ⟨https://ai.nejm.org/doi/full/10.1056/AIcs2300191⟩.
94. Gangwal A, Ansari A, Ahmad I, et al. Current strategies to address data scarcity in artificial intelligence-based drug discovery: a comprehensive review. *Comput Biol Med*. Sep. 2024;179, 108734. https://doi.org/10.1016/j.compbiomed.2024.108734.
95. Gupta R, Srivastava D, Sahu M, et al. Artificial intelligence to deep learning: machine intelligence approach for drug discovery. *Mol Divers*. Aug. 2021;25(3):1315–1360. https://doi.org/10.1007/s11030-021-10217-3.
96. Harrer S, Shah P, Antony B, Hu J. Artificial intelligence for clinical trial design. *Trends Pharmacol Sci*. Aug. 2019;40(8):577–591. https://doi.org/10.1016/j.tips.2019.05.005.
97. Fountzilas E, Tsimberidou AM, Vo HH, Kurzrock R. Clinical trial design in the era of precision medicine. *Genome Med*. Aug. 2022;14(1):101. https://doi.org/10.1186/s13073-022-01102-1.
98. Xu J, et al. Translating cancer genomics into precision medicine with artificial intelligence: applications, challenges and future perspectives. *Hum Genet*. Feb. 2019;138(2):109–124. https://doi.org/10.1007/s00439-019-01970-5.
99. Dias R, Torkamani A. Artificial intelligence in clinical and genomic diagnostics. *Genome Med*. Nov. 2019;11(1):70. https://doi.org/10.1186/s13073-019-0689-8.
100. S. Liu *et al.*, DrugAgent: Automating AI-aided Drug Discovery Programming through LLM Multi-Agent Collaboration. Nov. 24, 2024, *arXiv*: arXiv:2411.15692. doi: 10.48550/arXiv.2411.15692.
101. J. Gottweis *et al.*, Towards an AI co-scientist. Feb. 26, 2025, *arXiv*: arXiv:2502.18864. doi: 10.48550/arXiv.2502.18864.
102. Iftikhar M, Saqib M, Zareen M, Mumtaz H. Artificial intelligence: revolutionizing robotic surgery: review. *Ann Med Surg*. Sep. 2024;86(9):5401. https://doi.org/10.1097/MS9.0000000000002426.
103. Guni A, Varma P, Zhang J, et al. Artificial intelligence in surgery: the future is now. *Eur Surg Res*. Jan. 2024;65(1):22–39. https://doi.org/10.1159/000536393.
104. Wu J, Liang X, Bai X, Chen Z. SurgBox: agent-driven operating room sandbox with surgery copilot. presented at the 2024 IEEE international conference on big data (BigData). *IEEE Comput Soc*. Dec. 2024:2041–2048. https://doi.org/10.1109/BigData62323.2024.10825748.
105. Moghani M, et al. SuFIA: language-guided augmented dexterity for robotic surgical assistants. *2024 IEEE/RSJ Int Conf Intell Robots Syst (IROS)*. Oct. 2024:6969–6976. https://doi.org/10.1109/IROS58592.2024.10802053.
106. Rajpurkar P, Chen E, Banerjee O, Topol EJ. AI in health and medicine. *Nat Med*. Jan. 2022;28(1):31–38. https://doi.org/10.1038/s41591-021-01614-0.
107. Kraišniković C, Harb R, Plass M, et al. Fine-tuning language model embeddings to reveal domain knowledge: an explainable artificial intelligence perspective on medical decision making. *Eng Appl Artif Intell*. Jan. 2025;139, 109561. https://doi.org/10.1016/j.engappai.2024.109561.
108. Xu J, Glicksberg BS, Su C, et al. Federated learning for healthcare informatics. *J Healthc Inform Res*. Mar. 2021;5(1):1–19. https://doi.org/10.1007/s41666-020-00082-4.
109. Ficek J, Wang W, Chen H, et al. Differential privacy in health research: a scoping review. *J Am Med Inform Assoc*. Oct. 2021;28(10):2269–2276. https://doi.org/10.1093/jamia/ocab135.
110. Müller H, Holzinger A, Plass M, et al. Explainability and causability for artificial intelligence-supported medical image analysis in the context of the European In Vitro Diagnostic Regulation. *N Biotechnol*. Sep. 2022;70:67–72. https://doi.org/10.1016/j.nbt.2022.05.002.
111. Z. Xu, S. Jain, and M. Kankanhalli, Hallucination is Inevitable: An Innate Limitation of Large Language Models. Jan. 22, 2024, *arXiv*: arXiv:2401.11817. doi:10.48550/arXiv.2401.11817.
112. Argerich MF, Patiño-Martínez M. Measuring and improving the energy efficiency of large language models inference. *IEEE Access*. 2024;12:80194–80207. https://doi.org/10.1109/ACCESS.2024.3409745.
113. Finlayson SG, Bowers JD, Ito J, et al. Adversarial attacks on medical machine learning. *Science*. Mar. 2019;363(6433):1287–1289. https://doi.org/10.1126/science.aaw4399.
114. Smith H. Clinical AI: opacity, accountability, responsibility and liability. *AI Soc*. Jun. 2021;36(2):535–545. https://doi.org/10.1007/s00146-020-01019-6.
115. Raposo VL. The fifty shades of black: about black box AI and explainability in healthcare. *Med Law Rev*. Feb. 2025;33(1):fwaf005. https://doi.org/10.1093/medlaw/fwaf005.
116. Edwards L. The EU AI Act: a summary of its significance and scope. *Artif Intell EU AI Act*. 2021;1:25.
117. "FDA Perspective on the Regulation of Artificial Intelligence in Health Care and Biomedicine | Digital Health | JAMA | JAMA Network." Accessed: Mar. 10, 2025. [Online]. Available: ⟨https://jamanetwork.com/journals/jama/fullarticle/2825146⟩.
118. Holzinger A, Zatloukal K, Müller H. Is human oversight to AI systems still possible? *N Biotechnol*. Mar. 2025;85:59–62. https://doi.org/10.1016/j.nbt.2024.12.003.
119. 2025. "Open-Source Large Language Models in Radiology: A Review and Tutorial for Practical Research and Clinical Deployment. Radiology." Accessed: Feb. 03, 2025. [Online]. Available: https://pubs.rsna.org/doi/10.1148/radiol.241073.