



WHITE PAPER

on

Artificial Intelligence (AI) in Medicine

A Vision for Sri Lanka - Towards Excellence and Equity

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CEYLON COLLEGE OF PHYSICIANS



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White Paper on Artificial Intelligence (AI) in Medicine:

A Vision for Sri Lanka - Towards Excellence and Equity

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EXECUTIVE SUMMARY

Artificial intelligence (AI), particularly generative AI, is rapidly transforming healthcare worldwide. Generative AI refers to technologies that can produce new content such as text, images, or data simulations by learning from large datasets. From diagnostics and therapeutics to education, public health, and administration, AI offers unprecedented opportunities to improve care quality, efficiency, and equity. At the same time, it raises profound ethical, legal, and governance challenges that must be addressed to ensure responsible adoption.

This white paper provides a comprehensive overview of generative AI in medicine with a focus on the Sri Lankan context. It reviews key applications while also assessing the potential challenges regulatory framework and ethical concerns in the use of AI in medicine.

Opportunities

Generative AI can ease clinician workload through automated documentation, support diagnosis and interpretation of medical images, improve decision-making in complex cases, and streamline hospital administration. In public health, AI enables real-time surveillance, targeted health promotion, and better emergency preparedness. For education and research, it provides simulation-based training, personalized learning, and accelerates drug discovery.

Challenges

Adoption is constrained by fragmented health data, inequities in access, cybersecurity risks, limited digital literacy among clinicians, and weak regulatory frameworks. Over-reliance on AI risks undermining clinical skills and patient trust if safeguards are not in place.

Ethics and governance

Core principles of autonomy, beneficence, non-maleficence, and justice must guide AI use. Patients must be informed when AI contributes to care. Validation, bias mitigation, and accountability are essential. Transparency and equity must underpin all applications, with clinicians retaining ultimate responsibility for care decisions.

Sri Lankan context

AI could improve access for underserved populations, strengthen prevention and early diagnosis, optimize hospital and supply chain efficiency, and support marginalized groups facing stigma in healthcare. However, the absence of robust regulation, limited infrastructure, and skills gaps remain significant barriers.

Key Recommendations

Data governance and security: Establish national standards for health data collection, storage, and interoperability. Accelerate enforcement of the Personal Data Protection Act with healthcare-specific mechanisms. Mandate equity and bias audits in AI health applications. Strengthen cybersecurity infrastructure and institutional practices.

Equity and access: Ensure datasets reflect Sri Lanka's diversity by ethnicity, language, geography, and socioeconomic background. Subsidize AI tools for under-resourced public hospitals. Support open-source and collaborative projects to democratize access and reduce dependency on costly proprietary systems.

Capacity building: Embed AI and digital health literacy into undergraduate, postgraduate, and CPD curricula across health professions. Establish an AI in Medical Education Task Force to guide curriculum development. Invest in fellowships, structured training, and partnerships with global institutions to reduce skills gaps and mitigate brain drain.

Infrastructure and scalability: Invest in interoperable digital health systems, reliable connectivity, and sustainable financing. Introduce regulatory sandboxes for controlled piloting and gradual scaling of AI innovations in the state sector. Develop national strategies to ensure successful pilots translate into system-wide adoption.

Governance and regulation: Establish a sectoral advisory committee under the Section 32 of the Personal Data Protection Act No. 9 of 2022 to enable the Data Protection Authority in the formulation of draft rules or guidelines for use of AI in Medicine. Provide for a regulatory scheme within the existing medicines regulatory framework to evaluate, approve, and monitor AI tools in medicine to ensure its safe, ethical and rational use. Adopt staged validation and continuous post-market monitoring to ensure safety and reliability. Define clear accountability frameworks assigning responsibility to developers, institutions, clinicians and where relevant patients or general public.

Research and innovation: Require standardised reporting of AI-assisted research, including disclosure of tools used, level of assistance, and verification steps. Mandate external validation and reproducibility to protect scientific integrity. Promote open science initiatives while protecting privacy and intellectual property.

Public trust and engagement: Ensure patients are clearly informed when AI contributes to care and strengthen consent processes. Launch national communication campaigns in multiple languages to build

public awareness that AI supports rather than replaces clinicians. Engage civil society, professional bodies, and patient groups in governance structures to promote transparency and inclusivity.

Conclusion

Generative AI offers Sri Lanka a unique opportunity to strengthen its health system, expand access to underserved populations, and improve efficiency in care delivery. Yet its integration must be carefully governed, ethically anchored, and equitably implemented. With deliberate investment in governance, infrastructure, workforce capacity, and public trust, Sri Lanka can harness AI not as a replacement for human care, but as a powerful tool to reinforce the values of equity, resilience, and patient-centred medicine.

PURPOSE AND SCOPE

Artificial Intelligence (AI) has evolved from being a tool for executing predefined computer programs to systems capable of learning, adapting, and performing complex tasks once considered exclusive to human intelligence. This transformative technology is being applied across many aspects of society, and it is reshaping healthcare globally, offering unprecedented opportunities in clinical care, health system efficiency, medical education, and research.

AI is transforming multiple sectors including the field of medicine, offering unprecedented opportunities to improve patient care, optimize healthcare delivery, advance medical research, and enhance medical education. As the national academic body for physicians in Sri Lanka, the Ceylon College of Physicians (CCP) recognizes the need to assess the benefits, challenges, and ethical considerations associated with integrating AI into healthcare.

This white paper aims to:

- Provide an overview of AI's potential applications in medicine including clinical practice, education, research and development, health systems administration and public health.
- Examine the current and future utilization of AI in the Sri Lankan healthcare system acknowledging infrastructure limitations and unique national health priorities
- Identify ethical, legal, and societal concerns surrounding AI integration drawing on global best practices.
- Offer recommendations for responsible adoption of AI in medicine, emphasizing ethical governance, patient safety, and equitable access.

INTRODUCTION

Brief history, evolution and fundamentals of AI

Historically intelligence and emotions were considered attributes unique to humans and were used to distinguish humans from machines. Early computers were able to execute actions specifically designed and directed by humans. In recent decades, however, advances in machine learning and related fields have enabled machines to and learn from data, process information and perform tasks which were once considered in the domain of human intelligence (1). This capability is called artificial intelligence (AI). AI is simulation of human intelligence by a system or a machine, which could learn, think and mimic human behaviours, including perceiving, reasoning, and decision making (2).

The word “artificial intelligence” was first coined at the Dartmouth Summer Research Project on Artificial Intelligence, held from 18th June through 17th August of 1956 where researchers proposed that machines could simulate human learning and reasoning (3). Over subsequent decades, AI evolved through phases of enthusiasm and funding ‘winters,’ driven first by rule-based expert systems and later by the rise of machine learning (ML) algorithms that learned from data instead of relying on explicit programming (4). From the early 2000s, deep learning (DL) characterized by neural networks with multiple layers ushered in new capabilities for interpreting complex data, notably in medical imaging, speech recognition, and genomics (5). Concurrently, advances in natural language processing (NLP), particularly transformer architectures, enabled language understanding and generation at scale, foundational to today’s chatbots and clinical text tools (6).

The field has since entered a generative era driven by foundation models such as large language models (LLMs) and large multimodal models (LMMs) that generate content across modalities including text, images, and beyond (7). These systems are increasingly used in many fields including healthcare for diagnostic support, documentation, and decision-making. Despite their promise, these models introduce risks such as output hallucinations, ingrained biases, and broader system-level risks that demand robust governance and oversight (8).

Key concepts in AI

- **Machine Learning (ML)**

Machine learning (ML) is a subfield of artificial intelligence (AI) that enables algorithms to generate predictions or decisions by recognizing patterns in data (9). Unlike traditional programming, where explicit rules are coded by humans, ML systems are trained on large datasets and improve performance by learning from examples rather than fixed instructions. Common

approaches to ML include supervised learning, where models learn from labelled data; unsupervised learning, where the system detects hidden structures in unlabelled data; and reinforcement learning, where an agent learns optimal actions through trial and error, guided by rewards or penalties (10). Popular ML methods range from regression models, decision trees, and support vector machines to clustering algorithms. Among these, artificial neural networks, loosely inspired by the brain's architecture, are particularly effective at recognizing complex patterns in large datasets. Their advanced forms are known as deep learning.

- **Deep Learning (DL)**

Deep Learning (DL) is a subset of machine learning that uses multi-layered neural networks to learn hierarchical patterns from data (11). By passing information through successive layers of artificial neurons, DL models learn increasingly abstract representations. This approach enables them to excel in data-intensive tasks such as medical imaging, speech and language processing, and other high-dimensional problems (12). DL typically requires large datasets and significant computing power but has achieved state-of-the-art performance in many clinical domains.

- **Natural Language Processing (NLP)**

Natural Language Processing (NLP) is a branch of AI that enables machines to understand, interpret, and generate human language. Modern NLP relies heavily on transformer-based models trained on vast text and speech datasets (13). In healthcare, NLP applications include language translation to bridge communication gaps, sentiment analysis of patient feedback and public health data, chatbots and virtual assistants for education and triage, text summarization of clinical records and literature, and named entity recognition to extract key information such as diagnoses or medications from unstructured data (14). These applications help clinicians and patients navigate complex information more efficiently.

- **Computer Vision (CV)**

Computer Vision (CV) enables machines to interpret and analyse visual data such as images and videos. Using convolutional neural networks (CNNs) and newer architectures like vision transformers (ViTs), CV systems can identify patterns, segment structures, and classify images with accuracy comparable to or exceeding human experts in some domains. In healthcare, CV underpins many AI applications, including radiology (tumour detection in CT/MRI), pathology (digital slide analysis), ophthalmology (automated diabetic retinopathy screening), and dermatology (skin lesion classification). These tools demonstrate how AI can augment clinician expertise, improve efficiency, and enhance diagnostic accuracy, while also raising challenges related to validation, bias, and clinical integration.

Typologies in AI

AI systems can be categorized into distinct types, each with different implications for healthcare.

Narrow AI (Weak AI/Artificial Narrow Intelligence, ANI) refers to systems designed for highly specific tasks such as tumour detection in radiology, ECG interpretation, or laboratory automation. These applications are already widely used in healthcare, where they often perform at satisfactory levels within their defined domain. However, their scope is limited: a model trained for radiology cannot generalize to other tasks outside its programmed function.

General AI (Artificial General Intelligence, AGI) is a theoretical concept describing an AI system capable of performing any intellectual task that a human can. Such systems would be able to reason, plan, and adapt flexibly across diverse domains. While AGI has been discussed for decades in academic and policy circles, it remains unrealized and is not currently relevant to clinical practice.

Generative AI and Foundation Models including LLMs and LMMS represent a newer and rapidly evolving category. These systems are capable of producing novel content such as text, images, or molecular structures based on learned patterns. LMMs, sometimes described as general-purpose foundation models, can integrate multiple types of data and generate outputs across modalities. Their uptake has been unprecedented, with growing applications in healthcare, including clinical documentation, medical education, and decision support (7).

AI Integration with hardware and systems

The integration of artificial intelligence (AI) into medical hardware and clinical systems has evolved alongside broader advances in computing. Early robotic systems provided mechanical precision but relied heavily on direct human control. Subsequent incorporation of machine learning and sensor feedback enabled greater accuracy in surgical robotics and reduced clinician workload. The advent of edge computing allowed AI models to run on portable devices and wearables, extending monitoring and diagnostics beyond clinical settings. Advances in bio-signal interfaces further demonstrated AI's ability to interpret physiological signals for assistive technologies. More recently, embedding AI into CT and MRI systems has enabled real-time reconstruction and diagnostic optimisation. These developments illustrate the progressive shift from manually operated systems to AI-augmented platforms that expand the scope and impact of medical technology.

APPLICATIONS OF AI IN HEALTHCARE

With its ability to process enormous datasets and generate new insights, generative AI is rapidly transforming the landscape of healthcare. From supporting clinical decision-making to enabling more precise diagnoses and innovative treatment pathways, these technologies are beginning to demonstrate tangible benefits in patient care. Yet, while their promise is widely recognized, the full extent of their clinical utility and broader impact is still emerging. Understanding where and how generative AI can be most effectively deployed remains a key challenge for healthcare systems, particularly in settings with limited resources.

The following section reviews both established applications of AI in medicine and the growing opportunities for its use across clinical practice, public health, medical education and training, research and drug discovery and health systems administration.

AI IN CLINICAL PRACTICE

Generative AI is rapidly emerging as a transformative tool in clinical practice, with applications spanning documentation, diagnostics, imaging, and decision support. By automating routine tasks, synthesizing complex data, and offering new forms of clinical insight, these systems have the potential to reduce clinician workload, improve accuracy, and enhance patient care. At the same time, their safe and effective use requires careful validation, clear oversight, and integration into existing clinical workflows.

Clinical Documentation and Administrative Tasks

One of the most immediate applications of generative AI in healthcare is alleviating the burden of documentation. Physicians frequently report that electronic health records (EHRs) add significantly to their workload and contribute to burnout, diverting valuable time away from direct patient care (15). Even in settings where EHRs are not widely implemented such as many hospitals in Sri Lanka, documentation challenges persist. Patient records are often incomplete, inaccurate, or inconsistently maintained, posing risks to continuity of care and patient safety (16, 17).

Large language models (LLMs) are increasingly being used to automate documentation tasks such as drafting notes, letters, and patient communications (18). They can transcribe clinician–patient encounters and generate structured notes or referral letters. Evidence suggests these tools can improve efficiency: for example, AI-generated clinic letters from brief prompts were coherent and complete, while discharge summaries transformed into patient-friendly language were significantly more readable and easier to understand (19). Real-world pilots further demonstrate promise. A 2023 quality-

improvement study which integrated a HIPAA-compliant LLM into the EHR to draft responses to patient portal messages demonstrated that physicians reported reduced workload and emotional exhaustion (20). Other studies of AI documentation assistants found similar benefits, with less after-hours EHR use and greater clinician satisfaction (21). Importantly, these studies also highlighted the continued need for physician oversight to correct omissions or inaccuracies.

Generative AI scribes are also emerging, systems that listen to patient visits and automatically produce draft notes for physician review. Studies suggest these reduce documentation time and improve clinician–patient interaction, though accuracy concerns remain and physicians retain ultimate responsibility for records (22). As LLMs advance, they can be fine-tuned to institutional templates, ensuring drafts consistently include required elements such as problem lists, medication updates, and follow-up plans. Overall, the evidence indicates that generative AI can lessen documentation burdens, enhance efficiency, and reduce burnout, provided outputs are carefully reviewed and adapted for safe clinical use.

Furthermore, generative AI is increasingly being applied to streamline administrative work in healthcare, extending beyond clinical documentation to areas such as scheduling, billing, and insurance claims. AI-driven scheduling tools, often embedded in chatbots or voice assistants, can manage appointments by factoring in physician availability, patient preferences, and clinical urgency (23). Major electronic health record (EHR) vendors are also beginning to integrate these capabilities. For instance, in 2023 Epic Systems announced a collaboration with OpenAI to embed large language models into its platform, enabling functions such as automated chart summaries and problem-oriented synopses to assist clinicians during handovers and care transitions (24). In the insurance domain, generative models can review and validate claims, detect inconsistencies, and expedite approvals, reducing delays and minimizing errors. Similarly, billing tasks can be supported by AI systems that suggest appropriate codes and generate procedure justifications directly from clinical notes. Together, these innovations have the potential to reduce administrative workload, free up clinical time, and improve the overall efficiency and responsiveness of healthcare services.

Diagnosis and interpretation of medical imaging

One of the most promising applications of generative AI is in clinical decision support, where AI systems assist with diagnosis, treatment planning, and other complex medical decisions. By analysing and synthesising patient histories, laboratory data, imaging, and relevant literature, generative models can draft summaries, propose differential diagnoses, or highlight research insights functioning as a tireless virtual assistant for clinicians.

Large Language Models (LLMs) have demonstrated the ability to mimic aspects of clinical reasoning. When prompted with case descriptions, they can suggest possible diagnoses with supporting rationale. Studies benchmarking models such as GPT-4 show steadily improving diagnostic accuracy (25). Small clinical studies suggest GPT-4 can outperform traditional decision support systems in complex cases, though risks remain, such as the generation of false details (“hallucinations”) (26). To address this, methods like retrieval-augmented generation are being developed to ground outputs in real-world records and published evidence.

Machine learning models have achieved strong accuracy in diagnosis in many fields of medicine such as breast cancer detection, distinguishing Kawasaki disease in children, and predicting early progression of psychiatric disorders from EHR data (27-29). In paediatrics, AI-driven smartphone apps have shown potential for neonatal jaundice screening (30), while video-based models have detected autism-related behaviours with high concordance to clinician assessments (31).

Moreover, AI has already transformed radiology and pathology through tasks such as image classification, segmentation, and triage. AI applications in medical imaging span a wide range of specialties, from detecting diverticulitis on CT, retinal haemorrhages in CT scans, and quantify joint damage in rheumatoid arthritis radiographs to tools like BrainNERD are extracting structured data from head CT reports to support large-scale analysis (32, 33). Deep learning systems have shown promise in ophthalmology, dermatology, pathology, and radiology, uses demonstrated in diabetic retinopathy screening, cancer detection, and ECG interpretation (34-38). In oncology, AI-derived histologic features are being explored for improved risk stratification, and LLMs have been tested as support tools in precision oncology, offering novel but not always reliable treatment suggestions (31). Together, these examples highlight how AI can enhance diagnostic workflows by accelerating triage and providing decision support.

While challenges remain, these applications illustrate the growing role of AI in moving clinical practice toward more efficient and personalized care. The future applications of AI in medical practice are extensive. For example, AI-guided acquisition could enable non-experts to obtain diagnostic-quality ultrasounds (39), while echocardiographic quantification and ejection fraction assessment may be automated (40, 41). In pathology, digital platforms could pre-screen slides and highlight suspicious areas for review (42, 43).

Beyond diagnosis, generative models enhance image quality, reconstruct low-dose CT or accelerated MRI scans, and create synthetic pathological or radiological images to augment training datasets. These advances can improve diagnostic accuracy while reducing patient risk and scanning time. Generative AI extends its capabilities with multimodal LLMs that can generate full-text radiology reports. Early

studies show that LLMs fine-tuned on radiology data can produce coherent draft reports, helping standardize and speed up workflows, though radiologist oversight remains essential to prevent errors. AI in imaging is evolving from task-specific detection toward comprehensive interpretation and workflow support. Collectively, these tools have the potential to streamline workflows, reduce inter-observer variability, lessen physician workload, and increase throughput in both high- and low-resource settings. While results are encouraging, boosting sensitivity, reducing reporting times, and enabling precision medicine, clinical validation and human oversight remain critical before routine adoption.

Clinical decision support systems

Generative AI is extending the scope of clinical decision support beyond diagnosis to treatment planning and care management. Modern LLMs can synthesize data from guidelines, clinical trials, biomedical literature, and factor in patient-specific factors such as comorbidities or genetics to provide tailored treatment summaries. LLMs show particular promise in evaluating complex therapeutic trade-offs, such as balancing efficacy and adverse effects in precision oncology, polypharmacy, or chronic disease management (44). By presenting options in accessible language, they can also enhance shared decision-making between clinicians and patients.

By integrating imaging, genomic, and clinical data, AI models can identify prognostic and predictive markers that guide tailored therapeutic strategies. For example, deep learning applied to histopathology has been shown to predict genetic mutations and treatment responses in cancer, supporting more personalized care pathways (45). However, continuous benchmarking is required: in one study of 2,044 oncology-related questions, GPT-4 outperformed other LLMs but still displayed variable performance across subdomains, underscoring the importance of validation before clinical use (46).

Beyond oncology, AI has been applied to risk prediction and early intervention. Risk prediction using AI has been explored in multiple scenarios, including early detection of sepsis (47), targeted screening for hepatitis C (48), and paediatric intensive care to forecast neurologic morbidity (49). Most studies report encouraging results, highlighting the potential of these tools to support timely interventions and improve patient outcomes.

Generative AI is also being applied in acute care settings to support triage and critical decision-making. In emergency departments, AI-driven triage systems have been shown to improve patient risk stratification, identify critical cases earlier, and reduce waiting times, though alignment with clinician judgment remains essential (50). AI-assisted ECG interpretation has been shown to detect ST-elevation myocardial infarction (STEMI) more efficiently, reducing treatment delays, and demonstrating clear potential to improve triage and outcomes in acute coronary syndromes (51). AI has also enhanced

trauma care training, with guidance systems improving the quality of FAST ultrasound examinations performed by novice operators (52).

These developments highlight both the potential and limitations of AI in supporting clinical decision-making. Generative AI-enabled clinical decision support systems hold potential to improve therapeutic decision-making, personalize treatment strategies, and optimize resource use. Yet safe adoption depends on rigorous validation, integration of interpretability safeguards, and ensuring that final accountability remains with the clinician. While performance can rival clinicians in selected domains, challenges of reliability, explainability, and accountability persist. The most realistic role for generative AI in the near term is as a diagnostic safety net and supportive tool, expanding clinician capacity, surfacing overlooked possibilities, and moving practice closer to true precision medicine, but always under professional oversight.

AI IN PUBLIC HEALTH

Unlike clinical practice, which focuses on individual patient care, public health addresses health at the population level. Its core functions include health promotion, surveillance, health protection, population health assessment, disease and injury prevention, and emergency preparedness and response. Together, these activities form the backbone of resilient health systems and are vital for improving population well-being. Although the use of generative AI in public health is much less common and unexplored, it has immense potential to strengthen each of these functions and improve the speed, reach, and effectiveness of interventions (53).

Epidemiology and surveillance

Public health surveillance has traditionally relied on manual data collection and analysis, processes that are time-consuming and prone to delays or errors. The integration of new data sources and AI techniques now offers opportunities to detect emerging health threats more rapidly, generate finer-grained insights into disease patterns, and monitor risk factors with greater precision.

AI-powered approaches can process and analyse data streams in real time, offering timely and actionable intelligence. For example, during the COVID-19 pandemic AI tools were used to track transmission by combining electronic health records, news reports, and social media data (54). Syndromic surveillance platforms such as SENTINEL apply natural language processing to millions of tweets daily, predicting outbreaks and displaying geographic and temporal patterns on interactive dashboards (55). Similarly, AI applied to free-text death certificates has enabled earlier identification of drug overdose deaths than traditional coding systems (56).

In behavioural epidemiology, models can analyse data from mobile apps, wearables, and social media to track diet, physical activity, mobility, and even sentiments or beliefs and mental health issues (57-59). These tools also evaluate the impact of interventions and model trade-offs, linking behavioural insights to disease prevalence for a more holistic picture of population health.

Examples of AI use in public health service provision remain limited, and most current applications are still at the pilot or research stage. However, the above examples illustrate how AI can make epidemiology and surveillance faster, more accurate, and more comprehensive by drawing on diverse data sources. This enables earlier detection of threats, richer insights into risk factors, and timelier public health responses. With careful attention to data quality, privacy, and validation, AI has the potential to complement traditional methods and support the development of more resilient, evidence-driven surveillance systems.

Disease Prevention & Health Promotion

Generative AI also has applications in prevention, screening, and outreach. AI can support proactive case-finding by generating prioritized lists for screening in conditions such as hepatitis C, tuberculosis, diabetes, and chronic kidney disease, while incorporating risk and equity considerations. During the COVID-19 vaccination campaign, for instance, AI systems analysed demographic and geographic information to help identify optimal locations for vaccination sites, improving access and coverage (60, 61). Therefore, such use of AI tools has increased equitable access to healthcare and resources such as vaccination (62).

Furthermore, AI is emerging as a powerful tool for public communication. Conversational AI tools, such as the WHO's COVID-19 chatbot on WhatsApp, demonstrate how real-time, AI-powered platforms can answer questions, provide guidance on prevention, and direct the public to reliable resources (63). Evidence shows that these systems are effective in addressing misinformation and strengthening public trust in health communication (64). Generative AI also offers opportunities to move towards precision public health, offering a more personalized experience, ensuring that the right intervention reaches the right population at the right time (65). For example, sentiment analysis of social media content has been used to identify groups with mixed attitudes towards tobacco, allowing targeted campaigns to focus on those most likely to benefit (66). Similar techniques have also been applied to suicide prevention and mental health awareness (67).

Beyond communication, AI can analyse qualitative information, from hotline calls, community health worker notes, or patient feedback to highlight emerging concerns and guide the design of more responsive public health programs.

While these applications demonstrate clear promise, their long-term impact will depend on rigorous evaluation, responsible use of data, and integration into existing public health infrastructure. Continued research and collaboration are needed to ensure that generative AI enhances prevention and health promotion without introducing new risks or inequities.

Organizational Performance and Administrative Efficiency

Public health systems rely on regulations and accountability mechanisms that ensure transparency but often create heavy clerical workloads. Generative AI can ease this burden by automating document review, summarizing large volumes of text, and organizing data, allowing staff to focus on higher-value tasks.

For example, instead of manually reviewing hundreds of public comments on a policy proposal, AI tools can filter duplicates, extract key themes, and produce concise summaries for faster decision-making. Similarly, generative AI can draft grants, reports, and policies from rough notes, and natural language-to-code tools can simplify data analysis for both technical and non-technical staff. These applications have the potential to improve efficiency, reduce errors, and free staff to work at the top of their professional capacity.

MEDICAL EDUCATION AND TRAINING

Generative AI is reshaping medical education by supporting personalized learning and learning support, simulation, continuous professional development, assessments and curriculum review (68, 69). At the undergraduate level, introducing AI literacy early helps prepare future physicians to critically engage with these technologies (70). Training should go beyond technical knowledge to include awareness of ethical issues, algorithmic bias, and patient safety, while also emphasizing the enduring humanistic values of medicine (71). Case-based learning that pairs traditional clinical reasoning with AI-assisted outputs can strengthen reflective judgment and encourage judicious use of new tools. AI should be seen as a companion rather than a threat, supporting knowledge application and critical reasoning (72). Although AI systems can speed up personalized learning and feedback, they also pose risks of disinformation if teachers and learners do not possess the needed literacy to critically assess AI-generated content and there is overreliance without proper oversight (73).

At the postgraduate level, AI literacy must be strengthened to prepare physicians for specialty-specific applications. Training modules can address rapidly advancing areas such as cardiology, oncology, and infectious diseases, where AI is increasingly used for diagnostics, treatment planning, and predictive analytics (74). Case simulations that integrate generative AI as a “collaborator” or “challenger” can

stimulate deeper clinical reasoning and higher-order thinking, while reinforcing the principle that AI should augment, not override clinical judgment (72). The MedBiquitous AI Advisory Committee (2023) has already published global guidelines for competency-based AI education, which can be adapted to the Sri Lankan postgraduate context to ensure structured and outcome-focused training.

For practicing clinicians, CPD in AI is essential, particularly for those trained before the digital era (75). Modular programs can focus on practical applications such as AI-assisted guideline verification, documentation, patient education, and data interpretation. Workshops should highlight both benefits and limitations, reinforcing AI as an aid rather than a substitute for clinical expertise. Ethical priorities including data privacy, bias mitigation, and accountability must be central (76). Accrediting AI-related CPD and embedding it into lifelong learning frameworks can strengthen physician competence while ensuring adoption remains ethical, inclusive, and patient-centred.

MEDICAL RESEARCH AND DRUG DISCOVERY

Artificial intelligence is reforming medical research by enabling the analysis of large, complex datasets that surpass human capacity for integration and interpretation (77). Applications range from mining electronic health records (EHRs) and biomedical literature to identifying novel disease associations, stratifying patients in precision medicine, and accelerating genomic and proteomic research (78-80). In translational research, machine learning facilitates hypothesis generation, pattern recognition, and simulation studies, reducing the time and cost required to move from bench to bedside. AI also contributes to streamlining grant applications by automating literature reviews, detecting research trends, and assisting with proposal development, thereby reducing administrative burden and improving competitiveness. In public health, AI is applied to spatial modelling, risk prediction, surveillance, and disease forecasting, including the modelling of epidemics and pandemics (81). AI also supports real-world evidence generation by linking diverse data sources, thereby informing clinical guidelines, policy, and public health strategies (82).

Within medical research, drug discovery is among the most rapidly advancing areas of AI application (83). Deep learning models have demonstrated the ability to screen millions of compounds, predict drug-target interactions, and design novel molecules with optimized pharmacological properties (84). In addition, synthetic datasets and simulation platforms are being developed to model biological processes in low-resource settings, enabling researchers to explore early-stage hypotheses and drug discovery pathways without requiring extensive laboratory infrastructure. AI also accelerates drug repurposing by uncovering new therapeutic uses for existing medications, a particularly valuable approach in emerging infections and rare diseases (85). Furthermore, in clinical trials, AI can enhance

protocol design, identify eligible patient cohorts, and predict safety signals, thereby improving trial efficiency and reducing costs. Despite this promise, challenges persist, including data quality limitations, interpretability of complex models, integration and workforce training costs, variations in the regulatory landscape creating difficulties, and there is a need for robust ethical and regulatory frameworks before widespread adoption.

HEALTH SYSTEM ADMINISTRATION

Generative AI is increasingly being applied to streamline administrative processes and optimize the use of healthcare resources. By reducing manual tasks, improving efficiency, and supporting better decision-making, these tools can strengthen health system performance while alleviating staff burden (86).

Workforce Management

AI systems can analyse historical staffing patterns, availability, and workload data to generate optimized nurse and clinician schedules. This reduces conflicts, ensures adequate shift coverage, and helps minimize fatigue and burnout. Predictive rostering can further support workforce planning, lower overtime and improve staff retention.

Administrative Processes

Generative AI can automate repetitive but essential tasks such as patient appointment scheduling, billing, and claims processing (87). Algorithms can forecast patient flow to allocate appointment slots effectively, send reminders to reduce no-shows, and accelerate claims validation to reduce administrative delays. Virtual assistants and chatbots extend these benefits by answering routine questions on billing or paperwork, improving patient engagement and freeing staff to focus on complex issues.

Data Analysis and Reporting

AI can process large volumes of administrative and clinical data to identify inefficiencies, forecast resource needs, and support compliance reporting. Natural language processing and large language models (LLMs) can transform raw data or draft notes into structured reports, making information more accessible for healthcare managers and policymakers.

Resource and Supply Chain Optimization

In supply chain management, AI-driven models have been piloted for vendor-managed inventory and pharmaceutical logistics, showing improved forecasting of medication and blood product demand,

reduced inventory errors, and greater procurement efficiency (88, 89). For resource optimization, similar approaches are being applied to hospital bed management and broader resource allocation, critical in improving access and efficiency, especially in rural and underserved areas (90, 91). These tools improve forecasting of medication and blood product demand, reduce inventory errors, and enhance procurement efficiency.

HARNESSING AI FOR HEALTHCARE TRANSFORMATION IN SRI LANKA

Artificial intelligence (AI) holds significant promise for strengthening health systems in low- and middle-income countries (LMICs), where resource constraints, shortages of specialized expertise, and inequitable access to services remain persistent challenges (92). By leveraging software-based solutions, AI can deliver cost-effective innovations that reduce reliance on expensive equipment and infrastructure, while enabling earlier diagnosis, more personalized care, and improved patient engagement (93). In particular, AI-based tools are increasingly recognized for their potential to expand access in underserved areas, support vulnerable populations, and enhance public health preparedness (93). Evidence from LMICs demonstrates that AI can play a transformative role in screening, treatment planning, patient communication, epidemiological forecasting, and maternal-child health, offering practical pathways for improving both efficiency and equity in healthcare delivery. Similarly, generative AI has the potential to address several pressing challenges in Sri Lanka's health system, particularly those related to limited workforce capacity, high patient loads, and gaps service provision, resource management and access to care.

Improving access to healthcare

Generative-AI chatbots and messaging tools can expand reach where clinicians are scarce, offering multilingual health information, triage, reminders, and rapid answers that clinicians can later review. AI-supported messaging programmes can be deployed to improve patient care and follow-up through automated communication combined with human escalation, a model that has proven valuable in low-resource settings. Beyond this, AI can help overcome infrastructure limitations by substituting costly hardware with affordable software-based innovations (e.g., apps for vision testing or temperature monitoring), thereby improving service access in resource-constrained LMIC environments. Importantly, such tools can extend services to geographically isolated and rural communities, where traditional health facilities may be limited. By reducing waiting times through automated triage and preliminary screening, AI systems can streamline patient pathways and optimize clinic flow. Moreover, AI-enabled telehealth and decision-support platforms can broaden access to specialist expertise nationwide, minimizing disparities between urban tertiary hospitals and peripheral facilities. Together, these applications highlight AI's potential to enhance equity, efficiency, and reach in healthcare delivery.

Enhancing disease prevention and early diagnosis

AI is increasingly being used to strengthen screening and early diagnosis pathways in LMICs. For example, Thailand's national diabetic retinopathy program successfully deployed deep learning systems at primary-care sites to enable real-time image grading and referral, allowing earlier detection of vision-threatening disease and reducing the need for scarce ophthalmology specialists (94). Generative AI

tools also hold potential for diagnostic decision support, synthesizing multimodal inputs such as clinical notes, imaging, and laboratory results into case summaries that can assist frontline providers.

Beyond diagnosis, AI can identify at-risk populations for targeted screening, support risk stratification for non-communicable and infectious diseases, and enable prevention strategies. Predictive analytics and early warning systems can model disease progression or outbreak patterns, allowing timely interventions before conditions escalate. Importantly, in resource-limited settings, AI could reduce the costs of screening and treatment planning for conditions requiring advanced expertise or equipment that may be unavailable in rural hospitals making it particularly relevant for Sri Lanka's health system.

Optimizing utilization of human and other resources

Sri Lanka faces significant constraints in healthcare resources, including a limited workforce and infrastructure, making AI a valuable tool to optimize their use. AI can optimize healthcare system efficiency by improving scheduling, hospital flow, and supply management. It would support streamlining administrative processes through automation of routine documentation, correspondence, and other repetitive tasks. These applications not only reduce the workload of the healthcare team but also lessen the time and cognitive effort required for record-keeping and administrative. As a result, healthcare professionals are freed to focus more on complex decision-making and direct patient care. By alleviating administrative burdens, AI has the potential to improve clinician efficiency, satisfaction, and the overall quality of patient interactions.

Beyond workforce efficiency, AI can optimize broader healthcare resources by predicting patient admissions, managing bed occupancy, and reducing overcrowding. Machine learning models support pharmaceutical supply chains through accurate demand forecasting, minimizing shortages and wastage. AI also enhances use of infrastructure such as operating theatres, ICUs, and diagnostic equipment by streamlining scheduling and anticipating demand. Together, these applications improve the efficient use of staff, medicines, and facilities, strengthening system resilience and cost-effectiveness.

Addressing unmet healthcare needs of stigmatised and marginalised groups

In Sri Lanka, stigma remains a major barrier to accessing care for both mental health conditions and stigmatized illnesses such as HIV, sexually transmitted infections (STIs), and substance use disorders (95). National surveys indicate that more than one in ten Sri Lankans experience common mental disorders, yet only a fraction receive appropriate care due to shortages of psychiatrists and widespread social stigma around help-seeking (96). Similarly, marginalized groups such as men who have sex with men (MSM) and people living with HIV face barriers to timely diagnosis and treatment because of discrimination and confidentiality concerns (97).

AI-powered conversational agents and chatbots offer a discreet and accessible platform for support, allowing individuals to seek guidance without fear of judgment. Evidence from LMICs shows that such tools can provide confidential, on-demand assistance for depression, anxiety, and stress, while also offering psychoeducation and referral options. In the Sri Lankan context, these platforms could deliver culturally adapted, multilingual support to individuals reluctant to seek face-to-face care, while also extending outreach to vulnerable populations. By creating stigma-free entry points into the health system, AI can complement human services and help narrow Sri Lanka's treatment gap in mental health and marginalized care.

Capacity building and medical education

Sri Lanka faces persistent shortages of specialist educators and uneven distribution of training opportunities across medical schools and postgraduate programs. AI offers an avenue to strengthen workforce development by providing scalable, consistent, and accessible training tools. Simulation-based platforms powered by AI can expose undergraduates to complex clinical scenarios, improving diagnostic reasoning and procedural confidence even in settings with limited faculty supervision (98). Automated feedback systems can provide individualized learning support, helping students and trainees identify knowledge gaps and track progress.

For clinicians, AI-enabled continuing professional development (CPD) modules can deliver personalized learning pathways, adapting content to subspecialty needs and evolving clinical practice (99). In resource-limited contexts like Sri Lanka, this could mitigate disparities in access to expert educators, ensure more uniform training standards, and enhance lifelong learning. Such approaches align with international evidence that AI-supported education can improve training quality while addressing faculty shortages.

ETHICAL CONCERNS AND PRINCIPLES

Medical practice has long been guided by the four pillars of medical ethics, autonomy, beneficence, non-maleficence, and justice which provide the foundation for ethical decision-making and patient care (100). These principles ensure that patients retain control over their choices, that clinicians act in their best interests, that harm is avoided, and that care is delivered fairly and equitably across all groups. However, the growing integration of generative AI into medicine is reshaping the context in which these principles are applied. While AI offers opportunities to enhance efficiency, accuracy, and personalization of care, it also introduces new ethical challenges that complicate traditional notions of responsibility, consent, fairness, and trust.

The World Health Organization's guidance on Ethics and Governance of AI for Health underscores that adoption must be anchored in ethical principles and robust governance to prevent harm and inequity (101). Six core principles are emphasized: protecting autonomy through informed consent, privacy, and clinician control; ensuring well-being and safety via validation and monitoring; promoting transparency and explainability; assigning clear accountability with mechanisms for oversight; fostering inclusiveness and equity through representative data and fair access; and maintaining responsiveness and sustainability by adapting to evolving health needs, addressing affordability, workforce impacts, and environmental considerations.

ETHICAL CONCERNS IN USING AI IN CLINICAL PRACTICE

The integration of generative AI into clinical care brings both opportunities and ethical challenges. To ensure safe, equitable, and responsible adoption, key areas of concern must be addressed systematically.

Autonomy and informed consent

In clinical settings, AI directly influences patient care, making ethical safeguards critical. Autonomy and informed consent remain central: patients must be clearly informed whenever AI contributes to diagnosis, treatment planning, or care decisions, and clinicians must retain responsibility for explaining its role and limitations (102).

Validation and safety

As models performing well in controlled development may falter in real-world practice, a problem known as dataset shift or model drift. Without rigorous validation, these tools may cause unintended harm. Ethical deployment requires a staged approach: pre-deployment validation with external datasets, pilot testing in real-world environments, and structured post-market surveillance to monitor ongoing performance and safety.

Bias and equity

Furthermore, generative AI systems risk perpetuating existing inequities when trained on datasets that are non-representative or skewed toward high-resource settings (103). Generative AI systems risk perpetuating existing inequities when trained on datasets that are non-representative or skewed toward high-resource settings. Unequal representation by race, socioeconomic status, geography, or language can lead to poorer performance for marginalized groups and widen disparities in care (104). Practical strategies include active inclusion of underrepresented populations, equity audits, and continuous real-world performance monitoring to identify and correct biases early (105). Beyond data limitations, inequitable access to AI itself raises concerns of justice, as well-resourced hospitals may benefit disproportionately while underfunded facilities are left behind. To address these risks, inclusive data practices, equity audits, and real-world performance monitoring are essential. Complementary policy measures such as subsidizing AI for resource-limited settings, open-source initiatives, and regulations prioritizing equitable access are needed to ensure that the benefits of AI are shared fairly across populations (106).

Accountability and professional responsibility

In clinical practice, Accountability must remain with licensed professionals and institutions. The integration of AI into clinical workflows blurs traditional lines of accountability. Many AI systems particularly large language models operate as “black boxes,” with decision-making processes that are difficult to interpret. This opacity can erode both clinician confidence and patient trust. To mitigate this, AI tools must provide transparent documentation of their intended purpose, data sources, and limitations including mechanisms that enable users to trace and interrogate outputs. In this way, explainability and transparency serve not only as safeguards for safety and accountability but also as prerequisites for maintaining trust in the clinician–patient relationship.

If harm results from an AI-supported decision, responsibility must be clearly delineated. Current literature emphasizes that ultimate responsibility should remain with licensed professionals and institutions, supported by robust clinical governance structures. Oversight mechanisms including audits, incident reporting, and clear escalation pathways are necessary to safeguard patient safety and maintain public trust (107).

Human connection and empathy

Another concern is the potential erosion of the human relationship at the heart of healthcare. While AI can process data and generate recommendations, it cannot replicate the empathy and relational nuance that clinicians bring to patient interactions (108). Over-reliance on AI risks depersonalizing care, particularly in sensitive contexts such as psychiatry, paediatrics, or end-of-life care. Ethical use requires positioning AI as a complement to, rather than a substitute for, human compassion and judgment.

ETHICAL CONCERNS IN USING AI IN PUBLIC HEALTH

In public health, AI is increasingly applied to surveillance, outbreak prediction, and behavioural monitoring. Here, the ethical focus shifts toward equity, justice, and collective benefit vs a right to privacy, confidentiality and autonomy of an individual. For example, AI-driven surveillance systems can detect outbreaks in near real time but raise privacy concerns when drawing from social media or unstructured sources. Data federation offers a partial solution by enabling collaborative analysis across institutions without centralising sensitive datasets, thereby reducing risks of privacy breaches. Nonetheless, even with such techniques, the core ethical challenge remains how to maximise population-level benefit while safeguarding individual rights.

Bias is also a risk. If AI tools rely on incomplete or skewed datasets, vulnerable groups may be overlooked in disease prevention or resource allocation. Both academic commentaries and public health agencies emphasize the need for inclusive data practices and algorithmic transparency to mitigate these risks (109).

Another concern is public trust and communication. Generative AI chatbots have been deployed during pandemics to counter misinformation, but they must be accurate, culturally sensitive, and accessible in multiple languages and literacy levels. Finally, equitable access is key: without supportive regulation and subsidization, only wealthier systems may benefit from advanced AI for surveillance and health promotion, worsening global health inequities.

ETHICAL CONCERNS IN USING GENERATIVE AI IN MEDICAL EDUCATION

The adoption of generative AI within medical education offers vast potential, adaptive learning, realistic simulations, and customized instruction. However, navigating its ethical implications is essential to ensure it enhances rather than diminishes educational integrity and quality.

Academic integrity and fairness

One of the most immediate concerns is the potential misuse of generative AI by students to complete assignments, assessments, or even research projects without genuine engagement. Such practices risk undermining learning outcomes and academic honesty. Integrity hinges on designing assessments that require critical thinking and human insight, and that cannot be easily gamed by AI (110). Educators must also be supported with training to detect and address inappropriate use, ensuring fairness across cohorts.

Transparency, explainability, and AI literacy

Many AI systems, particularly large language models, operate as “black boxes,” producing outputs without clear reasoning. If students rely on these tools without understanding their limitations, there is a risk of fostering blind dependence rather than critical appraisal. Curricula should therefore embed AI literacy as a core competency, teaching students how algorithms function, the nature of their training data, and the potential for errors or bias. Beyond technical understanding, students should learn to question AI outputs, integrate them with human judgment, and reflect on their ethical implications in practice (111).

Equity and access

Access to AI-enhanced educational tools is uneven across institutions and regions. Well-resourced universities may adopt advanced AI platforms, while students in low-resource settings risk being left behind. Studies from Asia and elsewhere highlight that many medical students lack formal exposure to AI, compounding disparities in preparedness for AI-enabled practice. To mitigate this, open-access tools, cross-institutional collaborations, and targeted digital literacy initiatives are needed to ensure equitable learning opportunities. Policies should prioritize reducing gaps so that the benefits of AI in education are shared fairly across all training environments.

Privacy, consent, and data use

AI systems in education often rely on sensitive data, whether patient cases used for simulation or learner data used to tailor instruction. Ethical use requires robust safeguards, including anonymization, encryption, and secure storage, alongside transparent governance policies (111). Students and patients alike should be informed when their data are being used for AI-driven educational purposes and consent should be obtained where appropriate. Protecting privacy is essential not only for legal compliance but also for fostering trust in AI-enabled learning platforms.

Student perspectives and human-centred learning

Evidence from surveys of medical students shows cautious optimism: learners appreciate the potential of AI to enhance education but raise concerns about accuracy, data privacy, and over-reliance (112). These perspectives must inform curriculum design, ensuring that AI complements rather than replaces human teaching. Human qualities such as empathy, mentorship, and professional role modelling, remain irreplaceable. Over-reliance on AI risks depersonalizing education, just as in clinical care; thus, AI should be framed as a supportive tool that enhances but does not supplant human interaction.

Institutional innovation and competency frameworks

Some institutions have begun integrating structured AI ethics modules into their curricula, encouraging students to debate real-world dilemmas around privacy, bias, and professional responsibility. Scoping

reviews suggest that AI education should be competency-based, with domains spanning foundational understanding, applied practice, experimental innovation, and ethical reasoning. Such frameworks can guide curriculum development across pre-clinical, clinical, and research stages, ensuring that graduates are not only skilled in AI use but also capable of critically evaluating its risks and implications.

ETHICAL CONCERNS IN USING AI IN MEDICAL RESEARCH

AI has the potential to accelerate discovery in genomics, drug development, and clinical trials, yet its integration into research raises critical ethical challenges that must be addressed to maintain trust and scientific integrity.

Data governance and confidentiality

AI research relies on vast, sensitive datasets, often combining clinical, genomic, and imaging records. Beyond standard privacy protections, research settings must anticipate risks such as re-identification of anonymized data and unauthorized secondary use. Governance frameworks must therefore extend to secure storage, controlled data sharing, and oversight mechanisms that ensure compliance with local and international laws, while balancing the need for scientific collaboration.

Consent and secondary use of data

Traditional informed consent models are often inadequate for AI-driven research, where data may later be reused in contexts unforeseen at the time of collection. Participants should be informed not only of the immediate study objectives but also of potential downstream uses of their data in AI applications. Mechanisms such as broad or tiered consent, alongside transparent communication about risks and safeguards, are necessary to preserve autonomy and maintain public trust.

Reproducibility and scientific integrity

One of the central challenges in AI research is ensuring reproducibility. Opaque algorithms, poorly documented datasets, and selective reporting undermine credibility. Ethical research practice demands rigorous documentation of datasets, model parameters, and validation methods to enable independent verification. Open science approaches, including data sharing where appropriate and transparent reporting standards, are key to aligning AI research with established norms of scientific integrity.

Bias, generalizability, and equity of benefit

AI models trained on homogeneous cohorts risk generating misleading outputs that fail to generalise across diverse populations. In medical research, this can distort clinical trial results or drug development pipelines, ultimately disadvantaging underrepresented groups. Ethical practice requires deliberate inclusion of diverse datasets and equity audits. Moreover, beyond data representation, fairness extends

to equitable access to the benefits of AI-enabled research. Concentration of AI capacity in resource-rich institutions risks widening global disparities unless mitigated by open-source initiatives, subsidized infrastructure, or equitable research collaborations.

Regulatory gaps and adaptive oversight

Current regulatory frameworks for research were not designed for AI systems that evolve over time. Ethical governance requires adaptive oversight that accounts for “model drift,” cross-border data transfers, and the dual-use potential of AI systems. Ethics review boards and regulators must be equipped with AI-specific expertise to evaluate not only technical validity but also broader societal risks.

Sustainability and long-term monitoring

Finally, AI research does not end at model development. Continuous monitoring, post-study audits, and adaptive governance mechanisms are necessary to ensure that systems remain valid and beneficial as health needs, datasets, and technologies evolve. This also includes attention to the environmental impact of computationally intensive research, which should be weighed against potential health benefits

CONCLUSION

Generative AI holds immense promise across clinical practice, public health, education, and research, but its adoption must be guided by core ethical principles. Safeguarding autonomy, privacy, transparency, accountability, safety, and equity remains essential to maintain trust and fairness. While clinical care demands patient-centred responsibility, public health emphasizes balancing collective benefit with individual rights; education requires integrity and AI literacy; and research calls for robust governance and inclusivity. Ensuring responsible use of AI will require adaptive governance, continuous oversight, and inclusive dialogue so that innovation strengthens, rather than undermines, the ethical foundations of medicine.

REGULATORY AND LEGAL FRAMEWORK FOR USE OF AI IN HEALTHCARE

GLOBAL REGULATORY LANDSCAPE FOR AI IN HEALTHCARE

Across jurisdictions, the regulation of artificial intelligence in healthcare largely falls under existing medical device frameworks, particularly those governing Software as a Medical Device (SaMD). While this provides an entry point for oversight, many AI applications in healthcare such as administrative tools, wellness apps, or software providing clinical recommendations to qualified professionals often fall outside these regulations.

Recent global discussions, including those from the AI Governance Day 2024 report by the International Telecommunication Union, highlight that while existing medical device regulations provide a foundation, healthcare AI governance must extend further to cover data governance, algorithmic accountability, and oversight of computational resources (113). Regulation needs to be both dynamic and adaptable, ensuring transparency, fairness, and sustainability as technologies evolve. Importantly, many countries remain in the early stages of establishing AI governance, with frameworks often driven more by industry than by comprehensive policy. For healthcare, this underscores the importance of developing standardized benchmarks, strong international cooperation, and context-specific adaptations, particularly to support low-and middle-income countries in adopting AI responsibly while safeguarding patient rights and public trust.

Regulatory considerations by the World Health Organization

The World Health Organization (WHO) has outlined six key regulatory considerations for AI in health (114).

1. **Documentation and transparency:** Documentation and transparency are essential, with developers required to pre-specify and record the intended medical purpose, datasets, parameters, metrics, and any deviations or updates to allow tracing of the development steps. A risk-based approach should be used to determine the depth of record-keeping.
2. **Risk management and AI systems development lifecycle approaches:** A total product lifecycle approach is recommended, encompassing pre-market development, post-market surveillance, and change management, with proactive risk management addressing threats such as algorithmic bias, underfitting, and cybersecurity vulnerabilities.
3. **Intended use, and analytical and clinical validation:** The intended use of AI systems must be clearly defined, with rigorous analytical and clinical validation supported by transparent documentation of training and external datasets.
4. **Data quality:** Data quality must be ensured, with mechanisms to detect and mitigate errors or biases and the development of strong data ecosystems to facilitate access to reliable datasets.

5. Privacy and data protection: Privacy and data protection must be integrated into system design, with compliance programmes aligned with local laws and international best practices, covering cybersecurity and potential harms.
6. Engagement and collaboration: Engagement and collaboration among developers, regulators, clinicians, and patients is considered vital to streamline oversight, promote transparency, and accelerate safe innovation. Collectively, these principles highlight WHO's focus on a risk-based, evidence-driven, and collaborative approach to regulating AI in health.

Regulatory frameworks in selected countries

At present, most countries adopt a hybrid model of binding regulation and soft-law guidance. The latter includes professional guidelines, voluntary standards, and industry codes of conduct, which can adapt quickly to technological advances but lack enforceability. This places responsibility on both developers and users to ensure ethical, safe, and effective use of AI.

In the United States, the FDA regulates AI/ML tools under its Software as a Medical Device (SaMD) framework, with the AI/ML-based SaMD Action Plan (2021) highlighting good machine learning practices, transparency, bias mitigation, and real-world performance monitoring, alongside draft guidance for adaptive algorithms through a “Predetermined Change Control Plan” (115). In the United Kingdom, NICE's Evidence Standards Framework (2019) provides benchmarks for digital health evaluation, while the MHRA's Software and AI as a Medical Device Change Programme (2021) addresses cybersecurity, post-market monitoring, and challenges of evolving algorithms (116). In Australia, the Therapeutic Goods Administration (TGA) revised its Medical Devices Regulation (2002) in 2021 to classify SaMDs using a risk-based approach, excluding certain low-risk applications, while professional bodies have issued ethical guidance for clinical use (117). The European Union, however, has moved away from its initial soft law approach towards more stringent regulation with its AI Act proposed in 2021, which classifies healthcare AI as “high risk” and mandates strong data governance, transparency, and human oversight, complementing the existing EU Medical Device Regulation (118)

In Singapore, the National AI Strategy sets priorities for safe adoption, complemented by AI Verify (2022), the world's first governance testing framework based on 11 global ethical principles (119). In healthcare, the Health Sciences Authority applies lifecycle-based SaMD guidelines (2022) requiring clear purpose, safeguards, and post-market monitoring, while the Ministry of Health's AI in Healthcare Guidelines (2021) provide practical standards for developers and implementers. Together, these initiatives position Singapore as a frontrunner in embedding both regulatory oversight and ethical guidance for AI in healthcare.

SRI LANKA’S CURRENT REGULATORY AND GOVERNANCE FRAMEWORK FOR AI IN MEDICINE

In Sri Lanka, the regulation of artificial intelligence in healthcare is still evolving and is currently shaped by a mix soft-law approaches, and existing statutory instruments. The Personal Data Protection Act (PDPA, No. 9 of 2022) has been enacted but is not yet operational although the Data Protection Authority is currently being established as the Regulator , meaning that governance presently relies on a combination of professional guidelines, ethical oversight, and policy frameworks such as the National Digital Health Guidelines and Standards (NDHGS) 2.0 and the National AI Strategy.

The National Digital Health Guidelines and Standards (NDHGS) mandate that digital health solutions including AI-enabled systems must undergo independent evaluation and piloting before implementation (120). They require comprehensive documentation, including installation and user manuals, as well as provisions for updates and maintenance. Interoperability with the National Electronic Health Record (EHR) is mandatory, using standardized datasets and terminologies such as SNOMED-CT, ICD, and HL7 FHIR. Hosting of central health databases must occur within government-approved facilities, and security audits are required to ensure data protection and system integrity. Ethical approval is also mandatory for research use of identifiable patient data (120).

The draft National AI Strategy (2024) complements these efforts by setting a broader governance framework for responsible AI use across sectors, including healthcare (121). It emphasizes principles of transparency, accountability, fairness, and explainability, alongside a risk-based lifecycle approach covering development, deployment, and post-market monitoring. It also highlights the need to improve data quality and governance, develop national open data platforms, and promote multi-stakeholder collaboration across government, academia, industry, and civil society. Importantly, the strategy recognizes the importance of international cooperation and alignment with global standards.

Sri Lanka’s Personal Data Protection Act (PDPA) No. 9 of 2022 establishes the regulatory framework governing the collection, processing, and use of personal data by Controllers defined under the Act, with most health-related information designated as special categories of personal data (122). The Act permits the processing of such data under defined circumstances, including for public health purposes, the control of communicable diseases, emergency response, medical diagnosis and treatment, within lawful basis for processing, while also enabling processing for scientific or historical research within purpose specification criteria, provided that appropriate safeguards are in place. These safeguards include technical and organisational measures such as encryption, pseudonymisation, anonymisation, and access controls, designed to uphold confidentiality and integrity in order to prevent loss, destruction, damage or unauthorized or unlawful processing of personal data and protect the rights of

data subjects. In the context of generative AI in medicine, the PDPA implies that data-driven applications may be lawfully pursued only where they align with processing principles such as lawfulness, purpose specification, data minimization, accuracy, defined periods for retention, integrity & confidentiality, transparency and accountability

Furthermore, the PDPA currently requires that personal and health data managed by public authorities be stored and processed on servers within Sri Lanka, with cross-border transfers allowed only if these categories are identified for transfer under ministerial adequacy decisions and regulatory oversight. Private entities may use local cloud providers as processors or host data abroad subject to appropriate safeguards, ensuring that privacy and data protection obligations remain enforceable under Sri Lankan law. The PDPA amendment Bill of 2025, currently before Parliament makes significant changes to this provision and would address challenges related to data storage and cloud hosting, providing greater flexibility for the secure use of international platforms while maintaining robust protections for data subjects through safeguards, such as instruments for transfer to specified by the Data Protection Authority.

CONCLUSION

From a global perspective, AI governance is shifting from high-level ethical principles to more enforceable frameworks, yet the landscape remains fragmented and uneven. While initiatives such as the EU AI Act and the Council of Europe’s Framework Convention represent important steps toward binding regulation, most countries especially in the Global South, still lack comprehensive policies. The G20 has emphasized that AI should be harnessed “responsibly for good and for all,” with a focus on reducing inequality and supporting the Sustainable Development Goals (123). Similarly, the International Telecommunication Union’s, AI Governance Day 2024 report underscored the need to avoid fragmented governance, strengthen technical standards, and ensure inclusivity, noting that 85% of member states do not yet have AI-specific regulations (113).

For Sri Lanka, global lessons highlight the importance of adopting internationally harmonized standards while tailoring them to local needs. This approach can help the country overcome resource constraints, prioritize applications in healthcare, education, and public services, and ensure that governance frameworks remain inclusive, risk-based, and adaptable. At present, Sri Lanka’s regulatory approach to AI in medicine is guided by digital health standards. Policy frameworks that emphasize documentation, validation, data quality, privacy, and responsible governance, with data protection laws will provide additional safeguards. However, explicit AI-specific regulations for healthcare are still in development.

Moving forward, it is timely for stakeholders including medical associations, professional colleges, the Sri Lanka Medical Council, the Ministry of Health, and the digital industry to collaborate in shaping comprehensive regulatory frameworks that balance innovation with patient safety. The publication of this consensus document by the Ceylon College of Physicians marks an important first step and a foundation for future action.

AI IN HEALTHCARE: LIMITATIONS AND CHALLENGES IN THE SRI LANKAN CONTEXT

While generative AI has immense potential to transform healthcare, its deployment is constrained by several limitations and practical challenges. These concerns are universal, but they carry particular weight in countries such as Sri Lanka, where regulatory structures, infrastructure, and technical capacity remain limited.

Data dependency, quality and security

Generative AI systems depend heavily on the availability of large, representative, and high-quality datasets. If datasets are biased, incomplete, or poorly curated, outputs will mirror these flaws, producing skewed or unsafe recommendations. This remains a critical limitation Sri Lanka, where comprehensive, high-quality health data are scarce and fragmented across multiple institutions. Health data are often fragmented across institutions, poorly standardized, and incomplete. Electronic health record (EHR) adoption is patchy, and many records still rely on paper-based documentation, reducing interoperability and consistency. These weaknesses risk producing biased or unreliable outputs, limiting the accuracy and safety of AI-driven recommendations.

In addition, sensitive health data are vulnerable to breaches and unauthorized access due to limited cybersecurity infrastructure. Weak data governance frameworks and poor institutional practices further exacerbate risks, undermining both public trust and clinical reliability.

Bias, equity, and access

AI models trained predominantly on data from high-resource countries risk producing inequitable outcomes for underrepresented populations. Marginalized groups by geography, language, or socioeconomic status may receive poorer care if models are not validated in diverse local contexts (124). This inequity is compounded by disparities in access: advanced AI systems are often available only to well-funded hospitals or private-sector institutions, leaving public hospitals at a disadvantage. Addressing this requires inclusive data practices, equity audits, and, at the policy level, government support to subsidize AI deployment in under-resourced settings.

Transparency, explainability, and trust

In Sri Lanka, public trust in doctors and the healthcare system remains deeply ingrained, with patients often deferring to medical professionals in decision-making. While this trust is a strength, it can also amplify risks if AI-generated outputs are adopted without sufficient scrutiny.

Generative AI systems often function as “black boxes,” with decision processes that are opaque even to clinicians (125). Without clear explainability, patients may either unquestioningly accept AI-assisted decisions assuming that what is endorsed by a doctor or hospital is infallible or conversely, lose confidence if errors or inconsistencies are revealed. These risks are heightened by relatively low levels of health literacy in the population, which makes it difficult for patients to understand the role and limitations of AI in their care. For healthcare workers, limited AI literacy and training may further reduce their ability to critically evaluate or contextualize AI recommendations, raising the danger of both over-reliance and misuse. Building public trust will therefore require not only transparent, explainable AI systems but also investment in clinician training and public education to ensure that AI strengthens rather than undermines the longstanding trust between patients and the health system (126).

Human-AI collaboration and skills gap

In Sri Lanka, one of the major barriers to responsible adoption of generative AI in healthcare is the limited digital and IT literacy among healthcare professionals. Most doctors, nurses, and allied health staff receive little or no formal training in digital health, data governance, or AI applications during their professional education. As a result, many are ill-prepared to critically assess or effectively integrate AI tools into practice. This skills gap creates a dual risk: reluctance to engage with AI due to uncertainty and mistrust, or conversely, blind reliance without adequate oversight. Addressing this requires structured training programmes, integration of AI and digital health into medical curricula, and continuing professional development opportunities that build capacity in both technical understanding and ethical use. Crucially, AI systems must be designed to complement human expertise, ensuring that accountability, empathy, and professional judgment remain central to care delivery (127).

Deskilling and loss of clinical expertise

The increasing use of AI in healthcare raises concerns about deskilling, where clinicians may lose critical diagnostic, reasoning, and procedural skills due to over-reliance on technology (128). This risk is particularly relevant in training contexts, where reduced exposure to independent decision-making could impair the development of future healthcare professionals (129). In the longer term, overdependence on AI may undermine system resilience if clinicians are unable to function effectively during technical failures or when AI outputs are inaccurate. To mitigate this, AI should be framed as a supportive tool rather than a substitute, with curricula and clinical training designed to preserve core skills while enhancing AI literacy.

Validation, safety, and reliability

Models that perform well in controlled development often falter in real-world clinical settings, particularly where patient demographics or disease patterns differ from the training data. This dataset shift or model drift can result in unsafe recommendations. In Sri Lanka, where formal processes for

clinical validation of AI tools are not yet established, risks are heightened. Continuous monitoring, pilot testing, and structured post-market surveillance are critical but remain resource-intensive and underdeveloped.

Resource intensity and environmental burden

Developing and deploying generative AI solutions in Sri Lanka faces several systemic barriers. On the development side, building and maintaining large-scale AI systems requires substantial computational power, data storage, and technical expertise, resources that are scarce and expensive in the local context. The shortage of advanced AI engineering skills, compounded by ongoing brain drain, further limits the country's ability to design, adapt, and sustain robust AI solutions.

Even when pilot projects are successfully launched, integrating AI into existing health systems presents another layer of difficulty where scalability remains a critical challenge. Sri Lanka's digital health landscape is often siloed, with underfunded initiatives, poor interoperability between platforms, and inconsistent adoption across facilities. Expanding AI projects beyond pilot stages demands consistent infrastructure, reliable internet access, adequate hardware, and sustainable financing conditions not uniformly present across the country's health sector. The state health sector, including major institutions and government agencies as well as rural and underserved regions, will face significant constraints in adopting and maintaining AI systems. Without coordinated investment, interoperability standards, and long-term strategic planning, even successful AI applications risk remaining isolated initiatives rather than system-wide solutions.

Regulatory gaps and governance

Globally, frameworks such as the EU AI Act and FDA guidelines on Software as a Medical Device (SaMD) are shaping oversight of AI in health. In Sri Lanka, however, regulation remains underdeveloped. The Personal Data Protection Act (No. 9 of 2022) provides a framework for privacy and data governance, but its enforcement has been delayed and practical mechanisms for compliance are not yet robust. Furthermore, there is no AI-specific governance framework to address issues of algorithmic bias, accountability, or adaptive models that evolve after deployment. Weak enforcement of existing health technology regulations, combined with the absence of dedicated oversight bodies, leaves significant blind spots. Without clear accountability and redress mechanisms, patients and clinicians face uncertainty in cases of harm, limiting safe adoption of AI in healthcare.

Intellectual property and ethical concerns

The question of who owns AI-generated content, whether clinical notes, research outputs, or educational material remains unresolved. In Sri Lanka, where intellectual property protections are inconsistently enforced, this poses additional legal uncertainty. Ethical issues, including consent for secondary use of data and the potential commercialization of public health information, remain under-examined.

RECOMMENDATIONS FOR RESPONSIBLE AI INTEGRATION

The CCP endorses the adoption of AI in healthcare where it is proven to be safe, ethical, and equitable, enhances the capacity of clinicians to deliver high-quality care, and contributes to both improved patient outcomes and a supportive working environment for healthcare professionals. AI should not be viewed as a replacement for human knowledge, skills, or judgment, but rather as a complementary tool to enhance efficiency and support decision-making.

1. Strengthening data governance and security

- 1.1. Establish national standards for health data collection, storage, and interoperability, ensuring datasets are representative, standardized, and curated for quality.
- 1.2. Accelerate implementation of the Personal Data Protection Act (No. 9 of 2022) with clear mechanisms for enforcement in healthcare.
- 1.3. Mandate bias audits and transparent disclosure of mitigation strategies in all AI health applications.
- 1.4. Improve cybersecurity infrastructure and institutional practices to safeguard against data breaches, unauthorized access, and misuse of sensitive health information.
- 1.5. Promote federated learning and privacy-preserving techniques to enable multi-institutional collaboration without compromising patient confidentiality.

2. Addressing bias, equity, and access

- 2.1. Require inclusive dataset design that reflects Sri Lanka's ethnic, linguistic, socioeconomic, and geographic diversity.
- 2.2. Introduce equity audits and independent bias evaluations for all AI health applications prior to deployment.
- 2.3. Develop policies to subsidize AI adoption in the state sector and under-resourced hospitals, reducing inequities between private and public healthcare.
- 2.4. Encourage open-source and collaborative AI projects to democratize access and reduce dependency on proprietary tools.

3. Capacity building

- 3.1. Establish an AI in Medical Education Task Force to guide curriculum integration and governance across institutions.
- 3.2. Integrate AI and digital health literacy into undergraduate, postgraduate, and CPD curricula across all health professions, with a focus on data governance, algorithmic bias, and ethical deployment.

- 3.3. Foster interdisciplinary collaboration through structured platforms that unite clinicians, computer scientists, ethicists, public health experts, and policymakers to co-develop AI solutions relevant to local contexts.
- 3.4. Invest in workforce development by supporting specialized training, fellowships, and partnerships with international universities and industry, reducing the current skills gap and brain drain.
- 3.5. Encourage institutional readiness by strengthening hospital IT systems, ensuring interoperability, and embedding AI champions within clinical teams.
- 3.6. Design AI systems to augment human expertise and preserve clinical skills, ensuring clinicians remain accountable and resilient in decision-making.

4. Improving infrastructure, integration, and scalability

- 4.1. Invest in national digital health infrastructure, focusing on reliable internet access, interoperable systems, and sustainable financing.
- 4.2. Promote regulatory sandboxes that allow controlled testing and gradual scaling of AI projects within state health institutions.
- 4.3. Develop long-term strategic planning for scaling pilot projects, ensuring that successful innovations extend beyond isolated initiatives.
- 4.4. Encourage partnerships with international organizations and private sector actors to strengthen technical infrastructure while safeguarding national data sovereignty.

5. Ensuring safety, regulation, and governance

- 5.1. Develop national AI guidelines for health that align with international principles while being adapted to Sri Lanka's health priorities. These should emphasize transparency, documentation, risk management, and lifecycle oversight of AI systems.
- 5.2. Contextualize global frameworks (such as the EU AI Act, FDA SaMD approach, and WHO guidance) within Sri Lanka's legal and regulatory environment, including integration with the PDPA once enforced.
- 5.3. Establish a dedicated regulatory mechanism within the Ministry of Health or NMRA to evaluate, approve, and monitor AI-enabled tools. This body should ensure compliance with safety, validation, ethical standards, and ongoing post-market surveillance.
- 5.4. Ensure transparent governance in which regulatory processes should include civil society and professional representation, with mechanisms for public oversight and accessible avenues for redress.
- 5.5. Promote regulatory sandboxes to enable controlled testing and iterative refinement of AI solutions, balancing innovation with patient protection.

- 5.6. Adopt a staged validation framework which requires all AI applications to undergo analytical testing, independent clinical validation, and structured post-deployment monitoring to ensure safe and reliable performance. Establish systems to detect model drift, unsafe recommendations, or declining accuracy, with clear procedures for corrective action.
- 5.7. Define accountability frameworks clearly assigning responsibility to developers, institutions, and clinicians for harm caused by AI use, ensuring liability is transparent and enforceable.
- 5.8. Establish a monitoring and evaluation framework within the governance structure, to ensure objective assessment of programme with measurable outcomes supported by key performance indicators. This would enable transparent oversight and accountability.

6. Medical research and innovation

- 6.1. Require standardised reporting for AI-assisted research and conference submissions, including disclosure of tool identity, version, prompts used (where appropriate), level of assistance, verification steps, and impact on conclusions.
- 6.2. Establish institutional AI research governance committees to review high-risk projects, ensure ethical oversight, and verify compliance with data protection and medical device regulations.
- 6.3. Mandate external validation on representative datasets and prospective evaluation in contexts where patient safety could be affected, alongside post-deployment monitoring to detect performance drift or harms.
- 6.4. Promote transparency of datasets, model logic, and validation methods to ensure reproducibility and scientific integrity.
- 6.5. Promote openness of models, code, and evaluation reports where feasible, while balancing intellectual property and privacy through secure sharing mechanisms such as trusted research environments.
- 6.6. Prohibit use of identifiable patient data without consent and require disclosure and evaluation of synthetic data.
- 6.7. Maintain human oversight for all AI-generated outputs. Require author attestation of verification and train peer reviewers to evaluate AI-assisted methods.
- 6.8. Provide AI literacy training for clinicians and researchers, embed patient and public involvement in study design, and encourage interdisciplinary collaboration.

7. Enhancing transparency, public trust, and patient empowerment

- 7.1. Clear disclosure and explainability are essential; all AI systems must document their intended use, data sources, and limitations in a manner that is accessible to both clinicians and patients.
- 7.2. Strengthen informed consent protocols to explicitly note when AI is used in diagnosis or treatment. Clinicians must ensure patients understand AI's supportive role, its potential benefits, and its limitations, thereby safeguarding autonomy and accountability.

- 7.3. Launch national communication campaigns to educate the public on AI in healthcare, emphasizing that AI is a supportive tool rather than a replacement for medical professionals. Campaigns should address benefits, risks, and safeguards in multiple languages and literacy levels to build trust.
- 7.4. Promote fair access to AI tools across both state and private sectors through subsidies, public–private partnerships, and donor-supported initiatives, reducing inequities between well-resourced and under-resourced institutions.
- 7.5. Engage civil society, patient advocacy groups, and community representatives in AI governance structures, embedding transparency, inclusivity, and accountability in decision-making. Patients should have representation in committees and co-design processes to ensure that AI tools are developed to be user-friendly, respectful, and responsive to patient needs.

CONTRIBUTIONS

The development of this white paper was the result of a collaborative effort involving clinicians and external experts including medical educationists, researchers, experts in regulatory affairs, digital health and medical informatics ensuring that the document reflects both international best practices and local healthcare priorities.

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The AI Task Force will be responsible for providing overall direction for the Ceylon College of Physicians on the use of AI in medicine, guiding the framework, building consensus on recommendations, and ensuring alignment with the College's mission and values.

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REFERENCES

1. Muthukrishnan N, Maleki F, Ovens K, Reinhold C, Forghani B, Forghani R. Brief History of Artificial Intelligence. *Neuroimaging Clin N Am*. 2020;30(4):393–9.
2. Xu Y, Liu X, Cao X, Huang C, Liu E, Qian S, et al. Artificial intelligence: A powerful paradigm for scientific research. *Innovation (Camb)*. 2021;2(4):100179.
3. Moor J. The Dartmouth College Artificial Intelligence Conference: The Next Fifty Years. *AI Magazine*. 2006;27(4):87–91.
4. Maadi M, Akbarzadeh Khorshidi H, Aickelin U. A Review on Human-AI Interaction in Machine Learning and Insights for Medical Applications. *Int J Environ Res Public Health*. 2021;18(4).
5. Jones LD, Golan D, Hanna SA, Ramachandran M. Artificial intelligence, machine learning and the evolution of healthcare: A bright future or cause for concern? *Bone Joint Res*. 2018;7(3):223–5.
6. Supriyono, Wibawa AP, Suyono, Kurniawan F. Advancements in natural language processing: Implications, challenges, and future directions. *Telematics and Informatics Reports*. 2024;16:100173.
7. Sonicki Z. Large multi-modal models - the present or future of artificial intelligence in medicine? *Croat Med J*. 2024;65(1):1–2.
8. Choudhury M, Elyoseph Z, Fast NJ, Ong DC, Nsoesie EO, Pavlick E. The promise and pitfalls of generative AI. *Nature Reviews Psychology*. 2025;4(2):75–80.
9. Reis FJJ, Alaiti RK, Vallio CS, Hespanhol L. Artificial intelligence and Machine Learning approaches in sports: Concepts, applications, challenges, and future perspectives. *Braz J Phys Ther*. 2024;28(3):101083.
10. Choi RY, Coyner AS, Kalpathy-Cramer J, Chiang MF, Campbell JP. Introduction to Machine Learning, Neural Networks, and Deep Learning. *Transl Vis Sci Technol*. 2020;9(2):14.
11. LeCun Y, Bengio Y, Hinton G. Deep learning. *Nature*. 2015;521(7553):436–44.
12. Esteva A, Robicquet A, Ramsundar B, Kuleshov V, DePristo M, Chou K, et al. A guide to deep learning in healthcare. *Nat Med*. 2019;25(1):24–9.
13. Hirschberg J, Manning CD. Advances in natural language processing. *Science*. 2015;349(6245):261–6.
14. Locke S, Bashall A, Al-Adely S, Moore J, Wilson A, Kitchen GB. Natural language processing in medicine: A review. *Trends in Anaesthesia and Critical Care*. 2021;38:4–9.
15. Budd J. Burnout Related to Electronic Health Record Use in Primary Care. *J Prim Care Community Health*. 2023;14:21501319231166921.
16. Mallawarachchi S. Clinical Documentation Practice: A Study of Doctors' Medical Documentary Compliance in Government Hospitals in Gampaha District, Sri Lanka. *Hosp Top*. 2022;100(3):105–11.
17. De Silva Rajaratne H, Dahanayake D, R.M W, B.D.J.V P. Clinical audit on record keeping standards at a specialized child psychiatry unit in Sri Lanka 2021.

18. Ali SR, Dobbs TD, Hutchings HA, Whitaker IS. Using ChatGPT to write patient clinic letters. *Lancet Digit Health*. 2023;5(4):e179–e81.
19. Zaretsky J, Kim JM, Baskharoun S, Zhao Y, Austrian J, Aphinyanaphongs Y, et al. Generative Artificial Intelligence to Transform Inpatient Discharge Summaries to Patient-Friendly Language and Format. *JAMA Network Open*. 2024;7(3):e240357–e.
20. Garcia P, Ma SP, Shah S, Smith M, Jeong Y, Devon-Sand A, et al. Artificial Intelligence-Generated Draft Replies to Patient Inbox Messages. *JAMA Netw Open*. 2024;7(3):e243201.
21. Liu TL, Hetherington TC, Stephens C, McWilliams A, Dharod A, Carroll T, et al. AI-Powered Clinical Documentation and Clinicians' Electronic Health Record Experience: A Nonrandomized Clinical Trial. *JAMA Netw Open*. 2024;7(9):e2432460.
22. Duggan MJ, Gervase J, Schoenbaum A, Hanson W, Howell JT, III, Sheinberg M, et al. Clinician Experiences With Ambient Scribe Technology to Assist With Documentation Burden and Efficiency. *JAMA Network Open*. 2025;8(2):e2460637–e.
23. Kocaballi AB, Ijaz K, Laranjo L, Quiroz JC, Rezazadegan D, Tong HL, et al. Envisioning an artificial intelligence documentation assistant for future primary care consultations: A co-design study with general practitioners. *J Am Med Inform Assoc*. 2020;27(11):1695–704.
24. Microsoft and Epic Expand Strategic Collaboration with Integration of Azure OpenAI Service 2023 [Available from: <https://www.epic.com/epic/post/microsoft-and-epic-expand-strategic-collaboration-with-integration-of-azure-openai-service/>].
25. Singhal K, Tu T, Gottweis J, Sayres R, Wulczyn E, Amin M, et al. Toward expert-level medical question answering with large language models. *Nature Medicine*. 2025;31(3):943–50.
26. Shea Y-F, Lee CMY, Ip WCT, Luk DWA, Wong SSW. Use of GPT-4 to Analyze Medical Records of Patients With Extensive Investigations and Delayed Diagnosis. *JAMA Network Open*. 2023;6(8):e2325000–e.
27. Tsai CM, Lin CR, Kuo HC, Cheng FJ, Yu HR, Hung TC, et al. Use of Machine Learning to Differentiate Children With Kawasaki Disease From Other Febrile Children in a Pediatric Emergency Department. *JAMA Netw Open*. 2023;6(4):e237489.
28. Tong WJ, Wu SH, Cheng MQ, Huang H, Liang JY, Li CQ, et al. Integration of Artificial Intelligence Decision Aids to Reduce Workload and Enhance Efficiency in Thyroid Nodule Management. *JAMA Netw Open*. 2023;6(5):e2313674.
29. Konz N, Buda M, Gu H, Saha A, Yang J, Chłędowski J, et al. A Competition, Benchmark, Code, and Data for Using Artificial Intelligence to Detect Lesions in Digital Breast Tomosynthesis. *JAMA Network Open*. 2023;6(2):e230524–e.
30. Ngeow AJH, Moosa AS, Tan MG, Zou L, Goh MMR, Lim GH, et al. Development and Validation of a Smartphone Application for Neonatal Jaundice Screening. *JAMA Netw Open*. 2024;7(12):e2450260.

31. Barami T, Manelis-Baram L, Kaiser H, Ilan M, Slobodkin A, Hadashi O, et al. Automated Analysis of Stereotypical Movements in Videos of Children With Autism Spectrum Disorder. *JAMA Netw Open*. 2024;7(9):e2432851.
32. Gunturkun F, Bakir-Batu B, Siddiqui A, Lakin K, Hoehn ME, Vestal R, et al. Development of a Deep Learning Model for Retinal Hemorrhage Detection on Head Computed Tomography in Young Children. *JAMA Network Open*. 2023;6(6):e2319420–e.
33. Torres-Lopez VM, Rovenolt GE, Olcese AJ, Garcia GE, Chacko SM, Robinson A, et al. Development and Validation of a Model to Identify Critical Brain Injuries Using Natural Language Processing of Text Computed Tomography Reports. *JAMA Network Open*. 2022;5(8):e2227109–e.
34. De Fauw J, Ledsam JR, Romera-Paredes B, Nikolov S, Tomasev N, Blackwell S, et al. Clinically applicable deep learning for diagnosis and referral in retinal disease. *Nature Medicine*. 2018;24(9):1342–50.
35. Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, et al. Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. *JAMA*. 2016;316(22):2402–10.
36. Pei Q, Luo Y, Chen Y, Li J, Xie D, Ye T. Artificial intelligence in clinical applications for lung cancer: diagnosis, treatment and prognosis. *Clin Chem Lab Med*. 2022;60(12):1974–83.
37. Huang X, Wang H, She C, Feng J, Liu X, Hu X, et al. Artificial intelligence promotes the diagnosis and screening of diabetic retinopathy. *Front Endocrinol (Lausanne)*. 2022;13:946915.
38. Shafi S, Parwani AV. Artificial intelligence in diagnostic pathology. *Diagn Pathol*. 2023;18(1):109.
39. Pesapane F, Codari M, Sardanelli F. Artificial intelligence in medical imaging: threat or opportunity? Radiologists again at the forefront of innovation in medicine. *Eur Radiol Exp*. 2018;2(1):35.
40. Zhang J, Gajjala S, Agrawal P, Tison GH, Hallock LA, Beussink-Nelson L, et al. Fully Automated Echocardiogram Interpretation in Clinical Practice. *Circulation*. 2018;138(16):1623–35.
41. Ouyang D, He B, Ghorbani A, Yuan N, Ebinger J, Langlotz CP, et al. Video-based AI for beat-to-beat assessment of cardiac function. *Nature*. 2020;580(7802):252–6.
42. Vaassen F, Hazelaar C, Vaniqui A, Gooding M, van der Heyden B, Canters R, et al. Evaluation of measures for assessing time-saving of automatic organ-at-risk segmentation in radiotherapy. *Phys Imaging Radiat Oncol*. 2020;13:1–6.
43. Steiner DF, Nagpal K, Sayres R, Foote DJ, Wedin BD, Pearce A, et al. Evaluation of the Use of Combined Artificial Intelligence and Pathologist Assessment to Review and Grade Prostate Biopsies. *JAMA Netw Open*. 2020;3(11):e2023267.
44. Khosravi M, Zare Z, Mojtabaiean SM, Izadi R. Artificial Intelligence and Decision-Making in Healthcare: A Thematic Analysis of a Systematic Review of Reviews. *Health Serv Res Manag Epidemiol*. 2024;11:23333928241234863.

45. Coudray N, Ocampo PS, Sakellaropoulos T, Narula N, Snuderl M, Fenyö D, et al. Classification and mutation prediction from non-small cell lung cancer histopathology images using deep learning. *Nature Medicine*. 2018;24(10):1559–67.
46. Rydzewski NR, Dinakaran D, Zhao SG, Ruppin E, Turkbey B, Citrin DE, et al. Comparative Evaluation of LLMs in Clinical Oncology. *NEJM AI*. 2024;1(5).
47. Kamran F, Tjandra D, Heiler A, Virzi J, Singh K, King JE, et al. Evaluation of Sepsis Prediction Models before Onset of Treatment. *NEJM AI*. 2024;1(3):AIoa2300032.
48. Dagan N, Magen O, Leshchinsky M, Makov-Assif M, Lipsitch M, Reis BY, et al. Prospective Evaluation of Machine Learning for Public Health Screening: Identifying Unknown Hepatitis C Carriers. *NEJM AI*. 2024;1(2):AIoa2300012.
49. Horvat CM, Barda AJ, Perez Claudio E, Au AK, Bauman A, Li Q, et al. Interoperable Models for Identifying Critically Ill Children at Risk of Neurologic Morbidity. *JAMA Network Open*. 2025;8(2):e2457469–e.
50. Taylor RA, Chmura C, Hinson J, Steinhart B, Sangal R, Venkatesh AK, et al. Impact of Artificial Intelligence–Based Triage Decision Support on Emergency Department Care. *NEJM AI*. 2025;2(3):AIoa2400296.
51. Lin C, Liu W-T, Chang C-H, Lee C-C, Hsing S-C, Fang W-H, et al. Artificial Intelligence–Powered Rapid Identification of ST-Elevation Myocardial Infarction via Electrocardiogram (ARISE) — A Pragmatic Randomized Controlled Trial. *NEJM AI*. 2024;1(7):AIoa2400190.
52. Chiu I-M, Lin C-HR, Yau F-FF, Cheng F-J, Pan H-Y, Lin X-H, et al. Use of a Deep-Learning Algorithm to Guide Novices in Performing Focused Assessment With Sonography in Trauma. *JAMA Network Open*. 2023;6(3):e235102–e.
53. Panch T, Pearson-Stuttard J, Greaves F, Atun R. Artificial intelligence: opportunities and risks for public health. *Lancet Digit Health*. 2019;1(1):e13–e4.
54. Dong J, Wu H, Zhou D, Li K, Zhang Y, Ji H, et al. Application of Big Data and Artificial Intelligence in COVID-19 Prevention, Diagnosis, Treatment and Management Decisions in China. *J Med Syst*. 2021;45(9):84.
55. Şerban O, Thapen N, Maginnis B, Hankin C, Foot V. Real-time processing of social media with SENTINEL: A syndromic surveillance system incorporating deep learning for health classification. *Information Processing & Management*. 2019;56(3):1166–84.
56. Ward PJ, Rock PJ, Slavova S, Young AM, Bunn TL, Kavuluru R. Enhancing timeliness of drug overdose mortality surveillance: A machine learning approach. *PLoS One*. 2019;14(10):e0223318.
57. Saha K, Yousuf A, Boyd RL, Pennebaker JW, De Choudhury M. Social Media Discussions Predict Mental Health Consultations on College Campuses. *Sci Rep*. 2022;12(1):123.
58. Wang S, Liang C, Gao Y, Ye Y, Qiu J, Tao C, et al. Social media insights into spatio-temporal emotional responses to COVID-19 crisis. *Health Place*. 2024;85:103174.

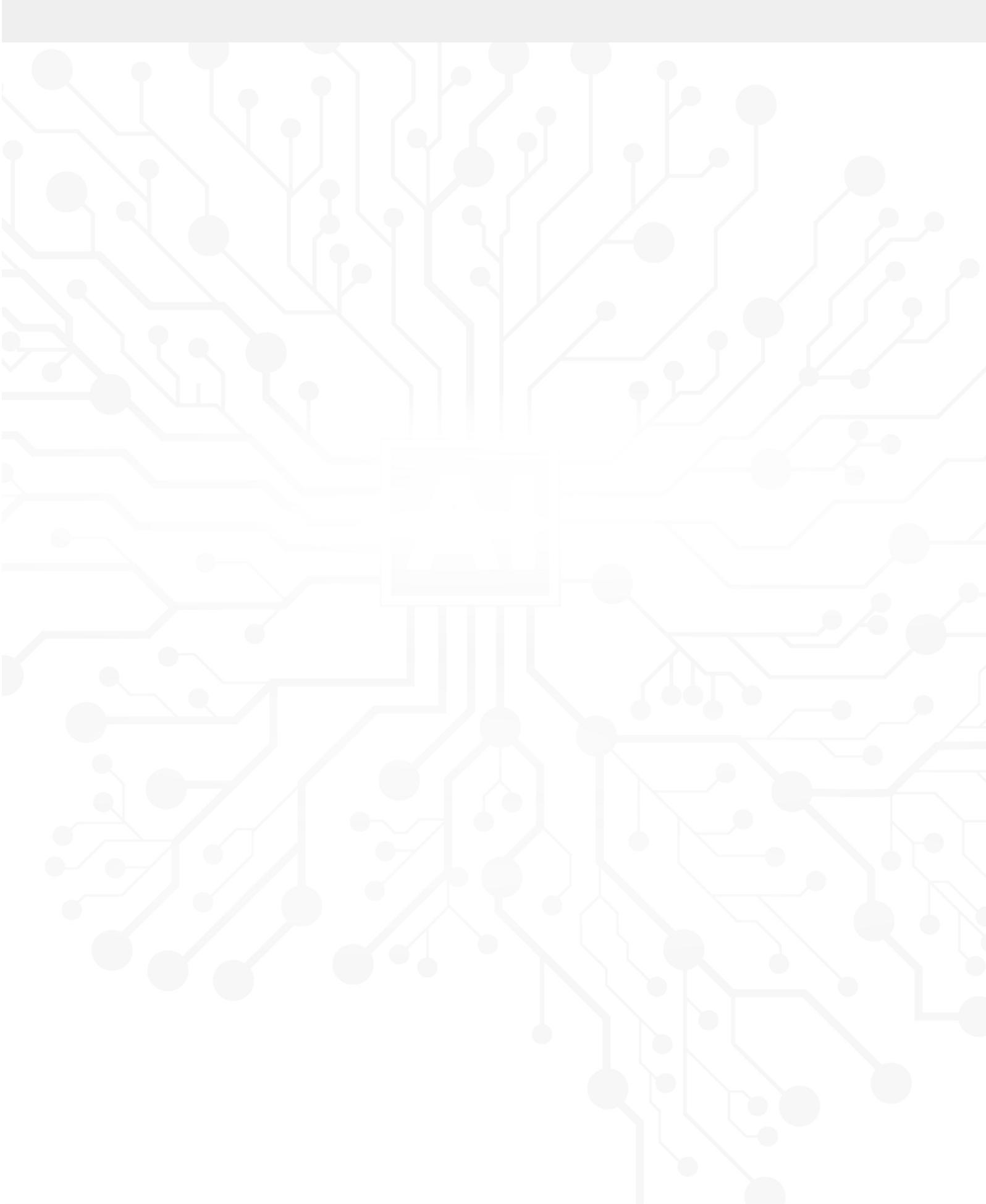
59. Mac Aonghusa P, Michie S. Artificial Intelligence and Behavioral Science Through the Looking Glass: Challenges for Real-World Application. *Ann Behav Med.* 2020;54(12):942–7.
60. Mellado B, Wu J, Kong JD, Bragazzi NL, Asgary A, Kawonga M, et al. Leveraging Artificial Intelligence and Big Data to Optimize COVID-19 Clinical Public Health and Vaccination Roll-Out Strategies in Africa. *Int J Environ Res Public Health.* 2021;18(15).
61. Stein N, Brooks K. A Fully Automated Conversational Artificial Intelligence for Weight Loss: Longitudinal Observational Study Among Overweight and Obese Adults. *JMIR Diabetes.* 2017;2(2):e28.
62. Anjaria P, Asediya V, Bhavsar P, Pathak A, Desai D, Patil V. Artificial Intelligence in Public Health: Revolutionizing Epidemiological Surveillance for Pandemic Preparedness and Equitable Vaccine Access. *Vaccines (Basel).* 2023;11(7).
63. Chatbots against COVID-19: Using chatbots to answer questions on COVID-19 in the user's language: World Health Organisation; 2022 [Available from: <https://www.who.int/news-room/feature-stories/detail/scicom-compilation-chatbot>].
64. Neuhauser L, Kreps GL, Morrison K, Athanasoulis M, Kirienko N, Van Brunt D. Using design science and artificial intelligence to improve health communication: ChronologyMD case example. *Patient Educ Couns.* 2013;92(2):211–7.
65. Khoury MJ, Iademarco MF, Riley WT. Precision Public Health for the Era of Precision Medicine. *Am J Prev Med.* 2016;50(3):398–401.
66. Kreps GL, Neuhauser L. Artificial intelligence and immediacy: designing health communication to personally engage consumers and providers. *Patient Educ Couns.* 2013;92(2):205–10.
67. Shen Y, Zhang W, Chan BSM, Zhang Y, Meng F, Kennon EA, et al. Detecting risk of suicide attempts among Chinese medical college students using a machine learning algorithm. *J Affect Disord.* 2020;273:18–23.
68. Chan KS, Zary N. Applications and Challenges of Implementing Artificial Intelligence in Medical Education: Integrative Review. *JMIR Med Educ.* 2019;5(1):e13930.
69. Gordon M, Daniel M, Ajiboye A, Uraiby H, Xu NY, Bartlett R, et al. A scoping review of artificial intelligence in medical education: BEME Guide No. 84. *Med Teach.* 2024;46(4):446–70.
70. Seth P, Hueppchen N, Miller SD, Rudzicz F, Ding J, Parakh K, et al. Data Science as a Core Competency in Undergraduate Medical Education in the Age of Artificial Intelligence in Health Care. *JMIR Med Educ.* 2023;9:e46344.
71. Knopp MI, Warm EJ, Weber D, Kelleher M, Kinnear B, Schumacher DJ, et al. AI-Enabled Medical Education: Threads of Change, Promising Futures, and Risky Realities Across Four Potential Future Worlds. *JMIR Med Educ.* 2023;9:e50373.
72. Dujeepa D, Samarasekera SSLHTJY. Artificial Intelligence in Health Professional Training: A companion or an adversary? *The Asia Pacific Scholar.* 2024;9(1):1–2.

73. Rincón EHH, Jimenez D, Aguilar LAC, Flórez JMP, Tapia ÁER, Peñuela CLJ. Mapping the use of artificial intelligence in medical education: a scoping review. *BMC Medical Education*. 2025;25(1):526.
74. Bissonnette V, Mirchi N, Ledwos N, Alsidieri G, Winkler-Schwartz A, Del Maestro RF, et al. Artificial Intelligence Distinguishes Surgical Training Levels in a Virtual Reality Spinal Task. *J Bone Joint Surg Am*. 2019;101(23):e127.
75. Charow R, Jeyakumar T, Younus S, Dolatabadi E, Salhia M, Al-Mouaswas D, et al. Artificial Intelligence Education Programs for Health Care Professionals: Scoping Review. *JMIR Med Educ*. 2021;7(4):e31043.
76. Xu Y, Jiang Z, Ting DSW, Kow AWC, Bello F, Car J, et al. Medical education and physician training in the era of artificial intelligence. *Singapore Med J*. 2024;65(3):159–66.
77. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. *Nat Med*. 2019;25(1):44–56.
78. Jha JP, Amgain K, Joshi LR. Use of Artificial Intelligence in Medical Research: A SWOT Analysis. *Kathmandu Univ Med J (KUMJ)*. 2024;22(88):464–70.
79. Aradhya S, Facio FM, Metz H, Manders T, Colavin A, Kobayashi Y, et al. Applications of artificial intelligence in clinical laboratory genomics. *Am J Med Genet C Semin Med Genet*. 2023;193(3):e32057.
80. Mann M, Kumar C, Zeng WF, Strauss MT. Artificial intelligence for proteomics and biomarker discovery. *Cell Syst*. 2021;12(8):759–70.
81. Olawade DB, Wada OJ, David-Olawade AC, Kunonga E, Abaire O, Ling J. Using artificial intelligence to improve public health: a narrative review. *Front Public Health*. 2023;11:1196397.
82. Ramezani M, Takian A, Bakhtiari A, Rabiee HR, Ghazanfari S, Mostafavi H. The application of artificial intelligence in health policy: a scoping review. *BMC Health Serv Res*. 2023;23(1):1416.
83. Nayariseri A, Khandelwal R, Tanwar P, Madhavi M, Sharma D, Thakur G, et al. Artificial Intelligence, Big Data and Machine Learning Approaches in Precision Medicine & Drug Discovery. *Curr Drug Targets*. 2021;22(6):631–55.
84. Gupta R, Srivastava D, Sahu M, Tiwari S, Ambasta RK, Kumar P. Artificial intelligence to deep learning: machine intelligence approach for drug discovery. *Mol Divers*. 2021;25(3):1315–60.
85. Pinzi L, Rastelli G. Molecular Docking: Shifting Paradigms in Drug Discovery. *Int J Mol Sci*. 2019;20(18).
86. Tariq MU, Poulin M, Abonamah AA. Achieving Operational Excellence Through Artificial Intelligence: Driving Forces and Barriers. *Front Psychol*. 2021;12:686624.
87. Fisher S, Rosella LC. Priorities for successful use of artificial intelligence by public health organizations: a literature review. *BMC Public Health*. 2022;22(1):2146.

88. Shen J, Bu F, Ye Z, Zhang M, Ma Q, Yan J, et al. Management of drug supply chain information based on "artificial intelligence + vendor managed inventory" in China: perspective based on a case study. *Front Pharmacol.* 2024;15:1373642.
89. Chen Q, Long P, Dong R, Li C, Mao S. The impact of artificial intelligence on sustainable development performance of public healthcare supply chain-an empirical study based on listed Chinese pharmaceutical companies. *Front Public Health.* 2025;13:1549283.
90. Zhou F. Methods to Improve the Efficiency of Rural Physical Education Teaching Resources Allocation and Utilization in the Context of Artificial Intelligence. *Comput Intell Neurosci.* 2022;2022:3226902.
91. Zhao J, Fu G. Artificial Intelligence-Based Family Health Education Public Service System. *Front Psychol.* 2022;13:898107.
92. Perianez A, Fernandez Del Rio A, Nazarov I, Jane E, Hassan M, Rastogi A, et al. The Digital Transformation in Health: How AI Can Improve the Performance of Health Systems. *Health Syst Reform.* 2024;10(2):2387138.
93. Guo J, Li B. The Application of Medical Artificial Intelligence Technology in Rural Areas of Developing Countries. *Health Equity.* 2018;2(1):174–81.
94. Ruamviboonsuk P, Tiwari R, Sayres R, Nganthavee V, Hemarat K, Kongprayoon A, et al. Real-time diabetic retinopathy screening by deep learning in a multisite national screening programme: a prospective interventional cohort study. *Lancet Digit Health.* 2022;4(4):e235–e44.
95. Fernando SM, Deane FP, McLeod HJ. The delaying effect of stigma on mental health help-seeking in Sri Lanka. *Asia Pac Psychiatry.* 2017;9(1).
96. Deivanayagam TA, Ni Chobhthaigh S, Devakumar D, Patel K, Rannan-Eliya RP. Mental health prevalence, healthcare use and access between 2018 and 2022 in Sri Lanka: an analysis of survey data. *Global Health Research.* Southampton (UK)2024.
97. Navaratna S, Kanda K, Dharmaratne SD, Tennakoon S, Jayasinghe A, Jayasekara N, et al. Awareness and attitudes towards HIV/AIDS among residents of Kandy, Sri Lanka. *AIDS Care.* 2015;27(3):387–91.
98. Dai C-P, Ke F. Educational applications of artificial intelligence in simulation-based learning: A systematic mapping review. *Computers and Education: Artificial Intelligence.* 2022;3:100087.
99. Karunathilake I, de Abrew A. The Impact of Artificial Intelligence in Advancing Continuing Health Professions Development in Southeast Asia. *South-East Asian Journal of Medical Education.* 2025;18(2).
100. Markose A, Krishnan R, Ramesh M. Medical ethics. *J Pharm Bioallied Sci.* 2016;8(Suppl 1):S1–S4.
101. Ethics and governance of artificial intelligence for health:WHO guidance. Geneva: World Health Organisation 2021.

102. Li F, Ruijs N, Lu Y. Ethics & AI: A systematic review on ethical concerns and related strategies for designing with AI in healthcare. *Ai*. 2022;4(1):28–53.
103. Hanna MG, Pantanowitz L, Jackson B, Palmer O, Visweswaran S, Pantanowitz J, et al. Ethical and Bias Considerations in Artificial Intelligence/Machine Learning. *Modern Pathology*. 2025;38(3):100686.
104. Cabitza F, Rasoini R, Gensini GF. Unintended Consequences of Machine Learning in Medicine. *JAMA*. 2017;318(6):517–8.
105. Chin MH, Afsar-Manesh N, Bierman AS, Chang C, Colón-Rodríguez CJ, Dullabh P, et al. Guiding Principles to Address the Impact of Algorithm Bias on Racial and Ethnic Disparities in Health and Health Care. *JAMA Network Open*. 2023;6(12):e2345050–e.
106. Nordling L. A fairer way forward for AI in health care. *Nature*. 2019;573(7775):S103–S5.
107. Polevikov S. Advancing AI in healthcare: A comprehensive review of best practices. *Clin Chim Acta*. 2023;548:117519.
108. Farhud DD, Zokaei S. Ethical Issues of Artificial Intelligence in Medicine and Healthcare. *Iran J Public Health*. 2021;50(11):i–v.
109. Abdelwanis M, Alarafati HK, Tammam MMS, Simsekler MCE. Exploring the risks of automation bias in healthcare artificial intelligence applications: A Bowtie analysis. *Journal of Safety Science and Resilience*. 2024;5(4):460–9.
110. Franco D’Souza R, Mathew M, Mishra V, Surapaneni KM. Twelve tips for addressing ethical concerns in the implementation of artificial intelligence in medical education. *Medical Education Online*. 2024;29(1):2330250.
111. Lu H, Alhaskawi A, Dong Y, Zou X, Zhou H, Ezzi SHA, et al. Patient Autonomy in Medical Education: Navigating Ethical Challenges in the Age of Artificial Intelligence. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*. 2024;61:00469580241266364.
112. Sami A, Tanveer F, Sajwani K, Kiran N, Javed MA, Ozsahin DU, et al. Medical students' attitudes toward AI in education: perception, effectiveness, and its credibility. *BMC Med Educ*. 2025;25(1):82.
113. AI Governance Day – From Principles to Implementation 2024 Report. 2024.
114. Regulatory considerations on artificial intelligence for health. Geneva: World Health Organization; 2023.
115. Harvey HB, Gowda V. How the FDA Regulates AI. *Acad Radiol*. 2020;27(1):58–61.
116. Darzi A. The Regulation of Artificial Intelligence as a Medical Device. Regulatory Horizons Council: London, UK. 2022.
117. Understanding if changes to software-based medical device regulation affect you. 2021.
118. Meszaros J, Minari J, Huys I. The future regulation of artificial intelligence systems in healthcare services and medical research in the European Union. *Front Genet*. 2022;13:927721.

119. Singapore's Approach to AI Governance: Personal Data Protection Commission; [Available from: <https://www.pdpc.gov.sg/help-and-resources/2020/01/model-ai-governance-framework>].
120. The National Digital Health Guidelines and Standards (NDHGS) 2.0 Sri Lanka: Ministry of Health
121. The National AI Strategy. Committee on Formulating a Strategy for Artificial Intelligence (CFSAI); 2024.
122. Personal Data Protection Act, No. 9 of 2022.
123. Radu R. The G20 and Global AI Governance. 2024.
124. Vyas DA, Eisenstein LG, Jones DS. Hidden in Plain Sight - Reconsidering the Use of Race Correction in Clinical Algorithms. *N Engl J Med*. 2020;383(9):874–82.
125. De Sio FS, Mecacci G. Four Responsibility Gaps with Artificial Intelligence: Why they Matter and How to Address them. *Philos. Technol*. 34, 4 (December 2021), 1057–1084. 2021.
126. Obasa AE, Palk AC. Responsible application of artificial intelligence in health care. *S Afr J Sci*. 2023;119(5-6).
127. Upadhyay U, Gradisek A, Iqbal U, Dhar E, Li Y-C, Syed-Abdul S. Call for the responsible artificial intelligence in the healthcare. *BMJ Health & Care Informatics*. 2023;30(1):e100920.
128. Garvey KV, Craig KJT, Russell RG, Novak L, Moore D, Preininger AM, et al. The Potential and the Imperative: the Gap in AI-Related Clinical Competencies and the Need to Close It. *Med Sci Educ*. 2021;31(6):2055–60.
129. Javaheri F, Khajeali N. The Importance of Modification: An Imperative to Incorporate Machine Learning in Medical Education. *J Adv Med Educ Prof*. 2024;12(4):274–5.



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