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Human AI Collaboration in Healthcare: Integrating Artificial Intelligence with Clinical Expertise

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A B S T R A C T

Artificial intelligence (AI) is changing the way healthcare is delivered, from disease prevention and diagnosis through to treatment, monitoring, drug discovery, and public health management. Techniques such as machine learning, deep learning, natural language processing, computer vision, and generative AI are now capable of analyzing the large, complex datasets that modern medicine produces, including electronic health records, medical images, genomic data, laboratory results, and information from wearable devices. Used well, these tools can sharpen diagnostic accuracy, bring disease detection forward in time, support more personalized treatment, and ease the workload carried by clinicians. AI has already been applied to cancer, cardiovascular disease, diabetes, infectious disease, neurological disorders, and eye disease, among other conditions. Its adoption, however, brings real challenges: data quality and bias, privacy, cybersecurity, clinical validation, regulation, and unequal access all need to be addressed before AI can be trusted at scale. AI is best understood as a tool that augments clinical judgement rather than replaces it, and its responsible use depends on human oversight, transparent evaluation, multidisciplinary collaboration, and ongoing monitoring after deployment. This review sets out the main applications of AI in health and disease, along with its benefits, limitations, ethical implications, and likely future direction.

Introduction

Artificial intelligence describes computational systems that can perform tasks normally associated with human intelligence like learning, recognizing patterns, making predictions, and supporting reasoning and decision-making. Machine learning, one of its major branches, allows algorithms to learn relationships from data rather than following rules that have been explicitly programmed. Deep learning, a subset of machine learning built on multilayered neural networks, has proven especially effective at working with complex data such as medical images, speech, genomic sequences, and clinical text (Bajwa *et al.,* 2021). Healthcare is, at its core, an information intensive enterprise. Different dyes used in the textile industry are predominantly synthetic and possess complex aromatic molecular structures, which enhance their chemical stability and resistance to biodegradation. Consequently, their persistence in the environment can lead to significant ecological pollution and may pose potential health risks to humans and other organisms (Jeyarani Varalakshmi *et al.,* 2021).

Clinical records, imaging systems, laboratory investigations, wearable sensors, genomic and proteomic data, and public health surveillance all generate volumes of information that conventional methods struggle to integrate. AI offers a way to draw connections across these heterogeneous sources like connections that might otherwise go unnoticed.

This has opened the door to AI-assisted early diagnosis, risk prediction, treatment selection, disease surveillance, drug development, and health promotion, spanning both communicable and non-communicable disease (Esteva *et al.,* 2019).

Growth in digital health data and computing power has pushed these applications well beyond simple image-based detection. AI now touches clinical risk prediction, drug development, remote monitoring, documentation, and population health management, so it is increasingly thought of as a feature of the entire care pathway rather than a diagnostic add on.

None of this means that technical capability automatically becomes a patient benefit. A model that performs impressively on a research dataset can lose accuracy when it meets a different population, health system, disease prevalence, or clinical setting. Questions of privacy, fairness, autonomy, accountability, and transparency complicate matters further, which is why the World Health Organization has placed ethics and human rights at the Centre of how AI should be designed, deployed, and used in health (World Health Organization, 2021).

This narrative review brings together the major applications of AI in health and disease and considers, critically, its benefits, its limitations, the ethical questions it raises, and where it is likely headed next.

Overview of AI Technologies in Healthcare

Several distinct AI techniques are relevant to healthcare, each suited to different kinds of data and tasks.

Machine Learning

Machine learning algorithms learn the relationship between input variables and outcomes from training data. Supervised learning is typically used for classification and prediction tasks, while unsupervised learning can surface patterns or patient subgroups that were not defined in advance (Rajkomar *et al.,* 2019)**.**

Deep Learning

Deep learning uses multilayered neural networks to build increasingly abstract representations of data. Convolutional neural networks are the workhorse of medical imaging, while other architectures are better suited to clinical text, time-series data, or information that combines several modalities at once (Shen *et al.,* 2017).

Natural Language Processing

Natural language processing (NLP) allows computers to read and generate human language. In healthcare this translates into extracting information from clinical notes, assisting with documentation, surfacing relevant material from the medical literature, and supporting clinical information retrieval (Hirschberg & Manning, 2015).

Computer Vision

Computer vision automates the interpretation of visual data and underpins many of the imaging applications in radiology, pathology, dermatology, ophthalmology, and endoscopy (Esteva *et al.,* 2019).

Generative Artificial Intelligence

Generative AI produces text, images, summaries, code, and other content. Large language models and large multimodal models are being explored for clinical documentation, patient communication, education, research, and decision support. Because these systems can produce inaccurate or fabricated output, their results need to be checked carefully rather than taken at face value.

The World Health Organization's 2024 guidance addresses the ethical and governance questions raised specifically by large multimodal models in health (World Health Organization, 2024).

Applications of AI in Health and Disease

Disease Diagnosis and Screening

Diagnosis and screening are among the most extensively studied uses of AI in medicine. Deep-learning systems can now analyze radiographs, CT and MRI scans, ultrasound images, retinal photographs, dermoscopic images, and histopathology slides.

In radiology, AI can help flag abnormalities, classify lesions, prioritize urgent scans, and quantify disease-related findings. In pathology, computer-vision algorithms can examine digitized tissue sections to help identify malignant cells or characterize tumours. Similar approaches are being explored in dermatology and ophthalmology (Litjens *et al.,* 2017).

Diabetic retinopathy screening is a well-known example: automated analysis of retinal images can identify patients at higher risk of vision-threatening disease and route them toward an ophthalmologist, which matters most where specialist care is scarce. AI has shown similar promise for detecting breast abnormalities, pulmonary disease, skin cancer, and cardiovascular disease (Esteva *et al.,* 2019).

That said, diagnostic performance shouldn't be judged on sensitivity, specificity, or AUC alone. How useful a system actually is depends on the population it's used in, how common the disease is there, how well it fits into existing workflows and referral pathways, and ultimately whether it changes outcomes for patients.

Risk Prediction and Early Detection

Predictive models built on AI can estimate the likelihood of disease onset, hospital admission, clinical deterioration, treatment response, or death. By combining demographic data, medical history, laboratory values, and physiological measurements, these models attempt to flag patients who are at elevated risk before problems become obvious.

This has been explored for cardiovascular events, diabetic complications, and progression of kidney disease, sepsis, cancer recurrence, and hospital readmission. Early-warning systems built into electronic health records can scan longitudinal data continuously and alert clinicians when a patient's trajectory starts to resemble one associated with deterioration (Rajkomar *et al.,* 2019).

Accuracy on its own is not enough to prove clinical value. These models need external validation in populations different from the ones they were built on, and they need to be assessed for calibration, real-world utility, and any unintended downstream effects (Topol, 2019).

Personalized and Precision Medicine

Much of conventional medicine is built on population averages, which is a reasonable starting point but a blunt instrument for any individual patient. Precision medicine tries to account for the biological, disease-specific, and environmental differences between patients, and AI is one of the tools making that more feasible — by combining clinical, genomic, transcriptomic, proteomic, metabolomics, and imaging data to identify meaningful subgroups within a diagnosis (Hasin *et al.,* 2017).

In oncology, this shows up in tumour classification, prognosis, treatment selection, radiotherapy planning, and the search for new therapeutic targets. In pharmacogenomics, AI is being used to predict how a patient's genetic makeup might affect how they metabolize or respond to a drug. Bringing AI together with multi-omics data may, over time, deepen our understanding of disease mechanisms and support more targeted therapies (Topol, 2019).

Doing this responsibly, though, calls for large, high-quality, representative datasets and rigorous clinical validation and governance becomes especially important once genomic data is linked with long term health records.

Drug Discovery and Development

Conventional drug discovery is slow and costly, moving through target identification, compound screening, toxicity testing, pharmacokinetic evaluation, formulation, and clinical trials.

AI has the potential to speed up several of these stages by analyzing chemical structures, predicting how molecules interact with their targets, screening large compound libraries, and estimating toxicity and pharmacokinetics (Vamathevan *et al.,* 2019).

AI also supports drug repurposing and identifying new therapeutic uses for medicines that are already approved. Advances in protein-structure prediction and computational molecular modelling have extended what's possible here, though every computational prediction still needs to be confirmed experimentally, through biochemical, cellular, preclinical, and ultimately clinical studies. AI, in other words, accelerates the research process; it does not replace the evidence that process is meant to produce (Jumper *et al.,* 2021).

Disease Monitoring and Digital Health

Wearables, smartphones, remote sensors, and telemedicine platforms now generate a continuous stream of health data like heart rate, activity levels, sleep, blood glucose, oxygen saturation, and more.

AI can turn that stream into something clinically useful, supporting the monitoring of patients with diabetes, cardiovascular disease, respiratory conditions, neurological disorders, and other chronic illness, and potentially catching deterioration earlier than a periodic clinic visit (Jafleh *et al.,* 2024).

AI-powered chat bots and virtual assistants can offer health information, appointment support, medication reminders, and basic symptom guidance. They are not, however, a substitute for professional assessment particularly where symptoms are severe, unusual, or could be life-threatening (Steinhubl *et al.,* 2015).

Public Health and Disease Surveillance

Beyond individual patient care, AI can support public health agencies in analyzing epidemiological data, spotting disease trends, forecasting outbreaks, planning vaccination campaigns, allocating resources, and identifying populations at greatest risk.

AI-assisted surveillance often draws on clinical records, laboratory reports, environmental data, and mobility patterns together, which can speed up outbreak detection and sharpen public health decisions (Ye *et al.,* 2016).

Population-level systems like these raise their own concerns, though around privacy, surveillance, data ownership, transparency, and the potential for sensitive information to be misused. Clear ethical and legal frameworks need to govern this space specifically.

Health Promotion and Preventive Care

AI also has a role in prevention. Digital interventions can offer personalized recommendations on physical activity, nutrition, smoking cessation, medication adherence, and self-management of chronic disease, adapting as new data comes in. Their real-world value, though, still depends on whether people stay engaged with them, how well they're integrated into clinical care, and whether they demonstrably improve health outcomes rather than just user activity metrics (World Health Organization, 2021).

Potential Benefits of AI in Healthcare

Taken together, the main potential benefits of AI in healthcare include (Topol, 2019):

- Earlier detection of disease, by identifying subtle patterns before they become clinically apparent
- Stronger diagnostic support for interpreting complex images, laboratory results, and clinical data
- More personalised care, through risk assessment and treatment selection tailored to the individual patient
- Greater efficiency, by automating repetitive administrative and analytical work
- Continuous monitoring, using wearable and remote technologies to track health over time
- Faster drug development, through target identification, molecular screening, and repurposing
- Wider access, extending screening services to areas where specialists are scarce
- Better public health planning, supporting surveillance, forecasting, and resource allocation

Even so, having the technical capability is not the same as delivering clinical benefit. Any AI system still needs to be judged on whether it actually improves outcomes, safety, efficiency, equity, or the patient's experience of care and not on how impressive its performance metrics look in isolation (World Health Organization, 2021).

Challenges and Limitations

Data Quality and Algorithmic Bias

AI systems are only as good as the data they are built on. Datasets that are incomplete, poorly labelled, or unrepresentative of the population being served will produce unreliable, and sometimes inequitable, results.

A model trained largely on data from one healthcare system or region may simply not transfer well to a population with different demographics, genetics, socioeconomic circumstances, or patterns of care. Diverse training data, subgroup analysis, external validation, and ongoing performance monitoring are all necessary safeguards (Chen *et al.,* 2023).

Privacy and Data Security

Health data is among the most sensitive information that exists, and AI tends to widen the circle of systems and organizations involved in collecting, processing, and sharing it. That creates real exposure to unauthorized access, cybersecurity breaches, and inappropriate secondary use. Good data governance needs to address consent, data minimization, access control, secure storage, encryption, auditability, and clear limits on how data can be reused (Price & Cohen, 2019).

Explainability and Interpretability

Many advanced AI models, particularly deep-learning systems, function as "black boxes" and their internal reasoning is not easy to trace. Clinicians are understandably cautious about relying on a recommendation they can't interrogate, especially in high-stakes decisions. Explanations also need to be clinically meaningful, not just a technical description of what the model did internally (Holzinger *et al.,* 2017).

Clinical Validation and Generalizability

One of the persistent gaps in healthcare AI research is between algorithmic performance and demonstrated clinical benefit. A model can look excellent on a retrospective dataset and still fail to improve care once it's deployed. Proper evaluation involves internal and external validation, prospective studies where feasible, assessment of real clinical utility, workflow testing, and monitoring after deployment because performance can drift over time as patient populations, clinical practice, equipment, or laboratory methods change (Kelly *et al.,* 2019).

Automation Bias and Over-Reliance

There is a documented tendency for clinicians to place excessive trust in AI output simply because it appears confident or precise, a pattern known as automation bias. Left unchecked, this can lead to incorrect predictions being accepted uncritically. AI tools should be designed to support clinical reasoning rather than substitute for it, and clinicians need training that makes both the strengths and the limits of these systems clear (Goddard *et al.,* 2012).

Regulatory and Legal Challenges

AI-enabled medical technologies need regulatory oversight that covers safety, effectiveness, cybersecurity, transparency, software updates, and post-market surveillance. The U.S. Food and Drug Administration, for example, maintains a public list of authorized AI-enabled medical devices, which gives some sense of how far AI has already moved into regulated medical technology. Because these systems can change through updates or adaptive learning after they've been approved, traditional regulatory models built around a fixed, unchanging product may need to evolve. Responsibility also needs to be clearly assigned for cases where an AI-supported decision contributes to patient harm (Food and Drug Administration, 2025).

Ethical Considerations

Implementing AI in healthcare responsibly means paying attention to several ethical principles.

Autonomy

Patients should retain meaningful control over decisions about their own health. AI is meant to support informed decision-making, not to substitute for it (Vayena *et al.,* 2018).

Beneficence and Non-Maleficence

Any AI application should offer a demonstrable, or at least reasonably supported, benefit, while keeping foreseeable harm to a minimum and both the intended and unintended consequences need to be evaluated (Morley *et al.,* 2020).

Justice and Equity

AI should not deepen existing health inequalities. This matters most when algorithms are trained on data that underrepresent disadvantaged or geographically diverse populations (Obermeyer *et al.,* 2019).

Transparency

Patients and clinicians should know when AI has played a significant role in a clinical decision, and a system's intended use, limitations, and performance should be clearly documented (Amann *et al.,* 2020).

Accountability

Responsibility for AI-supported decisions in healthcare needs to be clearly defined. Developers, healthcare organisations, clinicians, and regulators each carry different, but overlapping, obligations for safe implementation. WHO guidance frames this around protecting human autonomy, promoting wellbeing and safety, transparency, accountability, inclusiveness, and sustainability (World Health Organization, 2021).

Generative AI and Large Multimodal Models

Generative AI is one of the fastest-moving areas of healthcare technology. Large language models generate and process natural language, while large multimodal models combine text with images and other data types (Meskó & Topol, 2023).

Potential applications include:

1. Clinical documentation and summarisation
2. Patient education
3. Medical education and training
4. Literature searching and research assistance
5. Clinical decision support
6. Communication and translation
7. Biomedical research
8. Drug-development workflows

The risks are distinctive, too. These models can generate plausible-sounding but incorrect information, leave out clinically important details, misread context, or invent references outright. In a healthcare setting, where inaccurate information can directly affect patient safety, that matters more than in most other applications of generative AI (Singhal *et al.,* 2023).

WHO's 2024 guidance on large multimodal models sets out governance approaches that assign responsibility across governments, technology developers, healthcare organisations, and end users (World Health Organization, 2024).

AI-driven technologies, particularly machine learning (ML) and deep learning, provide powerful approaches for analysing complex medical data, including electronic health records, medical images, genomic information, clinical biomarkers and genome editing, a potent technique CRISPR (Abarna *et al.,* 2025). For now, generative AI is best treated as an assistive technology that requires verification, not as an autonomous source of clinical truth.

Human–AI Collaboration

The most realistic model for healthcare is collaboration between people and AI, not full automation. AI is good at processing large datasets quickly, spotting patterns, handling repetitive tasks, and generating predictions. Clinicians bring the contextual understanding, clinical reasoning, communication skills, ethical judgement, and knowledge of individual patient preferences that AI cannot replicate (Topol, 2019). An effective human AI system should:

- Define the intended role of AI clearly
- Preserve meaningful human oversight
- Communicate uncertainty honestly
- Provide explanations that are clinically useful
- Allow clinicians to challenge or override AI recommendations
- Monitor performance continuously
- Assign clear responsibility for decisions

The goal is to extend what healthcare professionals can do, not to sideline them, while keeping care centred on the patient (Char *et al.,* 2018).

Future Perspectives

Healthcare AI is likely to move toward greater integration of multimodal data like medical images, EHR data, laboratory results, genomic information, clinical notes, and real-time physiological measurements combined rather than analysed separately. Generative AI and multimodal foundation models will probably play a growing role in clinical documentation, biomedical research, medical education, patient communication, and decision support. That growth needs to be matched by equally rigorous evaluation, not outpace it (Moor *et al.,* 2023).

Priorities for future research include (Topol, 2019);

- Representative and diverse datasets, to reduce rather than reinforce health disparities
- Prospective and external validation in real clinical settings
- Clinically meaningful outcomes, not just technical performance
- Transparent reporting and reproducibility
- Explainability and honest uncertainty estimation
- Robust privacy and cybersecurity protections
- Continuous monitoring after deployment
- Attention to human factors and clinician training
- Cost-effectiveness and health-system impact
- Equitable implementation in low- and middle-income settings

Resource-limited settings deserve particular attention. AI systems that need relatively little computing power and can run on limited infrastructure could help extend screening and clinical decision support where specialist healthcare workers are in short supply.

But that kind of implementation has to account for local disease patterns, infrastructure, language, culture, workforce capacity, and data availability; it cannot simply be transplanted from a well-resourced setting (WHO, 2021).

Limitations of This Review

As a narrative review, this article offers a broad overview of AI's applications and challenges in healthcare rather than a systematic synthesis of all available evidence. The literature in this area is expanding quickly, and the technologies, regulatory approaches, and clinical applications discussed here can change substantially over short periods. The conclusions should therefore be read in light of the evidence available at the time of writing, and should not be treated as a substitute for systematic reviews or condition-specific clinical guidelines (Yu *et al.,* 2018).

In conclusion, Artificial intelligence is becoming a meaningful part of modern healthcare, with applications spanning disease prevention, screening, diagnosis, prognosis, personalised medicine, drug discovery, remote monitoring, and public health management.

The growing application of artificial intelligence (AI), particularly machine learning (ML), in the analysis and interpretation of epigenetic data is enhancing our understanding of epigenetic mechanisms and their role in the development and progression of various diseases (Abarna *et al.,* 2026). Machine learning, deep learning, natural language processing, computer vision, and generative AI each offer new ways of making sense of increasingly complex health data (WHO, 2025).

The potential benefits are real, but they shouldn't obscure the risks that come with implementation. Poor-quality data, algorithmic bias, privacy concerns, cybersecurity threats, limited explainability, weak clinical validation, automation bias, regulatory uncertainty, and unequal access can all undermine the safety and effectiveness of AI in practice (Food and Drug Administration, 2021).

The future of healthcare should not be built around replacing clinicians with autonomous AI systems. It should instead be built around carefully designed human AI workflows, where technology extends clinical capability while human professionals retain responsibility for contextual interpretation, ethical judgement, communication, and patient centred care (WHO, 2025). In the end, the success of healthcare AI will not be measured by how sophisticated an algorithm is, but by whether its responsible use leads to healthcare that is safer, more effective, more equitable, and more accessible (WHO, 2023).

Author Contributions

Thiruvengadam Abarna: Investigation, formal analysis, writing—original draft. Angappan Shanmugapriya: Validation, methodology, writing—reviewing. S. Gomathi:—Formal analysis, writing—review and editing. Ramasamy Manikandan: Investigation, writing—reviewing. Shobana Devi Pulraj: Resources, investigation writing—reviewing.

Data Availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

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Consent to Participate Not applicable.

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References

Abarna, T., Gomathi, S., Paulraj, S.D., Karpagam, T., Shanmugapriya, A. and Manikandan, R. (2026). Machine Learning and Computational Biology-Based Epigenetics for Uncovering Plant Adaptive Evolution. In Machine Learning and AI for Precision Plant Epigenetics, J.-T. Chen (Ed.). https://doi.org/10.1002/9781394380312.ch15

Abarna, Thiruvengadam and Karpagam, Thirunethiran and Shanmugapriya, Angappan and Thentral, Murugesan and Ilakkiya, Senthil Kumar and Pricilla, Raja Helan and Manikandan, Ramasamy and Anand, Arumugam Vijaya (2025). Epigenetics Strategies Based on the CRISPR/Cas System for Breeding of Climate-Resilient Crops. CABI Climate Change Series, (114–128), https://doi.org/10.1079/9781800626102.0006

Amann, J., Blasimme, A., Vayena, E., Frey, D., & Madai, V. I. (2020). Explainability for artificial intelligence in healthcare: A multidisciplinary perspective. *BMC Medical Informatics and Decision Making, 20*, 310. https://doi.org/10.1186/s12911-020-01332-6

Bajwa, J., Munir, U., Nori, A., & Williams, B. (2021). Artificial intelligence in healthcare: Transforming the practice of medicine. Future Healthcare Journal, 8(2), e188–e194. https://doi.org/10.7861/fhj.2021-0095

Char DS, Shah NH, Magnus D (2018). Implementing machine learning in health care—addressing ethical challenges. *New England Journal of Medicine*; 378(11): 981–983. doi: 10.1

Chen, I. Y., Pierson, E., Rose, S., Joshi, S., Ferryman, K., & Ghassemi, M. (2023). Ethical machine learning in healthcare. Annual Review of Biomedical Data Science, 6, 123–144.

Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., Cui, C., Corrado, G., Thrun, S., & Dean, J. (2019). A guide to deep learning in healthcare. *Nature Medicine, 25*, 24–29. https://doi.org/10.1038/s41591-018-0316-z

Food and Drug Administration. (2025). Marketing submission recommendations for a predetermined change control plan for artificial intelligence-enabled device software functions: Guidance for industry and Food and Drug Administration staff. U.S. Department of Health and Human Services

Goddard, K., Roudsari, A., & Wyatt, J. C. (2012). Automation bias: A systematic review of frequency, effect mediators, and mitigators. Journal of the American Medical Informatics Association, 19(1), 121–127. https://doi.org/10.1136/amiajnl-2011-000089

Hasin, Y., Seldin, M., & Lusis, A. (2017). Multi-omics approaches to disease. Genome Biology, 18, 83. https://doi.org/10.1186/s13059-017-1215-1

Hirschberg, J., & Manning, C. D. (2015). Advances in natural language processing. Science, 349(6245), 261–266. https://doi.org/10.1126/science.aaa8685

Holzinger, A., Biemann, C., Pattichis, C. S., & Kell, D. B. (2017). What do we need to build explainable AI systems for the medical domain arXiv. https://doi.org/10.48550/arXiv.1712.09923

Jafleh, E. A., Alnaqbi, F. A., Almaeeni, H (2024). The role of wearable devices in chronic disease monitoring and patient care: A comprehensive review. Cureus, 16(9), e68921. https://doi.org/10.7759/cureus.68921

Jeyarani Varalakshmi B, Jannathul Firdous, Karpagam T, ShanmugaPriya A, Suganya V, Anitha P, Gomathi S, Manikandan R, Abarna T, Abirami N (2021). Nano phytoremediation for textile dye degradation using abutilon indicum silver nanoparticles: photo catalytic activities. Journal of medical pharmaceutical and allied sciences, 10(4), 3960 - 3964

Jumper, J., Evans, R., Pritzel, A., Green, T., Figurnov, M., Ronneberger, O., Tunyasuvunakool, K., Bates, R., Žídek, A., Potapenko, A., Bridgland, A., Meyer, C., Kohl, S. A. A., Ballard, A. J., Cowie, A., Romera-Paredes, B., Nikolov, S., Jain, R., Adler, J., … Hassabis, D. (2021). Highly accurate protein structure prediction with AlphaFold. Nature, 596, 583–589. https://doi.org/10.1038/s41586-021-03819-2

Kelly, C. J., Karthikesalingam, A., Suleyman, M., Corrado, G., & King, D. (2019). Key challenges for delivering clinical impact with artificial intelligence. BMC Medicine, 17, 195. https://doi.org/10.1186/s12916-019-1426-2

Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., van der Laak, J. A. W. M., van Ginneken, B., & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. Medical Image Analysis, 42, 60–88. https://doi.org/10.1016/j.media.2017.07.005

Meskó, B., & Topol, E. J. (2023). The imperative for regulatory oversight of large language models in healthcare. *npj Digital Medicine, 6*, 120. https://doi.org/10.1038/s41746-023-00873-0

Moor M, Banerjee O, Abad ZSH. (2023) Foundation models for generalist medical artificial intelligence. *Nature*; 616: 259–265.

Morley, J., Machado, C. C. V., Burr, C., Cowls, J., Joshi, I., Taddeo, M., & Floridi, L. (2020). The ethics of AI in health care: A mapping review. *Social Science & Medicine, 260*, 113172. https://doi.org/10.1016/j.socscimed.2020.113172

Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science, 366*(6464), 447–453. https://doi.org/10.1126/science.aax2342

Price, W. N., II, & Cohen, I. G. (2019). Privacy in the age of medical big data. Nature Medicine, 25(1), 37–43. https://doi.org/10.1038/s41591-018-0272-7

Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. New England Journal of Medicine, 380(14), 1347–1358. https://doi.org/10.1056/NEJMra1814259

Shen, D., Wu, G., & Suk, H.-I. (2017). Deep learning in medical image analysis. Annual Review of Biomedical Engineering, 19, 221–248. https://doi.org/10.1146/annurev-bioeng-071516-044442

Singhal, K., Azizi, S., Tu, T., Mahdavi, S. S., Wei, J., Chung, H. W., Scales, N., Tan, M., Cole-Lewis, H., Pfohl, S., Payne, P., Seneviratne, M., Gamble, P., & others. (2023). Large language models encode clinical knowledge. *Nature, 620*, 172–180. https://doi.org/10.1038/s41586-023-06291-2

Steinhubl, S. R., Muse, E. D., & Topol, E. J. (2015). The emerging field of mobile health. Science Translational Medicine, 7(283), 283rv3. https://doi.org/10.1126/scitranslmed.aaa3487

Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. Nature Medicine, 25(1), 44–56. https://doi.org/10.1038/s41591-018-0300-7

U.S. Food and Drug Administration (2021). *Artificial Intelligence/Machine Learning (AI/ML)-Based Software as a Medical Device Action Plan*.

Vamathevan, J., Clark, D., Czodrowski, P., Dunham, I., Ferran, E., Lee, G., Li, B., Madabhushi, A., Shah, P., Spitzer, M., & Zhao, S. (2019). Applications of machine learning in drug discovery and development. Nature Reviews Drug Discovery, 18, 463–477. https://doi.org/10.1038/s41573-019-0024-5

Vayena, E., Blasimme, A., & Cohen, I. G. (2018). Machine learning in medicine: Addressing ethical challenges. *PLoS Medicine, 15*(11), e1002689. https://doi.org/10.1371/journal.pmed.1002689

World Health Organization (2021). *Ethics and governance of artificial intelligence for health: WHO guidance—Executive summary.* Geneva: World Health Organization; 2021. ISBN: 978-92-4-003740-3.

World Health Organization (2021). *Ethics and Governance of Artificial Intelligence for Health: WHO Guidance.* Geneva: World Health Organization; 2021.

World Health Organization (2023). *Regulatory considerations on artificial intelligence for health.* Geneva: World Health Organization; 2023. ISBN: 978-92-4-007887-1

World Health Organization (2025). *Ethics and governance of artificial intelligence for health: Guidance on large multi-modal models.* Geneva: World Health Organization; 2025. ISBN: 978-92-4-008475-9.

World Health Organization. (2021). Ethics and governance of artificial intelligence for health: WHO guidance. https://iris.who.int/handle/10665/341996

World Health Organization. (2024). Ethics and governance of artificial intelligence for health: Guidance on large multi-modal models. World Health Organization. https://doi.org/10.2471/9789240084759

Ye, Y., Li, J., & Chen, Y. (2016). Artificial intelligence-enabled public health surveillance—from local detection to global epidemic monitoring and control. Journal of Medical Internet Research, 18(9), e202. https://doi.org/10.2196/jmir.5671

Yu KH, Beam AL, Kohane IS (2018). Artificial intelligence in healthcare. *Nature Biomedical Engineering*. 2018; 2: 719–731. https://doi.org/10.1038/s41551-018-0305-z

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